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INCORPORATING QUALITY IN THE EFFICIENCY ASSESSMENT OF HOSPITALS USING A GENERALIZED DIRECTIONAL DISTANCE FUNCTION APPROACH

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JEL Classification: I12; I18; H75; D22

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Incorporating quality in the efficiency assessment of hospitals using a generalized directional distance function approach

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Abstract

The increasing pressure to cost containment in the public sector and, specifically, in health care provision raises concern on the potential adverse effects on the hospital quality that would imply the existence of an efficiency-effectiveness trade-off. This hypothesis calls for taking into account explicitly the relationship between efficiency and quality when analyzing hospitals' performance. This paper adopts a non-parametric approach to study the whole performance in the provision of hospital services in Italy. We employ a generalized directional distance function that allows incorporating both desirable outputs and undesirable outcomes (i.e. risk-adjusted mortality rates) in the estimation of efficiency, thus enabling for studying hospital performance thoroughly, and assess the impact of integrating quality in the efficiency assessment. We find that including quality does matter. In addition, considering that patients in the Italian National Health System do not directly pay for treatments and, thus, hospitals presumably compete on quality in a catchment area, we also study whether taking into account quality matters in studying spatial dependence in hospital performance.

Keywords: hospital efficiency; directional distance function; undesirable outputs; trade-off effectiveness-efficiency; spatial dependence.

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1. Introduction

Increasing interest has been devoted in recent years to the control and reduction of public expenditures and to improve the efficiency in the healthcare sector. The public debate on the healthcare reforms that have been implemented in several European countries, raised concern on the effects that incentives to improve efficiency may have on the quality in the provision of services and, thus, on the effectiveness (Baicker et al. 2006, Lisi et al. 2020). In fact, incentives to enhance efficiency may force hospitals' management to focus on cost containment at the expense of quality levels, leading to higher undesirable health outcomes, such as higher mortality and readmission rates for some medical procedures. Therefore, a trade-off between efficiency and effectiveness may arise, which is of major concern for the implied adverse social consequences.

Thus, parallel to the increasing budgetary pressures on healthcare providers, a considerable amount of empirical studies have dealt with the association between quality and efficiency in the provision of hospital services using different approaches and with mixed results (Nayar and Ozcan, 2008; Chang et al., 2011; Gok and Sezen, 2013; Yang and Zen, 2014; Martini et al., 2014). Traditional approaches to deal with quality in hospital services involve the use of mortality and readmission rates as measures of effectiveness. Their use in the context of frontier estimation techniques is not methodologically straightforward as mortality and readmissions are undesirable outcomes, i.e. negative output. In fact, such bad outputs are often transformed so as to include them among positive outputs (Hollingsworth and Wildman, 2003; Afonso and St. Aubyn, 2005; Chang et al., 2011; Yang and Zeng, 2014) or treated as inputs (Prior, 2006). In contrast, few studies treat them directly as negative (undesirable) outcomes, employing the Directional Distance Function (DDF) approach (Arocena and Garcia-Prado, 2007; Bilsel and Davutyan, 2014), which however have some limitations. In this paper, we use a more recent development of such method that has several advantages, namely the Generalized Directional Distance Function (GDDF) developed by Cheng and Zervopoulos (2014), to evaluate the overall performance of hospitals, and compare it with the pure efficiency evaluation, thus studying the effect of incorporating quality.

An additional crucial issue, which has been brought up by the reforms of health sectors, is the link among efficiency, quality, and competition, which has been widely debated in both the theoretical and empirical literature on hospital provision. The interest of scholars on such aspects has involved the effect of competition on quality (Propper et al. 2004; 2008; Cooper et al., 2011; Gaynor et al., 2013; 2016; Bloom et al. 2015) or efficiency (Cooper et al., 2012, Gaynor et al., 2013) and, more recently, the existence of spatial dependence in hospitals' behaviour (e.g., Gravelle et al., 2014; Cavalieri et al.; 2017; Longo et al., 2017), with mixed results. The main aspect arising from the very recent theoretical literature (e.g., Brekke et al. 2017) is that, on the one hand, the strategic choice of quality cannot be considered independently from the efficiency of production and, more generally, from the cost characteristics of hospitals' activity and, on the other hand, that the nature of the strategic interdependence among competing hospitals is not univocal. Therefore, in line with the above literature and to provide a deeper analysis of the impact of incorporating quality in the performance assessment, we also investigate the presence of spatial dependence in hospital behaviour, taking into account that the efficient choices can be intertwined with the quality choices. More precisely, we investigate the relationship between hospitals competition and the overall efficient performance of hospitals in terms of both volumes and quality, thus incorporating the potential trade-off between efficiency and effectiveness of care.

We use data on public or private hospitals working on behalf of the Italian National Health System (NHS) in 2010, drawn from the statistical office of the Italian Ministry of Health. In fact, the Italian NHS has been object of an extensive process of reform in the 90s' involving the devolution of health competences to Regions and the reform of financing schemes, which moved the NHS towards quasi-markets to promote competition among hospitals and, thus, enhance their performance (France et al. 2005)[1]. Considering that in such a system, patients do not directly pay for treatments, hospitals presumably compete on quality in a

[1] The devolution of competencies has resulted in marked heterogeneity among regions in the organization of health provision and, in turn in growing differences in terms of efficiency (Martorana, 2017; Cavalieri et al. 2018) and appropriateness (Guccio and Lisi, 2016; De Luca et al. 2019).

catchment area, which may reasonably lead to spatial dependence in the performance of hospitals.

Therefore, the contribution of this paper to the literature consists in studying the impact of incorporating quality both in the evaluation of hospital performance and in the analysis of spatial dependence.

Our results show that incorporating quality does matter. One the one hand, they indicates that the inclusion of quality in the estimation of the frontier is not neutral, and is necessary to avoid misspecification problems, thus allowing for a correct evaluation of hospital performance, in line with Fare et al. (1989) and Prior (2006). On the other hand, its inclusion also affects the assessment of spatial dependence in hospital behaviour. In fact, consistently with the previous literature, our results show that hospital efficiency is not spatially dependent. Conversely, we find evidence of positive spatial correlation in hospital performance, that is, when quality is included as an undesirable outcome.

The remainder of the paper is organised as follows. We describe the methodological framework in Section 2. Section 3 presents the dataset for the empirical analysis. Results are shown in Section 4. Section 5 gathers policy implications and some concluding remarks.

2. Methods

This paper employs a non-parametric frontier estimation technique to measure the efficiency of public hospitals. Frontier estimation techniques are grounded on the efficiency measure defined by Debreu (1951) and Koopmans (1951), and empirically developed by Farrell (1957). Among them, non-parametric techniques have an edge because of their flexibility, as they do not require the definition of the production function and have been commonly used for evaluating efficiency in several economic fields[2]. This class of models use linear programming technique to estimate the efficiency frontier by comparing the available combinations of inputs

[2] Among others, non-parametric frontiers have been used to assess the efficiency of banks (Casu and Girardone, 2010), higher education institutions (Agasisti and Dal Bianco, 2006; 2009; Guccio et al. 2016ab, 2017; Johnes, 2006); municipalities (Montèn and Thater, 2011; Guccio et al. 2019), tourism destinations (Cuccia et al. 2016, 2017; Guccio et al. 2017);, cultural institutions (Pignataro, 2002; Del Barrio-Tellado and Herrero-Prieto, 2019, Guccio et al. 2020abc).

and outputs in the sample. In turn, such models return a relative measure of efficiency (the efficiency score) of each Decision Making Unit (DMU) that represents its distance from the best practise frontier and identifies the potential efficiency improvement for an inefficient DMU to move to the full efficiency frontier, that is the amount of inputs (outputs) that the DMU has to reduce (increase) to be among the best performers. Traditional non-parametric frontier estimators such as the Data Envelopment Analysis (DEA, developed by Charnes, et al. 1978) and the Free Disposal Hull (FDH, DePrins et al. 1984) define outputs as positive objects, which have to be increased to improve DMUs' performance. However, a production process may involve the existence of negative outputs or outcomes (such as pollution, typically, or mortality in the case of health care) which should be considered directly when evaluating DMUs performance to avoid misspecification problems (Färe et al., 1989). Thus, scholars have developed several methods to deal with bad outputs.[3]

In the literature assessing efficiency in health care, undesirable outputs refer mainly to mortality and readmission rates, used to take into account the aspect of quality in the provision. In this strand of literature, undesirable outputs are either: a) transformed in desirable outputs (Afonso and St. Aubyn, 2005; Chang et al., 2011; Yang and Zeng, 2014); b) combined with desirable outputs to compute a life expectancy index to be used as a standard output (Hollingsworth and Wildman, 2003), or c) included among the input set (Prior, 2006)

Recently, Cheng and Zervopoulos (2014), developed a Generalized Directional Distance Function (GDDF) that allows for incorporating undesirable outputs explicitly, that is without requiring any of the above alternatives, by introducing a modified definition of the efficiency scores. Its properties make the GDDF the most appropriate method to assess hospital efficiency taking undesirable outcomes into account. To describe the GDDF, which will be used in this paper to estimate hospital efficiency, we start by defining the directional distance function following the notation in Cheng and Zervopoulos (2014):

$$\max \beta$$
$$s.t.\ X\lambda + \beta g_x \leq x_0$$

[3] See Cheng and Zervopoulos (2014) for a detailed discussion on these methods.

$$Y\lambda - \beta g_y \geq y_0$$
$$\lambda \geq 0$$
$$g_x \geq 0, g_y \geq 0$$

which can be formulated appropriately in the presence of undesirable outputs, as follows:

$$\max \beta$$
$$s.t. X\lambda + \beta g_x \leq x_0$$
$$Y\lambda - \beta g_y \geq y_0$$
$$B\lambda - \beta g_b = b_0$$
$$\lambda \geq 0$$
$$g_x \geq 0, g_y \geq 0, g_b \leq 0$$

(1)

where β is the efficiency measure, g_x, g_y, and g_b are the directional vectors of inputs *x*, positive outputs *y*, and bad outputs *b*. Conveniently, the directional vector associated to the bad outputs has to be negative, indicating that the decision making units need to reduce *b* to improve their efficiency, which is reasonable as *b* are undesirable outputs, such as mortality rates in the case we study. However, the above β can be greater than 1, which makes it incomparable with traditional inefficiency measures (radial and slack-based – SBM – models), unless the directional vectors are equal to the observed inputs and outputs[4]. To overcome such problem, Cheng and Zervopoulos (2014) developed the GDDF, such as radial and SBM can be seen as special cases:

$$\min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{bg_i}{x_{i0}}}{1 + \frac{1}{s}\sum_{r=1}^{s} \frac{bg_r}{y_{r0}}}$$
$$s.t.\ X\lambda + \beta g_x \leq x_0$$
$$Y\lambda - \beta g_y \geq y_0$$
$$\lambda \geq 0$$
$$g_x \geq 0, g_y \geq 0$$

and, in the presence of undesirable outputs:

[4] See Cheng and Zervopoulos (2014) for a detailed discussion on this point.

$$\min \frac{1-\frac{1}{m}\sum_{i=1}^{m} w_i \frac{bg_i}{x_{i0}}}{1+\frac{1}{s}\sum_{r=1}^{s} w_r \frac{bg_r}{y_{r0}}+\frac{1}{p}\sum_{t=1}^{p} w_t \frac{bg_t}{b_{t0}}}$$

$$s.t. X\lambda + \beta g_x \leq x_0$$

$$Y\lambda - \beta g_y \geq y_0$$

$$B\lambda - \beta g_b = b_0$$

$$\lambda \geq 0$$

$$g_x \geq 0, g_y \geq 0, g_b \leq 0$$

$$\sum_{i=1}^{m} w_i = \sum_{r=1}^{s} w_r + \sum_{t=1}^{p} w_t = 1$$

(2)

where s and p are the number of good and bad outputs, respectively; $\frac{bg_i}{x_{i0}}$ is the proportion of inputs' decrease, $\frac{bg_r}{y_{r0}}$ the proportion of good outputs' increase, and $\frac{bg_t}{b_{t0}}$ the proportion of bad outputs' decrease, and w_i, w_r, w_t are weights defined to indicate their relative importance. The efficiency scores β computed from (2) are independent of the length of the vector and, opportunely, range between 0 and 1.

To study whether incorporating quality affects the assessment of spatial dependence in the performance of hospitals, we perform the Moran's I tests using the spatial weight matrix where spatial weights w_{ij} are defined as follows:

$$w_{ij} = \begin{cases} 0 \; if \; i = j \\ 1 \; if \; d_{ij} \leq 50 \text{ km } and \; i \neq j \\ 0 \; if \; d_{ij} > 50 \text{ km} \end{cases}$$

where d_{ij} is the distance between hospitals i and j. We consider 50 km as the distance delimiting the interaction area, that is the area including hospitals that may affect hospital i's performance.[5]

3. Data, inputs and outputs

[5] Our results are robust to several different cut-offs. Estimates are available upon requests.

The selection of the most appropriate set of inputs and outputs is a critical choice for this class of models. In this paper we employ a set of three models of hospital behaviour following the existing literature as a basis for the selection of inputs and outputs. Our models include four input measures, that are commonly used in the literature (Daidone and D'Amico, 2009; Gok and Sezen, 2016; Martorana, 2017; Cavalieri et al. 2017; 2018; Auteri et al. 2019): 1)the number of available beds, as a proxy for hospital's capital endowment, as well as the number of 2)full-time equivalent physicians, 3)nurses and 4)other personnel. As for outputs, to capture the multidimensional nature of hospital provision, we include the a DRG-weighted measure of hospital revenues in all models, computed as follows: hospital revenues are estimated by applying the national DRG system and the tariff agreement for interregional mobility (*Tariffa Unica Convenzionale*, TUC, 2012) so as to offset inter- and intra- regional differences in tariffs.[6] Then, the estimated revenues are divided for the base DGR point (TUC, 2012 – 2049 €) so as to have a measure of revenues *per* DRG point. Model 2 and 3 incorporate quality in the estimation and include also the gross (Model 2) and the risk-adjusted (Model 3) mortality rates (MR) for acute myocardial infarction (AMI), which is indeed the most commonly used measure of quality of hospitals[7] (Kessler and McClellan, 2000; Cooper et al., 2011; Gaynor et al., 2013; Bloom et al., 2015; Moscelli et al. 2018). A full picture of inputs and outputs in our models is provided in Table 1.

<< Table 1 around here >>

We use data drawn from the statistical offices of the Italian Ministry of Health including information on the relevant inputs and outputs of public or private hospitals working on behalf of the Italian National Health Systems.[8] Data were examined for the presence of extreme values and errors and, after data cleaning, the dataset contains observations on 268 hospitals in 2010. The number of observation

[6] Interregional differences arise from different tariff systems, intraregional differences come from tariff differentiation based on hospital type (public/private, teaching/non-teaching, etc.)
[7] Although Readmission Rates (RR) are often considered in several studies as a proxy for quality, Fischer et al. (2011) argue that their validity should be addressed beforehand and Laudicella et al. (2013) showed that their inclusion in performance evaluation procedure may lead to incorrect inference due to sample selection bias.
[8] We exclude long stay structures and psychiatric hospitals which have very specific features.

is driven by the availability of reliable data on MR. Specifically, at least 75 cases are required to compute the adjusted MR, thus our sample include, mainly, large hospitals as evident from the mean values, gathered with the other usual descriptive statistics in Table 2.[9]

<< Table 2 around here >>

4. Non-parametric estimation results

In this section we present efficiency measurement based on the GDDF. As mentioned, we consider and compare results from three models. Model 1 is a traditional technical efficiency model which includes as output the volume of hospital provision, represented by the DRG weighted hospital revenues. Conversely, Models 2 and 3 incorporate quality as an undesirable output and thus provide a more comprehensive measure of hospital provision, which consider the hospital strategic choice on quality and volumes. Efficiency estimates according to the three models are shown in Table 3 where we also present their statistics per geographical area.[10] In model 1, Northern Italy displays the highest average efficiency (0.633), followed by Central Italy (0.605), while in Southern Italy average efficiency is notably lower (0.582). When considering quality in the estimation (Models 2 and 3), that is mortality as an undesirable output, differences among areas lessen remarkably, and surprisingly the ranking changes, eventually overturning the belief that providers in Northern Italy perform largely better than those in the South. Thus, incorporating quality in the estimation of the frontier is not neutral as it affects the evaluation of hospitals' performance. This result is consistent with those of Fare et al. (1989) and Prior (2006) and implies that the attribute of quality should be taken into account to avoid misspecification problems (Prior, 2006).

To show the extent to which quality affects the estimation of efficiency under GDDF, we report correlations among the estimated models and a set of quality and

[9] A larger dataset containing 440 observation, including data on the gross AMI MR has been used to employ Model 1 and 2 as a robustness check. Estimation outcomes are available upon request.

[10] In what follows we focus on the subsample including 268 observation to present results from model 3 which include the risk-adjusted MR. Estimates based on the full sample are available upon request.

productivity indexes in Table 4. As for productivity, we compute the ratio of the output representing volumes (the DRG weighted revenues) on inputs such as the number of beds and physicians. MR and risk-adjusted MR are used as quality indexes. It is worth noting that while productivity indexes are positively correlated with efficiency, quality indexes display no correlation with models 1 scores, since the latter does not take into account quality, and are negatively correlated with the efficiency measure from models 2 and 3. As expected, the GDDF including undesirable outputs penalises hospitals that have higher MR, thus providing a more comprehensive (and, thus, precise) measure of hospital performance.

<< Table 3 around here >>

<< Table 4 around here >>

4.1 Incorporating quality in assessing the presence of spatial dependence in hospital behaviour

As already mentioned, the most recent literature has devoted an increasing interest on analysing the interconnection between efficiency, quality and competition among providers. While the effect on competition on quality (Propper et al. 2004; 2008; Cooper et al., 2011; Gaynor et al., 2013; 2016; Bloom et al., 2015) and efficiency (Cooper et al., 2012, Gaynor et al., 2013) as well as the existence of spatial dependence in hospitals' behaviour (Gravelle et al., 2014; Cavalieri et al.; 2017; Longo et al., 2017) have been extensively investigated, the theoretical literature (Brekke et al. 2017) has emphasised the interconnection between providers' choices on quality and cost containment and the univocal nature of the strategic interdependence among hospitals. In line with this literature, we enrich our assessment on the impact of incorporating quality in the measuring hospitals' performance by investigating the existence of spatial correlation in hospital behaviour.

To provide a first overview on our hypothesis on the presence of spatial correlation in hospital performance, we run random effects ANOVA with intra-class correlation (Donner, 1986) on the set of productivity indexes and quality measures, which allow us to study whether quality and productivity of hospitals belonging to the same regional health authority are correlated (Table 5). As evident, we can reject the null hypothesis of no difference across regions for three over four indexes. Additionally, there is evidence of intra-region correlation, especially when considering quality. Apparently, hospitals in the same region tend to converge, at least on quality. We interpret such outcome as a sign of a distance-related behaviour which can be regarded as a clue of a potential competitive impact on the “choice” of quality.

At glance, there is evidence of spatial correlation in hospital performance, which call for studying this issue on hospital performance thoroughly, by considering quality and volumes jointly, as outputs of the same service provision process.

<< **Table 4 around here** >>

To study the presence of spatial correlation in hospital performance, we run the Moran I’s test using the above defined binary spatial matrix. In contrast to the ANOVA presented in the previous Section, which involved an institutional definition of contiguity, in what follows we define contiguity on the basis of the distance among hospitals. Figure 1, 2, 3 and Table 6 present our results on the estimated efficiency scores from the three models. There is evidence of a slightly positive spatial correlation. However, such correlation is statistically significant only when considering (risk-adjusted) quality, that is, in model 3. Indeed, neighbouring hospitals’ scores tend to converge and, moreover, the positive sign is a clue that the potentially competitive strategic interaction among neighbouring hospitals, given its impact on volumes and quality, may have positive effects on the overall performance of hospitals.

<< **Figure 1 around here** >>
<< **Table 6 around here** >>

5. Concluding remarks

This paper investigates the overall performance in the provision of hospital service in terms of volumes and quality in Italy. It uses a non-parametric frontier estimation technique, namely the GDDF, to incorporate quality in estimation of the efficiency frontier, using data from Italian hospitals from the year 2010. By employing the GDDF, we are able to assess whether the inclusion of quality in the estimation of the best-practise frontier is relevant. Our results show that incorporating quality remarkably affects the evaluation of hospitals' performance and is thus necessary to avoid misspecification problems, in line with the results in Fare et al. (1989) and Prior (2006). Comparing the scores from different model specifications, we show that in spite of a relatively high correlation among them, the inclusion of quality has a remarkable impact, eventually overturning the performance ranking among geographical areas and, with it, the commonly accepted belief that hospitals in Northern Italy perform largely better than those of the South. As an additional assessment of the impact of incorporating quality, and in line with the most recent literature on the connection among efficiency, quality and competition, we also study the presence of spatial dependence in hospitals' choices of quality and volumes. Considering that in a NHS such as the Italian one, in which patients do not pay directly for treatments, hospitals compete on quality in the catchment area, we study whether hospitals' quality levels and/or volumes are spatially dependent. Consistently with the previous literature on this issue, we do not find evidence of spatial dependence in hospital efficiency. Conversely, a positive spatial correlation emerges when considering quality within the output set as an undesirable output, that is, when considering the overall hospital performance.

Thus, our findings contribute to shed a light on the strategic choices of hospitals in a setting where providers compete to attract patients. On the one hand, the presence of spatial dependence on the overall hospital performance highlights that the strategic key for hospitals is the choice on quality. On the other hand the reported positive sign has important policy implications as it implies that the competitive strategic interaction among neighbouring hospitals may have positive effects on the overall performance of hospitals, thus supporting policies aiming at enhancing competition among providers as well as interventions to improve quality in the provision of hospital services.

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TABLES AND FIGURES

Table 1. Inputs and outputs

Variable	Model 1	Model 2	Model 3
Inputs			
BEDS	♦	♦	♦
PHYSICIANS	♦	♦	♦
NURSES	♦	♦	♦
O_PERS	♦	♦	♦
Outputs			
DRG_W_REVENUES	♦	♦	♦
AMI_GROSS		♦	
AMI_R_ADJ			♦

Source: our computation on data drawn from the Department of Healthcare and from the National Program of Outcome Assessment – year 2010.

Table 2. Descriptive statistics.

Variables	Meaning	Descriptive Statistics		
		Obs.	*Mean*	*S.D.*
Full sample				
DRG_W_REVENUES	Revenues weighted by TUC tariff for basic one point DRG (2,490 euro)	440	17,462.89	18,716.71
AMI_GROSS	Gross mortality rate for AMI	440	13.48	10.50
BEDS	Number of beds, at hospital level	440	275.81	269.70
PHYSICIANS	Number of full time equivalent physicians, at hospital	440	185.93	192.64
NURSES	Number of full time equivalent nurses, at hospital	440	409.09	430.36
O_PERS	Number of full time equivalent other personnel, at hospital	440	324.92	411.32
Sub sample with R_ADJ AMI data				
DRG_W_REVENUES	Revenues weighted by TUC tariff for basic one point DRG (2,490 euro)	268	24,132.42	20,822.97
AMI_GROSS	Gross mortality rate for AMI	268	10.43	3.88
AMI_R_ADJ	Risk adjusted mortality rate for AMI	268	10.85	3.91
BEDS	Number of beds, at hospital level	268	374.95	297.36
PHYSICIANS	Number of full time equivalent physicians, at hospital	268	255.78	209.90
NURSES	Number of full time equivalent nurses, at hospital	268	569.23	475.10
O_PERS	Number of full time equivalent other personnel, at hospital	268	445.26	476.92

Source: our computation on data drawn from the Department of Healthcare and from the National Program of Outcome Assessment – year 2010.

Table 3. GDDF estimates.

Index	Geographical area	Descriptive Statistics				
		Obs.	*Mean*	*S.D.*	*Min*	*Max*
Sub sample with R_ADJ AMI data						
Model 1	All sample	268	.6057945	.206386	.20076	1
	North	92	.6332207	.1909144	.20076	1
	Centre	70	.6050481	.2208539	.291708	1
	South and islands	106	.5824834	.2084796	.285149	1
Model 2	All sample	268	.7185131	.1351106	.531416	1
	North	92	.7145978	.1316898	.54286	1
	Centre	70	.7160398	.1415291	.531416	1
	South and islands	106	.7235446	.1348467	.549087	1
Model 3	All sample	268	.7455124	.1291313	.539603	1
	North	92	.7443403	.1238028	.569816	1
	Centre	70	.7552585	.1360033	.539603	1
	South and islands	106	.7400936	.1298811	.574476	1

Source: our computation on data drawn from the Department of Healthcare and from the National Program of Outcome Assessment – year 2010.

Table 4. Correlations among indexes and efficiency measures estimated through GDDF

	Model 1	**Model 2**	**Model 3**
Model 1	1		
Model 2	0.8744	1	
Model 3	0.785	0.9533	1
DRG_W_REVENUES/BEDS	0.597	0.5896	0.5574
DRG_W_REVENUES/PHYSICIANS	0.5815	0.5701	0.5486
AMI_GROSS	-0.0779	-0.3468	-0.3979
AMI_R_ADJ	0.0706	-0.1813	-0.3316

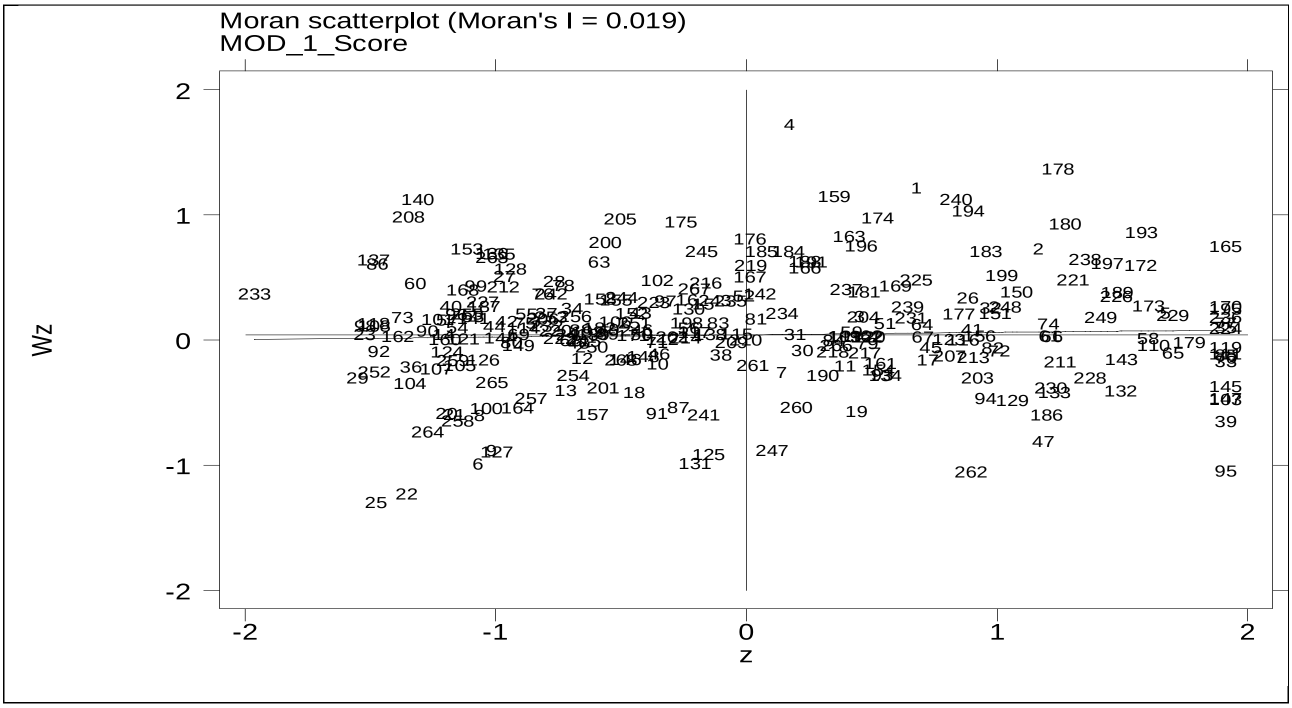
Source: our computation on data drawn from the Department of Healthcare and from the National Program of Outcome Assessment – year 2010.

Table 5. Random effects ANOVA with intra-class correlation. Productivity and quality indexes

Source	SS	df	MS	F	Prob>F
DRG_W_REVENUES/BEDS					
Between Regions	17305.24	19	910.8021	2.67	0.0003
Within Regions	84442.54	248	340.4941		
Total	101747.8	267	381.0778		
Intra-Regions correlation	0.11389				
DRG_W_REVENUES/PHYSICIANS					
Between Regions	34128.18	19	1796.22	1.5	0.0859
Within Regions	297114.2	248	1198.041		
Total	331242.4	267	1240.608		
Intra-Regions correlation	0.0369				
AMI_GROSS					
Between Regions	1018.432	19	53.6017	4.42	0.0000
Within Regions	3009.432	248	12.13481		
Total	4027.864	267	15.08563		
Intra-Regions correlation	0.20775				
AMI_R_ADJ					
Between Regions	711.1154	19	37.42713	2.76	0.0002
Within Regions	3365.494	248	13.57054		
Total	4076.609	267	15.2682		
Intra-Regions correlation	0.11887				

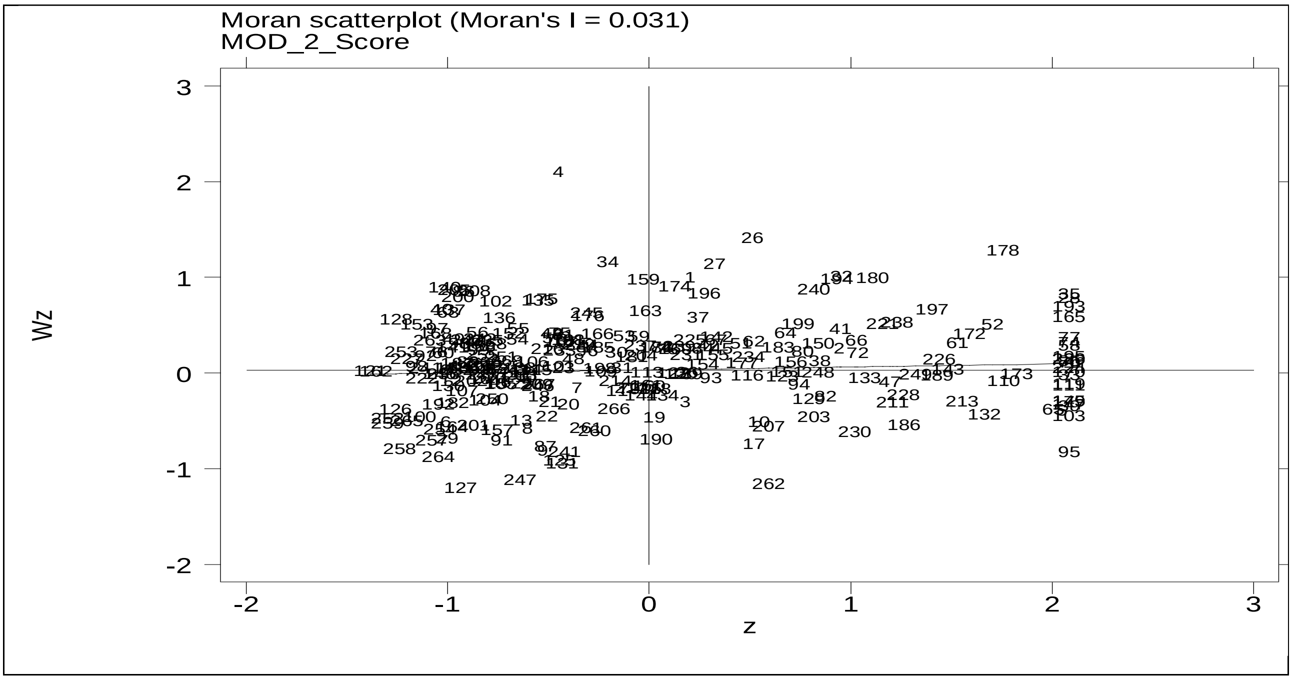
Source: our computation on data drawn from the Department of Healthcare and from the National Program of Outcome Assessment – year 2010.

Figure 1. Moran's I test scatterplot – Model 1.



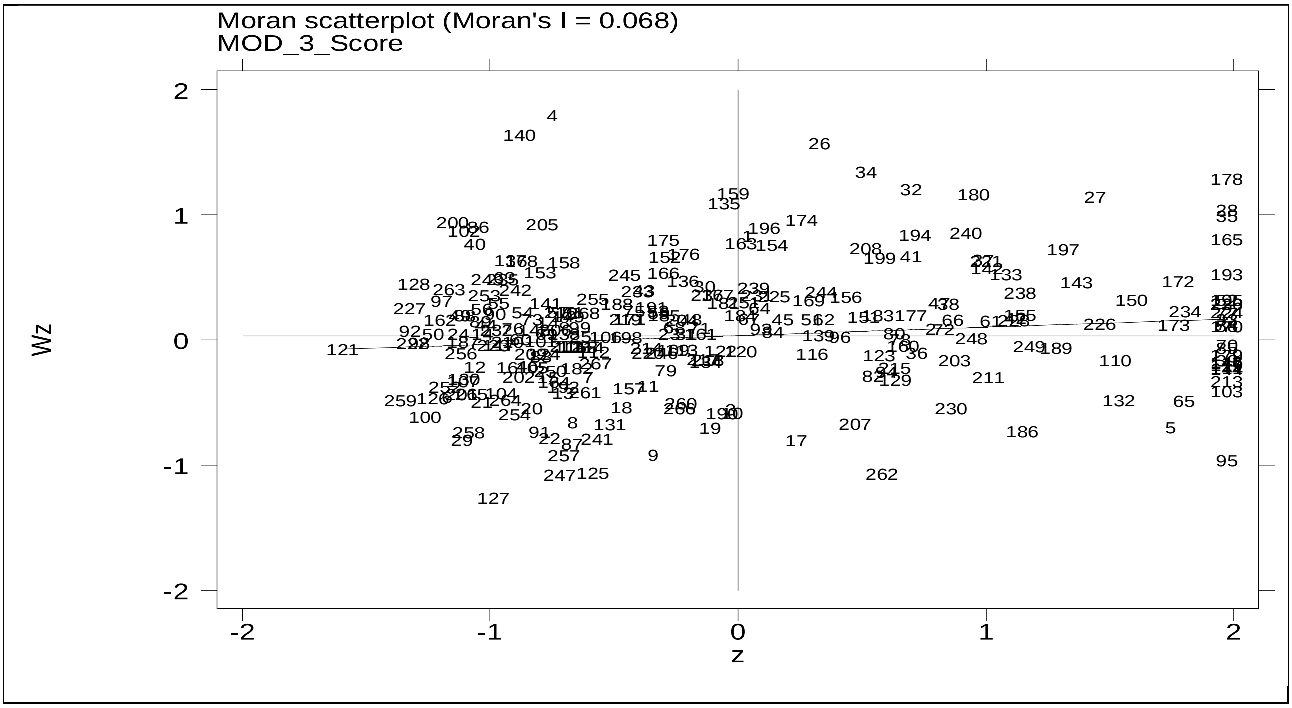
Source: our computation on data drawn from the Department of Healthcare and from the National Program of Outcome Assessment – year 2010.

Figure 2. Moran's I test scatterplot – Model 2



Source: our computation on data drawn from the Department of Healthcare and from the National Program of Outcome Assessment – year 2010.

Figure 3. Moran's I test scatterplot – Model 3



Source: our computation on data drawn from the Department of Healthcare and from the National Program of Outcome Assessment – year 2010.

Table 6. Moran's I test

Type: Distance-based (binary)				**Distance band: 0.0 < d <= 5.0**	
Row-standardized: Yes					
Moran's I					
Variables	I	E(I)	sd(I)	z	p-value*
Model 1	0.02	-0.004	0.04	0.589	0.278
Model 2	0.032	-0.004	0.4	0.901	0.184
Model 3	0.07	-0.004	0.04	1.842	0.033

Source: our computation on data drawn from the Department of Healthcare and from the National Program of Outcome Assessment – year 2010.