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Waiting times spillovers in a National Health Service hospital network: a little organizational diversity can go a long way

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Abstract

Background The objective of this study is to assess if waiting times for elective surgeries within the Portuguese National Health Service (NHS) are influenced by the waiting times at neighboring hospitals. Recognizing these interdependencies, and their extent, is crucial for understanding how hospital network dynamics affect healthcare delivery efficiency and patient access.

Methods We utilized patient-level data from all elective surgeries conducted in Portuguese NHS hospitals to estimate a hospital-specific index for waiting times. This index served as the dependent variable in our analysis. We applied a spatial lag model to examine the potential strategic interactions between hospitals concerning their waiting times.

Results Our analysis revealed a significant positive endogenous spatial dependence, indicating that waiting times in NHS hospitals are strategic complements. Furthermore, we found that NHS contracts with private not-for-profit hospitals not only reduce waiting times within these hospitals but also exert positive spillover effects on other NHS hospitals.

Conclusions The findings suggest that diversifying the organization of the NHS hospital network, particularly through contracts with private entities for marginal patients, can significantly enhance competitive dynamics and reduce waiting times. This effect persists even when patient choice is confined to a small fraction of the patient population, highlighting a strategic avenue for policy optimization in healthcare service delivery.

Keywords Waiting times, Not-for-profit hospitals, Mixed markets, Hospital competition

JEL Classification I11, L33, H44

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Introduction

In theory, the hospital network in National Health Services (NHS) is composed of public sector hospitals that do not compete for patients. In practice, however, policies designed to increase hospital competition have been introduced in several National Health Services, for instance, in England, Denmark, Sweden and Norway [1]. The impact of competition among hospitals is not as straightforward as it might be in other sectors. Some argue that the unique nature of healthcare markets renders meaningful competition either impossible or harmful [2]. Indeed, while competition in healthcare has the potential to enhance efficiency, spur innovation, elevate quality, and manage costs, it can also lead to negative consequences, such as diminished quality [3].

Reviews of the effect of competition in healthcare (see for instance [4–6]) generally conclude that the influence of increased competition on quality is ambiguous, mainly because quality may decrease with increasing competition, under price competition. These reviews also show that economic theory and most empirical studies conclude that under an exogenously determined fixed-price regime, as is usually the case in National Health Services, more competition increases quality. However, Brekke et al. [7] developed a model with regulated prices and semi-altruistic providers (i.e., not pure profit-maximizing agents, as it is the case for public or not-for-profit hospitals) and conclude that more competition may increase or reduce quality, and the same authors reach a similar conclusion when hospitals compete on waiting times, which can be seen as a detrimental aspect of quality [8]. Gowrisankaran and Town [9] also observed that competition adversely affected Medicare quality in Southern California, although most Medicare studies find that competition increases quality (e.g [10, 11]). Several studies for the English NHS also find that more competition increases quality [12–14].

The effects of competition on hospital performance depend on the health system, which include factors such as patient autonomy in choosing providers and access to information regarding their location, quality, and costs; the presence of several providers with straightforward processes for entry and exit; providers' autonomy over crucial service aspects and their efforts to attract patients; compensation for providers correlating with the number of patients they treat; and the degree to which goods and services can be substituted [3]. Competition provides strong incentives to profit maximizing firms, but results may differ if firms in the industry are not motivated by profits (because they are public hospitals) [6]. Also, soft budgets are a challenge for publicly owned hospitals because funders either partially cover deficits or confiscate profits, which can lead to reduced quality when cost-containment becomes a significant focus [15].

Formally the conditions for competition were not found in the Portuguese NHS hospital network, where the rules established no patient choice of provider, and publicly owned and centrally planned hospitals. However, in practice there was some competition for a limited fringe of patients, and not all hospitals in the NHS network were managed by the public sector.

Institutional setting

The Portuguese National Health Service provides universal healthcare that is tax-financed with small user charges for some services. Exemptions are provided (for more than half of the population during the analyzed period), ensuring that economic barriers do not prevent anyone in need from accessing healthcare services.

The structure of the National Health Service inhibited the evolution of competition among healthcare providers. Barros [16] states that "within the NHS, the use of tendering procedures was able to create competition for the market" (but) "there is little competition among healthcare providers within the NHS". Among NHS hospitals, competition was limited to SIGIC patients, as described below. Barros [16] and Simoes et al. [17] provide detailed descriptions of competition and other features of the Portuguese NHS, and here we will highlight those that were more relevant for our study.

Within the Portuguese NHS, patients are assigned to a primary care physician who serves as a gatekeeper. Should patients require potential surgical intervention, they must initially consult their primary care physician at the local NHS primary care center. Following this consultation, the primary care physician will refer the patient for a specialist outpatient appointment at the patient's residence,[1] NHS hospital. The patient's hospital was defined by geographical proximity to the patient's implying that as a rule there was no choice of hospitals by patients, although there were some exceptions to this rule (described below).

The NHS network is organized in five administrative regions. Hospitals are supervised, coordinated, and monitored by the respective Regional Health Administration. Annually the Regional Health Administration celebrates "contract-programs" with the hospitals in its region, where it is defined what services each hospital will provide to NHS patients and the total value the NHS pays for those services (the contractual hospital production). Financing for hospitals in the NHS network is calculated prospectively, based on the anticipated (or agreed upon)

[1] Since May 2016, NHS users can be referred to a hospital out of their residence area, as long as waiting times for a given procedure or outpatient consultation are shorter [17]. Since this change in patient choice rules may have significantly altered the conditions for competition in the NHS, we chose to limit the study to a period ending in 2015, when patient choice of hospital was much more limited.

activity levels and determined prices, using information from Diagnosis Related Groups.

The NHS hospital network was mainly composed of public sector hospitals, operating under different managerial and organizational models. In 2015, 65% of the total NHS contractual hospital production was provided by 22 Hospital Centers (HC); HC are public sector firms that include more than one hospital unit, usually as the result of mergers of previously independent hospitals aiming to increase efficiency through economies of scale and reorganization. In our empirical analysis, we classified the three hospitals specialized in oncology in a separate group (HSO), since cancer patients have specific waiting rules (HSO accounted for 5% of total NHS contractual hospital production in 2015). We also assigned to a specific group, HU, the other eight individual hospital units with their own management team, since these tend to be less efficient because they are smaller and allow managers less flexibility in resource allocation (HU accounted for about 10% of NHS contractual hospital production).

In eight areas of Portugal, NHS hospitals were integrated into Local Health Units (LHU). LHU are specialized institutional frameworks that bring together NHS hospitals with primary care units within their respective regions under a single management system, aiming to improve integration of care in a given geographical area (LHU accounted for 11% of total NHS contractual hospital production).

HC, HU, HSO and LHU operate as Public Sector Corporations, which have legal autonomy. The managers of Public Sector Corporations are designated by the government and operate according to regulations that closely resemble those of the private sector. Although in theory managers of these corporations are supposed to act as a private sector manager would, in practice managers' autonomy is limited, since they face strict borrowing constraints and need government authorization for most investment and staff recruiting decisions. There were one HC and two HU small hospitals that were still legally part of the traditional public sector administration, operating under traditional administrative rules, which in theory allow managers much lower autonomy. However, there were only minor differences in actual managerial practices between these three hospitals and Public Sector Corporations, given the strong limitations imposed in practice to managers of these corporations.

Four NHS hospitals (accounting for 7% of total NHS contractual hospital production) operated under Public–Private Partnerships (PPP), where a private sector firm manages a publicly owned hospital under a 10-year contract with annually revised production targets (Barros and Martinez-Giralt [18], Rodrigues and Carvalho [19], and Rodrigues [20] provide detail on the contracts of hospital PPP in Portugal). From the patients' perspective, there are no differences between PPP and other NHS public hospitals since access to care occurs under the same conditions (including the rule that access to a PPP hospital is determined by place of residence).

The NHS hospital network also includes Cooperation Agreements with some hospitals owned and managed by several "Santa Casa da Misericordia" (SCM), which are private not-for-profit organizations inspired by catholic faith [21]. Under these Cooperation Agreements, a SCM hospital provides a limited quantity of hospital services to NHS patients of a defined catchment area. SCM hospitals compete with other private sector hospitals for private patients (without restrictions) and compete with the local public sector NHS hospital for NHS patients but only up to the number of patients specified in the Cooperation Agreement. Competition for NHS patients arises because in areas with SCM hospitals primary care physicians can refer patients either to the local public sector hospital or to the SCM hospital (up to the annual contracted limit). There were 14 Cooperation Agreements with SCM hospitals in 2015, covering only a fraction of the Portuguese territory and accounting for only 1% of total NHS contractual hospital production.

Lengthy queues for consultations and planned surgeries have continually escalated as a chronic issue within the Portuguese National Health Service (NHS) [22], a phenomenon typical of NHS-model health systems. Extended waiting periods and lists contribute to patient dissatisfaction and broader public discontent [20], making waiting times politically sensitive and the object of many health policies that impacted on hospital management. Information on waiting lists and times is used for quality indicators and management targets [23, 24]. The list of patients waiting surgery is managed by a national information system called SIGIC.[2] If a hospital specialist determines that a patient requires surgery, they register the patient in SIGIC. If the patient's surgery does not take place within the legally defined "guaranteed maximum time of response" (which varies from 3 to 270 days, based on the patient's priority level as set by regulations), SIGIC then directs the patient to either another NHS hospital or a private hospital [25]. The hospital where the patient was initially enrolled in SIGIC pays for the patients that have surgery in other hospital (NHS or private) due to excessive waiting time. This creates an incentive for managers to reduce waiting times, and permits a degree of limited competition among hospitals, particularly when waiting periods for elective surgeries are unreasonably long [16]. In conclusion, the institutional setting in the period covered by our study implied that most NHS patients were

[2] "SIGIC" is the Portuguese acronym of "Sistema Integrado de Gestão de Inscritos em Cirurgia" (Integrated System for Managing Surgery Lists).

treated in hospitals managed by public sector organizations (all but the PPP and SCM hospitals that account for only 8% of total NHS contractual hospital production), and patient hospital choice was limited to a small minority of patients. Patient choice was limited to the patients that chose a SCM hospital (that provided only 1% of total NHS contractual hospital production), to the less than 4% of patients (in our sample) that had surgery in a hospital different than the one they were registered for surgery due to excessive waiting time, and to some possible informal choice whose magnitude is likely to be small. Barros [16] claims that there was some informal choice of hospital using false residential addresses (since the patient's hospital was determined by their home address, patients desiring a different hospital could use an incorrect address that matched their preferred location, or they might request a referral from their local hospital or primary care physician). The extent of this informal selection by patients is unclear, though it is presumed to be minimal.

Research objectives and hypothesis

This research aims to examine the presence of positive spillovers on waiting times for elective surgeries within the Portuguese National Health Service, utilizing data from patients scheduled for elective surgery in Portuguese NHS hospitals between 2013 and 2015. Initially, we compute an index for each hospital regarding waiting times, derived from patient data, as an indicator of hospital quality. This method eliminates all variables that could affect waiting times (such as the severity of medical conditions, demographic or socioeconomic traits of patients, or a varied mix of procedures) that are not directly linked to the hospital's attributes. Subsequently, we apply spatial panel models to explore patterns of spatial dependence, either endogenous or exogenous, among hospitals, considering elements like the hospitals' organizational structure, size, and teaching status, and we determine which hospital characteristics significantly influence waiting times.

Our main hypothesis is that positive spillover effects on waiting times can arise in health systems, even where the conditions for a positive effect of competition are limited primarily to marginal patients and hospitals. As described above, in the period under analysis, choice of provider in the Portuguese NHS was limited to a small percentage of patients, and most hospitals were managed by public sector organizations, with soft budgets and with profit-maximization not necessarily the main objective. Furthermore, by identifying different management and organization models in NHS hospitals, we assess whether increasing the organizational diversity within the NHS hospital network can have positive and significant effects on reducing waiting times, even when competition is limited to small groups of patients; diversity may act as a driver of competition, generating new competitive incentives and contributing to more substantial improvements in the provision of healthcare.

We focus on waiting times due to data availability.[3] Waiting times may be seen as one dimension of the quality of hospital service because waiting lists lower the quality of healthcare provided, since patients waiting for surgery experience decreased health, dissatisfaction, and significant emotional trauma, and are exposed to higher risk of mortality and complications, as previous studies have shown [26–30]. Waiting times are a key dimension of hospital quality, and, for the period under analysis, it is the only indicator that is available at a patient level. All other quality indicators are only available at the hospital level, and thus do not allow for corrections associated with differences in patient characteristics between hospitals. Furthermore, waiting times consistently capture the most public attention. Consequently, reducing these wait times is a key objective of policies designed to offer patients more choices in healthcare [31–33].

Methodology

Research on competition among hospitals is well-established within the field of health economics, with researchers developing metrics of market density, often using variations of the Herfindahl-Hirschmann Index, and then modeling these against a key variable (e.g. prices or a quality indicator) controlling for observable confounding variables [5]. Nonetheless, studies using the Herfindahl-Hirschmann Index to examine how hospital competition impacts quality face a constraint due to the endogeneity of market shares, as hospitals with higher quality tend to attract more patients [12].

We follow Mobley [34] alternative approach, employing spatial econometric techniques to explore strategic interactions among hospitals. Since the proximity to a hospital significantly influences patient choice [35], and given that consumers are spread across various regions, hospitals often compete for patients living within specific geographical areas [36]. Moreover, the distance between hospitals also affects how decisions in one hospital can impact those in another [37].

We examine whether a hospital's waiting times are influenced by the waiting times of its rivals. To do this, we identify rivals based on their spatial proximity and estimate hospital reaction functions accordingly. Following Gravelle et al. [37], we test whether waiting times are strategic complements, i.e. whether a provider responds

[3] We use the SIGIC database, primarily designed to manage and track surgical waitlists. However, it lacks detailed information on clinical outcomes or post-operative complications, which would also be valuable metrics for the quality of care provided.

to a decrease in waiting times from rival providers by decreasing their own waiting times.

Thus, our study contributes to the growing literature that explores the spatial dimension of health systems [38, 39]. Specifically, our study adds to the small literature that studies the impact of hospital competition on prices and quality by investigating strategic spatial interactions amongst hospitals. Mobley [34] and Mobley et al. [36] examined strategic complementarity in prices within the California hospital market, Gravelle et al. [37] used a similar approach to investigate the effect of competition on sixteen quality measures for English hospitals and found positive spillovers for seven of the measures (and no response for the other nine measures). Longo et al. [40] expanded this research by analyzing how hospitals in the English NHS react concerning quality and efficiency, discovering no signs of hospital spillovers, except for a mortality rate positive spillover. Lisi et al. [41] studied quality competition among hospitals in the Italian Lombardy region and found a modest yet significant interdependence among hospitals in their respective catchment areas. They also detected significant diversity across local markets and quality metrics. While most areas suggested that hospital qualities function as strategic complements, a select few demonstrated they act as strategic substitutes.

Model

Our research utilizes the theoretical framework for regulated pricing set forth by Gravelle et al. [37]. The demand function of hospital "i" is specified as follows:

$$D_i = D(q_i, q_{-i}, \gamma_i) \tag{1}$$

where q_i represents the quality of hospital "i" and q_{-i} denotes the quality of competing hospitals. It is anticipated that demand for hospital "i" will rise in response to an increase in its own quality, and will decline when the quality of adjacent hospitals improves. γ_i is associated with a vector of exogenous factors that influence the demand for the hospital.

The objective function of hospital "i" is:

$$U_i = p.D\left(q_i, q_{-i}, \gamma_i\right) - C(D_i,\ q_i,\ \mu_i) \tag{2}$$

In this context p is the price determined by a third-party payer and received by the hospital and $C(.)$ is the cost function. It is assumed that both demand and quality increase C. Additionally, μ_i represents the exogenous factors influencing hospital costs. The reaction function for hospital "i" is obtained by maximizing the objective function regarding q_i, and then solving for q_i

$${q_i}^R = {q_i}^R(q_{-i},\ \gamma_i,\ \mu_i) \tag{3}$$

Thus, the reaction functions of hospitals are shaped by the quality of nearby institutions and external factors thought to influence demand and costs. A weighted waiting time index is used to measure quality, which will be detailed further below. This quality metric, denoted as q^w, is stripped of all patient characteristics that typically affect demand. As a result, we can describe the hospital reaction function as:

$${q_i}^{Rw} = {q_i}^{Rw}({q_{-i}}^w,\ \ \mu_i) \tag{4}$$

where q_i has been substituted with our measure of hospital quality, the hospital waiting time index, denoted as ${q_i}^w$. Given the characteristics of ${q_i}^w$, we expect the relationship between ${q_{-i}}^w$ and ${q_i}^w$ will be influenced solely by hospital attributes (such as size and organizational structure), leading us to omit γ_i from the reaction function's arguments. It should be noted that q^w should be viewed as the average waiting time for each hospital, adjusted for patient demographics and other factors reflecting the type and complexity of the treatments. Thus, the index of waiting times is attributable directly to the hospital's unique aspects, rather than to the patient mix, which may include individuals with various pathologies, severity levels, or specific treatment needs that could otherwise impact waiting times. This approach addresses concerns like those raised by Brekke et al. [15], who highlight the necessity of accounting for patient characteristics in studies of competition and quality.

The empirical strategy unfolds in two phases. To start, we perform a high-dimensional fixed effects linear regression, using data at the patient level, to estimate the hospital waiting time index (q^w), which we use as the metric of hospital quality. Subsequently, we employ this quality metric as the dependent variable in a panel regression that considers potential spatial dependencies. This analysis is carried out with data aggregated at the hospital level, incorporating adjustments for various hospital characteristics, in alignment with the theoretical framework described earlier.

Hospital-waiting time index

We analyzed administrative data on 1.6 million NHS patients who underwent surgery between 2013 and 2015 to construct the hospital waiting time index, which consists of a weighted-adjusted average of waiting times. The data is limited to 2015 because a major policy change occurred in 2016, the introduction of freedom of choice for hospital outpatient care in Portugal, that is likely to have had a significant impact in the competitive dynamics among healthcare providers, thereby influencing the conditions relevant to our study.

The data obtained from SIGIC are at the patient level and provide information on each patient's characteristics and the surgical procedure.[4] Table 1 provides an overview of the descriptive statistics for selected variables.

The waiting time index was determined using the econometric specification specified as follows:

$$\boldsymbol{Y} = \boldsymbol{\beta}^{\,index}\boldsymbol{Hospital} \times \boldsymbol{Year} + \boldsymbol{X}\boldsymbol{\beta}^{\,COV} + \boldsymbol{\epsilon} \quad (5)$$

where $\mathbf{Y}$ corresponds to the log of waiting times (plus 1 day, to eliminate the zeros in the data) for every patient in the sample (i=1,...,N). We assess hospital quality using $\boldsymbol{\beta}^{\,index}$ – the coefficients for the interaction terms between hospital and year variables. We allow quality for each hospital to vary from year to year to accommodate changes in the available hospitals' resources, as well as potential shifts in leadership or operational procedures. $\mathbf{X}$ represents a set of covariates that accounts for multiple drivers of patient-specific heterogeneity.

$\mathbf{X}$ includes individual specific characteristics of the patients, such as gender, age, and place of residence (308 municipalities, that serve as a proxy of the socio-economic condition of the patient), given that different types of patients may experience different waiting times. $\mathbf{X}$ also includes information on the patient's clinical condition, namely an indicator for cancer patients and the clinical priority level.[5] Finally, $\mathbf{X}$ includes the type of service / medical specialty of the surgery (38 categories), since the balance between resources available and demand (and thus waiting lists) varies significantly across specialties, and the type of surgical procedure (about 3,300 categories), because different treatment complexities may lead to different waiting lists. Since $\mathbf{X}$ comprises all variables that are believed to influence waiting times that are independent of hospital characteristics, the quality measure $\boldsymbol{\beta}^{\,index}$ is a good measure of each hospital's quality of service, in terms of access to surgery: hospitals with higher $\boldsymbol{\beta}^{\,index}$ deliver more limited surgical access, since they face longer waiting times.

We categorized all variables to enhance the model's flexibility and address potential nonlinearities and introduced a dummy variable for each category. Due to the high dimensionality of some variables, which include many categories, we applied a high-dimensional fixed effect algorithm as suggested by Guimarães and Portugal [42].

Spatial interactions model

In the second phase of our empirical analysis, we implement a spatial econometrics model, with the hospitals' waiting time index from the first phase serving as the dependent variable, to investigate spatial interactions

Table 1 Descriptive statistics on patient/surgery characteristics and waiting times

Variable	# Obs. (% of total)	Waiting times (days)				
		Mean	Median	Std. Dev.	Min.	Max.
Gender						
Female	936,521 (57.2)	91.9	49	121.7	0	3707
Male	701,843 (42.8)	86.6	45	114.3	0	3596
Cancer						
Yes	135,162 (8.3)	28.0	21	32.1	0	898
No	1,503,202 (91.8)	95.2	53	122.0	0	3707
Priority level						
1	1,249,863 (76.3)	110.3	71	126.8	0	3707
2	268,818 (16.4)	31.5	20	48.3	0	2582
3	70,581 (4.3)	7.1	3	20.1	0	2165
4	49,102 (3.0)	1.8	1	8.3	0	622
Age groups						
< 15 years	95,801 (5.9)	106.3	77	104.6	0	1347
[15–30]	107,743 (6.6)	96.7	57	118.8	0	2293
[30–45]	236,659 (14.4)	92.5	51	122.4	0	3707
[45–60]	373,547 (22.8)	95.4	50	127.5	0	2722
[60–75]	473,225 (28.9)	89.5	44	120.7	0	3596
>=75 years	351,389 (21.5)	75.1	34	104.7	0	3475

[4] We obtained the SIGIC data through a formal request to the Administração Central do Sistema de Saúde (ACSS). The data provided was at the individual level but was fully anonymized before it was shared with us, ensuring that no individuals could be identified, thereby addressing potential ethical concerns regarding privacy.

[5] The clinical priority for surgery corresponds to the severity level attributed to the patient, based on their clinical situation, or need for treatment (for more information in SIGIC's information, see Cima et al. [22]. Note that higher priority levels are associated with lower "guaranteed maximum time of response", implying that hospitals that are more exposed to patients with higher priorities are expected to have shorter waiting times to meet the maximum time associated with those priority levels.

among hospitals. Since the hospital index can fluctuate over time, we adopt a panel data methodology.

Building on the literature we discussed earlier, we estimate hospital reaction functions that assume spatial interactions among the dependent variables. Our focus is on the spatial lag model (SAR) and the spatial Durbin model (SDM), with their respective specifications detailed below [43, 44]:

$$\boldsymbol{Y} = \rho \boldsymbol{WY} + \boldsymbol{X\beta} + \boldsymbol{\mu} + \boldsymbol{\epsilon} \tag{6}$$

$$\boldsymbol{Y} = \rho \boldsymbol{WY} + X\boldsymbol{\beta} + \boldsymbol{WX\theta} + \boldsymbol{\mu} + \boldsymbol{\epsilon} \tag{7}$$

where ***Y*** represents the waiting time index for each hospital i (i=1,...,N) across time dimension t (t=1,...,T), as derived from Eq. 5. The matrix ***W*** consists of spatial weights, where ***WY*** indicates the endogenous spatial interaction effects. The spatial autoregressive coefficient, ρ, known as the spatial autoregressive coefficient, serves as the slope of the reaction function, indicating the nature of inter-hospital waiting time relationships. A ρ higher than zero suggests that waiting times are complementary, enhancing each other, a ρ less than zero indicates that waiting times act as substitutes, where an increase in one leads to a decrease in another, and a ρ equal to zero means that waiting times are statistically independent, with no discernible spatial interactions [37]. The parameter $\boldsymbol{\mu}$ is designated to capture the hospital specific effects.

We adopt a random effects model in response to the static or barely changing nature of certain explanatory variables, which makes it impractical to use a fixed effects model for estimating their coefficients. The random effects approach is based on the assumption that spatial influences are identically and independently distributed random variables, characterized by μ conforming to a normal distribution [44]. ***X*** is a vector of explanatory variables (described below), and the matrix ***WX*** represents the exogenous spatial interaction effects. θ and β are parameters to be estimated. Lastly, $\boldsymbol{\epsilon}$ represents an error term that follows the conventional assumptions.

The spatial weights matrix, $\boldsymbol{W}$, is based on the inverse of time-distance between hospitals. Time-distance for each hospital pair was determined using Google Maps. Following the Portuguese Healthcare Regulatory Authority [45], we assume that the area of influence of a hospital does not extend beyond a 90 min travel time, and so hospitals that are more than 90 min apart do not interact. Hospitals located within 90 min travel distance are assigned decreasing weights as the travel time between them increases. Therefore, the generic element W_{ij} of the matrix which connects hospital i and hospital j is defined as follows before normalizing to ensure that each row sums to one.[6]

$$W_{ij} = \begin{cases} 0\, if\ i = j \\ \frac{1}{\mathrm{d_{ij}}}\, if\ \mathrm{d_{ij}} \leq\ 90\mathrm{min\ and\ i} \neq\ \mathrm{j} \\ 0\, if\ \mathrm{d_{ij}} > 90\mathrm{minand}\ i \neq\ j \end{cases} \tag{8}$$

The explanatory variables vector ***X*** includes variables that reflect hospital characteristics that might affect quality. First, we include the six organizational models described in section 2, to test if the organizational model affects quality. We add a variable indicating whether the hospital is a university teaching hospital, since it is recognized that hospitals' collaboration with universities in medical teaching creates new knowledge and improves healthcare provided to patients [46]. We also include variables to account for the possibility that quality is affected by economies of scale or scope: dimension and diversity of services are measured by the number of medical specialties. Finally, we include dummies for the administrative region to which the hospital belongs, to account for possible peer effects among hospitals operating under the same supervisory authority [47, 48].

The SAR method is a specific instance of the SDM; therefore, the initial step involves estimating the SDM model, which considers both endogenous and exogenous spatial effects. If θ is not significantly different from zero, the spatial exogenous effects are not significant, and the SAR model is more appropriate. Then we estimate the SAR method with random effects, and if ρ is significantly different from zero, the SAR is preferable to the simple random effects model.[7]

In spatial panel models, it is possible to evaluate both direct and indirect (also called spillover) effects of explanatory variables [44]. Specifically, the direct effects of the SAR approach (Eq. 6) quantify how the characteristic X of hospital A influences its own waiting time index. The indirect or spillover effect describes the interdependencies among the dependent variables, exemplified by the interaction between the waiting times of hospitals A and B.

Conversely, while the direct effect within the SDM approach (Eq. 7) follow the same logic as in the SAR, two types of indirect effects are examined: the first mirrors the indirect effect seen in the SAR, and the second

[6] We also employed an inverse distance squared spatial weights matrix to our model estimations to assign lower weights to longer distances and observed that the estimates remained qualitatively consistent in both cases.

[7] The Breusch and Pagan Lagrangian multiplier test for random effects produces significant results at the 1% level, implying that a simple OLS model is not appropriate.

Table 2 Waiting time index by hospital-specific variables

Variables	Obs. (%)	Mean	Median	Std. Dev.	Min.	Max.
Waiting time index	177 (100)	-0.1358	-0.0428	0.6658	-2.4217	0.9118
Organizational model						
HC (Hospital Centers)	66 (37.29)	0.0776	-0.0152	0.3549	-0.5495	0.9118
HU (Hospital units)	26 (14.69)	-0.0204	0.0461	0.5027	-1.1724	0.7072
LHU (Local Health Units)	24 (13.56)	0.3940	0.4194	0.3134	-0.4363	0.8906
HSO (Oncology hospitals)	9 (5.08)	0.1511	0.3816	0.4419	-0.4831	0.5116
PPP (Public–Private Partnerships)	12 (6.78)	0.0752	0.0083	0.2600	-0.2380	0.5580
SCM (private not-for-profit)	40 (22.60)	-1.0087	-0.9493	0.6625	-2.4217	0.2099
Medical teaching						
Teaching	24 (13.56)	-0.0762	-0.1644	0.3553	-0.4648	0.9118
Non-Teaching	153 (86.44)	-0.1452	0.0022	0.7025	-2.4217	0.8906
Regional Health Administration						
North	75 (42.37)	-0.3782	-0.1784	0.8113	-2.4217	0.8906
Center	39 (22.03)	-0.0756	-0.0393	0.5189	-1.4405	0.6749
Lisbon and Tagus Valley	48 (27.12)	0.0207	0.0057	0.3841	-0.9796	0.6168
Alentejo	12 (6.78)	0.3361	0.4343	0.3481	-0.4363	0.7208
Algarve	3 (1.69)	0.7468	0.8207	0.2118	0.5080	0.9118

Table 3 Selected statistics of the estimation of the spatial models

	SAR	SDM
ρ	0.3735***	0.3159***
Test of θ		18.75*
Observations	177	177
Hospitals (number) i	59	59
Number of periods t	3	3
Log PseudoL	-33.63	-28.12

***$p<0.01$; *$p<0.10$

assesses how an explanatory variable from hospital B affects waiting times at hospital A.

Quasi-maximum likelihood methods are used to estimate the two spatial panel models, as outlined in Belotti et al. [43]. The econometric analysis was conducted using Stata. We employ the "spatwmat" command [49] to generate the spatial weight matrix, and for estimating the spatial-panel models we utilized the "xsmle" command [43], both of which are user-written functionalities in Stata.

Results

Table 2 presents results for the waiting time index, categorizing them by various hospital-specific characteristics. Table 2 shows that SCM hospitals have the lowest waiting times and LHU have higher waiting times. Also, non-teaching hospitals have lower average waiting times than medical teaching hospitals, but these have lower median waiting times. There are regional differences in waiting times, with lower waiting times in the North region, and higher in the Algarve region.

Table 3 displays statistics related to the estimation of the spatial models. The SDM estimates reveal no statistical signs of exogenous spatial interactions (considering the level of significance of 5%), thus favoring the SAR model. Additionally, the positive and significant spatial lag parameter in both models suggests that waiting times at neighboring hospitals are complementary. In simpler terms, a change in waiting times at one hospital tends to be mirrored by similar changes in nearby hospitals.

Table 4 Estimated effects of hospital characteristics on waiting times (SAR)

	Direct Effects	Indirect Effects	Total effects
Organizational model			
HC (Hospital Centers)	0.9785***	0.5673***	1.5458***
HU (Hospital units)	0.4798	0.2690	0.7488
LHU (Local Health Units)	1.1746***	0.6812***	1.8558***
HSO (Oncology hospitals)	0.9732***	0.5667**	1.5399***
PPP (Public–Private Partnerships)	0.9243***	0.5339**	1.4581***
Teaching hospital (yes)	-0.3557**	-0.2052*	-0.5609**
Dimension (number of specialties)	-0.0047	-0.0029	-0.0076
Regional Health Administration			
Center	0.0407	0.0225	0.0632
Lisbon and Tagus Valley	0.1183	0.0664	0.1846
Alentejo	0.0829	0.0503	0.1332
Algarve	0.7361***	0.4197***	1.1558***

***$p<0.01$, **$p<0.05$, *$p<0.10$

Table 4 outlines the direct, indirect, and total effects of hospital-specific variables as estimated using the SAR model. The findings indicate that non-teaching hospitals generally have higher waiting times compared to medical teaching hospitals, though this difference is not statistically significant. Additionally, both the direct and indirect effects associated with hospital size are negative (indicating that larger hospitals tend to have shorter waiting times), but these effects lack statistical significance.

Regional variations show no significant statistical differences, with the exception of the Algarve region.

The model was estimated with SCM (the private not-for-profit hospitals with NHS Cooperation Agreements) as the reference category for the organizational model variables since these hospitals have lower waiting times (see Table 2). The results confirm that SCM hospitals have significantly lower waiting times than all other organizational models (with the exception of HU, which also have higher waiting times, but the difference is not statistically significant). LHU hospitals have the highest waiting times. The positive spillover effects estimated imply that hospitals that are near hospitals with organizational models associated with lower waiting times, like SCM, will also have lower waiting times.

The positive spillover effects are not just statistically significant, but also economically relevant. For example, take a hypothetical area with several HC (without medical teaching), whose average waiting time is 100 days. If one would transform one of these HC into a hospital with a cooperation agreement with SCM, given the estimated effects in Table 4, this would produce a spillover effect over the neighboring HCs that would reduce waiting times to 57 days, a relevant reduction of 43 days (please check the Appendix for details on this calculation). These are meaningful and relevant differences, suggesting that even the little competition provided by the SCM cooperation agreements can have a relevant impact in lowering waiting times.

Discussion

Our results show that waiting times exhibit a significant positive endogenous spatial dependence, indicating that waiting times are strategic complements for NHS hospitals, a result that is in line with previous work that found the same result for some (but not all) quality indicators [37, 40] or regions [41]. Gravelle et al. [37] found that healthcare providers tend to react more to changes in the quality of competitors, particularly in aspects of quality that are more visible. This suggests that competitors may prioritize improvements in those areas of quality that are actively measured [3]. Since waiting times in the Portuguese NHS are public and subject to strong political scrutiny, they are probably the most observable of the quality indicators. A similar assessment could be made about mortality rates in the English NHS. Thus, our result would be in line with previous work that found positive spatial dependence for the mortality rate indicator in the English NHS [37, 40].

Gravelle et al. [37], Longo et al. [40] and Lisi et al. [41] explain spatial dependence from models of hospital quality competition under fixed prices, applied to the English and Italian (Lombardy region) NHS. The institutional setting in the Portuguese NHS has similarities with the English and Italian NHS, but patient choice of hospital in Portugal was much more limited in the period under analysis. As a rule, in the Portuguese NHS patients were assigned to hospitals based on residential address, implying that there was no competition for patients, but there were exceptions to this rule that allowed for limited competition for marginal patients.

First, patients that wait longer than the legal "guaranteed maximum time of response" for elective surgery may choose another hospital, and in this case the origin hospital (the hospital where the patient was initially registered for surgery) pays for the surgery. Note that the origin hospital only suffers the penalty of paying for the surgery if the patient chooses to go to another hospital, and that is more likely when there are other hospitals with low waiting times in the region. This creates a financial incentive for hospitals to reduce waiting times when there are other hospitals in neighboring areas with low waiting times, since it lowers the costs of paying for surgeries of patients lost due to excessive waiting as origin hospital. In our data, less than 4% of patients had surgery in a hospital different than the one they were initially registered for, indicating that this form of patient competition applies only to a small fraction of patients.

Second, there is competition for patients between SCM hospitals and the local public sector hospital, but in this case also the number of patients involved is small. SCM hospitals provided only 1% of total NHS contractual hospital production and SCM are present only in a small fraction of the Portuguese territory, implying that competition with SCM hospitals applies only to a small fraction of patients. In conclusion, the institutional features of the Portuguese NHS that create competition for elective surgery apply only to a fraction of the patients. Thus, our result suggests that free choice of provider for all patients is not a necessary condition for the existence of positive effects of hospital competition on waiting times. Waiting times may reduce even if there is only competition for patients at the margin (for a small fraction of patients).

Existing literature shows that spatial dependence in hospital quality indicators may arise from factors other than competition. Guccio and Lisi [48] show that spatial dependence may arise from institutional constraints that can be geographically defined, such as belonging to the same regional health administrative authority. Such regional administrative organization is also present in the Portuguese NHS, and differences in supervision and contracting by Regional Health Administrations could generate differences in hospital waiting times that have a geographical dimension, thus generating spatial dependence. We did account for the possibility of these peer effects by including dummies for the Regional Health Administration the hospital belongs to in the SAR estimation, and as such one may conclude that the spatial dependence found does not arise from those regional peer effects.

It is also unlikely that the spatial dependence in waiting times arises from supply factors, as in Frank-Tewaag et al. [50]. One could argue that having more hospitals in some area reduces waiting times simply because there is more supply for a given demand. However, there is no direct correlation between the number of hospitals and the supply of services in an area, since one large hospital provides more services than three or four small hospitals: for example, there is one HC with only one hospital within its 90 m area of influence (and at a distance of exactly 90 m) that has a service capacity (measured by the contractual hospital production) four times larger than the combined capacity of one SCM and its four closest rivals. Furthermore, there are more hospitals in more populated areas where demand for hospital services is higher, implying that even if more hospitals are associated with more supply, there is no correlation between the number of hospitals and the supply/demand ratio, which is what is relevant for waiting times.

Knowledge spillovers could also cause spatial dependence. Baltagi and Yen [51] suggest that physicians acquire practice skills from their peers, which can then be transferred to other hospitals through job changes or because these physicians are employed at multiple facilities. This professional mobility heightens the likelihood of knowledge exchange among doctors, potentially leading to spatial dependence in clinical outcomes. Hospital level waiting times are more likely to be related with managerial skills than with physician skills, especially because our waiting time index is corrected for medical specialty and type of surgical procedure. However, hospital manager mobility is much less frequent than physician mobility, and thus less likely to produce the strong spatial dependence found in our results. Furthermore, Baltagi and Yen [51] also show that competition changes managerial decisions: not-for-profits tend to offer more profitable services in a high for-profit market, whereas for-profit hospitals in predominantly non-for-profit markets enhance their quality.

Therefore, the most plausible explanation for the significant positive endogenous spatial dependence for waiting times found in our results is the competition for patients that arises between hospitals that are spatially close. The willingness to travel of hospital patients is limited, and thus only hospitals that are within reasonable travel distance compete for patients. When there is more proximity, hospitals have incentives to adjust waiting times to hospitals nearby, because failure to do so would imply financial penalties for lost patients. Given that in the Portuguese NHS there is only competition for marginal patients, the large spillover effects we found suggest that a little competition can go a long way.

The results for the organizational model show that LHU hospitals are the ones with higher waiting times. LHU integrate all primary care units and public hospitals in a given region in the same Public Sector Corporation. This significantly reduces the scope for competition in that region, and it is likely that this lack of competition is driving waiting times to be higher for those hospitals.

PPP hospitals have higher waiting times than SCM and HU, probably because the design of the PPP contracts puts a lower weight on waiting times than on other quality indicators. PPP contracts establish strong financial penalties for not meeting several quality targets, including some targets on waiting times. However, since the contracts also establish strict limits on the number of services provided, including the number of elective surgeries, the targets on waiting times are suspended if the contractual limit for the number of elective surgeries is attained. In this case, PPP hospitals do not have to pay for surgeries in other hospitals of patients that exceed the "maximum time". This creates less incentive to reduce waiting times for managers in PPP than in other hospitals.

Our results also show that SCM hospitals have significantly lower waiting times than other hospitals, a result that was expected since Cooperation Agreements with SCM are intended to improve access and efficiency [21]. Coupled with the fact that SCM agreements are one of the few sources of (marginal) competition for patients in the NHS, this result suggests that if the NHS signed more Cooperation Agreements with private hospitals that could provide a significant increase in quality in the NHS, at least in terms of a significant reduction in waiting times. If Cooperation Agreements with not-for-profit organizations have a significant impact on competition, one would expect that similar agreements with profit-maximizing firms would have at least the same effect, even if the expenditure associated with these agreements is small. An increase in NHS hospital expenditure aimed at reducing waiting times would be more effective directed at new Cooperation Agreements with SCM than if directed at increasing the capacity of existing public sector hospitals. Note that this conclusion does not depend on marginal competition being the cause for the spillover effects we have identified. Instead, this conclusion depends only on the results that show a significant spatial dependence and lower waiting times for SCM hospitals.

These results suggest that increasing organizational diversity within the NHS hospital network—particularly by incorporating hospitals with distinct operational models—can enhance positive spatial spillovers and reduce waiting times. Having different types of hospitals increases the differences in waiting times; since competition drives waiting times towards the level of the hospital with lowest waiting times, diversity further increases these positive spillover effects, contributing to greater efficiency across the network. Therefore, we argue that organizational diversity plays a crucial role in fostering competitive dynamics by introducing varied organizational practices and incentives. Even in contexts where competition may be limited, diversity itself appears to drive these competitive forces, leading to the observed improvements in performance.

Finally, the results suggest that medical teaching hospitals have lower waiting times and positive spillover effects, highlighting the importance of the dissemination of innovation and knowledge associated with teaching hospitals.

Conclusion

This research assesses the impact on waiting times of organizational diversity in NHS hospitals, by estimating spatial dependence in waiting times for elective surgery among Portuguese NHS hospitals between 2013 and 2015.

We conclude that organizational diversity can have a significant and relevant impact on waiting times in NHS hospitals, even if competition for patients is limited to a small fraction of patients (competition at the margin can be sufficient for the benefits of competition to emerge). We have shown that increased organizational diversity in an NHS hospital network (more hospitals of different organizational types) generates positive quality spillovers. The main policy implication of our results is that in NHS systems, governments can reduce waiting times through increased organizational diversity, for instance by celebrating contracts with private hospitals to provide services to NHS patients. We found that these contracts can have significant positive spillover effects in all NHS hospitals, even if these contracts apply only to a fraction of NHS patients.

Appendix

The example in the main text about the spillover impact on waiting times produced by the transformation of a typical HC into a SCM hospital assumes an area in the North region where there are several average HCs that are not classified in the category of university teaching hospitals. We also assume that the transformation will not change the size of the hospital. The difference between the indirect effects of HC and SCM is:

$$E\left(Y/HC=1\right)-E\left(Y/SCM=1\right)=0.5673$$

Given that the average waiting time of a HC (without medical teaching) is 100 days, the transformation of one HC into SCM would generate a spillover effect that would reduce the the waiting times in neighboring average HCs to $56.71=100/\exp(0.5673)$ days, a reduction in waiting times of 43 days. If the median was used instead of the mean, the waiting time would reduce from 64 days to 36 days, a reduction of 28 days.

Abbreviations

HC	Hospital centers
HSO	Hospitals specialized in oncology
HU	Individual hospital units
LHU	Local Health Units
NHS	National Health Service
PPP	Public–Private Partnerships
SAR	Spatial lag model
SCM	Santa Casa da Misericordia
SDM	Spatial Durbin model
SIGIC	Integrated System for Managing Surgery Lists

Author contributions

JC and AA contributed to the design of this study. JC managed the data and conducted the econometric analysis. Both JC and AA drafted the manuscript. Both authors collaborated on the revisions and approved the final manuscript.

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Data availability

Portuguese Central Administration of Health System (ACSS) owns the administrative data analyzed in the paper. Therefore, these data cannot be made publicly accessible. The data generated by the results of the current study are available from the authors on reasonable request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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References

1. Cooper Z, McGuire A. Competition on the Hospital Sector, in Encyclopedia of Health Economics. San Diego: Elsevier; 2014. pp. 117–20. A.J. Culyer, Editor.
2. Gaynor M, Vogt WB. Antitrust and competition in health care markets, in Handbook of Health Economics, A.J. Culyer and J. Newhouse, Editors. 2000. pp. 1405–1487.
3. Barros PP, Brouwer WB, Thomson S, Varkevisser M. Competition among health care providers: helpful or harmful? Eur J Health Econ. 2016;17(3):229–33.
4. Dranove D, Satterthwaite MA. The industrial organization of health care markets, in Handbook of Health Economics, A.J. Culyer and J. Newhouse, Editors. 2000. pp. 1093–1139.
5. Gaynor M, Town RJ. Chapter nine - competition in Health Care markets. In: Pauly MV, McGuire TG, Barros PP, editors. Handbook of Health Economics. Editors: Elsevier; 2011. pp. 499–637.

6. Pauly MV. Competition in medical services and the quality of care: concepts and history. Int J Health Care Finance Econ. 2004;4(2):113–30.
7. Brekke KR, Siciliani L, Straume OR. Hospital Competition and Quality with regulated prices. Scandinavian J Econ. 2011;113(2):444–69.
8. Brekke KR, Siciliani L, Straume OR. Competition and waiting times in hospital markets. J Public Econ. 2008;92(7):1607–28.
9. Gowrisankaran G, Town RJ. Competition, payers, and Hospital Quality. Health Serv Res. 2003;38(6p1):1403–21.
10. Kessler DP, Geppert JJ. The effects of competition on variation in the quality and cost of medical care. J Econ Manag Strategy. 2005;14(3):575–89.
11. Kessler DP, McClellan MB. Is hospital competition socially wasteful? Q J Econ. 2000;115(2):577–615.
12. Bloom N, Propper C, Seiler S, Van Reenen J. The impact of competition on management quality: evidence from public hospitals. Rev Econ Stud. 2015;82(2):457–89.
13. Cooper Z, Gibbons S, Jones S, McGuire A. Does hospital competition save lives? Evidence from the English NHS patient choice reforms. Econ J. 2011;121(554):F228–60.
14. Gaynor M, Moreno-Serra R, Propper C. Death by Market Power: Reform, Competition, and patient outcomes in the National Health Service. Am Economic Journal: Economic Policy. 2013;5(4):134–66.
15. Brekke KR, Gravelle H, Siciliani L, Straume OR. Patient choice, mobility and competition among health care providers, in Health care provision and patient mobility., R. Levaggi and M. Montefiori, Editors. 2014, Springer. pp. 1–26.
16. Barros PP. Competition policy for health care provision in Portugal. Health Policy. 2017;121(2):141–8.
17. Simoes JA, Augusto GF, Fronteira I, Hernandez-Quevedo C. *Portugal: Health System Review*. Health systems in transition. Vol. 19. 2017, Denmark: World Health Organization, on behalf of the European Observatory on Health Systems and Policies. 1-184.
18. Barros PP, Martinez-Giralt X. Contractual design and PPPs for hospitals: lessons for the Portuguese model. Eur J Health Econ. 2009;10(4):437–53.
19. Rodrigues NJP, Carvalho JMS. Public-private partnership in the Portuguese health sector. Heliyon, 2023. 9(8).
20. Rodrigues NJP. PPP in the Portuguese Health Sector: contractual compliance assessment. Procedia Comput Sci. 2023;219:2093–102.
21. Almeida A. The role of private non-profit healthcare organizations in NHS systems: implications for the Portuguese hospital devolution program. Health Policy. 2017;121(6):699–707.
22. Cima J, Guimarães P, Almeida A. Explaining the gender gap in waiting times for scheduled surgery in the Portuguese National Health Service. Portuguese J Public Health. 2021;39(1):3–10.
23. Law TJ, Stephens D, Wright JG. Surgical wait times and socioeconomic status in a public healthcare system: a retrospective analysis. BMC Health Serv Res. 2022;22(1):579.
24. Dimakou S, Dimakou O, Basso HS. Waiting time distribution in public health care: empirics and theory. Health Econ Rev. 2015;5(1):61.
25. Cima J, Almeida A. The impact of cancellations in waiting times analysis: evidence from scheduled surgeries in the Portuguese NHS. The European Journal of Health Economics; 2021.
26. Ackerman IN, Bennell KL, Osborne RH. Decline in Health-Related Quality of Life reported by more than half of those waiting for joint replacement surgery: a prospective cohort study. BMC Musculoskelet Disord. 2011;12(1):108.
27. Koomen EM, Hutten BA, Kelder JC, Redekop WK, Tijssen JGP, Kingma JH. Morbidity and mortality in patients waiting for coronary artery bypass surgery. Eur J Cardiothorac Surg. 2001;19(3):260–5.
28. Martinez DA, Zhang H, Bastias M, Feijoo F, Hinson J, Martinez R, Prieto D. Prolonged wait time is associated with increased mortality for Chilean waiting list patients with non-prioritized conditions. BMC Public Health. 2019;19(1):233.
29. Oudhoff JP, Timmermans DRM, Knol DL, Bijnen AB, van der Wal G. Waiting for elective general surgery: impact on health related quality of life and psychosocial consequences. BMC Public Health. 2007;7(1):164.
30. Siciliani L, Hurst J. Tackling excessive waiting times for elective surgery: a comparative analysis of policies in 12 OECD countries. Health Policy. 2005;72(2):201–15.
31. Fernandez-Perez A, Jimenez-Rubio D, Robone S. Freedom of choice and health services' performance: evidence from a national health system. Health Policy. 2022;126(12):1283–90.
32. Dawson D, Gravelle H, Jacobs R, Martin S, Smith PC. The effects of expanding patient choice of provider on waiting times: evidence from a policy experiment. Health Econ. 2007;16(2):113–28.
33. Simoes J, Augusto GF, Fronteira I. Introduction of freedom of choice for hospital outpatient care in Portugal: implications and results of the 2016 reform. Health Policy. 2017;121(12):1203–7.
34. Mobley LR. Estimating hospital market pricing: an equilibrium approach using spatial econometrics. Reg Sci Urban Econ. 2003;33(4):489–516.
35. Smith H, Currie C, Chaiwuttisak P, Kyprianou A. Patient choice modelling: how do patients choose their hospitals? Health Care Manag Sci. 2018;21(2):259–68.
36. Mobley LR, Frech H III, and, Anselin L. Spatial interaction, spatial multipliers and hospital competition. Int J Econ Business. 2009;16(1):1–17.
37. Gravelle H, Santos R, Siciliani L. Does a hospital's quality depend on the quality of other hospitals? A spatial econometrics approach. Reg Sci Urban Econ. 2014;49:203–16.
38. Moscone F, Tosetti E. Spatial econometrics: theory and applications in health economics, in Encyclopedia of Health Economics. 2014, Elsevier. pp. 329–334.
39. Tosetti E, Santos R, Moscone F, Arbia G. The Spatial Dimension of Health Systems, in Oxford Research Encyclopedia of Economics and Finance. 2018.
40. Longo F, Siciliani L, Gravelle H, Santos R. Do hospitals respond to rivals' quality and efficiency? A spatial panel econometric analysis. Health Econ. 2017;26:38–62.
41. Lisi D, Moscone F, Tosetti E, Vinciotti V. Hospital quality interdependence in a competitive institutional environment: evidence from Italy. Regional Science and Urban Economics; 2021. p. 89.
42. Guimarães P, Portugal P. A simple feasible procedure to fit models with high-dimensional fixed effects. Stata J. 2010;10(4):628–49.
43. Belotti F, Hughes G, Mortari AP. Spatial panel-data models using Stata. Stata J. 2017;17(1):139–80.
44. Elhorst JP. In: Folmer H, et al. editors. *Spatial econometrics: from cross-sectional data to spatial panels*. SpringerBriefs in Regional Science. Springer; 2014.
45. ERS. Estudo para a Carta Hospitalar. Entidade Reguladora da Saúde; 2012.
46. Ayanian JZ, Weissman JS. Teaching hospitals and quality of care: a review of the literature. Milbank Q. 2002;80(3):569–93.
47. Atella V, Belotti F, Depalo D, Piano A, Mortari. Measuring spatial effects in the presence of institutional constraints: the case of Italian Local Health Authority expenditure. Reg Sci Urban Econ. 2014;49:232–41.
48. Guccio C, Lisi D. Thus do all. Social interactions in inappropriate behavior for childbirth services in a highly decentralized healthcare system. Reg Sci Urban Econ. 2016;61:1–17.
49. Pisati M. sg162: tools for spatial data analysis. Stata Tech Bull. 2001;60:21–37.
50. Frank-Tewaag J, Bleek J, Günster C, Schneider U, Horenkamp-Sonntag D, Marschall U, Sundmacher L. Regional variation in coronary angiography rates: the association with supply factors and the role of indication: a spatial analysis. BMC Cardiovasc Disord. 2022;22(1):1–11.
51. Baltagi BH, Yen Y-F. Hospital treatment rates and spillover effects: does ownership matter? Reg Sci Urban Econ. 2014;49:193–202.

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