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Hospital quality interdependence in a competitive institutional environment: Evidence from Italy

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A B S T R A C T

In this paper we explore the geographical scope of hospital competition on quality, using Italian data on over 207,000 patients admitted to 174 hospitals located in the Lombardy region in the years 2008–2014. We propose an economic framework that incorporates both local and global forms of quality competition among hospitals, the latter emerging from periodically released hospital performance rankings. Under this framework, we derive the hospital reaction functions and, accordingly, we characterize the structure of interdependence among hospital qualities. We employ recent methods from the graphical modelling literature to estimate the set of local rivals for each hospital, as well as the degree of global interdependence among hospitals. Consistently with our micro-founded framework, our results show a significant positive degree of short- and long-range dependence, suggesting the existence of forms of local and global competition amongst hospitals with relevant implications for health care policy.

1. Introduction

In recent years, several central and local governments in Western countries have implemented pro-competition reforms in the health care sector with the view that, when prices are regulated, an increase in competition amongst providers would lead to improvements in the quality of health care, which would then translate into better health outcomes. Between 2002 and 2008, the UK government launched several pro-competition reforms in the health care sector that have given patients free choice of the provider where to be admitted (Department of Health, 2004). Similarly, in 1997 the Italian regional Lombardy government implemented a pro-competition health care reform that allowed patients to choose among all providers located within the region, including accredited private hospitals.

There is currently a debate within the scientific community on the real effects of these reforms on hospital quality, with empirical evidence reporting contrasting results. While some studies corroborate the hypothesis that more competition amongst hospitals leads to better health outcomes (e.g., Bloom et al., 2015; Gaynor et al., 2016), other studies report no significant association between quality and competition (e.g., Mukamel et al., 2002; Berta et al., 2016; Colla et al., 2016), while yet other studies provide evidence that more competition may even harm the health of people (e.g., Propper et al., 2004, 2008). One common feature of these studies is that they assume that hospitals compete with a pre-specified set of providers within their local market, or catchment area. This is typically defined using geographical or travel time distance (see, among others, Propper et al., 2004; Gravelle et al., 2014; Longo et al., 2017). Several of these studies measure competition by means of the Herfindahl-Hirschman Index (HHI), namely the sum of the squared market share of each hospital (e.g., Kessler and McClellan, 2000; Cooper et al., 2011).

In this paper we address the issue of the geographical scope of hospital competition on quality. In particular, we relax the common, but restrictive assumption of a pre-specified set of competitors within the local hospital market, and incorporate a global form of competition (i.e., outside the local market) that might emerge in a competitive institutional environment. We do so by adopting the latest graphical modelling techniques to identify the set of rivals for each hospital (Friedman et al., 2008; Moscone et al., 2017) and by then embedding these techniques into a spatial econometrics approach in which the spatial lag of quality is

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interpreted as the slope of the reaction function, as suggested by a recent literature (Mobley, 2003; Mobley et al., 2009; Gravelle et al., 2014; Guccio and Lisi, 2016; Longo et al., 2017). This approach allows us to test whether hospital qualities are strategic complements, strategic substitutes or independent.

In order to characterize the hospital reaction function, we develop a theoretical model of hospital quality competition under regulated prices. Relative to the traditional framework (e.g., Brekke et al., 2011, 2012; Gravelle et al., 2014), we allow both for the presence of a local competition, that is hospitals competing locally in quality to attract patients, as typically done in the literature, and of a long-range, or global, competition, emerging from periodically released hospital performance rankings. In particular, the model assumes that hospital managers are reappointed the next period according to a probability distribution that depends on the (relative) quality performance that is periodically released.[1] We use this framework to characterize the structure of interdependence amongst hospital qualities arising in a competitive institutional environment. We then empirically test our model predictions by estimating the hospital reaction function, following the spatial approach suggested by a recent literature (Mobley, 2003; Mobley et al., 2009; Gravelle et al., 2014; Guccio and Lisi, 2016; Longo et al., 2017). We use data on 207,930 admissions in 174 hospitals located in the Lombardy region in Italy over the period 2008 to 2014. The Lombardy health care system resembles quite well the institutional environment in our theoretical model. We focus on a set of quality indicators for emergency and elective admissions that are used to create rankings of hospitals within the quality evaluation program in the Lombardy region (see Section 2). In particular, we consider 30-days mortality rate from Acute Myocardial Infarction (AMI), Ischaemic Stroke (IS), Haemorrhagic Stroke (HS), Hip Fracture (HF), and 1-year readmission rate following Hip Replacement (HR) and Knee Replacement (KR). Mortality rate for Coronary Artery Bypass Graft (CABG) surgery, which is a common outcome for the quality of elective care (Gaynor et al., 2016), is not considered in this paper as this surgical procedure is provided by too few hospitals in the region. The large range of outcomes increases the robustness of our findings both by taking into account the advantages and limitations of each indicator, such as the extent of selection bias due to patient choice, and by capturing potentially different dimensions of the quality of care.

The approach presented in this paper is novel insofar as it does not rely on geographical distance to construct local hospital markets; instead, for the first time, we employ graphical modelling techniques to identify the set of rivals for each hospital. More specifically, we estimate the hospital reaction functions by assuming that hospital quality follows a Conditional Autoregressive (CAR) model (Cressie, 1993; Parent and Lesage, 2008). CAR models are often seen as an alternative to the well-known Spatial Autoregressive (SAR) processes (Whittle, 1954). Similarly to a SAR specification, a CAR model captures dependences of the data at a given spatial location with data in neighboring locations, and is used in health economics studies to represent the hospital reaction function. The neighborhood structure is represented by means of the so-called spatial weights matrix, which summarizes the set of rivals for each hospital. This is usually assumed to be known a-priori by the researcher, by exploiting information on the distance between units, such as the geographic, economic, policy, or social distance (e.g., Gravelle et al., 2014; Guccio and Lisi, 2016; Longo et al., 2017). Adopting a CAR specification allows us to keep the spatial weights matrix unknown. In particular, we exploit methods from the graphical modelling literature to estimate this matrix, thanks to a link between the CAR specification and what is also known as a conditional Gaussian model, which represents the baseline for all graphical models.

Given the large number of unknown parameters to be estimated, we adopt a penalised likelihood approach (Friedman et al., 2008), and use the Flexible Block-GLASSO procedure advanced by Moscone et al. (2017) to estimate efficiently the spatial weights matrix of the CAR model. This empirical model will indirectly return both the number of rivals with which each hospital competes, locally and globally, and thus an estimate of the degree of "local" and "global" interdependence amongst hospitals, respectively. Our results point at a significant interdependence among hospital qualities, which is only in part explained by local interactions. Indeed, model selection criteria show, consistently among the quality indicators, that models allowing for both local and global interdependence are preferred to those allowing only for local interdependence, despite the larger number of parameters. This suggests that global dependencies are a significant feature in our data.

This paper provides a number of contributions to the literature on hospital competition. Existing literature usually assumes that hospitals compete with a pre-specified set of providers within their local market (e.g., Propper et al., 2004; Cooper et al., 2011; Gravelle et al., 2014; Longo et al., 2017), and only one parameter (either the regression coefficient of the HHI, or the so-called spatial parameter of the spatial lag) is estimated. This implicitly assumes that strategic complementarity or substitutability, as indicated by the estimated parameter, holds between all pairs of hospitals within the local markets. This, in turn, rules out possible local heterogeneity in the interdependence amongst hospitals, as well as possible interdependence amongst hospitals located outside the catchment area. However, such an assumption may be restrictive and may not fully account for the complexity of the process of competition occurring amongst hospitals. For example, hospitals may compete only with a subset of nearby hospitals, because of different specialization and technological levels. At the same time, hospitals may perceive as competitors also providers outside their catchment area. An important source of "long-range" competition among hospitals can derive from the public reporting of hospital rankings, like the one implemented in the Italian Lombardy region. Indeed, when hospital performances are periodically evaluated, a provider can observe the quality of other hospitals and react to this, given its link with the professional reputation, social status, or compensation of its managers (e.g., Kolstad, 2013). In certain health care systems, hospital rankings may also impact, sometimes dramatically, on their managers' future career.

In this study, we relax this restrictive assumption of a pre-specified set of local competitors. First, our economic model of hospital quality competition under regulated prices allows for a more complex form of interaction among providers, and our results indeed suggest that hospital competition arising in certain health care systems might not be only of a local nature. Empirically, the adoption of graphical modelling techniques gives us the advantage on the one hand of estimating the rivals in the market without relying on some pre-specified assumption on the spatial weights, and on the other hand of allowing for heterogeneity in the local competition network amongst hospitals. Indeed, our empirical findings highlight a significant heterogeneity in the interdependence amongst hospitals belonging to the same local market. Furthermore, consistently with our economic framework, our results suggest that the ranking system introduced in a health care system represents an incentive for hospitals to look at the quality set by other hospitals, regardless of where the hospitals are located. Hence, interdependence amongst hospitals reflects only in part a mechanism of local competition. Our findings are also relevant from a policy perspective, providing insightful implications that we discuss in the last part of the paper.

The remainder of the paper is organized as follows. Section 2 briefly describes the Lombardy health system and the reforms that have introduced competition amongst hospitals. Section 3 lays out the economic model, and Section 4 presents the empirical model. Section 5 discusses the data, while the empirical results are presented in Section 6. Section 7 concludes with policy implications and final remarks.

2. The Lombardy health care system and quality evaluation program

The Italian National Health System (NHS) is a highly decentralized

[1] In Section 2 we support this by providing some anecdotal evidence.

system, where financial resources are transferred through an allocation formula to the regions, which are then responsible for the organization and management of their (regional) health care systems (e.g., France et al., 2005; Cappellari et al., 2016). Among these, the Lombardy region has been the first to implement, in 1997 (Regional Law N. 31 of 11/07/1997), an innovative health care model that promotes competition among agents and patient choice. The reform has introduced a net distinction between the role of 15 Local Health Authorities (LHA) and that of hospitals within the health care system. While the 15 LHAs in the region are responsible for financing and controlling the quality and quantity of NHS activities in their target area, hospitals provide health care services purchased by the LHA (i.e., a form of quasi-market model similar to the English NHS). Such distinction between the purchaser (the LHA) and the provider (the hospital) has led the former to develop tools for monitoring the quality of providers, and the latter to aim at improving its quality and technical efficiency. The health reform has also introduced freedom of choice of the hospitals where to be admitted, and competition between public and "accredited" (by the region) private providers.

Since 1995, the Lombardy health care system has adopted a prospective payment system to reimburse the hospitals for each patient on the basis of their Diagnosis Related Group (DRG), which is established by using clinical information reported in the Hospital Discharge Chart. Differently from other regions, the DRG tariffs are set at the regional level, so as to provide specific incentives to hospitals,[2] and the hospital funding due to the per-case payments represents the highest share of the total funding.

In 2002, the Lombardy government established an evaluation program to assess the performance of hospitals and their top managers in terms of quality of services (Berta et al., 2013). The evaluation process is managed by the Regional Observatory on the Quality of Health Service.[3] Every year the regional authority uses data from hospital discharge charts to estimate a set of risk-adjusted outcome indicators of quality for each accredited hospital in the region, including mortality rates within 30 days from discharge, intra-hospital mortality rates and 1-year readmission rates for various medical procedures. All outcome-based indicators employed in our empirical analysis are included in the quality evaluation program, though they represent a subset of all data considered in it. For each ward (i.e., medical speciality), the regional health authority publishes a classification of hospitals into three groups, depending on whether the quality is significantly above, not different, or significantly below the regional average performance.[4] The region publishes the results on a web portal to which accredited hospitals can access and see their ranking with respect to all other hospitals. By allowing providers to look at their relative performance, the intent is to encourage hospitals and their top managers to perform well and, thus, to promote improvements in health care quality.

While the program is not "officially" aimed at penalizing hospitals and their top managers on the basis of their performance, sharing periodically the performance rankings makes all health care stakeholders aware of hospitals' performances. The regional health authority is also responsible for the recruitment of hospital managers, and it takes into account their previous performance when reappointing them.[5] Hospitals' top managers (i.e., the chief executives) also have an explicit financial incentive to compete with each other, as the evaluation system is used by the regional government to decide on an annual bonus that proportionate to their performance ranking. This can reach a maximum of €31,000, equivalent to 20 per cent of the basic salary of a hospital manager (DPCM n. 502/1995).[6] Finally, even if the web portal is not open to the public, every year there is a large discussion in the regional press on the results of the evaluation system in Lombardy, making health managers and the regional government more accountable in the management of the health care system.[7] Therefore, the results of the evaluation program may have an impact on the future state of hospital managers, such as employability, professional reputation, social status, financial bonus, and thus on the hospital competition process. Overall, the described institutional context makes the Lombardy health care system a competitive environment for hospital management.

It is worth noting that the Italian government has recently approved a nation-wide reform that introduces a mechanism of health managers' appointment and evaluation very similar to the Lombardy model. The new legislation introduces a merit-based national register of health managers from where each region can choose and, most importantly, a periodic evaluation system of hospital performances that explicitly contemplates the possibility to replace hospital managers with a negative evaluation and remove their name from the national register.

3. Theoretical model for local and global forms of competition

In this section we extend the traditional framework on hospital competition (see, for example, Ma and Burgess, 1993; Brekke et al., 2011; 2012; Gravelle et al., 2014) to take into account the specific incentives for hospitals in such a competitive institutional environment. Our theoretical model provides a well-grounded micro-founded structure of interdependence among hospitals that will be tested in the empirical part of the study.

Consider N hospitals in the regional health authority and let q_{it} be the quality of hospital i at time t, with $t = 1,2, \ldots$. The quality performance ranking periodically produced by the regional health authority for all hospitals may have a number of effects on the future state of hospital managers, such as an increase in the risk of not being reappointed, a damage of their reputation or an increase in their compensation. In our stylized model we assume that managers are not reappointed the next period with a probability that depends on the relative quality performance. While not being reappointed is only one of the possible outcomes, adopting an extended model with many states (e.g., damaged professional reputation, financial bonuses) would not change the nature of strategic interdependence amongst hospitals, at the expenses of a very complicated dynamic framework.

The strategic environment in this context can be represented by a simple stochastic game with N players (i.e., hospital managers), in which the state of each player changes according to a probability distribution where the probability of each state depends on the actions of the players involved (e.g., Shapley, 1953; Mertens, 2002). In our model, in each period t, hospital managers choose simultaneously (i.e., a simultaneous stage game) the quality of health care services $\boldsymbol{q}_t$. Then, at the beginning of the next period $t+1$ the "nature" chooses the state S_{t+1} for each player between "being appointed" ($S = A$) and "not being appointed" ($S = NA$) as hospital manager, drawing from a probability distribution $Pr(S_{t+1} | \boldsymbol{q}_t)$

[2] An example of this use of regional DRG tariffs can be found in childbirth services, wherein the Lombardy region pays the same tariff to hospitals for a vaginal and a caesarean delivery, to provide an incentive to reduce the inappropriate use of caesarean deliveries (e.g., De Luca et al., 2021).

[3] Instituted by the Regional Decree N. VI/38121 of 06/08/1998.

[4] More details on the quality assessment program in the Lombardy region can be found here: www.crisp-org.it/research/healthcare/manuale-del-sistema-di-valutazione-della-performance-degli-ospedali-lombardi/.

[5] As anecdotal evidence on the impact of performance rankings on the probability of being reappointed as hospital manager, see, for example, www.laprovinciacr.it/news/cremona/131164/Asl-e-ospedali–cambio-al.html showing that worse (according to the performance ranking) hospital managers face a higher risk of not being reappointed in the office by the regional government.

[6] As evidence of this annual system of financial bonus, see, for example, www.ilgiorno.it/milano/salute/bonus-direttori-sanita-lombardia-1.356052, www.quotidiano.net/file_generali/documenti/PDF/2014/10/giulia.pdf.

[7] As an example of the discussion in the regional press on the yearly evaluation of the hospital performances, see, for example, the following journal articles www.ilgiornale.it/news/classifica-degli-ospedali-i-voti-migliori-niguarda.html, www.varesenews.it/2013/02/asl-e-ospedali-ecco-le-pagelle-dei-dirigenti/66521/.

that depends on the quality of all players at time t. Finally, each player that has not been reappointed leaves the game permanently and is replaced by a new hospital manager, implying that each hospital manager is not expected to play the game infinitely.

The stage payoff function for each player is the standard profit function of hospitals (e.g., Brekke et al., 2011; Gravelle et al., 2014), implicitly thought to include also the managers compensation.[8] In this institutional context, hospitals are reimbursed through a per-treatment prospectively fixed price p. Therefore, in order to attract more patients, they compete on quality with neighboring hospitals belonging to the same catchment area g, with $g = 1, 2, \ldots, G$. Specifically, the demand function of hospital i, for $i = 1, 2, .., N$, is $x_i = x(q_i, \boldsymbol{q_j}; \boldsymbol{\delta_i}, \boldsymbol{\phi_g})$, which depends also on the quality of potentially all other hospitals j belonging to the same catchment area. Existing literature on hospital competition, once the boundaries of the catchment areas have been pre-specified (for instance, through administrative boundaries or distance limits), usually assume that the demand function of hospital i depends on the quality of all other hospitals within the same catchment area (e.g., Propper et al., 2004; Gravelle et al., 2014; Longo et al., 2017). In this paper, we relax this restrictive assumption and, instead, we estimate the set of local rivals j for each hospital, as it will be described below. This implies that the group of local rivals for hospital i might also be (we put no restrictions on it) a subset of hospitals in the same catchment area.

Therefore, we assume that the demand of hospital i is increasing in its own quality, q_i, and decreasing in the quality of rival hospitals in the same catchment group g, $\boldsymbol{q_j}$, that is $\frac{\partial x_i}{\partial q_i} > 0$ and $\frac{\partial x_i}{\partial q_j} < 0 \; \forall j \neq i$. Then, we also assume that $\frac{\partial^2 x_i}{\partial q_i^2} \leq 0$, and $\frac{\partial^2 x_i}{\partial q_i \partial q_j} \geq 0$. Finally, $\boldsymbol{\delta_i}$ and $\boldsymbol{\phi_g}$ capture other factors affecting the demand for hospital i, such as the location of patients with respect to hospital i and patients' preferences over distance and quality that might also be area-specific.

The cost of providing treatments for hospital i is given by the cost function $C_i = C(x(q_i, \boldsymbol{q_j}; \boldsymbol{\delta_i}, \boldsymbol{\phi_g}), \; q_i; \boldsymbol{\gamma_i})$ increasing in quantity and quality, that is $\frac{\partial C_i}{\partial x_i} > 0$ and $\frac{\partial C_i}{\partial q_i} > 0$, and convex in quality, $\frac{\partial^2 C_i}{\partial q_i^2} > 0$. We put no restrictions on the marginal costs of quantity, thus the marginal cost of treatment for hospital i could be either increasing, $\frac{\partial^2 C_i}{\partial x_i^2} > 0$, or decreasing, $\frac{\partial^2 C_i}{\partial x_i^2} < 0$, in output (Gravelle et al., 2014). Similarly, we allow for both cost complementarity ($\frac{\partial^2 C_i}{\partial q_i \partial x_i} < 0$) and cost substitutability ($\frac{\partial^2 C_i}{\partial q_i \partial x_i} > 0$) between quantity and quality (Breeke et al., 2011). The former implies that the marginal cost of quality decreases when more patients are treated, which applies, for instance, in the presence of learning-by-doing effects (e.g., Birkmeyer et al., 2002; Gaynor et al., 2005). On the other hand, the latter implies that increasing quality is more costly when more patients are treated. Finally, the parameter vector $\boldsymbol{\gamma_i}$ captures other exogenous factors potentially affecting the costs of hospital i. Putting all this together, the instantaneous profit function of hospital i is given by:

$$\pi_i = p \cdot x\left(q_i, \; \boldsymbol{q_j}; \boldsymbol{\delta_i}, \boldsymbol{\phi_g}\right) - C\left(x\left(q_i, \; \boldsymbol{q_j}; \boldsymbol{\delta_i}, \boldsymbol{\phi_g}\right), q_i; \boldsymbol{\gamma_i}\right). \tag{1}$$

However, hospital managers are not only concerned with the instantaneous profit but also with their future state and, thus, they also consider the continuation value when they choose quality. In particular, the value of being appointed as hospital i's manager, V_i^A, can be expressed using the following recursive formulation:

$$V_i^A = \max_{q_i} \left\{ \pi_i + \beta \left[Pr\left(A_i^{'} \middle| \, q_i, \boldsymbol{q_{-i}}; \boldsymbol{\theta}\right) V_i^A + \left(1 - Pr\left(A_i^{'} \middle| \, q_i, \boldsymbol{q_{-i}}; \boldsymbol{\theta}\right)\right) V^{NA} \right] \right\}, \tag{2}$$

where β is the discount factor and $Pr(A_i^{'}|q_i, \boldsymbol{q_{-i}}; \boldsymbol{\theta})$ is the probability of being reappointed as hospital manager, which depends on the quality of hospital i but also on the quality of all other hospitals in the region, that is $\boldsymbol{q_{-i}} = (q_1, q_2, \ldots, q_{i-1}, q_{i+1}, \ldots, q_N)$, as well as on other exogenous factors $\boldsymbol{\theta}$. Finally, V^{NA} is the asset value of not being reappointed which includes all states other than that of being reappointed as hospital i's manager, such as being unemployed or employed in a different job. While different alternative states may give different utilities, the only important condition needed in our model is that the value of being reappointed is higher than the value of not being reappointed, $V_i^A > V^{NA}, \; \forall i = 1, 2, \ldots, N$, which can be interpreted as a participation condition for each player in this model.[9]

As for the probability function $Pr(A_i^{'}|q_i, \boldsymbol{q_{-i}}; \boldsymbol{\theta})$, we make the mild assumption that a higher own quality q_i – increasing the hospital i's performance ranking – increases at a non-increasing rate the probability of being reappointed, while a higher quality of other hospitals $\boldsymbol{q_{-i}}$ – reducing the hospital i's performance ranking – decreases the probability for hospital i manager of being reappointed, that is $\frac{\partial Pr_i}{\partial q_i} > 0$, $\frac{\partial^2 Pr_i}{\partial q_i^2} \leq 0$ and $\frac{\partial Pr_i}{\partial \boldsymbol{q_{-i}}} < 0$. Finally, we also assume that the increase in Pr_i due to a higher own quality q_i is more effective when the quality of other hospitals $\boldsymbol{q_{-i}}$ is higher, that is $\frac{\partial^2 Pr_i}{\partial q_i \partial \boldsymbol{q_{-i}}} > 0$. The last assumption captures one essential feature of our economic model on hospital interdependence in a competitive institutional environment. In particular, when a hospital is surrounded by many underperforming hospitals, its relative performance will be higher and, thus, a further increase in its quality does not have a significant impact on the probability of being reappointed for the hospital manager. On the other hand, when the performance of surrounding hospitals is higher, an increase in its quality is important in increasing the probability of being reappointed for the hospital manager.

From (2), the choice of the optimal quality q_i depends on two different vectors of qualities. The first, $\boldsymbol{q_j}$, includes all rival hospitals for hospital i belonging to the same catchment group, that is the standard set of neighboring hospitals considered in the hospital competition literature (note that in the empirical part we estimate the set of local rivals for each hospital). The second, $\boldsymbol{q_{-i}}$, includes all hospitals different from i in the regional health authority, which represents a second level of competition amongst hospitals. Therefore, our model captures two levels of competition among hospitals: a local form of competition to attract patients within a catchment area and a global form of competition for the performance ranking, which potentially affects the future state of all hospital managers. This framework could be appropriate also in other contexts where hospital rankings are released, as long as performance rankings have some impact on the managers' future states.

Hospital managers simultaneously choose qualities to maximize the present discounted value (2). Following the literature on stochastic games, we consider Markov strategies to capture the simplest behavior consistent with rationality (Maskin and Tirole, 1987, 1988; Mertens, 2002). Since in our model the payoff function and the transition probability are (state-dependent but) time-invariant, a Markov Perfect

[8] In this setting, when hospital managers are called to play, they know the full history of the game, given by the previous states and actions of each player ($\boldsymbol{S}_0$, $\boldsymbol{q}_0, \boldsymbol{S}_1, \boldsymbol{q}_1, \ldots, \boldsymbol{S}_{t-1}, \boldsymbol{q}_{t-1}, \boldsymbol{S}_t$). However, following the literature on stochastic games, the actions available to each player and the stage payoff function depend only on the current state $\boldsymbol{S_t}$ and not on the specific history. That is, the current state $\boldsymbol{S_t}$ is the payoff-relevant history of the game (e.g., Mertens, 2002).

[9] To see this point, let q_i^* and $\boldsymbol{q}_{-i}^*$ be the equilibrium qualities of all players derived by the N maximization problems (2), and assume for simplicity that in the state V^{NA} players receive for each period the reservation utility u^R, such that $V^{NA} = \frac{u^R}{1-\beta}$. Then, the asset value of being appointed for the hospital i's manager is.

$$V_i^A = \frac{p \cdot x\left(q_i^*, \; \boldsymbol{q}_j^*; \boldsymbol{\delta_i}, \boldsymbol{\phi_g}\right) - C\left(x\left(q_i^*, \; \boldsymbol{q}_j^*; \boldsymbol{\delta_i}, \; \boldsymbol{\phi_g}\right), \; q_i^*; \boldsymbol{\gamma_i}\right)}{\left(1 \; - \; \beta Pr\left(A_i^{'} \middle| q_i^*, \; \boldsymbol{q}_{-i}^*; \boldsymbol{\theta}\right)\right)} + \frac{\beta\left(1 - Pr\left(A_i^{'} \middle| q_i^*, \; \boldsymbol{q}_{-i}^*; \boldsymbol{\theta}\right)\right) \; u^R}{\left(1 \; - \; \beta Pr\left(A_i^{'} \middle| q_i^*, \; \boldsymbol{q}_{-i}^*; \boldsymbol{\theta}\right)\right) \; (1 \; - \; \beta)}$$

Equilibrium (MPE) can be characterized as the best response correspondence among the N time-invariant Markov reaction functions (Fudenberg and Tirole, 1991). The first-order condition for the hospital i's maximization must satisfy $\frac{\partial \pi_i}{\partial q_i} + \beta \frac{\partial Pr_i}{\partial q_i}(V_i^A - V^{NA}) = 0$, that is:

$$\frac{\partial x_i}{\partial q_i}\left(p - \frac{\partial C_i}{\partial x_i}\right) + \beta \frac{\partial Pr_i}{\partial q_i}\left(V_i^A - V^{NA}\right) = \frac{\partial C_i}{\partial q_i}, \tag{3}$$

which defines implicitly the time-invariant Markov reaction function of the hospital i manager $q_i^R = q_i^R(\boldsymbol{q}_{-i})$, that is well-defined since $\boldsymbol{q_j} \subset \boldsymbol{q}_{-i}$. Condition (3) states that the optimal quality must balance the marginal benefit and the marginal cost of quality. Similarly to the standard competition framework, the marginal benefit of quality includes the increase in profit due to the marginal increase in demand, $\frac{\partial x_i}{\partial q_i}\left(p - \frac{\partial C_i}{\partial x_i}\right)$. In addition to this, our model also includes the increase in the expected continuation value due to the marginal increase in the probability of being reappointed, $\beta \frac{\partial Pr_i}{\partial q_i}(V_i^A - V^{NA})$.[10]

Solving algebraically for the equilibrium of the model would require a more explicit functional form. Instead, our main focus is on the strategic interdependence amongst hospitals. This can be studied by looking at the slopes of the time-invariant reaction curves. Specifically, applying the implicit function theorem to (3), the slopes of the reaction function are given by:

$$\frac{\partial q_i^R}{\partial q_j} = \begin{cases} -\dfrac{\dfrac{\partial^2 \pi_i}{\partial q_i \partial q_j} + \beta \dfrac{\partial^2 Pr_i}{\partial q_i \partial q_j}\left(V_i^A - V^{NA}\right)}{SOC} \lesseqgtr 0 & \forall\, i, j \mid g_i = g_j \\ -\dfrac{\beta \dfrac{\partial^2 Pr_i}{\partial q_i \partial q_j}\left(V_i^A - V^{NA}\right)}{SOC} > 0 & \forall\, i, j \mid g_i \neq g_j \end{cases} \tag{4}$$

where $\frac{\partial^2 \pi_i}{\partial q_i \partial q_j} = \frac{\partial^2 x_i}{\partial q_i \partial q_j}\left(p - \frac{\partial C_i}{\partial x_i}\right) - \frac{\partial x_i}{\partial q_j}\left(\frac{\partial^2 C_i}{\partial x_i \partial q_i} + \frac{\partial^2 C_i}{\partial x_i^2}\frac{\partial x_i}{\partial q_i}\right) \lesseqgtr 0$ and SOC is the strictly negative second order condition of the hospital i's maximization problem.

From (4), it emerges that strategic interdependence is not limited only to hospitals within the same catchment group. In particular, the second line in (4) shows that the competition for the performance ranking induces an additional source of interdependence among hospitals. Therefore, we can say that in this context hospitals' qualities could be strategic interdependent both within and outside the catchment areas, but at two different intensities implied by the corresponding slopes in (4). As discussed above, the different slopes of the reaction function are explained by the two sources of competition in our setting: the standard local competition to attract more patients, which concerns only rival hospitals within the same catchment group, and the global competition for the performance ranking, which instead concerns all hospitals in the regional health authority.

To sum up, our theory model predicts that in such a competitive institutional environment:

- the slopes of the reaction function $q_i^R = q_i^R(\boldsymbol{q}_{-i})$ with respect to hospitals outside the catchment area ($\forall\, i, j \big| g_i \neq g_j$) are unambiguously positive, thus qualities are strategic complements outside the catchment areas because of the global competition for the performance ranking;
- the slopes of the reaction function with respect to hospitals within the same catchment area ($\forall\, i,j \big| g_i = g_j$) strictly depend on the sign of $\frac{\partial^2 \pi_i}{\partial q_i \partial q_j}$ and might also be equal to zero,[11] thus the interdependence amongst hospital qualities could be heterogeneous within local hospital markets (i.e., qualities could be either strategic complements or substitutes).

A potential limitation of our theory model is that, while the performance ranking in the Lombardy region gives rise to an annual classification of hospitals into three groups (above, not different, below the average performance), in our model the strict inequalities on the probability of being reappointed the next period, $\frac{\partial Pr_i}{\partial q_i} > 0$ and $\frac{\partial Pr_i}{\partial \boldsymbol{q}_{-i}} < 0$, are more consistent with a continuous version of the performance ranking. This is mainly done for simplicity, since algebraically is much easier to treat the continuous model than the discrete version in three groups of hospitals. It is also true that, when hospital managers are called to act, in reality they do not know *ex-ante* the quality of other hospitals and, in turn, the annual distribution of hospitals among the three groups; this implies that, in reality, any perceived improvement in the quality of other hospitals in the region has the potential to stimulate the quality of hospital i.[12] Finally, as explained in Section 2, the evaluation system is used by the regional government to decide on the annual bonuses of hospital managers, which are proportional (in a continuous way) to their relative performance ranking (see footnote 4 and the evidence therein). For all these reasons, the continuous version of the performance ranking (as mirrored by the strict inequalities $\frac{\partial Pr_i}{\partial q_i} > 0$ and $\frac{\partial Pr_i}{\partial \boldsymbol{q}_{-i}} < 0$) should represent only a minor limitation of our model with respect to the quality evaluation program in the Lombardy system.

Overall, denoting with M_g the dimension (i.e., the number of hospitals) of the catchment area g, the structure of the quality interdependence amongst the N hospitals in this health care system can be represented by the following $N \times N$ symmetric matrix with a block-wise structure:

$$\frac{\partial \boldsymbol{q}_i^R}{\partial \boldsymbol{q}_j} = \begin{pmatrix} \boldsymbol{w}_{11} & w_{12}1_{M_1\times M_2} & \cdots & w_{1g}1_{M_1\times M_g} & \cdots & w_{1G}1_{M_1\times M_G} \\ w_{21}1_{M_2\times M_1} & \boldsymbol{w}_{22} & \cdots & w_{2g}1_{M_2\times M_g} & \cdots & w_{2G}1_{M_2\times M_G} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ w_{g1}1_{M_g\times M_1} & w_{g2}1_{M_g\times M_2} & \cdots & \boldsymbol{w_{gg}} & \cdots & w_{gG}1_{M_g\times M_G} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ w_{G1}1_{M_G\times M_1} & w_{G2}1_{M_G\times M_2} & \cdots & w_{Gg}1_{M_G\times M_g} & \cdots & \boldsymbol{w}_{GG} \end{pmatrix} \tag{5}$$

where $1_{M_l \times M_k}$, for each $l \neq k$, denotes a $M_l \times M_k$ matrix of ones and w_{lk} is equal to the slope of the reaction function with respect to hospitals outside the catchment area, that is the last line in (4). Then, in the diagonal $\boldsymbol{w_{gg}}$ are $M_g \times M_g$ symmetric matrixes which contain the slopes of the reaction function with respect to local rivals within each catchment area g, that is with off-diagonal elements equal to the first line in (4) and

[10] The following second-order condition guarantees that the quality defined in (3) is indeed the optimal quality for the hospital i's manager: $\frac{\partial^2 x_i}{\partial q_i^2}\left(p - \frac{\partial C_i}{\partial x_i}\right) - \frac{\partial x_i}{\partial q_i}\left(\frac{\partial^2 C_i}{\partial x_i \partial q_i} + \frac{\partial^2 C_i}{\partial x_i^2}\frac{\partial x_i}{\partial q_i}\right) + \beta \frac{\partial^2 Pr_i}{\partial q_i^2}(V_i^A - V^{NA}) < 0.$

[11] More specifically, when the marginal cost of treatment for hospital i is increasing in quantity $\frac{\partial^2 C_i}{\partial x_i^2} > 0$, and there is cost substitutability, $\frac{\partial^2 C_i}{\partial q_i \partial x_i} > 0$, then hospitals are strategic complements in quality; in this case, in fact, the increase in rivals' quality reduces the demand (i.e., the amount of treatments) for hospital i and, due to the increasing marginal cost of treatment, it increases the profit margin, leading hospital i to increase its quality. On the other hand, when the marginal cost of treatment is decreasing in quantity, $\frac{\partial^2 C_i}{\partial x_i^2} < 0$, and there is cost complementarity, $\frac{\partial^2 C_i}{\partial q_i \partial x_i} < 0$, then hospitals may also be strategic substitutes in quality, as long as the financial incentives for the instantaneous profit offsets the incentives for the continuation value, $\beta \frac{\partial^2 Pr_i}{\partial q_i \partial q_j}(V_i^A - V^{NA})$. In this case, because of the decreasing marginal cost of treatment, the increase in rivals' quality decreases the profit margin, incentivizing hospital i to reduce its quality.

[12] Worthy of note is that, *ceteris paribus*, in a relative (to the average) performance ranking any change in the quality of a hospital in the region changes the average performance and, in turn, the relative performance of the other hospitals with respect to the average (though not necessarily the relative ranking of all hospitals in the system).

Table 1
Definition of quality indicators and descriptive statistics.

Name	Description	n. adm.	Quality indicator			
			Min	Av.	Sd	Max
AMI	30-day mortality rate for acute myocardial infarction	244,060	0.000	0.116	0.168	1.000
IS	30-day mortality rate for ischaemic stroke	192,849	0.000	0.214	0.213	1.000
HS	30-day mortality rate for haemorrhagic stroke	140,456	0.000	0.139	0.158	1.000
HF	30-day mortality rate for hip fracture	104,532	0.000	0.060	0.119	1.000
HR	1-year readmission rate following hip replacement	119,657	0.000	0.038	0.034	0.250
KR	1-year readmission rate following knee replacement	121,853	0.000	0.036	0.036	0.333

diagonal elements equal to one.

In our empirical application we will estimate hospital reaction functions $q_i^R = q_i^R(\boldsymbol{q}_{-i})$. We follow the approach suggested by a recent literature (Mobley, 2003; Mobley et al., 2009; Gravelle et al., 2014; Guccio and Lisi, 2016; Longo et al., 2017) in which hospital reaction functions are estimated in reduced form adopting spatial econometrics methods. In this spatial approach, the coefficient of the spatial lag (in the SAR model) can be interpreted as the sign of the slope of the reaction function. Therefore, it allows to test whether hospital qualities are strategic complements, strategic substitutes or independent (see, e.g., Gravelle et al., 2014).

Crucially, in all previous related studies (Mobley, 2003; Mobley et al., 2009; Gravelle et al., 2014; Guccio and Lisi, 2016; Longo et al., 2017) the weights w_{ij} of the spatial matrix $\boldsymbol{W}$ are usually pre-specified following standard criteria to define boundaries of the catchment areas, such as spatial or travel time distance between units, and only one parameter (i.e., the so-called spatial parameter δ of the spatial lag $\boldsymbol{Wy}$) is estimated. This implicitly assumes that strategic complementarity or substitutability, as indicated by the spatial parameter, holds between all pairs of spatial units. This, in turn, rules out possible local heterogeneity in the interdependence amongst hospitals, as well as possible interdependence amongst hospitals outside the catchment area. In fact, as predicted by our theory model, both phenomena can emerge in hospital markets.

In our empirical strategy, instead, the weights matrix that appears in the spatial model is not pre-specified as usual, but is estimated through a Graphical Least Absolute Shrinkage and Selection Operator (GLASSO) approach (Friedman et al., 2008). Estimating the spatial weights w_{ij} without imposing restrictions (like those implicit in the standard specification of the spatial matrix), our empirical approach accommodates both heterogeneity in local interdependence and possible global interdependence (i.e., outside the catchment areas), and thus it allows to test for our model predictions. To efficiently estimate the spatial weights of the spatial matrix we exploit, as explained below, the micro-founded block-wise structure (5) in the interdependence amongst hospital qualities (Moscone et al., 2017).

4. The empirical model

On the basis of the above economic framework, we assume that hospital quality follows a Conditional Autoregressive specification (CAR). Introduced by Besag (1974), CAR models have been widely adopted in applied work, in areas ranging from image processing, disease mapping, disease spreading, environmental studies, and the analysis of technology diffusion (see, among others, Cressie, 1993; Parent and Lesage, 2008). CAR models are often seen as an alternative to the well-known Spatial Autoregressive (SAR) processes. Both CAR and SAR models represent data for a given spatial location as a function of data in neighboring locations, and are used to study how a particular unit is influenced by neighboring units.

Under the CAR specification, we assume that hospital quality, q_i, $i = 1,2, \ldots,N$, has a Gaussian conditional distribution with conditional mean and variance given by

$$E(q_i|q_j, j=1,2,\ldots,n, j\neq i) = \boldsymbol{\beta}' z_i + \sum_{j=1, j\neq i}^{n} w_{ij}(q_j - \boldsymbol{\beta}' z_j) \tag{6}$$

$$Var(q_i|q_j, j=1,2,\ldots,n, j\neq i) = \sigma_i^2$$

where $\boldsymbol{\beta}$ is a k-dimensional vector of unknown parameters, is a vector of characteristics of hospital i and belongs to a $N\times N$ matrix, $\boldsymbol{W}$, known as spatial weights matrix, and such that $= 0$. In a spatial weights matrix the rows and columns correspond to the cross section observations, and the generic element, can be interpreted as the strength of potential interaction between hospital i and j. $\boldsymbol{W}$ is often written as $\delta\boldsymbol{W}^*$ where $\boldsymbol{W}^*$ is a matrix pre-specified by the user, while δ is an unknown parameter that needs to be estimated, the so-called spatial parameter, measuring the amount of spatial dependence in the data. $\boldsymbol{W}^*$ is usually built using information on distance between units, such as the geographic, economic, policy, or social distance. Under this assumption, estimation of the unknown parameters, δ, $\boldsymbol{\beta}$ and, is carried out by maximum likelihood (Cressie, 1993). In this paper, rather than assuming $\boldsymbol{W}^*$ as known and estimating one single parameter, δ, we will keep $\boldsymbol{W}$ unknown and estimate its elements w_{ij}.

CAR models are known in the graphical modelling literature as conditional Gaussian models, and the spatial weights matrix for CAR models can be estimated by adopting methods from the Gaussian graphical modelling literature for estimating inverse covariance matrices. In particular, it can be shown that model (6) on the conditional distribution implies the following joint normal distribution of $\boldsymbol{q} = (q_1, q_2, \ldots, q_N)'$ (Besag, 1974):

$$\boldsymbol{q} \sim N\left(\boldsymbol{Z\beta}, (\boldsymbol{I}_N - \boldsymbol{W})^{-1}\boldsymbol{\Lambda}\right), \tag{7}$$

with $\boldsymbol{\Lambda} = \mathrm{diag}(\sigma_1^2,\ldots,\sigma_N^2)$, provided that $\boldsymbol{\Sigma} = (\boldsymbol{I}_N - \boldsymbol{W})^{-1}$ is invertible and $(\boldsymbol{I}_N - \boldsymbol{W})^{-1}\boldsymbol{\Lambda}$ is symmetric and positive-definite. It is interesting to note that the reverse also holds (Mardia, 1988). That is, if $\boldsymbol{q} \sim N(\boldsymbol{Z\beta},\boldsymbol{\Sigma})$, where $\boldsymbol{\Sigma}$ is a $N\times N$ positive definite matrix, then (6) holds, with

$$w_{ij} = -\frac{\sigma^{ij}}{\sigma^{ii}} \tag{8}$$

for $i\neq j$, where σ^{ij} is the (i,j)th element of $\boldsymbol{\Sigma}^{-1}$. It follows that the problem of estimating w_{ij} in the CAR model (6) is equivalent to determining whether q_i and q_j are conditionally independent, i.e., $\sigma^{ij} = 0$, given the link between the inverse covariance matrix, or precision matrix, and the conditional independence graph. We remark that block GLASSO allows us to estimate the conditional independence graph outlined in equation (8) with the block structure provided in equation (5), thus providing us with a consistent estimate of the reaction function.

The link between CAR and graphical models allows one to exploit the latest inferential procedures proposed by the graphical modelling literature to estimate the precision matrix. In particular, in this paper we will use penalised likelihood estimation via the Graphical Least Absolute Shrinkage and Selection Operator (GLASSO) approach to estimate $\boldsymbol{\Sigma}^{-1}$ (Friedman et al., 2008). This is particularly effective in cases when the number of units is very large and/or the resulting graph is expected to be sparse. In particular, let $\boldsymbol{S}$ be the empirical covariance matrix and let

Table 2
Correlation between quality indicators with p-values for significance in brackets.

	AMI	IS	HS	HF	HR
IS	0.149				
	[0.00]				
HS	0.056	0.145			
	[0.07]	[0.00]			
HF	0.112	0.114	−0.015		
	[0.00]	[0.00]	[0.65]		
HR	−0.018	0.074	−0.023	0.020	
	[0.63]	[0.05]	[0.53]	[0.60]	
KR	−0.024	−0.009	−0.002	−0.025	0.097
	[0.52]	[0.81]	[0.95]	[0.52]	[0.01]

Table 3
Hospital characteristics included in the regression model of hospital quality.

	AMI	IS	HS	HF	HR	KR
Teaching (%)	12.500	12.575	11.834	11.348	15.094	14.286
Private (%)	29.762	30.539	28.994	29.787	29.245	29.524
Specialist (%)	8.929	7.784	11.243	5.674	0.943	0.952
Catheritization lab (%)	47.619	48.503	48.521	55.319	67.925	67.619
Health expenditure (average £ in logs)	5693	5737	7413	6540	8609	8602
Milan (%)	15.476	16.168	15.385	16.312	16.038	15.238

Notes: AMI: 30-day mortality rate for acute myocardial infarction; IS: 30-day mortality rate for ischaemic stroke; HS: 30-day mortality rate for haemorrhagic stroke; HF: 30-day mortality rate for hip fracture; HR: 1-year readmission rate following hip replacement; KR: 1-year readmission rate following knee replacement.

$\boldsymbol{\theta} = \boldsymbol{\Sigma}^{-1}$. Then the GLASSO approach maximizes the penalised log-likelihood function:

$$l_1(\boldsymbol{\theta}) = log|\boldsymbol{\theta}| - Tr(\boldsymbol{S\theta}) - \rho\|\theta\|_1, \tag{9}$$

where ρ is a regularization parameter controlling the trade-off between sparsity and fit. By shrinking the elements in $\boldsymbol{\Sigma}^{-1}$ to zero, the above penalised estimator encourages the sparsity of the precisions matrix, and hence of the corresponding spatial weights matrix, thus picking only the most significant pairwise dependencies.

The standard GLASSO approach (Friedman et al., 2008) does not impose any structure on the inverse covariance matrix. Following our economic model, we will assume that $\boldsymbol{\Sigma}^{-1}$ and hence the spatial weights matrix, have a block-wise structure as in (5). The simplest approach would be to assume the same precision value within each block and a different same value for the diagonal in each block. This could however be too restrictive. Thus, we adopt the Flexible Block-GLASSO approach proposed by Moscone et al. (2017) where we allow for different, but similar, estimates of within-block (catchment spatial weights) as well as between-block spatial weights. To select the optimal regularization parameter ρ we use the Rotation Information Criterion (RIC) by Lysen (2009), a widely implemented selection criterium (see, among others, Kuismin and Sillanpää, 2020)). This leads to the optimal precision matrix $\boldsymbol{\Sigma}^{-1}$.

From this, we exploit (8) to estimate the slopes of the hospital reaction functions represented by $\boldsymbol{W}$. The resulting within-block spatial weights will produce an estimate of the number of rivals within the catchment group, also showing how a hospital reacts to the quality of care set by its rivals. This gives an indication of the level of *local* competition among hospitals in attracting patients. Conversely, computation of between-block spatial weights will provide an estimate of the reaction of hospitals within a block to the quality of care set by hospitals in other blocks. Such estimate provides an indication of the level of *global* competition due to performance rankings. We remark that our empirical approach allows us to estimate consistently the reaction function in equation (5).

A potential limitation of our empirical approach is that we cannot consider overlapping blocks (Moscone et al., 2017), implying that hospitals must be grouped into non-overlapping catchment areas. In this respect, the most reasonable criterion to define the boundaries of non-overlapping blocks is to take the LHAs as local hospital markets. Indeed, as confirmed by our exploratory analysis on patient admissions in Section 5, the LHAs cover an area wide enough to contain all potential local rivals for each hospital.

5. Data

We gathered administrative data on all patients admitted to any hospitals in Lombardy, in the years 2008–2014. Most studies in the literature of hospital competition generally focus on Acute Myocardial Infarction – also known as heart attack – patients, stating that hospital quality for urgent and non-urgent patients are highly correlated (e.g., Propper et al., 2004; 2008; Cooper et al., 2011; Bloom et al., 2015). In this paper we focus on 6 alternative quality indicators, both for urgent and elective care. We take patients admitted for Acute Myocardial Infarction (AMI), Ischaemic Stroke (IS), Haemorrhagic Stroke (HS) and

Table 4
Number of rivals and estimated spatial coefficients from a SAR model by quality indicator.

	Catchment area: 30 km radius					Catchment area: Local Health Authority				
	n. rivals	Raw quality indicator		Risk-adjusted quality indicator		n. rivals	Raw quality indicator		Risk-adjusted quality indicator	
		Coeff.	Std. err.	Coeff.	Std. err.		Coeff.	Std. err.	Coeff.	Std. err.
AMI	36.060	0.024	0.083	0.029	0.083	16.786	0.030	0.074	0.095	0.069
IS	38.743	0.000	0.085	0.003	0.084	16.689	−0.037	0.080	−0.047	0.080
HS	37.728	0.036	0.081	0.094	0.079	17.166	0.142***	0.065	0.124*	0.066
HF	32.695	0.067	0.080	0.052	0.081	14.135	0.073	0.072	0.056	0.073
HR	24.019	−0.013	0.079	−0.030	0.079	10.434	−0.020	0.078	−0.005	0.077
KR	22.667	−0.023	0.081	−0.044	0.082	10.048	−0.006	0.078	−0.006	0.079

Notes: *,**,***: Significant at the 10%, 5%, 1% significance level, respectively. Notes: AMI: 30-day mortality rate for acute myocardial infarction; IS: 30-day mortality rate for ischaemic stroke; HS: 30-day mortality rate for haemorrhagic stroke; HF: 30-day mortality rate for hip fracture; HR: 1-year readmission rate following hip replacement; KR: 1-year readmission rate following knee replacement.

Table 5
GLASSO estimation of CAR model by quality indicator.

	Raw		Risk-adjusted		Raw		Risk-adjusted		Raw		Risk-adjusted	
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
	AMI				IS				HS			
Teaching	−0.036**	0.015	−0.031**	0.015	0.012	0.016	0.058***	0.016	−0.002	0.019	−0.041**	0.018
Private	−0.009	0.012	−0.013	0.011	0.030***	0.010	0.022**	0.011	0.012**	0.014	0.030**	0.013
Specialist	−0.037**	0.017	−0.026	0.017	0.003	0.017	0.009	0.015	−0.015	0.020	0.044**	0.019
Catheritization lab	−0.032***	0.011	−0.025**	0.010	0.015*	0.010	0.015**	0.009	0.107***	0.012	0.025**	0.011
Health expenditure	0.015***	0.002	0.012***	0.002	0.013***	0.002	0.015***	0.002	0.016***	0.002	0.025***	0.002
Milan	−0.030	0.026	−0.009	0.028	−0.040*	0.022	−0.023	0.019	−0.048	0.037	−0.059*	0.035
	Av. Sp. Weight	Av. n. rivals	Av. Sp. Weight	Av. n. rivals	Av. Sp. Weight	Av. n. rivals	Av. Sp. Weight	Av. n. rivals	Av. Sp. Weight	Av. n. rivals	Av. Sp. Weight	Av. n. rivals
Within block (av.)	−0.003	9.821	0.002	9.798	0.019	9.844	0.011	9.970	0.012	9.361	0.005	9.243
Bergamo	0.013	15.077	0.001	14.615	−0.012	17.846	−0.013	17.539	−0.006	14.615	−0.024	14.769
Brescia	0.014	22.769	0.006	24.154	0.028	20.615	0.020	21.231	0.006	25.385	−0.004	24.769
Como	0.023	5.231	0.009	5.231	0.035	6.154	0.021	5.539	0.064	6.000	0.078	5.692
Cremona	−0.058	3.846	−0.079	3.846	0.027	3.539	−0.056	3.692	0.051	2.462	0.078	2.923
Lecco-Lodi	−0.028	3.846	−0.024	3.385	0.042	4.462	0.050	5.385	−0.005	5.231	−0.047	4.615
Mantova	−0.129	5.077	−0.075	4.615	−0.045	3.077	−0.016	3.231	0.147	3.539	0.105	4.000
City of Milan	0.014	32.308	0.015	30.615	0.013	31.231	0.002	29.462	0.015	28.615	0.015	27.692
Milan 1	0.001	4.769	0.031	4.769	−0.007	4.615	0.015	4.923	0.034	3.846	−0.099	3.539
Milan 2	−0.068	4.923	−0.087	5.231	0.032	4.769	−0.050	4.462	−0.018	4.154	0.026	4.615
Milan 3	−0.033	4.000	0.022	4.462	0.101	5.385	0.082	6.154	−0.024	6.462	−0.021	6.769
Pavia	−0.020	12.154	0.009	12.154	0.005	13.385	−0.001	14.154	0.073	8.769	0.055	8.308
Sondrio-Breno	0.155	0.923	0.143	0.923	0.147	0.923	0.198	0.769	−0.342	0.923	−0.277	0.769
Varese	0.008	12.000	0.025	12.615	0.045	10.462	0.039	11.539	−0.027	11.692	−0.010	11.692
Between blocks	0.048	9.385	0.053	9.077	0.047	9.385	0.039	9.385	−0.001	9.385	0.003	9.077
BIC (within)	10644.0		12861.5		13147.77		16235.01		10417.48		10195.44	
BIC (within+between)	10135.0		11653.0		11965.57		14407.86		10157.29		10063.14	
	HF				HR				KR			
Teaching	−0.019	0.013	−0.012	0.014	−0.008*	0.005	−0.004	0.005	−0.018	0.013	−0.013	0.012
Private	−0.021*	0.011	−0.009	0.011	−0.004	0.003	−0.006*	0.003	0.003	0.003	0.003	0.003
Specialist	−0.002	0.018	0.025	0.017	−0.003	0.110	−0.008	0.110	0.031	0.097	0.030	0.095
Catheritization lab	0.005	0.010	−0.001	0.010	0.000	0.003	−0.001	0.003	0.005*	0.003	0.004	0.003
Health expenditure	0.007***	0.002	0.006***	0.002	0.005***	0.001	0.005***	0.001	0.004***	0.001	0.004***	0.001
Milan	−0.019	0.022	−0.011	0.023	−0.029***	0.010	−0.038***	0.011	0.000	0.014	−0.009	0.014
	Av. Sp. Weight	Av. n. rivals	Av. Sp. Weight	Av. n. rivals	Av. Sp. Weight	Av. n. rivals	Av. Sp. Weight	Av. n. rivals	Av. Sp. Weight	Av. n. rivals	Av. Sp. Weight	Av. n. rivals
Within block (av.)	0.059	9.397	0.062	9.248	−0.003	7.613	0.008	7.698	0.022	7.724	0.022	7.629
Bergamo	0.086	13.462	0.063	15.385	−0.012	10.154	−0.001	10.000	0.072	8.462	0.078	8.077
Brescia	0.044	11.846	0.050	11.692	−0.039	9.692	−0.044	9.615	−0.017	10.231	−0.020	10.000
Como	0.098	6.615	0.096	6.154	−0.030	2.308	−0.007	2.308	−0.091	3.231	−0.110	3.231
Cremona	0.100	1.539	0.030	1.539	0.182	1.539	0.180	1.539	0.159	1.539	0.161	1.539
Lecco-Lodi	0.096	3.077	0.090	3.231	0.171	1.539	0.125	1.539	0.016	2.308	0.022	2.308
Mantova	0.069	3.077	0.111	3.231	−0.117	1.539	−0.107	1.539	−0.272	1.539	−0.172	1.539
City of Milan	0.020	29.846	0.016	28.615	−0.019	16.923	−0.010	17.154	−0.012	17.000	−0.011	16.769
Milan 1	0.084	4.923	0.112	4.615	0.130	3.231	0.141	3.231	0.150	3.077	0.152	3.231
Milan 2	0.059	3.077	0.091	3.077	0.177	1.539	0.279	1.539	−0.031	1.539	−0.046	1.539
Milan 3	0.133	4.154	0.158	4.154	0.103	3.231	0.133	3.231	0.107	2.308	0.121	2.154
Pavia	0.060	6.462	0.074	6.154	−0.120	4.077	−0.017	4.231	0.184	4.077	0.144	4.308
Sondrio-Breno	0.093	0.923	0.120	0.923	−0.126	0.462	−0.126	0.462	0.153	0.462	0.149	0.462
Varese	0.062	12.923	0.079	11.539	−0.024	5.846	−0.062	6.385	0.007	6.615	0.007	6.462
Between blocks	0.093	9.539	0.093	10.000	0.005	9.846	−0.005	9.846	0.027	9.692	0.026	9.846
BIC (within)	18156.7		19579.0		73618.9		72721.7		61921.9		60609.4	
BIC (within+between)	14839.0		14579.9		54551.6		53949.7		38412.4		37807.4	

Notes: *, **, ***: Significant at the 10%, 5%, 1% significance level, respectively. Spatial weights have been estimated using eq. (8), where σ^{ij} have been estimated using the GLASSO. The average spatial weight is the average of the non-zero elements of the estimated spatial weights matrix, W. The average number of rivals is the average number of non-zero elements in W. The last two rows of the table report the BIC selection criterion for the model that allows only correlation within blocks (BIC (within)) and the model that allows for both within and between blocks correlation (BIC (within+between)).

Notes: *, **, ***: Significant at the 10%, 5%, 1% significance level, respectively. Spatial weights have been estimated using eq. (8), where σ^{ij} have been estimated using the AMI: 30-day mortality rate for acute myocardial infarction; IS: 30-day mortality rate for ischaemic stroke; HS: 30-day mortality rate for haemorrhagic stroke; HF: 30-day mortality rate for hip fracture; HR: 1-year readmission rate following hip replacement; KR: 1-year readmission rate following knee replacement.

Hip Fracture (HF) on any Lombardy hospitals. These are urgent patients having little choice regarding the hospital where to be admitted. For these patients we take as health outcome the mortality rate within 30 days from discharge. We then consider patients admitted for Hip Replacement (HR) and Knee Replacement (KR), and take as quality indicator the readmission rate for the same condition within one year from discharge. Their health outcomes are likely to reflect the quality of health care for elective patients. When calculating 1-year readmission, we take both urgent and non-urgent readmission for the same condition, and assign the readmission episode to the provider from which the patient has been discharged in the year before the readmission. As mentioned before, all these indicators are included in the quality evaluation program in Lombardy, though they represent a subset of all data considered in it. At least for the quality dimension, however, it can be argued that these six indicators represent a highly significant subset of indicators used in the quality evaluation program.

We refer to Table 1 for a description of the quality indicators included in our analysis. This table shows a marked variation in the number of admissions across quality indicators, ranging from 120,000 for hip and knee admissions (circa 3% of the sample of admissions) to 244,000 for heart attack (circa 12% of the sample admissions). It is important to note that these figures have been obtained after eliminating records with missing entries on either the hospital or the patient identifier.

Table 2 reports the correlation between quality indicators. This analysis shows that most of these indicators are uncorrelated or weakly correlated, thus suggesting the importance of replicating our empirical analysis with different quality measures to test the robustness of our findings, as commented also by Gravelle et al. (2014).

Data on patients have been extracted from the Hospital Discharge Chart available for each patient. These include socio-demographic characteristics such as age and gender, known to account for a large share of case-mix variability in the quality indicators (Propper and Van Reenen, 2010); clinical information like principal diagnosis, severity of illness, length of stay, the type of admission (planned or via the emergency room), the ward of admission, type of discharge (e.g., death) and financial information such as the DRG, and the Hospital Discharge Chart reimbursement. We also gathered information on the zip code of residence of patients and their mortality from the General Register Office. We use these patient characteristics to calculate risk-adjusted quality indicators. In fact, our analysis may suffer from some spatial sorting problem, if people who are more likely to use healthcare services tend to live near hospitals rather than far from them (Bertoli and Grembi, 2017). To mitigate this problem, risk-adjusted indicators are calculated by estimating a linear regression of each indicator on a set of variables, namely, gender, age on admission, co-morbidities, number of procedures, whether the admission occurs via the emergency room. Residuals from this regression are our risk-adjusted quality indicators (see Moscone et al., 2019 for details). After risk-adjustment, we calculate averages per hospital, hence the risk adjusted quality measures can be seen as averages at hospital level of the difference between actual and predicted mortality. In the empirical section, we present the results both with raw, unadjusted, quality indicators and with their risk-adjusted versions.

The characteristics of each hospital include its ownership (e.g., private or public), teaching status, whether it specializes in a particular area of treatment (in the table, specialist) and aggregate health expenditure. We also have information on whether the hospital has a catheterization laboratory, namely an examination room with diagnostic imaging equipment used to support catheterization procedures, which can be taken as a proxy for the technological standards of the hospital. Finally we include in the model a dummy variable indicating whether the hospital is located in Milan, in order to control for aggregate factors, such as the better availability of highly qualified medical professionals in a large city like Milan that may affect the quality of health care. We refer to Table 3 for a description of the hospital-level variables that have been included in our analysis. We only kept records for public or private hospitals that are accredited by the region, thus providing free health care (see Section 2).

The data cover all 15 LHAs, although two very small LHAs have been incorporated with their contiguous LHA, leading to a total of 13 LHAs. It is interesting to note that for Acute Myocardial Infarction admissions the average distance patient to hospital is 10.52 km with 95 per cent of patients admitted to a hospital that is within 30 km of their residence, while nearly 100 per cent of patients are admitted to a hospital that is located in the LHA of residence. As for Hip Replacement admissions, the average distance patient to hospital is 14.60 km, with nearly 90 per cent of patients admitted to a hospital that is within 30 km and nearly 100 per cent admitted to a hospital within the LHA of residence. Although there exist a few differences amongst the 6 quality indicators, our exploratory analysis on patient admissions shows that nearly 100 per cent of patients are admitted to a hospital within their LHA of residence; this suggests that, by and large, the use of LHAs represents a reasonable criterion to define the boundaries of local hospital markets.[13]

6. Empirical results

In order to highlight the value of our contribution with respect to existing literature, we first carry out the estimation of hospital reaction functions by a SAR model, as for instance in Gravelle et al. (2014) and Longo et al. (2017). Then, we compare the results with the estimation of the proposed CAR model (6) in which we estimate the weights of the spatial matrix.

6.1. SAR model

We employ two alternative specifications for the spatial weights matrix, both of which entail only local competition amongst hospitals. First, we assume as spatial weight w_{ij} the inverse of the distance between hospital i and hospital j, taking a 30 km threshold, so that we set $w_{ij} = 0$ if the geographical distance is larger than 30 km. Such specification is often assumed to delineate market boundaries when estimating the effect of competition and hospital reaction functions (e.g., Cooper et al., 2011; Bloom et al., 2015; Longo et al., 2017). As a second case, we consider a specification where the catchment area is determined by the Local Health Authority.

Table 4 displays the estimated spatial coefficients and relative standard errors, as well as the average number of rivals assumed in the spatial weights matrix. For five out of six quality indicators, the results show evidence of no spatial correlation, either when using the 30 km threshold or the LHA catchment area to build the spatial weights matrix. This is valid both when taking raw quality indicators or risk-adjusted indicators. Overall, we see evidence supporting the hypothesis of no association between hospital quality and competition, in line with some results reported in the previous literature (Mukamel et al., 2002; Colla et al., 2016) one of which uses similar Italian data (Berta et al., 2016). One possible explanation for this result might be that patients are likely to gather information on hospital quality from other sources, for example interacting with family and friends, which does not necessarily lead to choosing a high quality hospital. For example, patients may give importance to attributes, such as appearance, comfort, and convenience of hospital, which are not necessarily related to clinical quality (Berta et al., 2016). Hence, hospital managers may be reluctant in engaging in such competition (Moscone et al., 2012).

However, one major concern with the above results is that the metrics used to select competing hospitals is, on the one hand, arbitrary and, on the other hand, it does not allow for heterogeneity in the local competition network, which instead could be relevant as also underlined by our theoretical framework. This arbitrariness may ultimately impact on the estimated reaction function, since hospitals may not necessarily compete in the way expressed by the pre-defined spatial weights matrix. Moreover, the form of competition among providers may not be only of a local nature, implying that the estimate of the spatial parameter δ could be

[13] The definition of the boundaries of local hospital markets through LHAs in Italy, other than being supported by our exploratory analysis on patient admissions, can be reasonably considered a good approximation of the standard criteria used in the literature to define the relevant catchment areas for hospital services, such as the 30-min drive time distance (e.g., Propper et al., 2008; Gravelle et al., 2014) or the 30 km geographical distance (e.g., Cooper et al., 2011; Bloom et al., 2015; Longo et al., 2017).

affected by a restrictive pre-specification of the spatial matrix.

6.2. CAR model

Table 5 reports the results on the estimation of the CAR model (6) for each quality indicator. In this regression the spatial weights matrix employed is not pre-specified as usual but is estimated through a Graphical LASSO approach where we assume the block-wise structure (5) in the interdependence amongst hospital qualities, taking as blocks the LHA (Moscone et al., 2017). Differently from the literature, we now estimate who the competitors are in the catchment area (i.e., within the block), and we also allow for an additional type of competition amongst hospitals that is global, represented by the interdependence between catchments (i.e., between blocks).

It is interesting to observe that the average number of rivals (i.e., a non-zero spatial weight in $\boldsymbol{W}$) estimated within each catchment is around 7–10, which is much smaller than the average number of rivals implicitly assumed using the geographical metric (around 8–36 neighbors, depending on the criterion, see Table 4). Hence, at least with these data, the local competition process with neighboring hospitals seems slightly more restricted than the one assumed with the traditional approach based on a distance threshold assumption. This suggests that each hospital looks at a restricted number of rivals, instead of looking at all hospitals within the local markets, as usually assumed in the previous literature. The spatial effects, although small in size, are picked by the GLASSO approach as pairwise dependencies that are significantly different from zero. The results point at an average spatial weight within blocks ranging between -0.003 and 0.062, depending on the quality indicator considered and whether it has been risk-adjusted. We observe that for each indicator the estimated weights calculated within blocks are rather heterogeneous, with the standard deviations of these values varying between 0.201 and 0.702 across blocks and quality indicators. This supports the use of our flexible GLASSO procedure.

As suggested by the previous literature (Mobley, 2003; Mobley et al., 2009; Gravelle et al., 2014; Guccio and Lisi, 2016; Longo et al., 2017), the spatial parameter (in our case, the estimated spatial weights) can be interpreted as the slope (in our case, the slopes) of the hospital reaction function. In general, we find that the majority of non-zero spatial weights within blocks are positive, except for HR. Thus, our estimates provide evidence that hospital qualities tend to be strategic complements, suggesting that quality of a rival has on average positive spillovers onto the quality of other providers within the same market.

However, for each quality indicator, we find a significant heterogeneity in spatial weights across LHAs. For instance, if one focuses on the city of Milan, hospital qualities are strategic complements and the average number of rivals is large. This suggests, not surprisingly, that the city of Milan is a highly competitive hospital market. Conversely, in smaller LHAs, such as Mantova, the few hospitals tend to be strategic substitutes in qualities. Overall, our findings suggest that the interdependence amongst hospital qualities is rather heterogeneous within local hospital markets. Indeed, this evidence underlines the importance of allowing for heterogeneity in the local competition network and, thus, the relevance of our contribution with respect to the literature.

Looking at the interdependency between blocks (i.e., the 13 LHAs), we find that the average number of non-zero spatial weights is around 9–10, consistently across quality indicators. Further, we find that most non-zero spatial weights between blocks are positive. Therefore, our estimates provide strong evidence that most hospital qualities are strategic complements between blocks. This suggests that, at least in such a competitive institutional environment, hospital managers do care about the hospital quality set by other managers regardless of the geographical location of the hospital.

As for the other regressors included in the model, teaching hospitals tend to have lower mortality and readmission rates, though the effect is not the same for all quality indicators (e.g., IS). This finding is consistent with the results provided by Gravelle et al. (2014) for UK hospitals. The variable ownership has in many cases a statistical significant effect, suggesting quality differences between private and public hospitals. However, these results must be taken with caution as it is well known that the ownership coefficient may be biased and, in particular, it may be driven by the unobservable differences between private and public hospitals (Lien et al., 2008; Moscone et al., 2020). The variable specialist is not statistically significant for the majority of quality indicators, probably due to the low presence of specialized hospitals in a particular area of treatment in our data (see Table 3). However, it is negative and significant for AMI, indicating that specialized hospitals have lower mortality rates. This may suggest the presence of learning-by-doing effects in the provision of health care services, consistently with a few previous studies (e.g., Birkmeyer et al., 2002). Further, our proxy for the technological standards of the hospital is not statistically significant for the majority of quality indicators, though it is negative and significant for AMI, indicating that hospitals with higher technological standards have lower mortality rates. This mixed evidence may be due to our measure of technological standards (i.e., hospitals with a catheterization laboratory) which could be relevant for some procedures but not for others. As for the health expenditure, one concern in this application is the problem of reverse causation; that hospitals with a higher level of unobserved illness will lead to higher levels of spending, thus biasing regression estimates. Restricting attention to specific conditions, for example, AMI, is one approach to reducing the potential for endogeneity, since hospitals with worse health may have more people who have a myocardial infarction, but conditional on having an AMI of a specific type, and with specific comorbidities, there's much less chance of unobservable factors unrelated to the health system biasing the estimates. Numerous studies, motivated by the question of whether more spending "buys" better health outcomes, found a null or negative association (e.g., Skinner et al., 2005; Moscone et al., 2019), while others showed a positive association (e.g., Doyle et al., 2015). Our results show that, consistently among quality indicators, a larger expenditure increases mortality and readmission rates, suggesting that more spending "does not buy" better health outcomes.

Finally, Table 5 shows the Bayesian Information Criterion (BIC) for each model and each quality indicator. Specifically, we report the BIC for two alternative specifications, a graphical model that only allows for local interdependence (within) and the full model that allows for both local and global interdependence (within + between). The results show that the BIC (within + between) is always lower than the BIC (within) for all quality indicators, despite the penalty for the larger number of parameters in the full model (within + between). This unambiguously indicates that the model allowing for both local and global interdependence provides a better fit than the model that allows only for local rivals. Indeed, this evidence strongly supports the hypothesis that the form of competition among providers is not only of a local nature, and that global interdependence is a key feature in this health care context.

To sum up, the inferential results allow us to appreciate that there exists a marked heterogeneity in the nature and intensity of local interdependence among rivals within blocks, which is usually not allowed in the application using a pre-specified set of local rivals. On the other hand, the evidence on the degree of global interdependence is consistent among quality indicators, showing that hospital qualities are strategic complements between blocks. In contrast with the results of the SAR model, the estimates of the CAR model (6) allow to better capture the nature of interdependence among hospitals, as also suggested by model selection criteria. Overall, the empirical results in Table 5 appear to provide strong evidence in favor of our theoretical predictions on the slopes of hospital reaction functions and, thus, on the structure of quality interdependence.

7. Concluding remarks

There is a large debate in the literature over the effect of hospital competition on the quality of health care. The popular vision is that, in a fixed priced market, hospitals compete on quality to attract patients within their catchment area, thus focusing on a local form of competition. This paper extends the existing literature on hospital competition by looking at both local and global sources of competition amongst hospitals. Firstly, in our theoretical framework, we characterize the structure of interdependence amongst hospitals that arises in a competitive institutional environment, where hospital performance rankings are periodically released. Secondly, we employ for the first time graphical modelling techniques and spatial econometrics to estimate who the competitors are in hospital reaction functions, using data on 6 quality indicators in the Lombardy region in the years between 2008 and 2014.

Our results point at the presence of small but significant hospital interdependence within catchment areas. On the other hand, we observe a marked heterogeneity among local markets and quality indicators, with the majority of areas indicating that hospital qualities are strategic complements, but also a few that are strategic substitutes. Conversely, our results on global interdependence are consistent among quality indicators, indicating that in our context hospital qualities tend to be strategic complements also outside catchment areas. This seems to suggest that hospital managers' decisions with regards to the level of quality are influenced also by other hospitals outside their local market. We posit that this strong evidence of long-range strategic complementarities in hospital qualities is due to the global competition for performance ranking, which concerns all hospitals in the Lombardy region. Overall, the empirical findings are consistent with the micro-founded structure of interdependence emerging from our theoretical framework.

From a policy perspective, our paper entails important implications. On the one hand, our estimates on the degree of strategic interdependence within local markets suggest that hospital competition, introduced in a market where prices are fixed, can potentially lead to an increase in the quality of health care services, while recognizing that the local competition process is heterogeneous among local hospital markets. This may depend on the characteristics of both health care providers and patients, though further research is needed to understand the determinants of the local competition process. On the other hand, our paper suggests that, in certain health care systems, the competition process may not necessarily be only of a local nature. More specifically, our results point at the important role played by quality assessment programs, highlighting that a well-designed assessment program may induce an additional competition mechanism amongst hospitals and, as a result, it has the potential to improve the quality of the health care system. In this respect, the current Italian reform of the health managers' evaluation system goes towards the right direction, even if the effectiveness of the new system will depend on the real extent of the hospital managers' evaluation. Finally, the main institutional context that we examine – namely, a market with many public and private hospitals reimbursed using regulated prices – is common in many health care systems. This may suggest that our results are likely to be useful also in other countries, though further empirical analysis of this kind is clearly needed in other institutional contexts.

Overall, this study adds support to the current emphasis on pro-competition interventions in health care policy, in line with the most recent literature on hospital competition (e.g., Cooper et al., 2011; Bloom et al., 2015; Gaynor et al., 2016). Our findings suggest that health care systems could benefit not only from more competitive local hospital markets, but also from making their institutional environment more competitive for hospital management.which implies that

$$V_i^A - V^{NA} = \frac{p \cdot x\left(q_i^*,\ \boldsymbol{q}_j^*; \boldsymbol{\delta}_i, \boldsymbol{\phi}_g\right) - C\left(x\left(q_i^*, \boldsymbol{q}_j^*; \boldsymbol{\delta}_i,\ \boldsymbol{\phi}_g\right), q_i^*; \boldsymbol{\gamma}_i\right)\ -\ u^R}{\left(1\ - \beta Pr\left(A_i' | q_i^*,\ \boldsymbol{q}_{-i}^*; \boldsymbol{\theta}\right)\right)}$$

Therefore, the condition $V_i^A > V^{NA}$ only requires that $p\cdot x(q_i^*,\boldsymbol{q}_j^*;\boldsymbol{\delta}_i,\boldsymbol{\phi}_g) - C(x(q_i^*,\boldsymbol{q}_j^*;\boldsymbol{\delta}_i,\ \boldsymbol{\phi}_g),q_i^*;\boldsymbol{\gamma}_i) > u^R$, meaning that the instantaneous payoff in equilibrium has to be higher than the reservation utility given by the best alternative, which can be seen as an innocuous participation condition for the players.

Declaration of competing interest

Dear Editors, the authors declare there is no conflict of interest.

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