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Spatial dependence in hospitals efficiency: A spatial econometric approach for Ecuadorian public hospitals

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Spatial dependence in hospitals efficiency: A spatial econometric approach for Ecuadorian public hospitals*.

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This study aims to analyze whether the efficiency of Ecuadorian public hospitals experiences spatial dependence. The paper explores the question of whether demand variations are affecting the public hospitals' efficiency performance through direct and spillover effects, especially after the adoption of the new constitution in 2008. We exploit a two-stage approach, wherein the first stage we use an innovative panel-data DEA to estimate the hospital efficiency; a spatial econometric framework is then applied to disentangle direct and spillover effects. The results confirm positive spatial interactions among public hospitals' efficiency, and positive direct and spillover effects coming from demand increases, that got reinforced after 2008.

Keywords: Healthcare efficiency, spatial dependence, healthcare reforms.

JEL Classification: C21, D61, I11, I18.

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1. Introduction

In recent years, the assessment of the ability of public hospitals to optimally utilize their resources for the provision of healthcare (i.e. how efficiently they are performing) has become a topic of interest that has driven the attention of academics, healthcare managers, and policymakers on measures to contain healthcare costs. The attention in this matter has gained much relevance as spending in healthcare continues to rise exponentially, which drives policymakers to seek ways to pursue health objectives at the same time as containing cost pressures (Papanicolas and Smith, 2014). The increase in hospital expenditures has led to a series of reforms in developed economies to induce hospital efficiency improvements, e.g. the introduction of activity-based hospital budget (Pross et al., 2018).

However, healthcare efficiency improvement is not just a concern of developed economies. The efficiency of public hospitals' resource use is crucial in developing countries, given the pressing need for their proper allocation, due to its scarcity and limited health budget (James et al., 2005; Kumbhakar, 2010; Hafidz et al., 2018). The importance to care about it is highlighted by the World Health Organization (WHO, 2000) to decrease the gap of mortality between rich and poor countries, and within countries. It is also important to ensure that resources are well targeted to promote the goal of universal health coverage (UHC) and ensure equity of access to medical services (Hafidz, Ensor, and Tubeuf, 2018; WHO, 2010).

Despite its importance, studies in healthcare efficiency have been mainly performed in developed economies (Hafidz et al., 2018), with a small but growing number of applied literature to developing countries (Hollingsworth, 2008). However, the methods to study healthcare efficiency in developing economies have had little consideration for other variables that are specific to their local setting (Au et al., 2014). Under this perspective, healthcare efficiency can be influenced by different factors that vary from socio-economic, environmental, political, structural and geographical (Hafidz et al., 2018).

One important and common evidence shared by contribution in the literature is the relevance of the spatial dimension as a catalyst for the effectiveness of selected determinants in shaping the degree of efficiency achieved by the different healthcare providers. That spatial dependence can impact on the needs of the population and the behavior of healthcare providers across a wide geographical area, causing geographical concentration of needs and risk factors as well as the rise of network effects that are often detected in the data (Tosetti et al., 2018) and translates into a structure correlation, also known as spatial dependence (Anselin, 2010).

In developing economies, this spatial structure can take the form of heavy territorial concentration that can derive in agglomeration economies.[1] The presence of agglomeration economies would lead to interactions in the health system that could be related to this spatial pattern, generating some

[1] Here we will associate the concept of spatial unit to a region, or an area or a territory in an alternative manner.

complementarities and indivisibilities such as spillover effects (Behrens and Robert-Nicoud, 2015) that shape the healthcare behavior and efficiency performance of the system if they are proven to be significant (Bhattacharjee et al., 2014; Kinfu and Sawhney, 2015). But, once again, the literature on public healthcare efficiency that accommodates the analysis to include the spatial structure in the data for developing countries has been rather limited (Kinfu and Sawhney, 2015). In this respect, one of the contributions of this paper is to fill the existing gap in the literature of public healthcare efficiency for developing countries. To do so, we focus our analysis on hospital efficiency, and we apply it to the Ecuadorian context.[2]

The Ecuadorian case represents an adequate context of analysis, since it is characterized by big territorial disparities and spatial dependence that arise due to the existence spillovers effects as it has been pointed out in recent studies (Szeles and Mendieta Muñoz, 2016; Mendieta Muñoz and Pontarollo, 2016). Ecuador has been facing a process of continuous deterioration (along with other Latin American countries) of its public healthcare system due to neoliberal reforms carried out in the 1990s (Homedes and Ugalde, 2005) and the crisis of 2000. As a consequence, Ecuador suffered from a deep worsening of its healthcare equity and efficiency (widening the existing urban-rural and inter-regional inequalities (De Paepe et al., 2012), and a structural segmentation and fragmentation of the healthcare system (Hartmann, 2016). These effects incurred in a significant technological heterogeneity between public healthcare institutions (Piedra Peña and Prior, 2019),[3] being the hospitals with higher technology the ones that concentrate in the most developed cantons.[4]

Given the deteriorated condition of the healthcare sector, the government of Rafael Correa carried out a series of political reforms, which introduced many changes towards equalitarian access to medical attention. These reforms started in 2008, with the new Constitution establishing the healthcare access as a right guaranteed by the state. The gratuity of health services provided by the Ministry of Health's hospitals (widely advertised by government's campaigns), jointly with new social security and criminal-code laws that made insurance coverage compulsory, are among the most salient country's policies (De Paepe et al., 2012). The new access to medical attention derived in a higher inflow of patients for public hospitals. According to the Public Ministry of Health (MSP), between 2006 and 2010 the number of surgeries increased in 47% while the hospital discharges reported an increase of 43% (Ministerio de Salud Pública, 2012).

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[2] In this study, we intend hospital efficiency as the optimal use of hospital's inputs in order to produce a given healthcare output. This is commonly understood in the healthcare efficiency measurement literature as *technical efficiency* (for a survey of the literature see Hollingsworth, 2008). Additionally, hospital inputs mean hospital resources that are often measured as number of physicians, beds, medical equipment, etc. Whereas hospital outputs are viewed as the units of delivery of hospital services, that are usually measured as number of discharges, or procedures carried out.

[3] Here we consider technology as the set of constraints defining how one can combine or convert inputs into outputs in the production process. In this particular context, this can relate to the availability of human capital, infrastructure, etc.

[4] In Ecuador, cantons are the second level administrative divisions. The Republic of Ecuador is divided into 24 provinces, which in turn are divided into 221 cantons. The cantons in turn are subdivided into parishes.

In light of this evidence, we can expect that the potential increase of the demand has an effect on hospitals efficiency in the short-run. The rationale is the following: a higher amount of treated patients can lead to better use of hospitals' resources, which are usually well endowed but inefficiently exploited in developing economies (Hafidz et al., 2018). In other words, hospitals account for spare resources that are not used to provide medical treatment. The increase in the bulk of patients would force the hospital managers to make use of these unexploited resources, hence, increasing hospital efficiency.

However, the increase (decrease) of efficiency might not just affect a given hospital, but also those surrounding ones given that hospitals can have strategic interactions in terms of quality and efficiency (Longo et al., 2017) that is linked to the mobility of the demand.[5,6] The intuition of these interaction effects is the following: when the new reforms decrease the barriers of access to healthcare, patients will seek treatment in hospitals where they perceive to benefit from higher quality services (which might be the high-tech hospitals) or they could also be referred from low-tech hospitals to receive treatment for a complex pathology. In Ecuador, the criteria for the distribution of public funding for healthcare services follow the health necessities and the size of served population (Villacrés and Mena, 2017). Hence, this system generates incentives for hospitals to attract more patients. As a consequence, within a bounded area, surrounding hospitals can perceive how bigger hospitals are behaving and adapting to a changing reality and can react by trying to capture some of this new-created demand by increasing their own quality (which will be constrained by their technological endowment). If the costs of providing more quality are increasing, then higher costs stemming from higher demand will reduce the incentives for cost control; hence, reducing hospital efficiency.[7] Given that hospitals have to take a decision over their efficiency, they can also react by increasing or decreasing (strategic complements and strategic substitutes, respectively) their efficiency in reaction to the changes in the efficiency of neighboring hospitals.

Moreover, taking into account the technological differences of the healthcare system, an increase in the demand can lead to a congestion effect for high-technology hospitals, which account for the vast majority of treated patients in Ecuador (Piedra Peña and Prior, 2019). If these hospitals cannot manage their resources efficiently, the increase in the number of patients can lead to a decrease in their performance (Cozad and Wichmann, 2013). Thus, surrounding hospitals could increase their quality to capture some of the demand that cannot

[5] The term "strategic interactions" is used in the literature to refer to the interdependence among features or actions of selected units stemming from the competition among those units. Strategic interactions arise due to the existence of spillover effects (Brueckner, 2003) that cause that the levels of the variables of one unit are affected by the levels of the same variables of neighbouring units.

[6] We make use of the hospital occupancy rate to measure the demand. The occupancy rate has been widely used as an index to show the actual utilization of an inpatient health facility for a given time period, and commonly applied in the literature to proxy medical resource utilization (Town and Vistnes, 2001; Herwartz and Strumann, 2014).

[7] In fact, according to Villacrés and Mena (2017) the current funding scheme of the country can generate inefficiencies, given that the hospitals have an incentive to attract patients and inflate the costs.

be met by high-tech ones, and this reaction, in turn, can affect their efficiency in the same manner aforementioned.

In light of this evidence, the aim of this study is to analyze whether public hospitals in the Ecuadorian healthcare system adapt their efficiency in response to changes in the efficiency of neighboring hospitals. We tackle the question of whether demand variations are affecting the efficiency of public hospitals through direct and spillover effects, and whether that level of efficiency has significantly changed after 2008 (when the new constitution came into force). We make use of the hospital occupancy rate to measure the demand. The occupancy rate has been widely used as an index to show the actual utilization of an inpatient health facility for a given time period, and commonly applied in the literature to proxy medical resource utilization (Town and Vistnes, 2001; Herwartz and Strumann, 2014).

Our research covers the period 2006-2014 and we deal with hospital and cantonal data gathered from the public statistics of the Ecuadorian Institute of Statistics and Censuses (INEC) and the Ecuadorian Central Bank (BCE).

We contribute to the existing literature by generalizing the approach by Longo et al. (2017) by means of the non-parametric efficiency measurement analysis that accounts for both the panel structure of the data and the technological differences of the healthcare system developed by Piedra Peña and Prior (2019) to obtain robust time-varying efficiency scores. By adopting efficiency measurement techniques, we can account for one efficiency measure that considers the use of multiple inputs to produce a given level of healthcare output, rather than relying on different productivity ratios that might produce mixed results. Also, we adopt spatial panel econometric techniques as a framework of analysis for performing our second part of the empirical analysis by taking into account the spatial dependence of the data and disentangle direct and spillover effects that can affect the hospitals' efficiency performance.

By doing so, we combine two strands of literature that have been little exploited jointly to implement our empirical framework referring to developing economies (Kinfu and Sawhney, 2015). If spatial autocorrelation in hospital efficiency is found, then the relevance of being able to assess spatial dependence stands in the importance in planning public policies. If so, hence when spatial dependence is identified, policymakers cannot neglect the existence of spillover effects for achieving pre-established levels of efficiency when implementing new healthcare public policies (Mobley et al., 2009). In this study, we bring new evidence to understand the way the spatial dimension may contribute to shape more effective actions for fueling the territorial healthcare access and the resource allocation, above all when dealing with very heterogeneous settings as the ones in developing countries.

Our main results identify a positive significant spatial dependence among hospitals in Ecuador, suggesting that their healthcare services are perceived as complements in terms of efficiency. Also, the higher demand for medical treatments reflects a positive association with efficiency, regardless of the technological group; and, this demand is affecting the efficiency of those surrounding hospitals as well, providing evidence of spillover effects. Both direct and spillover effects have significant increased after 2008. This result suggests that reforms carried out after the constitution boosted the efficiency of the public healthcare system.

The organization of this paper is as follows. In Section 2, we outline short description of the institutional setting in Ecuador relevant to learn about the local healthcare system. The literature review is presented in Section 3. Section 4 introduces the theoretical framework as developed by Longo et al. (2017), and the empirical strategy discussed in Section 5. Section 6 describes our dataset, while estimation results and conclusions are presented in Section 7 and Section 8, respectively.

2. Institutional Setting

The Ecuadorian healthcare system accounts for public and private service sectors, being the former sector that accounts for most of the insured population. According to the Survey of Life Conditions (ECV) of INEC, around 66% of the population was covered by public insurance in 2014, while private insurance accounts for 6% only.

The public healthcare sector is the result of the actions patronized by the MSP, Ministry of Social and Economic Inclusion (MIES), the municipal health services and social security institutions.[8] The MSP provides health services for the whole population. The MIES and the municipalities establish and finance healthcare programs to guarantee medical treatment services to the uninsured citizens, which by 2014 represented around 33% of the national population, according to the ECV. Finally, social security institutions sponsor medical services to those covered by social insurance. (Lucio et al., 2011).

As for the funding sources, public services are financed mainly through the general public budget, but they also receive funding from extra-budgetary sources, emergency and contingency funds, other contributions from national and international projects. The social security services for employees works on a contributive base and it is financed by the contributions of affiliated workers and are secured through the Social Security Law, as a right of protection for Ecuadorian workers (Organización Panamericana de la Salud, 2008).

Since the approval of the new constitution in 2008, many reforms have been carried out to promote higher access to medical treatment to uninsured citizens. For instance, the gratuity of medical services provided by the MSP in 2008, the coverage for children under 18 years old in 2010, and the civil responsanility with penal charges for the employer who does not affiliate their employees within a maximum period of 30 days in 2011. After the implementation of these policies, there has been an increase in the annual growth rate of active beneficiaries

[8] Ecuadorian Social Security Institute (IESS), Social Security Institute of the Armed Forces (ISSFA) and Social Security Institute of the National Police (ISSPOL)

(Orellana et al., 2017),[9] while the number of attended patients in public hospitals increased around 40% between 2006 and 2014 (Piedra Peña and Prior, 2019).

3. Literature review

The importance of healthcare services around the globe is widely recognized. The healthcare investment has been rapidly rising as well as healthcare costs as a proportion of GDP and, as a result, there is great policy emphasis on improving efficiency (Bloom et al., 2015). The territorial assessment of healthcare services is a key aspect, as there may be many sources of geographic variation that might produce different health outcomes according to the area of study (Chandra and Staiger, 2007; Allin et al., 2016; Williams et al., 2016). Also, the recognition of significant geographical concentration for many health indicators has motivated an extensive use of spatial methods to analyze health economic issues (Moscone and Tosetti, 2014).

In this strand of literature, there have been many applications related to different topics in health economics that address a spatial perspective; a complete review for most of this literature can be found in Moscone and Tosetti (2014), Baltagi et al., (2018) and Tosetti et al. (2018).

A wide body of this literature focuses on knowledge spillovers, hospital competition and agglomeration. Common findings suggest that agglomeration economies in healthcare market promote a faster learning process of a new innovation among firms, mainly hospitals (Chandra and Staiger, 2007; Cohen and Morrison Paul, 2008; Baicker et al., 2013; Goodman and Smith, 2018). It is the interaction and competition between these hospitals that impact some market variables like prices (Mobley, 2003; Mobley et al., 2009) or the quality and efficiency of services (Gravelle et al., 2014; Longo et al., 2017; Longo et al., 2019).

Although spatial economic methods have been largely applied in the literature, there is a lack of empirical research that addresses the spatial dependence in the healthcare efficiency analysis. The consideration of efficiency analysis under a spatial approach can provide several benefits to health providers, planners and policymakers alike. It can help decision-makers to identify geographic units that can attain a better outcome without increasing the allocation of resources. Also, it can provide information on the exogenous factors whose presence (or absence) affects the performance of services and hence health outcomes in the country (Kinfu and Sawhney, 2015).

There are few and very recent papers that address a joint study of healthcare efficiency analysis under a spatial perspective. Herwartz and Strumann (2012) study whether the introduction of prospective hospital reimbursements based on diagnosis-related groups (DRG) has caused an increase in the negative spatial autocorrelation of hospitals´ efficiency due to the competition for low-cost patients. Using Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) methods to measure hospitals efficiency in a first stage, and

[9] Orellana et al. (2017) present descriptive data of social insurance beneficiaries and describe an annual growth rate of 10% after 2010, compared with a 7% growth rate of previous years.

Spatial Autoregressive Models with Autoregressive Disturbances (SARAR) in a second stage; they find a statistical significative presence of negative spatial autocorrelation among hospitals in Germany which significantly increase after the financial reform. Herwartz and Strumann (2014) extend the analysis in Germany in order to identify efficiency gains as a consequence of the same financial reform. They follow two different approaches. First, they consider a two-stage approach, starting with the decomposition of Malmquist index technical efficiency, and, then, they complete the analysis with a SARAR models. In the second approach, they use a one-step fixed effects SFA model, accounting for technological change and spatial dependence. Both methods fail to find any efficiency gains from the new incentive structure in Germany. Felder and Tauchmann (2013) also study the efficiency of healthcare provision in Germany, considering the spatial perspective, which they state is important due to the regional competition and patient migration. They adopt a longitudinal approach for German´s regions. Utilizing order-m DEA method to measure regional efficiency, and a spatial autoregressive model in a second step. Their findings show that accounting for spatial dependence increase the estimated effects of federal states on district efficiency. This may be a way to find a rationale why more efficient states are less affected by spillovers. Hence, introducing spatial dependence in the economic analysis clarifies the importance of health policy at the state level. Herwartz and Schley (2018) depart from these findings and consider socio-economic characteristics that influence the regional efficiency in the provision of healthcare services in Germany. By means of the SFA approach, they identify that income, unemployment, the share of immigrants and educational level have an effect in shaping the efficient provision of healthcare services in German districts.

Martini et al. (2014) analyze the trade-offs between hospital health outcomes (such as mortality) and efficiency using a ward-level set of hospitals in Lombardy, Italy. Their findings support the existence of a trade-off between mortality rates and efficiency, where more efficient hospitals have higher mortality rates but lower readmission rates. Also, they point out the role of the spatial dimension, since mortality rates are higher for hospitals subject to a high degree of horizontal competition but lower for those hospitals having strong competition but high efficiency.[10]

Most of the literature that referring to efficiency measurement and spatial structure has been elaborated for developed countries. To our knowledge, only one paper provides evidence about the change in efficiency for health institutions in developing countries. Kinfu and Sawhney (2015) estimate the determinants of the efficiency of institutional delivery of maternal care in India. They exploit SFA models accounting for spatial interactions and heterogeneity in a one-step approach, finding substantial inefficiencies in maternal care services between and within states.

In this study, we contribute to this new emerging strand of literature and extend it for Latin American countries such as Ecuador. We depart from the framework

[10] In their analysis, the authors claim that when there is a national health insurance, money prices are irrelevant for the consumer hospital choice. This makes competition among hospitals mainly focused on location, which they refer as horizontal competition (Tay, 2003).

proposed by Longo et al. (2017), but we extend its application by taking into account robust efficiency measures over time. Also, we consider hospital technological heterogeneity in a spatial panel econometric approach in order to account for different effects in the efficiency derived from hospital technological restrictions. This methodology represents an important advance in applied literature that can eventually be extended to other countries sharing realities similar to Ecuador. For example, the methodology that could be applied in other Latin American countries, considering that they share many socio-economic, political and cultural characteristics (Levy and Schady, 2013) as well as deep territorial disparities and spatial dependence (Cuadrado-Roura and Aroca, 2013).

4. Theoretical Framework

The building blocks of the theoretical model we refer to in this analysis grant to Gravelle et al. (2014) and Longo et al. (2017). Their theoretical model considers strategic interactions in hospital quality and efficiency arising from spillover effects within a geographical area. The intuition is that, if hospitals compete within a given area, they would attract patients by increasing their quality. If neighboring hospitals react by increasing (decreasing) their own quality, then we identify that hospitals are strategic complements (substitutes) in their quality. Furthermore, the reduction in a hospital demand that follows from an increase in their closest neighbor's quality also has an effect on its efficiency. The cost of increasing the quality to attract higher demand might reduce incentives to control costs, reducing efficiency. So, hospitals can be also strategic complements (or substitutes) in their efficiency as higher neighboring hospital's efficiency might induce an increase or decrease on its own efficiency.

In order to present the framework in terms of the strategic interaction in efficiency, as in Longo et al. (2017) we consider a two-provider model of quality competition (q) and cost-reduction effort (e).[11] Let assume q_i as the healthcare quality of hospital *i* and q_j the healthcare quality of hospital *j*, with $i \neq j$. The demand function for hospital *i* is given by $D_i = (q_i, q_j)$, such that $D_{iq_i} = \frac{\delta D_i}{\delta q_i} > 0$ and $D_{iq_j} = \frac{\delta D_i}{\delta q_j} < 0$, so it is increasing in its own quality but decreasing in the quality of hospital *j.* This assumption implies that hospitals are demand (imperfect) substitutes: patients switch from a hospital to another in accordance with the variation of the quality of healthcare of the two hospitals. However, switching from one hospital to another entails costs in terms of time and transfer costs. Here, we define the objective function of hospital *i* as:

$$\pi_i = [p - c_i(q_i, e_i; \theta_i)]D_i\big(q_i, q_j; \theta_i\big) - G_i(q_i, e_i; \theta_i) \quad (1)$$

Where *p* is a fixed price per treatment that the hospital *i* receives from a third-party payer, like the Government in our case, $c_i(q_i, e_i)$ are the variable treatment costs, given that $c_{iq_i} = \frac{\delta c_i}{\delta q_i} > 0$ and $c_{ie_i} = \frac{\delta c_i}{\delta e_i} < 0$, they are increasing in quality and decreasing in efficiency, e_i. $G_i(q_i, e_i)$ are monetary and non-monetary fixed

[11] The cost-reduction effort is interpreted as an efficiency improvement. As the more efficient the resources are used to obtain a given output, the less costs for the hospital.

costs, with $G_{iq_i} = \frac{\delta G_i}{\delta q_i} > 0$ and $G_{ie_i} = \frac{\delta G_i}{\delta e_i} > 0$, whereas θ_i is a vector of shift parameters, such as location of patients and other hospitals, input prices, demographics, central policies, type of hospital, etc. The authors assume that quality and efficiency are substitutes $\left(G_{iq_i,e_i} = \frac{\delta^2 G_i}{\delta q_i \delta e_i} > 0\right)$, meaning that an increase in quality would require a decrease in cost-reduction effort. Also, for sake of simplicity Longo et al. (2017) make the assumption of independence in variable costs, that is $c_{iq_i,e_i} = \frac{\delta^2 C_i}{\delta q_i \delta e_i} = 0$. The first order conditions to the equation (1), by which hospital *i* maximizes its profit with respect to quality and efficiency is as follows:

$$\pi_{iq_i} = \frac{\delta \pi_i}{\delta q_i} = [p - c_i(q_i, e_i; \theta_i)] D_{iq_i}(q_i, q_j; \theta_i) - c_{iq_i}(q_i, e_i; \theta_i) D_i(q_i, q_j; \theta_i) - G_{iq_i}(q_i, e_i; \theta_i) = 0 \quad (2)$$

$$\pi_{ie_i} = \frac{\delta \pi_i}{\delta e_i} = -c_{ie_i}(q_i, e_i; \theta_i) D_i(q_i, q_j; \theta_i) - G_{ie_i}(q_i, e_i; \theta_i) = 0 \quad (3)$$

with $D_{iq_i} > 0$, $c_{iq_i} > 0$ and $G_{iq_i} > 0$. The optimal quality is achieved when the marginal profit from one additional unit of demand is equal to the correspondent marginal cost. Instead, the optimal level of efficiency is such that the marginal benefit from lower costs and higher profits are equal to the marginal disutility from efficiency.

Since the scope of Longo et al. (2017) is to propose a model to examine hospitals´ strategic interactions, they find the interaction functions of hospital *i*´s quality (q_i) and efficiency (e_i) as a function of the choice of quality by hospital *j.* The reaction functions defined by the first-order conditions (2) and (3) satisfy:

$$q_i = q_i^R(q_j; \theta_i) \quad (4)$$

$$e_i = e_i^R(q_j; \theta_i) \quad (5)$$

Here, it would seem that the quality and efficiency of hospital *i* are independent from the efficiency of hospital *j* because neither of the first order conditions of hospital *i* depends on the efficiency of hospital *j.* But, the total differentiation of the first-order conditions yields:

$$\frac{\delta q_i^R}{\delta q_j} = \left\{-\pi_{iq_i,q_j}\pi_{ie_i,e_i} + \pi_{ie_i,q_j}\pi_{iq_i,e_i}\right\}\Delta^{-1} = \left\{-\left[(p - c_i)D_{iq_iq_j} - c_{iq_i}D_{iq_j}\right]\pi_{ie_i,e_i} - c_{ie_i}D_{iq_j}\pi_{iq_ie_i}\right\}\Delta^{-1} \quad (6)$$

With $\Delta = \pi_{iq_i,q_i}\pi_{ie_i,e_i} - {\pi_{iq_i,e_i}}^2 > 0$. The first term in the square brackets is the direct effect of the neighbor's quality on the marginal profit from higher quality. It is not clear whether an increase in the hospital *j*'s quality increases or decreases the marginal demand of hospitals *i*, so the sign of $D_{iq_iq_j}$ is unknown. For the sake of simplicity, if we assume that $D_{iq_iq_j} = 0$, this will lead to a reduction in the variable costs (second term in the square brackets), because the increase in the neighbor's quality reduces demand and so the marginal cost of output of hospital *i*, which will respond with an increase in quality. However, the second term in the curly brackets is also emphasizing another effect. Lower demand will also reduce incentives to control for costs (lowering efficiency) and so, variable costs may increase.

Hospitals then can be affected by the patients' perception in their quality; if the quality of a hospital is perceived to be high, this will end in an increase in patients' demand for this hospital, switching from its neighbors and yielding less efficiency. However, this is conditioned to the spatial structure. The strategic interaction will be stronger for closer hospitals. Changes in quality and efficiency will matter because of hospitals are close to each other, and because of the decay effect of spillovers.

In our case, the health reforms that have been implemented relax some barriers to access to medical services, allowing citizens to select between different hospitals. In the short run, a hospital gains more patients when it increases its quality since the patients have the opportunity to choose and opt for those hospitals which they perceive as better qualified. But the effect that the reforms can have in the demand of a particular hospital is ambiguous. It will depend on the quality of other hospitals, and the geographical distribution of the patients and hospitals (Gravelle et al., 2014). So, patients will decide to switch from one hospital to another depending on the travel distance and transfer costs. Neighboring hospitals can react to the increase in quality of a hospital by either increasing or decreasing their own quality, and so, affecting the final demand; and therefore, the hospitals´ efficiency.

Therefore, in order to test the spatial interaction in hospital efficiency we use the following function:

$$e_i = f(e_{i-1}, Z_i, \varepsilon_i) \tag{7}$$

With e_i being the efficiency of hospital $i = (i, \dots, I)$; e_{i-1} is the efficiency of hospital *i* 's neighbor; Z_i is the vector of covariates, including hospital variables (e.g. occupancy and mortality rate, market share, etc.), and cantonal variables (e.g. GVA, density, etc.).

5. Empirical Strategy

The first stage of our empirical strategy involves defining a measure of efficiency. We make use of the efficiency scores obtained in Piedra Peña and Prior (2019). Their empirical strategy is mainly based on the panel Data Envelopment Analysis (panel-data DEA) proposed by Surroca et al. (2016) and Pérez-López et al. (2018). The advantage of this approach over other efficiency measurement analyses like classical DEA or other dynamical approaches like Malmquist index is that it allows to estimate time-invariant coefficients of efficiency for the period of analysis, considering the inherent panel data structure. Additionally, these time-invariant efficiencies can be broken down into time-variant ones, calculating efficiency values for each year under evaluation. One of the principal advantages of this approach is that the results are robust to outliers and temporal random shock, which provides efficiency scores representative to the complete time period.

Piedra Peña and Prior (2019) extend this approach to account for technological heterogeneities of Ecuadorian public hospitals applying multivariate techniques (factor analysis in combination with clustering methods) to obtain panel data-DEA efficiency scores for three different groups (clusters): High-tech, intermediate-tech and low-tech.

In this paper, we follow an input-oriented efficiency measurement. We assume a variable returns to scale (VRS) model to deal with heterogeneous observations.[12] The efficiency frontier is developed by optimizing the weighted input/output ratio of each Decision Making Unit (DMU),[13] subject to the condition that this ratio can be equal, but never exceed one for any other DMU in the data set (Charnes et al., 1978).

We use the same notations as Piedra Peña and Prior (2019). Assuming that we have I DMUs $(i = 1, 2, \dots, I)$ and we obtain S clusters $(s = 1, 2, \dots, S)$, there are M outputs $[y_1^{i,s}, \dots, y_m^{i,s}, \dots, y_M^{i,s} \in \Re_M^+]$ produced by N inputs $[x_1^{i,s}, \dots, x_n^{i,s}, \dots, x_N^{i,s} \in \Re_N^+]$. We denote $[y_1^{o,s}, \dots, y_m^{o,s}, \dots, y_M^{o,s} \in \Re_M^+]$ and $[x_1^{o,s}, \dots, x_n^{o,s}, \dots, x_N^{o,s} \in \Re_N^+]$ as the observed units under analysis. We define a time variable t $(1,2, \dots, T)$, so we have $[y_{1,t}^{i,s}, \dots, y_{m,t}^{i,s}, \dots, y_{M,T}^{i,s} \in \Re_M^+]$ outputs and $[x_{1,t}^{i,s}, \dots, x_{n,t}^{i,s}, \dots, x_{N,T}^{i,s} \in \Re_N^+]$ inputs. The input-oriented VRS (time-invariant) program for the cluster panel data-DEA is:

$$\max_{u_0^{ti,s}, u_m^{ti,s}, v_n^{ti,s}} \tilde{\propto}^{ti,s} = u_o^{ti,s} + \sum_{m=1}^{M} u_m^{ti,s} \tilde{y}_m^{o,s}$$

$$s.t. \sum_{n=1}^{N} v_n^{ti,s} \tilde{x}_n^{o,s} = 1$$

$$u_o^{ti,s} + \sum_{m=1}^{M} u_m^{ti,s} y_{m,t}^{i,s} - \sum_{n=1}^{N} v_n^{ti,s} x_{n,t}^{i,s} \leq 0; \quad i = 1,2, \dots, I; \; s = 1,2, \dots, S$$

$$u_m^{ti,s} \geq 0; \; v_n^{ti,s} \geq 0; \; m = 1,2, \dots, M; \quad n = 1,2, \dots, N \tag{8}$$

With, $u_m^{ti,s}$ and $v_n^{ti,s}$ are weights for outputs and inputs, in the cluster s, for the observed unit 'o'; the parameter $u_o^{ti,s}$ is a scalar that can take positive or negative values, depending of the prevailing returns to scale. Different from the classical cross-sectional DEA approaches, $\tilde{\propto}^{ti,s}$ is an average value that represents the one time-invariant efficiency coefficient for the cluster s. $\tilde{y}_m^{o,s} = \sum_{t=1}^{T} y_{m,t}^{o,s} / T$ is the average value, corresponding for the output m in the cluster s, for the time period

[12] This is also tested in the empirical application with the Simar and Wilson (2002, 2011) returns-to-scale test.

[13] We can call DMU to any unit of analysis, say, individuals, departments, firms, municipalities, or in the case of this study, hospitals.

T; and $\tilde{x}_n^{o,s} = \sum_{t=1}^{T} x_{n,t}^{o,s}/T$ is the average value, corresponding for the input n in the cluster s, for the time period T. By applying this program, we obtain MxI output weights and NxI input weights corresponding to the I hospitals classified in the S clusters.

Finally, the cluster time-invariant efficiencies ($\tilde{\propto}^{ti,s}$) can be broken down in time variant efficiencies. Pérez-López et al. (2018) demonstrated that the time-invariant panel-data efficiencies are equal to the weighted average of the time-variant panel-data efficiency coefficients. The approach is extended by Piedra Peña and Prior (2019) considering the technological clusters. Considering an input-oriented approach, and taking one input, one output, the time-variant efficiency scores for the cluster s can be derived in the following way:

$$\tilde{\propto}^{ti,s} = \tilde{\alpha}_1^{tv,s} \frac{x_{n,1}^{o,s}}{\sum_{t=1}^{T} x_{n,t}^{o,s}} + \cdots + \tilde{\alpha}_t^{tv,s} \frac{x_{n,t}^{o,s}}{\sum_{t=1}^{T} x_{n,t}^{o,s}} + \cdots + \tilde{\alpha}_T^{tv,s} \frac{x_{n,T}^{o,s}}{\sum_{t=1}^{T} x_{n,t}^{o,s}}$$

$$\tilde{\propto}^{ti,s} = \sum_{t=1}^{T} \tilde{\alpha}_t^{tv,s} w_t^s \tag{9}$$

So that time-invariant panel-data efficiencies are equal to the weighted average of the time-variant panel-data efficiency coefficients for each cluster.

The second step of our strategy defines a convenient spatial model, our main idea is to assess whether hospitals´ efficiency is associated with the efficiency of nearby hospitals and to other observed and unobserved variables. For this, spatial econometrics literature has developed models that treat three different types of interaction effects among units of analysis (Halleck Vega and Elhorst, 2015). These interaction effects account for (i) endogenous interaction effects among the dependent variable; (ii) exogenous interaction effects among the explanatory variables; and (iii) interaction effects among the error terms.

The identification of the source of spatial autocorrelation needs to be carried out in order to avoid model misspecifications and omitted variable bias. Following the strategy described in LeSage and Pace (2009) and Elhorst (2010), we begin with an SDM setting as a general specification and, then, test for alternatives. The process of model selection can be found in Appendix 2. We also provide Lagrange Multiplier (LM) lag and error tests for spatial panel models (Anselin et al., 2006) and their robust counterparts (Elhorst, 2010), commonly used in the literature to make inference for spatial interaction effects.

To select between random and fixed effects model, we run the robust Hausman test (Hausman, 1978), and found robust evidence for the fixed effects model. Elhorst (2014) also recommends the selection of the fixed effects in spatial panel models when space-time data of adjacent spatial units are located in unbroken study areas. Also, given the assumption of orthogonality between the individual-specific component and the explanatory variables is particularly restrictive and difficult to hold in empirical applications (Baltagi, 2013; Baltagi et al., 2018).

The model selection points out a SAC model as our appropriate framework of analysis.[14] This is consistent with similar applications in the existing literature (Felder and Tauchmann, 2013; Herwartz and Strumann, 2014; Herwartz and Strumann, 2012), suggesting that the sources of autocorrelation occur in the efficiency performance of hospitals and unobservable factors that we cannot measure. Thus, from equation (7) we specify the following spatial panel data SAC model estimated by Quasi-Maximum Likelihood (QML):

$$\log(e_{it}) = \rho \sum_{j \neq i} w_{ij} \log(e_{jt}) + \beta' \log(Z_{it}) + \emptyset_i + \gamma_t + \varepsilon_{it}$$
$$\text{with } \varepsilon_{it} = \lambda \textstyle\sum_j w_{ij} \varepsilon_{jt} + \epsilon_{it} \qquad (10)$$

The variable e_{it} is the logarithm of the efficiency of the hospital i at time t, e_{jt} is the logarithm of the efficiency of hospital i´s neighbor ($j \neq i$) at time t, w_{ij} are the spatial weights that capture the pattern of spatial dependence and the strength of potential interaction between units *i* and *j*. The variable Z_{it} is the vector including variables as occupancy rate, market share, mortality rate and regional demographics, that can affect the efficiency of the hospital. The variable $\emptyset_i$ captures the hospital fixed effects, and γ_t is the time effect. Finally, ε_{it} is the error term. We define equation (10) in matrix form as:

$$\boldsymbol{e}_t = \rho \boldsymbol{W} \boldsymbol{e}_t + \boldsymbol{Z}_t \boldsymbol{\beta} + \emptyset + \boldsymbol{\gamma}_t + \boldsymbol{\varepsilon}_t \qquad \text{with } \boldsymbol{\varepsilon}_t = \lambda \boldsymbol{W} \boldsymbol{\varepsilon}_t + \boldsymbol{\epsilon}_t \qquad (11)$$

As for the specification of the components of the weight matrix $\boldsymbol{W}$, we use two different specifications. The former (hereinafter $\boldsymbol{W}_d$) is the inverse of the shortest Euclidean distance between any pair of spatial units (*i* and *j*) that has been commonly used in the literature when the data covers healthcare providers (Tosetti et al., 2018). The latter (hereinafter $\boldsymbol{W}_v$) uses the inverse shortest time travel distance by car still between any pair of locations (*i* and *j*), as in Gravelle et al., (2014).

The key parameters to be estimated for the spatial autocorrelation are the coefficients ρ and λ. They measure the strength of the spatial dependence due to efficiency changes and to unobservable factors in neighboring hospitals respectively, conditional on the vectors of explanatory variables. If $\rho > 0$ then a positive autocorrelation is found in the efficiency of hospital *i* and the efficiency of their neighboring hospitals, and similarly for λ.

One of the main advantages of using spatial econometrics is the possibility to empirically assess the magnitude and significance of spillover effects (Elhorst, 2014). In this sense, spatial regression models exploit the dependence structure among hospitals: the effect of the change of an explanatory variable for a specific hospital will affect the hospital itself, and, potentially, all other neighboring hospitals indirectly. This implies the existence of direct, indirect (spillover) and

[14] The acronym SAC is consistent with the terminology of LeSage and Pace (2009) but other authors treat this model with the acronym SARAR, that stands for Spatial Autoregressive Models with Autoregressive Disturbances.

total effects. We can estimate these effects by obtaining the matrix of partial derivatives of the expected values of e_{it}, as proposed by (LeSage and Pace, 2009). So far, the literature on spatial healthcare economics identified the existence of spatial spillovers based on the coefficient estimates (Baltagi et al., 2018). We improve the empirical approach by accounting for the direct, indirect and total effects of independent variables. As stated by LeSage and Pace (2009) the partial derivative interpretation of the impacts coming from changes in the independent variables provides a more valid basis for testing the existence of spillover effects. Here, we are also interested in measuring the effects of the hospitals' occupancy rate, which can bring tangible evidence of how the demand for medical services is affecting the efficiency of a given hospital and whether this is also affecting neighboring hospitals due to spillover effects. In addition, we carry out the LeSage and Pace (2009) partitioning analysis of the spatial multiplier.[15] With this, we are able to trace the effect of the linkages between demand levels of neighboring hospitals. Thus, we do not only concentrate on analyzing the direct, spillover and total effects, but we determine the impacts that the demand itself has over the higher order of contiguity. In other words, we are able to examine how the impact of hospital demand manifests itself over space (Jensen and Lacombe, 2012). Finally, by means of hypotheses testing, we can check for its significant increase (or decrease) of the direct and indirect effects after 2008.

To test the statistical variations of the healthcare demand upon the hospitals' efficiency before and after 2008, we interact the logarithm of the occupancy rate with time dummies ($ocrate_t$). Specifically, we build the following test: $H_o: ocrate_1 = ocrate_2$, where $ocrate_1 = 1/2 \sum_{t=2007}^{2008} ocrate_t$ and represents the subperiod before the constitution;[16] while $ocrate_2 = 1/6 \sum_{t=2009}^{2014} ocrate_t$ constitutes the subperiod after the constitution. Hypotheses are tested by means of two-sided t-test.[17]

6. Data and Variables

We are dealing with a database covering the period from 2006 (two years before the new constitution was approved) to 2014. Hospitals' information was collected from the Annual Survey of Hospital Beds and Discharges and the Survey of Health Activities and Resources provided by the INEC. We excluded the psychiatric, dermatologic and geriatric hospitals, and took out from the sample outliers.[18] We retrieved a panel data of 186 hospitals for which an average of 21 hospitals per year had missing values that were imputed by means of Predictive Mean Matching imputation (Rubin, 1986).[19] Whereas, cantonal economic and

[15] Refer to Appendix 3 for an explanation on LeSage and Pace (2009) spatial effects and its respective partitioning analysis.
[16] The constitution came into force in October 2008.
[17] The logarithmic transformation of the efficiency scores, ensures an unbounded dependent variable and thus enables a consistent maximum likelihood estimation (Simar and Wilson, 2007).
[18] We excluded psychiatric, dermatologic and geriatric hospitals as they focus on specific illness and patients that require different treatments that could bias the efficiency values. For example, psychiatric hospitals might require inpatients to stay for long periods of time, wherein our analysis would reflect it as a criteria for less efficiency.
[19] The imputation results were diagnosed by means of displays of completed data, distribution comparison and checks for fit of the data suggested by Abayomi, Gelman, and Levy (2008).

demographic variables were retrieved from the BCE and INEC's public statistics respectively. The description for all the variables is presented in Appendix 1.

6.1. Variables for the efficiency measurement

As previously mentioned, we employ the efficiency estimations granted from Piedra Peña and Prior (2019). The selection for both input and output variables is related to the existing literature on hospital efficiency measurement. A complete overview is proposed by Hollingsworth (2008), O'Neill et al. (2008) and Cantor and Poh (2018).

In our study, the input variables (controlled by the hospitals) are the number of beds, the medical equipment, and the availability of the infrastructure that is widely used as a proxy for the hospital size and the capital investment (O'Neill et al., 2008).[20] To proxy labor costs, clinical staff is usually included (Hollingsworth, 2008; Hollingsworth, 2003). To that end, we introduce the number of physicians and healthcare professionals beyond the number of physicians of the hospital.

To measure the final production of health of public hospitals, the number of hospital discharges is employed. In addition, this proxy of the output needs to be adjusted by the patients' case heterogeneity. That is, the illness for which each patient is treated. It is common knowledge in the healthcare efficiency measurement literature that not all diseases can be treated with the same amount of resources, and not all hospitals have the means nor the capacity to treat the more severe cases. To control for this heterogeneity, we need to weight it by an index that accounts for the severity of the illness, what is known as the case-mix index (Cantor and Poh, 2018).

In this study, we use the case-mix index proposed by Herr (2008), which relies on the assumption of a positive correlation between length of stay and the severity of illness. The index is constructed with the three-digit International Statistical Classification of Diseases and Related Health Problems (ICD-10) (see Appendix 4).

6.2. Variables for the spatial econometric model

To account for the changes in the number of treated patients we use the logarithm of the hospital occupancy rate.[21] Herwartz and Strumann (2012, 2014) point out that the importance of this variable in relation to healthcare efficiency. It serves as a proxy to determine whether hospitals are adjusting promptly their working staff to the increase of treated patients. Thus, hospitals with a relatively low occupancy rate can be interpreted as having an oversized staff, unlikely to meet the demand of patient care efficiently. This issue has been recently highlighted for low-and-middle-income countries, which present an occupancy rate well below that recommended by the WHO (Hafidz et al., 2018).

[20] The reader can refer to the Appendix 1 for a description of the input variables.
[21] All the variables expressed as percentages were in a 0-100 scale prior to obtain the logarithms to facilitate the estimations and the results' interpretations.

To provide a proxy for market structure in the hospitals' respective canton, we use the logarithm of the hospital's market share. The market share has often been used as an explanatory variable in research regarding healthcare efficiency in developed economies, to provide a measure of concentration (or competition). For example, Longo et al. (2019) identify hospitals that compete in a given district to proxy the patients choice of provider. Hence, the higher competition in a district, the wider the range of healthcare providers that the patients can choose from. This reaction is expected to drive hospitals to compete in quality and increase the incentives to increase efficiency to contain costs. Despite its importance, few studies have embedded this variable in the case of setting involving developing economies (Hafidz et al., 2018). In developing economies experiencing marked healthcare heterogeneities, market share might also have an additional implication, considering that there would be just a few hospitals for which the patients perceive to be able to get a quality treatment for their disease. Therefore, higher market share could also be – to a certain extent – proxying the patients' quality perception of a hospital. In our context, we envisage two scenarios. In the first case, larger market shares could be related to larger hospitals, which are often located in more developed cantons. Piedra Peña and Prior (2019) find that these types of hospitals are those with better technology and better performance (hence, the most efficient). The second case would represent those hospitals located in less developed cantons (hence, with lower technology and efficiency) which do not have to deal with many close competitors.

One of the limitations that we faced was finding appropriate variables in the dataset that can properly measure the quality of the hospitals. To address hospital quality, the variables commonly used in the literature range from mortality, readmission or health satisfaction rates (Hollingsworth, 2008; Hafidz et al., 2018). Unfortunately, the former two are not available in our data. In this respect, we decide to take into account hospitals' quality by including the logarithm of the hospital and cantonal mortality rates. Other morbidity variables were also included, such as the number of disease-specific treated patients, to provide additional controls on the complexity of cases treated. Hospital whose performance displays a significant positive relationship with these morbidity variables might be suggesting not just a higher quality on the treatment of the disease but also a process of learning-by-doing (Gobillon and Milcent, 2013), as they would be showing an increasing experience in treating these diseases over time.

The technological differences are included as a dummy interacting with different hospital independent variables to estimate their differential effect on the hospitals' efficiency scores.

As for canton specific variables, we included the logarithm of the density and gross value added (GVA) to control for the canton's level of urbanization and proxy some exogenous socio-economic factors respectively (Herwartz and Strumann, 2014; Herwartz and Strumann, 2012). Many authors address the influence of elder population on hospital efficiency (e.g. Herr, 2008; Longo et al., 2017) as they are likely to be more cost and resource intensive and present more complications in the treatment. In addition, Orellana et al. (2017) provide evidence of over-utilization of medical treatment in the Ecuadorian public health system for people over 60 years old which can negatively affect the systems' performance as they might be using medical resources that could be employed for higher priority or more severe cases. Here, we use the logarithm of the population over 65 years old to control for this effect.

Finally, we use the logarithm of the cantonal patient migration measured as the number of patients treated in cantons different from the ones of their place of residence. Felder and Tauchmann (2013) state the importance of accounting for regional patient migration as it can be potentially correlated with inefficiency. Patient migration can explain efficiency differences between territories as it could be capturing deprivation effects (Herwartz and Schley, 2018). Bigger hospitals located in the high-developed regions are very likely to treat patients from outer regions, as patients in low-developed regions have access restrictions to good healthcare quality and perceive these bigger hospitals to have higher quality than those located in their residence area (Martini et al., 2014). This way smaller hospitals - likely located in low-developed areas – can present higher efficiencies that are not due to more efficient use of their inputs, but rather a lower local demand due to patient migration (Herwartz and Schley, 2018).

The descriptive statistics of our data are presented in Table 1. We split the sample in technology cluster according to the criterion proposed by Piedra Peña and Prior (2019) (low-tech, intermediate-tech and high-tech). At first sight, this table emphasizes the important heterogeneity in the Ecuadorian public healthcare system. Low-tech hospitals are the majority in the system, but they have a much lower amount of healthcare inputs on average than their high-tech counterpart. However, these high-tech hospitals are treating more than 14 times the patients attended by the low-tech hospitals.

Regarding the hospital demand, we see a higher occupancy rate for the high-tech group (73.80%). Despite presenting the higher demand, this occupancy rate suggest an inefficient utilization of hospital resources: there seems to be spare hospital inputs that are not currently used for treatment, implying that there is still a room for improvement for public hospitals, in general. Furthermore, high-tech hospitals settle in regions that concentrate a bigger amount of population and economic production. The lower market share (18.48%) shows that there is more competition in these areas with respect to the low-tech hospitals' regions, which also present a lower level of patient migration. This preliminary evidence anticipates the need to adjust the hospitals' efficiency performance to the patients' needs with strategies tailored accordingly to the technological groups.

Table 1: Variables' summary statistics

Variable	Cluster 1 (Low) n=156				Cluster 2(Intermediate) n=21				Cluster 3(High) n=9			
		SD				SD				SD		
	Mean	Overall	Between	Within	Mean	Overall	Between	Within	Mean	Overall	Between	Within
Output												
Number of discharges (weighted)	15034	439416.60	141543.50	414089.60	2006	3348.90	3350.20	641.78	221772	1827255	647701.2	1720670
Inputs												
Number of physicians	44	56.59	50.76	23.64	47	87.52	81.39	35.78	213	126.16	105.72	76.43
Number of beds	71	103.96	100.93	17.28	81	146.10	146.41	26.65	273	136.24	137.05	40.38
Number of hospital personnel	96	144.79	137.84	38.10	98	218.03	207.83	77.10	445	242.12	226.42	111.40
Number of equipment and infrastructure	68	81.92	74.50	34.44	64	60.80	59.98	15.57	255	137.41	106.81	92.73
Explanatory Variables												
Ocupancy rate (%)	57.91	26.13	19.75	17.17	45.89	28.95	21.42	19.98	73.80	20.63	18.27	11.20
Market share (%)	67.23	40.55	37.80	14.95	45.86	41.76	38.02	18.98	18.48	17.31	16.07	8.20
Mortality rate (% hospital)	0.84	1.49	1.32	0.70	0.61	0.67	0.54	0.42	2.65	1.42	1.05	1.02
Number of disease 1	224	377.24	331.29	182.16	195	255.86	225.66	129.25	800.53	1293.10	1056.21	817.36
Number of disease 2	152	504.12	491.79	116.86	381	1043.97	960.01	455.48	1019	895.49	723.62	575.01
Number of disease 3	25	48.42	44.71	18.89	33	76.26	67.71	37.76	217	170.60	146.48	98.96
Number of disease 4	253	384.47	352.57	155.63	255	394.24	341.21	209.66	998	834.42	763.30	414.59
Number of disease 5	50	69.10	62.75	29.32	55	74.36	58.67	47.27	198	171.79	162.85	75.12
Number of disease 6	1490	3188.42	3113.28	727.17	1010	1507.23	1359.28	709.04	1845	2115.75	2015.82	905.11
Number of disease 7	205	707.51	627.11	330.98	125	240.65	197.48	143.44	387	503.81	418.82	309.76
Number of disease 8	34	114.34	109.11	35.19	30	69.89	62.42	33.97	365	493.50	470.79	209.91
Number of disease 9	291	536.01	493.68	212.07	285	520.75	486.98	210.06	1572	1599.99	1375.53	925.80
GVA(thousand $)	2064886	4188748.00	4154598.00	619145.20	1576364	3638626.00	3668601.00	594701.10	8318914	5342403	5445905	1359843
Density (population per Km2)	264.25	485.06	485.16	35.32	202.25	205.92	209.61	18.39	465.80	142.19	146.47	30.16
Mortality rate (% cantonal)	0.41	0.12	0.10	0.05	0.39	0.12	0.12	0.04	0.48	0.06	0.05	0.03
Total population over 65	24969	43875.11	43949.93	2107.82	19921	36822.14	37517.95	2858.56	91658	51679.52	54191.08	5269.397
Total patient migration	7684	15001.32	14963.12	1556.07	4530	6034.01	6050.24	1166.84	25511	18520.74	19297.82	2802.24

Source: The author.

6.3. Exploratory Spatial Data Analysis

Before performing the more quantitative analysis, it is important to assess the true existence of spatial dependence in the distribution of the health resources in the Ecuadorian territory. Hence, we are performing an exploratory spatial data analysis (ESDA) to identify different patterns of spatial association and regional clusters or atypical locations (Anselin et al., 2006) of our observations and gain a better understanding of the spatial structure of the data.

The aim of our spatial data analysis is to test whether strategic interaction between hospitals is occurring. This interaction can arise from the concentration of health resources in selected areas that can yield similar patterns of efficiency (Longo et al., 2017). We test for the spatial autocorrelation and proximity of the data by means of the Moran's I-statistic (Moran, 1948). Moran's I has been widely used in the literature to test for spatial dependence (LeSage and Pace, 2009). If the statistic is positive and significant, this means that hospitals with high amounts of healthcare resources are clustered.

Figure 1 depicts the Moran's map and scatterplot for the mean of four different hospital features between 2006 and 2014: number of physicians, beds, medical equipment, and hospital personnel (outside physicians).[22] Whilst, Table 2 reports

[22] A better description of this is presented in the data section.

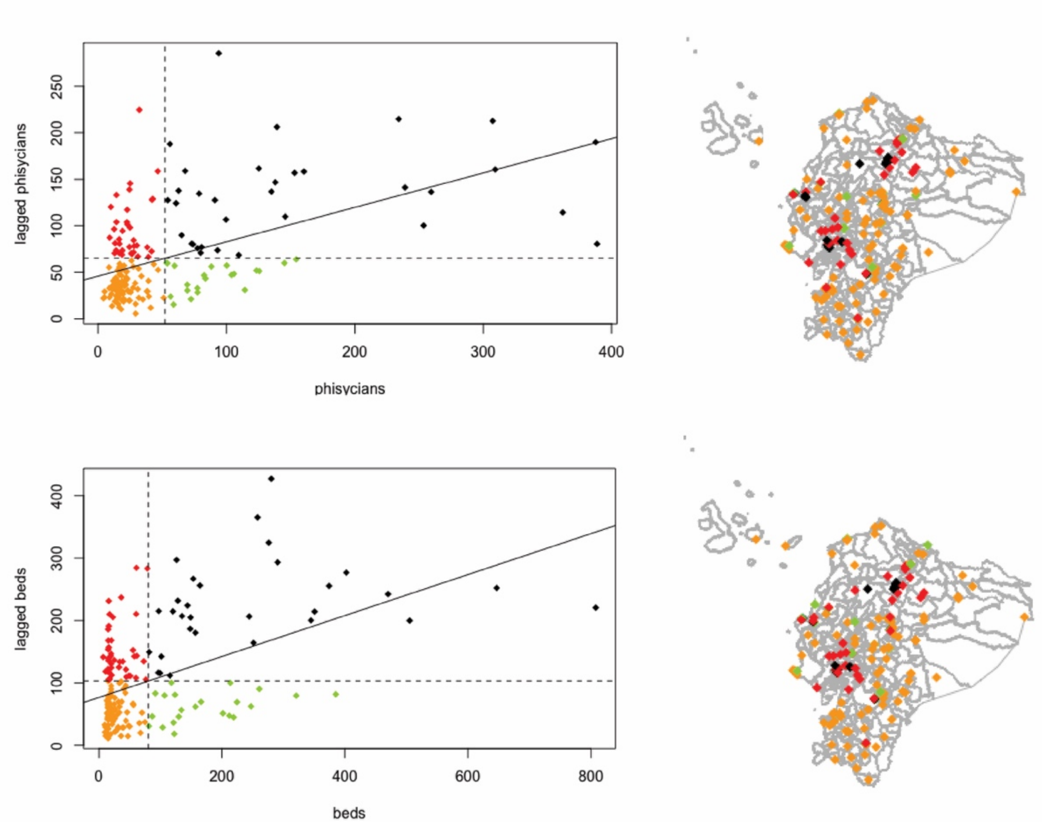
the Moran's I test results, using the weight matrix $\boldsymbol{W}_d$ based on the inverse Euclidean (shortest) distance between hospitals.[23]

Table 2: Moran's I test of spatial dependence

Hospital Inputs	**Moran's I**	**Prob**
Physicians	0.3698	0.0000
Beds	0.3279	0.0000
Hospital Personnel	0.3638	0.0000
Equipment and Infrastructure	0.3145	0.0000

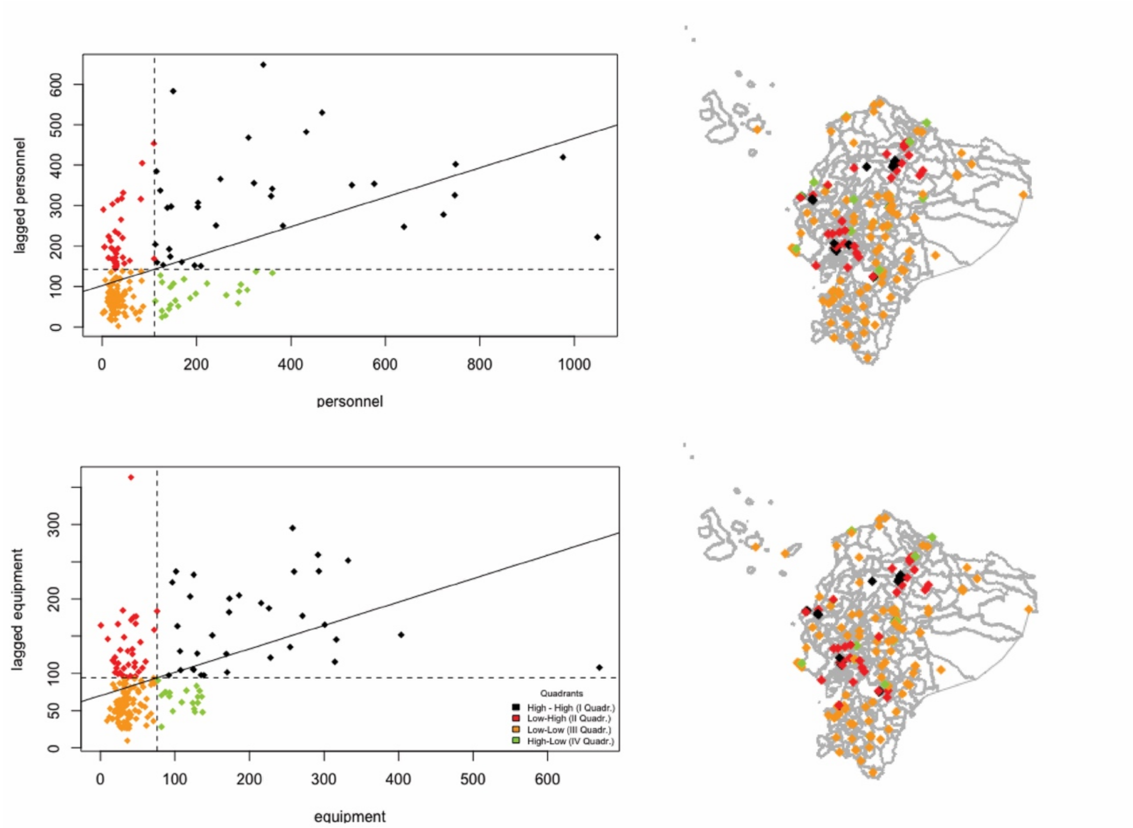
Source: The author.

Figure 1: Moran's map and Moran's Scatterplot



[23] We also used different weight matrices such as the inverse of the shortest time travel distance, and the inverse of the squared distance and time travel distance. The results are similar in all cases.

Figure 1 (continue): Moran's map and Moran's Scatterplot



Source: The author.

The evidence shown in Table 2 points out an average positive spatial correlation for all the hospital features considered. Looking at the maps, the hospitals that present positive spatial autocorrelation (black points) are clustered around Quito and Guayaquil, which are the two bigger and most developed cantons in Ecuador (Mendieta Muñoz and Pontarollo, 2016). It is also worth noticing that the spatial pattern changes as hospitals move further away from these cantons. Hospitals that surround them present dissimilar amounts of resources, represented by the reddish points (low-high), and present a negative correlation as they move farther away, as depicted by the orange points (low-low).

The corresponding scatterplots confirm the finding of positive autocorrelation. Most of the hospitals’ resources cluster in the quadrant III, whereas few are in quadrant I. This result is assessing not only the high heterogeneity in terms of the technological endowment for healthcare in Ecuador, but also the uneven distribution of these high-tech hospitals in the territory, which confirms the findings of the descriptive statistics abovementioned.

The evidence issued from this preliminary analysis implies that classic econometric approximations to study the public healthcare Ecuadorian system would fail to obtain unbiased results given the existence of spatial dependence. We need to consider a proper model that incorporates this dependence and disentangle the spillovers effects that are causing it (Anselin, 1988).

In order to perform our analysis, we need an appropriate measure that allows us to estimate to what extent healthcare resources are efficiently used in the production of a healthcare output. In this respect, many methods have been proposed in the literature (Cantor and Poh, 2018) but a few of them have been applied in combination with spatial econometric techniques, (Felder and Tauchmann, 2013).

Another novelty of this contribution is to bridge these two strands of literature by proposing an empirical two-stage approach. In the first stage we estimate Piedra Peña and Prior (2019) efficiency scores robust over time that have the advantage of considering the technological differences in the public healthcare Ecuadorian sector. Instead, in the second stage, we select these measures of efficiency as dependent variables to perform spatial panel econometric estimates. In this way, we can determine the spatial dependence in efficiency across hospitals. Additionally, this empirical framework allows for disentangling to what extent direct and spillover effects issuing from external factors - particularly hospitals occupancy rates - affect the efficiency performance of hospitals over time.

7. Estimation Results

Our empirical analysis moves from linear program (9). Table 3 summarizes the time-variant efficiencies estimated. The results show the remarkable differences in efficiency when technological disparities are considered in the analysis. On average, high-tech hospitals display a higher performance than their counterparts. The value of 0.64 for the high-tech group shows that there is still a 45% room for improvement of their input use to be fully efficient. In addition the results emphasize a constant problem of inefficiency over time, even stronger for low-tech hospitals if we consider their efficiency value of 0.42, showing that they still need to improve their input consumption on 57% to achieve full efficiency. Our results show that there is still a big room of improvement for public hospitals that policymakers and hospital managers should be aware of, once one also takes into account the existence of a spatial correlation across data, that demands for a deeper analysis of the problem.

Table 3: Time-variant efficiencies, summary statistics

Cluster	Mean	Median	SD	Min	Max
High	0.6495	0.6154	0.2044	0.3196	1
Intermed.	0.5818	0.5500	0.2616	0.0537	1
Low	0.4291	0.4232	0.1685	0.0738	1

Source: The author.

Table 4 shows the regression results from the SAC spatial econometric model for equation (11). The first set of estimations refers to the model with the selected weight matrices and without incorporating the technological discrepancies. Hereinafter, we label this first type of setting as the baseline model.

The results confirm the existence of positive spatial dependence among hospital efficiency in the sample. These results are robust for both type of spatial matrices.

Considering the weight matrix based on the shortest travel time distance, [24] the estimate of ρ indicates that 1% increase in the efficiency of neighboring hospitals *j* is increasing the efficiency of the hospital *i* by 0.45%. Referring to our efficiency measurement setting, the results suggest significant strategic complementarity effects in hospitals efficiency. These results contrast with the ones in Longo et al. (2017), in which they use different efficiency ratios to proxy efficiency.

The statistical significance of the estimates for λ suggests the presence of a negative spatial error correlation. This result involves the existence of other sources of spatial correlation in our sample that we are not properly captured in the model. The results are in line with previous findings in the literature. The existence of spatial error correlation is not new in spatial health econometrics (Baltagi et al., 2018). There are several risk factors that are difficult to measure but they are so geographically concentrated to affect health outcomes (Tosetti et al., 2018). These factors may not be necessarily linked to interactions among hospitals, but rather be associated with interactions among spatial units observed at a different scale. For instance, Martini et al. (2014) discuss the importance of ward level analysis in measuring efficiency, as similar behavior can occur among wards that provide homogeneous treatments, rather than hospital aggregation. The spatial interaction in hospital efficiency can also come from a more in dept disaggregation. For example, hospital efficiency can be affected by the physicians productivity (Johannessen et al., 2017): the concentration of these physicians in large hospitals, mostly located in developed cantons can generate interactions among them, giving rise to a spatial pattern that cannot be captured by the data. Conversely, the sources of spatial dependence can also come from macroeconomic phenomena like immigration or unemployment which can cause inefficiency in the provision of healthcare services (Herwartz and Schley, 2018), and are very likely to be influencing hospital performance in Ecuador, given its strong spatial dependence (Mendieta Muñoz and Pontarollo, 2016; Szeles and Mendieta Muñoz, 2016).

Another potential source of spatial correlation in errors could come from the omission of budgetary information, which has proved to be a relevant factor of influence in hospital's efficiency and quality, especially when there are financial pressures due to budget constraints (Herr, 2008; Mas, 2015). In this respect, it is worth pointing out an important limitation of our dataset that is the impossibility to retrieve the quality for hospitals budgetary information or public investment to properly match with our dataset.

Due to the scarce literature that exploits a similar approach above all for Latin American countries, a comparative analysis becomes difficult. Nevertheless, the sign of the spatial correlation and the effect of both the spatially lagged efficiency score and the error term go in line with those of Felder and Tauchmann (2013). Although they perform a cross-sectional analysis at the district level in Germany, the average effect of spatial dependence for the hospital's efficiency – measured by efficiency measurement nonparametric models – does not seem to be unrealistic in the Ecuadorian context.

[24] Henceforth it will be used for interpretation as it is a more realistic matrix of hospital interactions rather than the one of Euclidean distances ($\boldsymbol{W}_d$).

Table 4 provides additional information about spillover effects. We present total effects disaggregated in direct and indirect (spillover) effects (LeSage and Pace, 2009). The logarithm of occupancy rate shows that an increase in 1% in a hospital's occupancy rate increases the efficiency of the same hospital in 0.13% and the efficiency of all neighboring hospitals in 0.09%. These findings would reject the hypothesis that higher demand for medical services (translating into higher occupancy rates) could be the source of the decrease in hospitals' efficiency, and rather, it has boosted it.[25] This finding is in line with the argument of the inefficient use of the spare resources in the public healthcare system, as in Herwartz and Strumann (2014).

Table 4: Spatial regression results. Direct, indirect and total effects

Variables	$\boldsymbol{W_d}$			$\boldsymbol{W_v}$		
	Direct	Indirect	Total	Direct	Indirect	Total
log occupancy rate	0.140***	0.0706***	0.211***	0.130***	0.0983***	0.228***
	(0.019)	(0.018)	(0.0311)	(0.0189)	(0.0211)	(0.0354)
log market share	-0.0372***	-0.0188***	-0.0560***	-0.0342***	-0.0259***	-0.0601***
	(0.011)	(0.0069)	(0.0166)	(0.0108)	(0.0094)	(0.0195)
log mortality rate	-0.0317***	-0.0160***	-0.0478***	-0.0289***	-0.0220***	-0.0509***
	(0.008)	(0.0057)	(0.0134)	(0.0083)	(0.0074)	(0.0151)
disease 1	-0.00759***	-0.00384**	-0.0114***	-0.00580**	-0.00440**	-0.0102**
	(0.003)	(0.0016)	(0.0041)	(0.0026)	(0.0022)	(0.0047)
disease 2	-0.00308	-0.00152	-0.00460	-0.00341	-0.00255	-0.00596
	(0.003)	(0.0014)	(0.0039)	(0.0026)	(0.002)	(0.0046)
disease 3	0.0784***	0.0395***	0.118***	0.0841***	0.0639***	0.148***
	(0.02)	(0.015)	(0.0366)	(0.0240)	(0.0219)	(0.0440)
disease 4	0.0232***	0.0117***	0.0350***	0.0212***	0.0161***	0.0373***
	(0.004)	(0.0034)	(0.0066)	(0.0039)	(0.0042)	(0.0075)
disease 5	-0.0255	-0.0129	-0.0384	-0.0289	-0.0221	-0.0510
	(0.018)	(0.0101)	(0.0283)	(0.0184)	(0.0149)	(0.0329)
disease 6	0.00665***	0.00336***	0.0100***	0.00672***	0.00511***	0.0118***
	(0.0008)	(0.0008)	(0.0015)	(0.0009)	(0.0011)	(0.0018)
disease 7	0.00558***	0.00283**	0.00841***	0.00452**	0.00345**	0.00796**
	(0.002)	(0.0012)	(0.0031)	(0.002)	(0.0017)	(0.0036)
disease 8	-0.0302***	-0.0152**	-0.0454***	-0.0294**	-0.0224**	-0.0518**
	(0.012)	(0.0067)	(0.0176)	(0.0118)	(0.009)	(0.0211)
disease 9	0.00601**	0.00301**	0.00902**	0.00591**	0.00447**	0.0104**
	(0.0025)	(0.0014)	(0.0038)	(0.0025)	(0.002)	(0.0045)
log GVA	0.0877**	0.0438**	0.131**	0.0650*	0.0490*	0.114*
	(0.036)	(0.0199)	(0.0545)	(0.0357)	(0.0278)	(0.0625)

[25] We tested the direction of the causality between hospital efficiency and the demand by means of Granger (1969) causality test for panel data models adapted by Dumitrescu and Hurlin (2012). The test rejects the null hypothesis of non-causality.

Table 4 (continue): Spatial regression results. Direct, indirect and total effects

Variables	$\boldsymbol{W_d}$			$\boldsymbol{W_v}$		
	Direct	Indirect	Total	Direct	Indirect	Total
log density	-0.610**	-0.300**	-0.910**	-0.663***	-0.499***	-1.162***
	(0.248)	(0.130)	(0.363)	(0.132)	(0.114)	(0.224)
log mortality (cantonal)	0.0678*	0.0342	0.102*	0.0515	0.0391	0.0906
	(0.038)	(0.0215)	(0.0584)	(0.0377)	(0.03)	(0.0669)
log pop > 65	-0.0126	-0.00753	-0.0201	-0.126	-0.0976	-0.224
	(0.120)	(0.0606)	(0.180)	(0.115)	(0.0933)	(0.207)
log inpatient migration	0.00446	0.00230	0.00676	0.00455	0.00348	0.00803
	(0.012)	(0.006)	(0.0177)	(0.0117)	(0.009)	(0.0206)
ρ	0.355***			0.453***		
	(0.053)			(0.0454)		
λ	-0.419***			-0.513***		
	(0.064)			(0.0627)		
N	1,674			1,674		
Number of hospitals	186			186		

Note: Dependent variable is log of hospital efficiency. ML estimations were also run and are comparable. Direct, indirect and spillover effects and related standard errors in parentheses computed using 2000 draws. *** p<0.01, ** p<0.05, * p<0.1.
Source: The author.

Instead, market share is associated with a negative estimated coefficient.[26] Its direct and indirect effects show that 1% increase of this variable diminishes the efficiency performance by 0.03% for the selected hospital and 0.02% for all the neighboring hospitals. This implies that hospitals that host more patients tend to experience an inefficient use of resources. However, the magnitude of this effect could be different in accordance with the type of hospital we are dealing with.

In addition, it is interesting to review the negative effect of cantonal density, which means that hospitals located in denser areas tend to record lower performance. However, as we have previously mentioned, the higher level of efficiency in less populated cantons does not necessarily mean that these hospitals are outperforming those in denser territories, but it might be the result of patient migration outflow to the former ones.[27] Furthermore, the non-significative effect of the cantonal inpatient migration, might not necessarily mean that it has no effect on hospital efficiency but just that it is failing to capture the true effect of patient migration.[28]

The negative effect of hospital mortality provides evidence that a high performance rate is positively correlated with low mortality, which has been a common finding in recent literature (Ferreira and Marques, 2019; Herwartz and Strumann, 2012; Herwartz and Strumann, 2014).

[26] For the definition of market share, refer to the Appendix 1
[27] We provide more evidence on this when we consider the technological effects.
[28] This issue is definitely an important topic of analysis for future research.

However, the previous results do not accommodate technological heterogeneities among hospitals. We go a step further in the applied literature and include technological differences as interactions with hospital-related variables, being the ones that tend to be relevant for the analysis (Piedra Peña and Prior, 2019).

Table 5 presents the estimated results including technological interactions. Model (1) presents the baseline model using $\boldsymbol{W}_v$. Models (2), (3) and (4) show the estimation results with the covariates at the hospitals level interacted with two dummies of cluster 2 (intermediate-tech) and cluster 3 (high-tech).[29] For sake of simplicity, we exclude from the table the morbidity estimations' parameters.[30]

The most interesting finding refers to the market share. The estimated coefficient is significant and robust, positively associated with the technological endowment of public hospitals: the estimates are positive for high-and-intermediate-tech hospitals, something at odds with previous results. Indeed, the estimations provide evidence that in case of more concentration, high-and-intermediate-tech hospitals' efficiency performance increases, enforcing spillover effects. These results are not far from recent findings in the literature. Pross at al. (2018) assess that regional and hospital level concentration can improve quality and resource efficiency. Gobillon and Milcent (2013) identify that the higher local concentration of patients in a few large hospitals rather than many small ones improve the hospitals' performance. As these authors state, this can be the result of a learning-by-doing process. The hospitals with the best technology (better equipment, more specialized physicians, better infrastructure, etc.), having treated more patients and more severe cases over time, experience improvements in their treatment capacity through experience. These results might evidence policy recommendations for public investment in favor of hospital competition (which usually seek higher quality and efficiency of the health system) but well targeted in order to avoid a negative impact. The concentration of resources in high-developed areas (where most of the high-tech hospitals locate) can be beneficial for the hospital performance in those areas. It is desirable that public investment could target less-developed areas where the low-tech hospitals concentrate without having many close competitors. Increasing the number of hospitals in less-developed areas would yield hospitals to compete by increasing their quality and performance in order to avoid the patient's outflow. It could also attract skilled and specialized physicians to these regions given the demand for qualified personnel over there. As a consequence, more patients could be tempted to receive treatment there, if they perceive that these hospitals are increasing in quality and efficiency (Ippoliti and Falavigna, 2012), and, hence, enhancing the regional performance of the health sector.

Our estimations also stress that there are no significant changes in occupancy rate and mortality rate when referring to the technological endowment. Regardless of the technological differences, higher demand is translating into higher efficiency. The rationale might be that all hospitals, regardless of their technological level, show low levels of efficiency, implying an inefficient use of

[29] Estimation results with the other weight matrix are comparable and available upon request.
[30] Complete results' tables are available upon request.

their spare inputs which gives them room for improvement when there is a higher demand for medical treatment.

To find out how the occupancy rate has influenced the efficiency of public hospitals, we draw in Figure 2 the tendency of the total effect of $ocrate_t$ over time. We can appreciate a cut in the total effect after 2008, suggesting that the increase in demand after this year yields an increase in the performance of the hospitals due to a more efficient use of spare resources. This effect might also be the result of a proper managerial planning that could have anticipated an increase of the bulk of patients, given that the Ecuadorian population had time to get informed about the potential changes that the constitution embraced.

To verify whether this discontinuity in efficiency was statistically significant, Table 6 presents the correspondent hypotheses tests for both direct and indirect effects. The test rejects both hypotheses at 95% of confidence. This result implies that the period after the adoption of the new constitution enforced not only a significant upturn in the direct effect that an increase in demand generated in a specific hospital, but bigger spillover effects for neighboring hospitals as well.

The results presented so far highlight the importance that covariates (mainly higher demand and more competition) can bring to the efficiency performance of public healthcare system, and the potential effect that policy implementation can have on it in the case to be well planned at the territorial level. As it has been proved, these policies do not exclusively bring benefits for the selected hospital, but they also affect neighboring hospitals due to spillovers. Nevertheless, it is worth pointing out that there are still some explanatory variables that are worsening the performance of the system. Some of these are still unknown, and more research must be done in this direction.

Finally, Table 7 presents the different neighboring order coefficient estimates of the partitioning analysis. The direct partitioning effect in Table 7 shows a significant impact beyond the so called zero-order neighbor (W^0, see appendix 3) that decreases significantly in size from W^1on.[31] Implying that for direct impacts, those immediate neighbors play a strong role.[32]

Regarding the indirect partitioning effects, these are significant for the second, third and fourth-order neighbor (and significant at 90% of confidence for the firth-order neighbor, considering $\boldsymbol{W}_v$) and strongly decreasing in size after W^3. This effect suggests that, although significant, demand has a limited effect over space for hospital efficiency, with spillover effects being strong in small concentrated areas and generating small feedback effects.

[31] The reader will appreciate that the coefficients for W^2 and for W^1 in Table 7 are zero for the direct and indirect partitioning effects, respectively. This is because the first term of the series expansion in (14) (see appendix 3) contains zeros on the off-diagonal. Consequently, W^2 will always be equal to zero for the direct effect. Conversely, given that the spatial weight matrix $\boldsymbol{W}$ contains zero on the main diagonal, by definition; W^1 will always be zero for the indirect effect (Jensen and Lacombe, 2012).

[32] The impact of the marginal change of demand of hospital *i* on its own efficiency is the result of local effects plus feedback effects that pass mainly through its direct neighbor *j*.

The abovementioned results provide a useful tool for policy decisions. We have demonstrated here not just the existence of positive spillover effects of demand on hospital efficiency, but those spillover effects spread to a limited extent in small concentrated areas. Policy reforms that enhance hospital demand will have positive effect on efficiency performance, but this will spread through spillover effects to a limited extent due to the concentrated spatial territory of the country only.

Table 5: Spatial panel regression results, including technological interactions.

Variables	(1)			(2)			(3)			(4)		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
log occupancy rate	0.130***	0.0983***	0.228***	0.127***	0.0784***	0.205***	0.132***	0.0740***	0.206***	0.129***	0.0726***	0.202***
	(0.0189)	(0.0211)	(0.0354)	(0.0223)	(0.0218)	(0.0396)	(0.0223)	(0.0211)	(0.0388)	(0.0222)	(0.0198)	(0.0368)
log market share	-0.0342***	-0.0259***	-0.0601***	-0.0374***	-0.0232***	-0.0607***	-0.0603***	-0.0337***	-0.0940***	-0.0598***	-0.0337***	-0.0934***
	(0.0108)	(0.00937)	(0.0195)	(0.0109)	(0.00850)	(0.0184)	(0.0120)	(0.0104)	(0.0204)	(0.0120)	(0.0105)	(0.0204)
log mortality rate	-0.0289***	-0.0220***	-0.0509***	-0.0310***	-0.0192***	-0.0502***	-0.0289***	-0.0162***	-0.0451***	-0.0215**	-0.0122**	-0.0337**
	(0.00831)	(0.00745)	(0.0151)	(0.00857)	(0.00701)	(0.0147)	(0.00854)	(0.00603)	(0.0138)	(0.00924)	(0.00620)	(0.0149)
log GVA	0.0650*	0.0490*	0.114*	0.0915**	0.0566**	0.148**	0.113***	0.0627**	0.175***	0.109***	0.0616**	0.171***
	(0.0357)	(0.0278)	(0.0625)	(0.0364)	(0.0259)	(0.0602)	(0.0390)	(0.0257)	(0.0616)	(0.0384)	(0.0265)	(0.0621)
log density	-0.663***	-0.499***	-1.162***	-0.640***	-0.392**	-1.032***	-0.730***	-0.400***	-1.130***	-0.714***	-0.395***	-1.109***
	(0.132)	(0.114)	(0.224)	(0.240)	(0.161)	(0.385)	(0.242)	(0.142)	(0.362)	(0.240)	(0.145)	(0.366)
log mortality (cantonal)	0.0515	0.0391	0.0906	0.0740*	0.0454*	0.119*	0.0706*	0.0396	0.110*	0.0725*	0.0412	0.114*
	(0.0377)	(0.0300)	(0.0669)	(0.0407)	(0.0265)	(0.0658)	(0.0408)	(0.0256)	(0.0651)	(0.0395)	(0.0261)	(0.0640)
log pop > 65	-0.126	-0.0976	-0.224	-0.0523	-0.0339	-0.0862	-0.0530	-0.0317	-0.0847	-0.0407	-0.0247	-0.0654
	(0.115)	(0.0933)	(0.207)	(0.122)	(0.0790)	(0.200)	(0.122)	(0.0712)	(0.192)	(0.114)	(0.0668)	(0.179)
log inpatient migration	0.00455	0.00348	0.00803	0.00268	0.00160	0.00428	0.00478	0.00251	0.00730	0.00556	0.00302	0.00858
	(0.0117)	(0.00902)	(0.0206)	(0.0119)	(0.00766)	(0.0195)	(0.0122)	(0.00717)	(0.0193)	(0.0121)	(0.00708)	(0.0191)
log occupancy rate*cluster 2				0.0311	0.0190	0.0500	0.00850	0.00435	0.0128	0.0130	0.00754	0.0206
				(0.0369)	(0.0241)	(0.0604)	(0.0376)	(0.0218)	(0.0590)	(0.0376)	(0.0223)	(0.0595)
log occupancy rate*cluster 3				-0.00229	-0.00173	-0.00402	-0.0477	-0.0248	-0.0725	-0.0340	-0.0187	-0.0527
				(0.169)	(0.112)	(0.279)	(0.169)	(0.0976)	(0.265)	(0.169)	(0.0995)	(0.267)

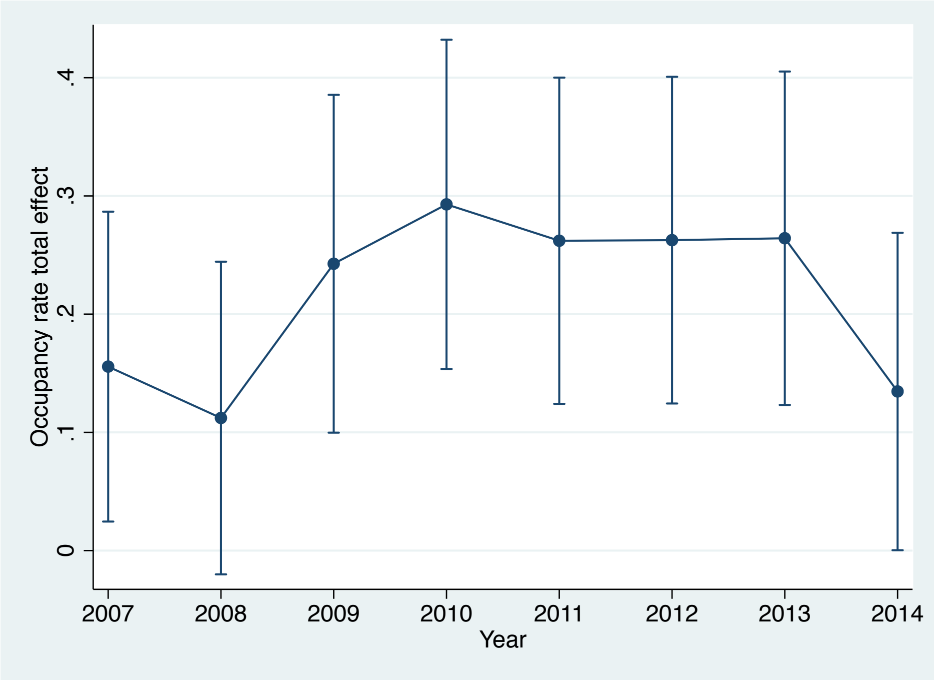
Table 5 (continue): Spatial panel regression results, including technological interactions.

Variables	(1)			(2)			(3)			(4)		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
log market share*cluster 2							0.106***	0.0588***	0.165***	0.100***	0.0560***	0.156***
							(0.0280)	(0.0192)	(0.0436)	(0.0282)	(0.0197)	(0.0447)
log market share*cluster 3							0.284***	0.159***	0.443***	0.250***	0.142**	0.392**
							(0.0883)	(0.0613)	(0.142)	(0.0938)	(0.0647)	(0.153)
log mortality rate*cluster 2										-0.0474*	-0.0266	-0.0740*
										(0.0273)	(0.0163)	(0.0426)
log mortality rate*cluster 3										-0.0637	-0.0355	-0.0992
										(0.0595)	(0.0350)	(0.0935)
ρ	0.453***			0.397***			0.373***			0.375***		
	(0.0454)			(0.0527)			(0.0580)			(0.0575)		
λ	-0.513***			-0.486***			-0.447***			-0.451***		
	(0.0627)			(0.0678)			(0.0745)			(0.0740)		
N	1,674	1,674	1,674	1,674	1,674	1,674	1,674	1,674	1,674	1,674	1,674	1,674
Number of hospitals	186	186	186	186	186	186	186	186	186	186	186	186

Note: Dependent variable is log of hospital efficiency. ML estimations were also run and are comparable. Direct, indirect and spillover effects and related standard errors in parentheses computed using 2000 draws. *** p<0.01, ** p<0.05, * p<0.1.

Source: The author.

Figure 2: Occupancy rate's total marginal effect with 95% CI



Source: The author.

Table 6: Occupancy rate effects and hypotheses tests

	Effect		
Occupancy rate	Direct	Indirect	Total
2007	0.114**	0.0147**	0.129**
	(0.0477)	(0.00638)	(0.0538)
2008	0.0662	0.00847	0.0747
	(0.0493)	(0.00638)	(0.0555)
2009	0.161***	0.0207***	0.181***
	(0.0534)	(0.00716)	(0.0600)
2010	0.187***	0.0241***	0.211***
	(0.0486)	(0.00658)	(0.0545)
2011	0.160***	0.0206***	0.180***
	(0.0487)	(0.00664)	(0.0549)
2012	0.175***	0.0226***	0.197***
	(0.0510)	(0.00714)	(0.0576)
2013	0.180***	0.0233***	0.203***
	(0.0512)	(0.00723)	(0.0578)
2014	0.0751	0.00962	0.0847
	(0.0479)	(0.00621)	(0.0539)
Test statistics			
$H_o: ocrate_1 = ocrate_2$	6.43**	6.02**	6.45**

Note: Dependent variable is log of hospital efficiency. Direct, indirect and spillover effects and related standard errors in parentheses computed using 2000 draws. *** p<0.01, ** p<0.05, * p<0.1.
Source: The author.

Table 7: Spatial partitioning results of direct, indirect and total effects of hospital demand

	Direct	
	log occupancy rate ($\boldsymbol{W}_d$)	log occupancy rate ($\boldsymbol{W}_v$)
W^1	0.12799***	0.12571***
	(6.02202)	(5.82393)
W^2	0.00000	0.00000
W^3	0.00272***	0.00265***
	(2.90945)	(3.35807)
W^4	0.00021**	0.00034**
	(2.05552)	(2.42271)
W^5	0.00018	0.00023*
	(1.56598)	(1.85795)
W^6	0.00002	0.00005
	(1.25065)	(1.38788)
W^7	0.00001	0.00003
	(1.02999)	(1.12931)

	Indirect	
	log occupancy rate ($\boldsymbol{W}_d$)	log occupancy rate ($\boldsymbol{W}_v$)
W^1	0.00000	0.00000
W^2	0.04151***	0.04744***
	(4.56186)	(4.90785)
W^3	0.01074***	0.01525***
	(2.90945)	(3.35807)
W^4	0.00415**	0.00641**
	(2.05552)	(2.42271)
W^5	0.00123	0.00231*
	(1.56598)	(1.85795)
W^6	0.000004	0.00091
	(1.25065)	(1.38788)
W^7	0.000002	0.00033
	(1.02999)	(1.12931)

Table 7(continue): Spatial partitioning results of direct, indirect and total effects of hospital demand

	Total	
	log occupancy rate ($\boldsymbol{W}_d$)	log occupancy rate ($\boldsymbol{W}_v$)
W^1	0.12799***	0.12571***
	(6.02202)	(5.82393)
W^2	0.04151***	0.04744***
	(4.56186)	(4.90785)
W^3	0.01346***	0.01791***
	(2.90945)	(3.35807)
W^4	0.00436**	0.00675**
	(2.05552)	(2.42271)
W^5	0.00141	0.00255*
	(1.56598)	(1.85795)
W^6	0.00002	0.00096
	(1.25065)	(1.38788)
W^7	0.00001	0.00036
	(1.02999)	(1.12931)

Note: Dependent variable is log of hospital efficiency. Z-values in parenthesis computed using 2000 draws for the direct, indirect and total effects. *** p<0.01, ** p<0.05, * p<0.1.
Source: The author.

7.1. Robustness checks

To test for the robustness of the results of previous estimations, we run the same estimations for the model (4) by applying the Generalized Method of Moments (GMM) models for endogeneity to control for heteroscedasticity. Although this method displays some advantages over ML methods (Tosetti et al., 2018), GMM have been little exploited in spatial health economics, and its application has been recently encouraged (Baltagi et al., 2018). We also examine whether the results are sensitive when we consider the remoteness between hospitals by introducing the inverse of the squared distance to define the weight matrix $\boldsymbol{W}_{d^2}$ and time travel distance for the weight matrix $\boldsymbol{W}_{v^2}$, so those hospitals quite far apart weight less.

Table 8 presents GMM estimations as well as the results with the new squared matrices. The estimation is based on the Kelejian and Prucha (1999) model that was first extended to the panel case by Druska and Horrace (2004) and later by Kapoor, Kelejian, and Prucha (2007) for the case of the random effects. The estimation in a fixed effects framework was later adapted by Mutl and Pfaffermayr (2011). One drawback of this method is that it does not provide an estimate of the dispersion of λ, so no significance test is possible (Croissant and Millo, 2018).

Looking at the ρ coefficients of the first two models, the estimations show no substantial difference with respect to the previous estimates. Even if we cannot determine whether the coefficients λ are statistically significant. Regarding the effects of the covariates, the results are robust, and the size of the estimation is comparable. Occupancy rates are still significant regardless of the technological disparities, whilst the opposite occurs for the market share. Although, the spillover effects of market share for intermediate-and-high-tech hospitals display no statistical significance taking into account the squared weight matrices. It might be shown that the indirect effect issued from the concentration of hospitals has an impact on the closest neighbors only, and this effect decays proportionally with their distance. The findings support the partitioning analysis carried out in section 7, demonstrating weaker spillover effects of demand in efficiency after the second-order neighbor.

In addition, we identify a weaker effect for ρ. Despite the magnitude of the estimates, once more, spatial dependence in efficiency is confirmed.

Furthermore, we test the robustness of the results of the competition detected among hospitals. There is the possibility that the heterogeneity that we recognize in terms of technology may also be visible in terms of the spectrum of diseases treated. Therefore, the spatial dependence found might not be due to competition for a greater demand for patients, but due to the existence of specialized hospitals versus other general hospitals that include more treatments, which do not compete. To test this statement, we run the equation (11) on three different subgroups provided by our dataset: acute, chronic, and basic hospitals. Hence, we analyze homogeneous hospitals in terms of functioning and treatment.

Table 9 shows the estimations of the baseline model on the three subgroups using the weight matrix based on the shortest travel distance.[33] For basic hospitals the results are robust and comparable with the previous ones, supporting the exitance of spatial strategic interactions in hospital efficiency. Instead, acute, and chronic hospitals do not display spatial dependence in hospital efficiency (although, chronic hospitals present a significant spatial dependence in the error term, comparable to previous results). This could be suggesting that basic hospitals (which constitute more than 50% of the sample) are those that compete in terms of efficiency with their neighbors. However, the estimations should be interpreted with caution given the loss of information in the regressions when we split the sample. Future research will focus on expanding the time span to reach concluding results.

Finally, it is interesting to remark that inpatient migration turns significant for chronic hospitals, especially when these are mainly oncologic. The variable suggests a negative relationship with the efficiency performance of chronic hospitals and sets new insights for future research on hospital patient migration dynamics.

[33] As we consider three different subgroups of hospitals, the spatial weight matrix was calculated for each hospital type. Also, these regressions were run by QML to be comparable with the main results.

Table 8: Spatial regression results. GMM estimators

Variables	$\boldsymbol{W}_d$			$\boldsymbol{W}_v$			$\boldsymbol{W}_{d^2}$			$\boldsymbol{W}_{v^2}$		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
log occupancy rate	0.134***	0.07***	0.204***	0.134***	0.065**	0.1989***	0.135***	0.022*	0.157***	0.135***	0.0197	0.154***
	(0.0241)	(0.0268)	(0.0435)	(0.0244)	(0.0316)	(0.0471)	(0.0238)	(0.0134)	(0.0309)	(0.0239)	(0.0155)	(0.0324)
log market share	-0.061***	-0.032**	-0.093***	-0.064***	-0.031**	-0.095***	-0.0622***	-0.0101*	-0.072***	-0.063***	-0.0093	-0.073***
	(0.0138)	(0.0136)	(0.0243)	(0.0136)	(0.0166)	(0.0265)	(0.0135)	(0.0061)	(0.0165)	(0.0137)	(0.0074)	(0.0176)
log mortality rate	-0.024**	-0.013*	-0.037**	-0.024**	-0.012	-0.036**	-0.024**	-0.0038	-0.027**	-0.024**	-0.0035	-0.027**
	(0.0106)	(0.0078)	(0.0175)	(0.0108)	(0.009)	(0.0186)	(0.0107)	(0.003)	(0.0128)	(0.0107)	(0.0034)	(0.013)
log GVA	0.095**	0.049*	0.145**	0.102**	0.049*	0.151**	0.102**	0.017	0.1183**	0.105**	0.0154	0.1207**
	(0.0444)	(0.0287)	(0.0692)	(0.0447)	(0.034)	(0.0735)	(0.045)	(0.0117)	(0.0519)	(0.0452)	(0.0138)	(0.0534)
log density	-0.565*	-0.296*	-0.861*	-0.638**	-0.309*	-0.947**	-0.749**	-0.122	-0.8716***	-0.775***	-0.113	-0.8883***
	(0.2964)	(0.1675)	(0.4399)	(0.2966)	(0.1904)	(0.4533)	(0.2976)	(0.0777)	(0.3361)	(0.2988)	(0.0894)	(0.3416)
log mortality (cantonal)	0.075	0.039	0.114	0.078*	0.038	0.116	0.072	0.012	0.083	0.074	0.0108	0.0847
	(0.0474)	(0.0308)	(0.0756)	(0.0469)	(0.0345)	(0.0776)	(0.0475)	(0.0109)	(0.0556)	(0.0475)	(0.0127)	(0.0568)
log pop > 65	-0.051	-0.026	-0.077	-0.039	-0.019	-0.058	-0.0012	-0.0002	-0.0014	-0.0016	-0.00024	-0.0018
	(0.1465)	(0.0875)	(0.2311)	(0.1467)	(0.0952)	(0.2381)	(0.1475)	(0.0288)	(0.1733)	(0.1482)	(0.0316)	(0.1762)
log inpatient migration	0.004	0.002	0.006	0.003	0.0016	0.0048	0.0058	0.00094	0.0067	0.0052	0.00076	0.006
	(0.0139)	(0.008)	(0.0217)	(0.0138)	(0.0087)	(0.0222)	(0.0138)	(0.0027)	(0.0162)	(0.014)	(0.003)	(0.0166)
log occupancy rate*cluster 2	0.017	0.009	0.026	0.015	0.007	0.0221	0.014	0.0023	0.0167	0.0136	0.002	0.0157
	(0.0433)	(0.0253)	(0.0676)	(0.0432)	(0.0275)	(0.0694)	(0.0432)	(0.0086)	(0.0509)	(0.0433)	(0.0094)	(0.0515)
log occupancy rate*cluster 3	-0.079	-0.041	-0.1197	-0.086	-0.042	-0.128	-0.079	-0.0129	-0.092	-0.0872	-0.0128	-0.1
	(0.1791)	(0.1047)	(0.2802)	(0.1782)	(0.1139)	(0.287)	(0.1788)	(0.0363)	(0.2111)	(0.178)	(0.0399)	(0.2128)
log market share*cluster 2	0.121***	0.063**	0.184***	0.125***	0.0604**	0.185***	0.124***	0.0202	0.144***	0.1254***	0.0184	0.144***
	(0.0321)	(0.0299)	(0.0566)	(0.0321)	(0.0361)	(0.0618)	(0.0314)	(0.0131)	(0.039)	(0.0311)	(0.0149)	(0.0391)

Table 8 (continue): Spatial regression results. GMM estimators

Variables	$\boldsymbol{W}_d$			$\boldsymbol{W}_v$			$\boldsymbol{W}_{d^2}$			$\boldsymbol{W}_{v^2}$		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
log market share*cluster 3	0.264**	0.138*	0.402**	0.257**	0.125*	0.382**	0.247**	0.0402	0.287**	0.2471**	0.0362	0.284**
	(0.1064)	(0.0801)	(0.1761)	(0.1069)	(0.0904)	(0.1843)	(0.1042)	(0.0314)	(0.1259)	(0.1056)	(0.0362)	(0.1304)
log mortality rate*cluster 2	-0.042	-0.022	-0.064	-0.042	-0.0203	-0.062	-0.043	-0.007	-0.0502	-0.044	-0.0064	-0.0502
	(0.0309)	(0.0187)	(0.0481)	(0.0312)	(0.021)	(0.0504)	(0.0307)	(0.0073)	(0.0364)	(0.0311)	(0.0082)	(0.0375)
log mortality rate*cluster 3	-0.084	-0.044	-0.128	-0.081	-0.039	-0.121	-0.083	-0.0135	-0.096	-0.084	-0.0122	-0.096
	(0.0637)	(0.0418)	(0.1027)	(0.0633)	(0.0449)	(0.1045)	(0.0654)	(0.0161)	(0.0788)	(0.0651)	(0.0177)	(0.0793)
ρ	0.364***			0.339***			0.146**			0.132*		
	(0.07966)			(0.08863)			(0.0721)			(0.0811)		
λ	-0.180			-0.144			-0.078			-0.057		
N	1,674			1,677			1,674			1,674		
Number of hospitals	186			189			186			186		

Note: Dependent variable is log of hospital efficiency. *** p<0.01, ** p<0.05, * p<0.1

Source: The author.

Table 9: Spatial regression results. Direct, indirect and total effects by hospital type

Variables		***Acute***			***Chronic***			***Basic***	
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
log occupancy rate	0.104***	0.0029	0.107***	0.456***	0.0276	0.483***	0.121***	0.0659***	0.187***
	(0.0278)	(0.0155)	(0.0340)	(0.0592)	(0.0477)	(0.0602)	(0.0257)	(0.0197)	(0.0408)
log market share	0.0825***	0.0019	0.0845***	-0.0836***	-0.005	-0.0886***	-0.151***	-0.0826***	-0.233***
	(0.0171)	(0.0120)	(0.0213)	(0.0308)	(0.0096)	(0.0327)	(0.0144)	(0.0198)	(0.0273)
log mortality rate	-0.0407***	-0.0009	- 0.0416***	-0.129***	-0.008	-0.137***	-0.014	-0.008	-0.0215
	(0.0142)	(0.006)	(0.0156)	(0.0240)	(0.0140)	(0.0279)	(0.0100)	(0.00615)	(0.0159)
log GVA	-0.0423	-0.0006	-0.0429	-0.0885	-0.002	-0.09	0.0695*	0.0377	0.107*
	(0.0761)	(0.0124)	(0.0777)	(0.249)	(0.0307)	(0.264)	(0.0421)	(0.0242)	(0.0649)
log density	-2.202***	-0.0157	-2.217***	4.264**	0.231	4.495**	-0.532**	-0.286*	-0.819*
	(0.572)	(0.305)	(0.525)	(2.159)	(0.497)	(2.248)	(0.272)	(0.160)	(0.419)
log mortality (cantonal)	0.0633	-0.0002	0.0630	-0.006	-0.002	-0.0089	-0.006	-0.003	-0.00976
	(0.0968)	(0.0172)	(0.0996)	(0.367)	(0.0472)	(0.392)	(0.0421)	(0.0240)	(0.0657)
log pop > 65	0.210	-0.006	0.203	1.078	0.079	1.157	0.028	0.0128	0.0407
	(0.223)	(0.0435)	(0.222)	(0.746)	(0.159)	(0.817)	(0.199)	(0.110)	(0.308)
log inpatient migration	0.0196	-2.91e-5	0.0196	-0.184**	-0.01	-0.194**	0.0024	0.0014	0.00378
	(0.0281)	(0.0048)	(0.0288)	(0.0809)	(0.0212)	(0.0850)	(0.0123)	(0.00693)	(0.0191)
ρ	0.0141			0.060			0.378***		
	(0.133)			(0.0941)			(0.0570)		
λ	-0.0848			-0.655***			-0.515***		
	(0.147)			(0.0890)			(0.0718)		
N	711			81			882		
Number of hospitals	79			9			98		

Note: Dependent variable is log of hospital efficiency. ML estimations were also run and are comparable. Direct, indirect and spillover effects and related standard errors in parentheses computed using 2000 draws. *** p<0.01, ** p<0.05, * p<0.1.

Source: The author.

8. Conclusions

This study proposes to analyze the spatial dependence of hospital efficiency in Ecuador. To address this question, we apply an innovative methodology proposed by Piedra Peña and Prior (2019) to obtain robust efficiency scores for a sample of public hospitals in Ecuador between 2006 and 2014, taking into account their technological differences to avoid biased results. Then, we use this efficiency score as a dependent variable of a spatial econometric SAC model to consider spatial autocorrelation in efficiency and disturbances. The results confirm that an increase in the efficiency of surrounding hospitals is increasing the efficiency of a selected hospital. The direction of these effects is robust to different specifications and estimation methods. Spatial autocorrelation and spillover effects seem to be diminishing as the hospitals locate further away from the most developed areas. As Longo et al. (2017) state, the positive dependence between neighboring hospitals suggests that they are acting as strategic complements in efficiency.

We also address the question of whether the variations in demand for a given hospital – that we measure through occupancy rates – are affecting nearby hospitals' efficiency through spillover effects. The results confirm that increases in demand for medical services for public hospitals are causing that neighboring hospitals attract some of this demand, and this is boosting their own efficiency, regardless of the technological endowment of the hospitals. [34] A big portion of this positive effect can be explained because the public healthcare hospitals show low levels of occupancy rates, which might be implying the existence of spare resources that are inefficiently used to produce healthcare outputs. The increase of demand forces hospitals to make better use of this spare resources, hence, increasing its efficiency performance. In addition, the estimates assess that after 2008, the direct and indirect impact of occupancy rates in the efficiency performance significantly increased. While waiting for the approval of the new constitution, which was expected to entail an increase in the number of patients looking for medical treatments, hospital managers could have planned strategies to adapt to these changes, and this could be reflected in part of this higher effect after 2008.

The technological disparities among hospitals also play a key role, especially when analyzed jointly with market share. We find evidence that high-and-intermediate-tech hospitals have a differential effect. That is, the increase of concentration of patients in technologically better hospitals increases their efficiency and that of surrounding hospitals, whereas the opposite effect is found for low-tech hospitals. These results are providing some evidence of a potential learning-by-doing process in high-and-intermediate-tech hospitals.

These differences have important policy implications. Taking into consideration that high-tech hospitals are mostly concentrated in well-developed areas, policy decisions and public funding should be allocated taking into consideration the territorial development within the country. The rationale is that policy reforms and public investment that imply more competition (by investing in the construction more hospitals) can be counterproductive for the healthcare performance of well-developed areas but beneficial for less-developed ones.

In this line, policymakers could exploit spillover effects in well-developed areas to reinforce the hospital performance. However, they should be aware that these spillover effects will spread to a limited extent over space, emphasizing the importance of well targeted policy decisions. Clearer criteria of public funding allocation and stronger regulation on hospital resource consumption controlling (or limiting) for hospital costs inflation can have a positive impact in these regions. With more control to prevent costs' inflation, hospitals would have incentives to increase their profits by improving their resource use, hence, increasing their

[34] Focusing on the types of hospitals, the results hold for basic hospitals, whilst acute and chronic hospitals do not show spatial dependence in efficiency. However, these results should be taken with caution due to the information loss when splitting the sample.

efficiency. Due to spillover effects, this efficiency improvement would spread throughout the region, enhancing the performance of the public healthcare system without increasing the allocation of resources or public investment. Instead, public investment and resource allocation could focus on less-developed areas, where higher supply of hospitals could motivate existing hospitals to compete for patient inflow by increasing their quality and efficiency. These improvements can be a potential solution to decrease the existing regional gap in the Ecuadorian healthcare system.

The empirical application carried out in this study can also be extended to other Latin American countries that share many socio-economic, political and cultural characteristics (Levy and Schady, 2013; Atun et al., 2015) and whose spatial disparities have been well documented (Cuadrado-Roura and Aroca, 2013).

However, this study leaves some open questions for future research. In a country with an important heterogeneity in the healthcare system, it should be interesting to understand whether internal patient migration flows are affecting or being affected by the hospitals' performance. High-performing hospitals might be attracting patients from low-performing ones in neighboring regions. Understanding the mobilization patterns of patients is crucial to attain improvement of the healthcare system. Understanding interregional patient migration patterns can help central and local authorities as well as hospitals themselves to identify under-performing hospitals, which could benefit from an increase in health budget and resource allocation, in order to improve their performance and attract more demand. Also, patient mobility flows are likely to follow a spatial pattern, as patients will be willing to travel to the nearest high-performing hospital. In this sense, policymakers can identify spatial clusters of hospitals and promote policies that encourage efficiency gain.

Further methodological innovations can also be implemented. In this analysis, we assume that hospitals interact with each other within a bounded area, in the presence of local competition. However, hospitals can experience global forms of interactions that might not necessarily depend on their geographical distances but rather in long-range interdependencies (Lisi et al., 2017). By keeping w_{ij} unknown, and estimating it by graphical modeling (Moscone et al., 2018; Moscone et al., 2017), future research could test the existence of these interdependencies in case of developing countries like Ecuador. Moreover, one-stage SFA panel models that account for hospital heterogeneity and address spatial dependence such as those recently proposed by Pross et al. (2018) can also be implemented to control for possible bias in the efficiency estimations in tow-stage approaches (Simar and Wilson, 2007).[35] However, the main setback of SFA approximations is that we need to rely on a production function that has to be defined a priori (O'Neill et al., 2008), and that cannot be simply proposed in the context of a developing country. Future work defining the theoretical

[35] The main setback of two-stage approaches relies on the impossibility to know the underlying Data Generating Process of DEA efficiency estimates, which raises some doubts of what is being estimated in the second stage. Plus, DEA estimates are serially correlated which consequently lead to unreliable inference (Simar and Wilson, 2007). We control for this latter issue by accounting for panel-data robust efficiency estimations that take into consideration the panel structure of the data.

framework of a proper production function is then desirable to provide the background for empirical applications.

Finally, we need to point out some issues referring to data availability. It is recommended that future research take into account further information that has been proved to have a significant effect on hospitals' efficiency, such as the quality of treatments and budgetary information. Here, we proxy the hospital's quality with mortality variables, which have been widely used to approximate hospital quality and performance (Hafidz et al., 2018; O'Neill et al., 2008; Lisi et al., 2017). However, mortality can be influenced by other external factors, like the severity of the disease that patients suffer when they enter the hospital or other complications that the hospitals cannot control for, and that does not reflect the quality of the treatment received. The same type of comment applies to the readmission rates, the level of specialization (Gravelle et al., 2014; Longo et al., 2017) or the nosocomial infections (Prior, 2006) that could bring more elements for better understanding the public healthcare quality-efficiency relationship in the healthcare system.

Another relevant missing information refers to hospital budget and public investments. Hospitals can adopt a different behavior when they face financial pressures (Mas, 2015). Those troubles are quite common in developing economies such as Ecuador where hospitals might be forced to make efforts towards cost limitations that could affect their performance. The large public investment made by the government after 2008 is very likely to have an impact on hospital efficiency. It is expected to relax some financial pressures and could have been targeted from a territorial viewpoint and, hence, affecting health outcomes directly. Future research should fill this gap of information to derive in additional empirical research to bring relevant insights for policy decisions. In this line, a clear suggestion for policymakers is to implement strong monitoring systems that provide researchers and healthcare managers with reliable and robust data.

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Appendix 1. Data Description

Table A1: Variables' description

Variable	Description	Variable construction
Output		
Number of discharges (weighted)	Treated patients in a given hospital	Number of discharges*Case-Mix index
Inputs		
Number of physicians	Physicians and general physicians in a given hospital	Total number of physicians
Number of beds	Total amount of beds per hospital	Total number of beds
Number of hospital personnel	Medical staff not including physicians. E.g. Nurses, technologists, administrative staff, dentist, etc.	Total number of hospital personnel
Number of equipment and infrastructure	Physical infrastructure (surgery rooms, intensive care rooms, etc.) and medical equipment (imaging, diagnosis, sterilization, etc.)	Total number of equipment and infrastructure
Explanatory Variables		
Occupancy rate	Inpatients days of care per beds available in a given hospital	(Inpatient days of care/Bed days available) *100
Market share	Concentration of inpatients in a given hospital relative to the total amount of patients in the canton	(Total number *ith* hospital inpatients/Total number of cantonal patients)*100
Mortality rate	percentage of deceased patients in a given hospital	Hospital mortality*100
Number of disease 1	Inpatients with certain infectious and parasitic diseases	Total inpatients with disease/100
Number of disease 2	Inpatients with neoplasms	Total inpatients with disease/100
Number of disease 3	Inpatients with diseases of the nervous system	Total inpatients with disease/100
Number of disease 4	Inpatients with diseases of the respiratory system	Total inpatients with disease/100
Number of disease 5	Inpatients with diseases of the skin and subcutaneous tissue	Total inpatients with disease/100
Number of disease 6	Inpatients with pregnancy, childbirth and the puerperium	Total inpatients with disease/100
Number of disease 7	Inpatients with certain conditions originating in the perinatal period	Total inpatients with disease/100
Number of disease 8	Inpatients with congenital malformations, deformations and chromosomal abnormalities	Total inpatients with disease/100
Number of disease 9	Inpatients with injury, poisoning and certain other consequences of external causes	Total inpatients with disease/100
GVA	Gross Value Added	Total, cantonal
Density (population per Km2)	Cantonal population per Km2	Population/Km2
Mortality rate (% cantonal)	Percentage of deceased patients in a given canton relative to cantonal population	Cantonal mortality*100
Total population over 65	Cantonal population over 65 years old	Total, cantonal
Total patient migration	patients treated in a given hospital residing at a different canton where they are treated	Total, cantonal

Source: The author.

Appendix 2. Model specification

The following selection model strategy begins with a baseline model and develops around some tests to achieve an econometric specification that fits the data at hand. First, we present the panel LM and robust-LM tests to provide an initial clue of the potential sources of spatial autocorrelation in Table A2. To develop these tests and the following model specification in this appendix, we rely on the matrix of the inverse Euclidean distance $\boldsymbol{W}_d$.

The robust test fails to reject the null hypothesis of no spatial autocorrelation (at 90% and 95% of confidence) in both, the dependent variable, and the errors. The initial evidence leads to take into consideration both types of spatial autocorrelation.[36]

Table A2: LM and robust-LM tests

	Value	**Prob**
LM-Lag	0.2929	0.5884
LM-Err	1.386	0.2391
Robust LM-Lag	3.2491	0.0715
Robust LM-Err	4.3422	0.0372

Source: The author.

Then, we compare the appropriateness of a scope of spatial models taking a fixed effects model as a benchmark in Table A3. The Hausman test rejects the null hypothesis of no systematic difference between fixed and random effects, so it is coherent to apply a fixed effect estimation. Following LeSage and Pace (2009) and Elhorst (2010), we explore the most suitable econometric estimation by starting with the general SDM model and, then, refining it towards a SAR or SEM model. Following the SDM model, we cannot find statistical evidence of spatial dependence in efficiency. SAR and SEM models produce the same results in efficiency and error spatial dependence, respectively. Instead, the SAC model provides significant evidence of spatial dependence both in dependent variable and error term. Merging these outcomes with the results of the LM-tests, the SAC model seems to be the most convenient to apply to our data. However, the SAC model is not nested within the SDM model (Elhorst, 2014), and, hence, we can rely on alternative information criteria to select between them (Belotti et al., 2016). Akaike and Bayesian information criteria endorse the selection of the SAC model as the best specification. The recent literature in this regard supports this finding and SAC models, usually account for spatial dependence in efficiency and potential unmeasurable variables that can affect the hospitals' efficient performance (Felder and Tauchmann, 2013; Herwartz and Strumann, 2014; Herwartz and Strumann, 2012).

[36] The reader must take these initial results with caution, given that the classical panel data tests (Anselin et al., 2006) and their robust counterpart (Elhorst, 2010) do not allow for any spatial or time-specific effects. The tests run here are controlled in and *ad hoc* way for individual effects by demeaning the data as in Croissant and Millo (2018).

Table A3: model specification

Variables	Panel	SDM	SAR	SEM	SAC
log occupancy rate	0.142***	0.153***	0.142***	0.143***	0.135***
	(0.046)	(0.019)	(0.019)	(0.019)	(0.018)
log market share	-0.037	-0.041***	-0.037***	-0.038***	-0.036***
	(0.038)	(0.011)	(0.011)	(0.011)	(0.011)
log mortality rate	-0.032*	-0.034***	-0.032***	-0.032***	-0.032***
	(0.017)	(0.009)	(0.009)	(0.009)	(0.009)
disease 1	-0.007	-0.008***	-0.007***	-0.007***	-0.007***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
disease 2	-0.005	-0.006**	-0.005*	-0.005*	-0.003
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
disease 3	0.076*	0.077***	0.076***	0.077***	0.075***
	(0.045)	(0.025)	(0.025)	(0.025)	(0.023)
disease 4	0.024***	0.024***	0.024***	0.024***	0.023***
	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)
disease 5	-0.023	-0.025	-0.023	-0.023	-0.024
	(0.047)	(0.020)	(0.020)	(0.020)	(0.019)
disease 6	0.007***	0.007***	0.007***	0.007***	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
disease 7	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
disease 8	-0.032*	-0.033***	-0.032***	-0.032***	-0.029**
	(0.017)	(0.012)	(0.012)	(0.012)	(0.011)
disease 9	0.007*	0.007***	0.007***	0.007***	0.006**
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
log GVA	0.093	0.019	0.094**	0.096**	0.087**
	(0.073)	(0.051)	(0.043)	(0.043)	(0.037)
log density	-0.811*	-0.519	-0.823***	-0.836***	-0.606***
	(0.470)	(0.343)	(0.274)	(0.271)	(0.233)
log mortality (cantonal)	0.068	0.043	0.068	0.068	0.068*
	(0.047)	(0.050)	(0.045)	(0.045)	(0.039)
log pop > 65	0.033	0.051	0.036	0.037	-0.012
	(0.173)	(0.169)	(0.139)	(0.138)	(0.115)
log inpatient migration	0.003	-0.006	0.003	0.003	0.003
	(0.016)	(0.014)	(0.013)	(0.013)	(0.011)
Lagged Independent Variables					
log occupancy rate		0.019			
		(0.032)			
log market share		-0.020			
		(0.021)			
log mortality rate		0.005			
		(0.019)			

Table A3 (continue): model specification					
Variables	**Panel**	**SDM**	**SAR**	**SEM**	**SAC**
disease 1		-0.007			
		(0.008)			
disease 2		0.005			
		(0.005)			
disease 3		0.113**			
		(0.055)			
disease 4		-0.009			
		(0.009)			
disease 5		0.009			
		(0.039)			
disease 6		0.001			
		(0.002)			
disease 7		-0.005			
		(0.007)			
disease 8		0.002			
		(0.028)			
disease 9		0.003			
		(0.005)			
log GVA		0.268***			
		(0.096)			
log density		-0.867			
		(0.539)			
log mortality (cantonal)		0.135			
		(0.091)			
log pop > 65		-0.118			
		(0.227)			
log inpatient migration		0.046**			
		(0.023)			
Spatial					
rho		-0.054	-0.011		0.355***
		(0.035)	(0.033)		(0.053)
lambda				-0.026	-0.419***
				(0.034)	(0.064)
Hausman (p-value)	0.0000	0.0000	0.0002	0.0000	
AIC	91.93	85.05	79.82	79.35	66.84
BIC	227.5	280.3	182.9	182.4	175.3
Observations	1,674	1,675	1,674	1,674	1,674
Number of hosp	186	187	186	186	186

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix 3. Spatial Effects

Following LeSage and Pace (2009), if a particular explanatory variable in an observed spatial unit changes (e.g. the change in the demand of hospital *i*), not only will the dependent variable in that unit itself change (efficiency of hospital *i*) but also the dependent variable in other units (efficiency of hospital *j*). The former called *direct effects* and the latter *indirect (spillover) effects.* In the SAC model, direct effects are the result of local effects plus feedback effects mediated by spatial spillovers.[37]

In particular, taking the matrix of partial derivatives of the expected value of the logarithm of the efficiency $\boldsymbol{e}_t$ with respect to the z_{th} explanatory variable of $\boldsymbol{Z}_t$ in all hospitals (from 1 to 186) for the SAC model, we have:

$$\left[\frac{\delta E(\boldsymbol{e}_t)}{\delta z_{1,t}}, \dots, \frac{\delta E(\boldsymbol{e}_t)}{\delta z_{186,t}}\right] = (\boldsymbol{I} - \boldsymbol{\rho W})^{-1}\beta_z \tag{12}$$

Where β_z is the vector of coefficients. LeSage and Pace (2009) define the diagonal element of (12) as the direct effects, while the off-diagonal contain the indirect effects. The infinite series expansion of the spatial multiplier matrix $(\boldsymbol{I} - \boldsymbol{\rho W})^{-1}$ can be expressed as follows:

$$(\boldsymbol{I} - \boldsymbol{\rho W})^{-1} = \boldsymbol{I} + \rho\boldsymbol{W} + \rho^2\boldsymbol{W}^2 + \rho^3\boldsymbol{W}^3 + \cdots + \rho^q\boldsymbol{W}^q \tag{13}$$

Note that, since the off-diagonal elements of the identity matrix $\boldsymbol{I}$ are zero, the term represents a direct effect of a change in $\boldsymbol{Z}_t$. Furthermore, since the diagonal elements of $\rho\boldsymbol{W}$ are zero by assumption, the term represents the indirect effect of a change in $\boldsymbol{Z}_t$. The remaining terms in the right-hand side of (13) represent the second and higher order direct and spillover effects. Thus, the spatial multiplier, as shown in (13) can be expanded to determine the impacts that the explanatory variables have on the higher order of contiguity in the following manner:

$$(\boldsymbol{I} - \boldsymbol{\rho W})^{-1}\beta_z = \underbrace{\boldsymbol{I}\beta_z}_{W^0} + \underbrace{\boldsymbol{\rho W}\beta_z}_{W^1} + \underbrace{\rho^2\boldsymbol{W}^2\beta_z}_{W^2} + \underbrace{\rho^3\boldsymbol{W}^3\beta_z}_{W^3} + \cdots + \underbrace{\rho^q\boldsymbol{W}^q\beta_z}_{W^q} \tag{14}$$

The power of the autoregressive parameter, ρ, ensures that the marginal effect of a given variable decreases with a higher order of contiguity. In other words, the effect of a change of an explanatory variable declines as we move over space (LeSage and Pace, 2009).

However, the presentation of both direct and indirect effects can be challenging, since they vary from different units in the sample. Therefore, LeSage and Pace (2009) propose to report direct effects as the average of the diagonal elements, while one spillover effect can be measured by the average row sums of the off-

[37] This feedback effect is derived from the impacts passing through neighboring hospitals and back to the hospital where the change came from (from hospital *i* to *j* to *k* and back to hospital *i*).

diagonal elements. The sum of the average direct and spillover effects is the total effect.

In order to draw inferences regarding the statistical significance of the direct and spillover effects, LeSage and Pace (2009) propose to simulate the distribution of the direct and spillover effects using the variance-covariance matrix implied by the ML estimates. This is because it cannot be simply seen from the coefficient estimates and the corresponding standard errors or t-values of the variance-covariance matrix whether the indirect effects in models containing endogenous interaction effects are significant (see LeSage and Pace, 2009; Elhorst, 2014).

Appendix 4. Case-mix weights

To control for the severity of cases in this study, we construct the case-mix weight following the approach developed by (Herr, 2008). These weights are based on the across-hospital average length of stay (LOS) of each diagnosis relative to the overall length of stay. In developing a list of diagnostic categories (cases), we use the three-digit *International Statistical Classification of Diseases and Related Health Problems* (ICD-10).

The weights then are constructed as followed. A mean of LOS by year and main diagnosis $m = 1, \dots, M$ over N hospitals is calculated using the following formula:

$$LOS_m = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{days_{mi}}{cases_{mi}}\right) \tag{15}$$

Then, the mean LOS over all diagnoses and all hospitals is denoted by LOS_G and the final weights π_m are obtained by:

$$\pi_m = \frac{LOS_m}{LOS_G} \tag{16}$$

The weights π_m will be bigger (smaller) than one if the treatment of diagnosis m takes more (less) time than the overall average LOS. These weights rely on the assumption of a correlation between the length of stay and the severity of illness, so the idea is that the more days of stay of the patient, the more severe the disease and the more resources are used.

Finally, the weighted number of discharges are obtained by multiplying the number of discharges of each case times π_m and adding them up for every hospital.

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