Spatial effects in hospital expenditures: a district level analysis

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1. Introduction

Health expenditures display large variability across practices, municipalities or regions, and spatial clustering has been documented, this meaning that expenditures for geographically close units tend to be more similar compared to those located far apart (Skinner 2011). This has fostered the study of spatial interactions in health expenditures across jurisdictions (e.g. Costa-Font and Moscone 2009, Yu *et al*. 2013) for a broad range of clinical areas (e.g. Costa-Font and Pons-Novell, 2007; Moscone *et al*., 2007; Bech and Lauridsen 2009; Ehlhert and Oberschachtsiek, 2014).

The main causes of spatial spillovers in hospital expenditures have been identified in supply characteristics such as competition and knowledge transfers, and in heterogeneity of patients' health profiles and preferences on the demand side (Gravelle *et al*., 2014; Baltagi and Yen 2014). A relatively unexplored issue is to what extent spillovers differ across types of treatments (e.g. complex vs. basic ones). This distinction is relevant, because policy interventions at various levels may be associated with different types of spillovers. For instance, conditions sensitive to ambulatory care can be especially affected by community and primary care policies pursuing appropriate utilisation of hospital services (Dusheiko *et al*., 2011), whereas the delivery of more complex procedures may reflect investments in health technologies. Moreover, knowledge spillovers and diffusion of practice styles may differ across treatments. In the light of this, assessing the magnitude and direction of spillovers for different types of hospital services could ensure a better understanding of the interactions across health jurisdictions and support the effort of policymakers to coordinate interventions between different levels of responsibilities.

In this paper we use spatial econometric methods to analyse spillovers in hospital expenditures across Health Districts (HDs) of Italy's Emilia Romagna Region. We estimate spatial models that allow for global spillovers (Spatial Autoregressive and Spatial Durbin models) and we distinguish between the expenditures associated with potentially avoidable hospitalisations from those associated with complex medical procedures. By doing so, we separate hospitalisations more likely to be affected by community and primary care policies, from those more directly influenced by hospitals' technological and high skilled human capital endowment. We also investigate the possible different contribution of geographical and institutional proximity in generating spatial spillovers, since, in multi-tier government systems, the nature of the institutional connections between jurisdictions may significantly affect spillovers (Arbia *et al.*, 2010; Atella *et al.*, 2014). Since in the Italian National Health System (NHS) each Local Health Authority (LHA) is subdivided into Health Districts (HDs), those sharing a common upper-level authority operate under the same regulatory framework and face similar constraints and incentives. From a policy perspective it is important to understand whether there are differences in spatial spillovers between neighbouring districts, that may also belong to different LHAs, and those observed among districts that are part of the same LHA.

Our findings show that interactions across districts follow different patterns according to the type of treatment considered. When considering potentially inappropriate expenditures we observe positive and significant spatial effects, suggesting that jurisdictions are more virtuous when surrounded by low-spending neighbours. Conversely, we find that the effects of spatial interactions for complex procedures go in the opposite direction and are in most cases not significant.

2. Institutional setting

In Italy Local Health Authorities (LHAs) are financed by Regional Governments using an adjusted capitation formula and are responsible for providing health care to their residents. Hospital care is free at the point of need[1]. Patients are referred to the hospital by the GP or admitted through the Emergency Department. Mobility is allowed both within and across regions and patients may shop around in response to perceived differences in quality and in waiting times (Fattore *et al.*, 2013). The available evidence shows that long-distance mobility concentrates on highly specialised treatments, while local mobility may also involve more basic services (Fabbri and Robone, 2010; Balia *et al*., 2014). Diagnosis Related Groups (DRGs) are central for hospital financing (Cappellari et al., 2016). In fact, the main funding for HTs is a prospective payment scheme based on DRGs but tariffs are used also to quantify the activity of LHA-run hospitals according to which they receive financial transfers from the LHA. In addition to that, hospitals benefit from specific funding to cover expenditures for activities characterized by high fixed costs such as emergency care.

Community and primary care services fall under the responsibility of HDs. The HD's management is appointed by the LHA and is in charge of planning local health policies at the community level, including the establishment of an effective link between primary and secondary care. Primary care is free of charge with GPs providing ambulatory care to their enrolled patients and referring them to the specialist or to the hospital. The system is list-based and the choice of the physician can be modified at any time. As for practice organisation, the NHS is experiencing an increase in the creation of formal collaborative

[1] The large hospitals enjoy the status of Hospital Trusts (HTs), while the others are directly run by LHAs, and consist of medium-sized providers located in urban contexts (type A Hospitals), and community hospitals located in small towns or rural contexts (type B Hospitals).

professional networks of family physicians to favour information sharing about clinical best practices and substitution in case of absence (Lippi Bruni *et al.*, 2016). Moreover, GPs establishing networks may share medical equipment, nursing staff and premises. Still, citizens are registered with a specific physician and not with the network. GPs are paid using a nationally-contracted capitation scheme. Remuneration can be topped up by additional payments agreed at the district level[2]. Community and primary care policies are characterised by large heterogeneity across districts. Local programs may promote the achievement of specific health policy targets, including disease management for chronic conditions or post-acute follow-up (Iezzi *et al.*, 2014).

3. Sources of spatial spillovers in Health Districts expenditures

Depending on whether there are feedback effects which imply that a change in a region does not only affect neighbouring/connected units but also sets in motion a transmission of effects in potentially all the units, spatial spillovers can either assume a *global* or a *local* connotation (Anselin, 2003; LeSage, 2014).

For public expenditures, spatial spillovers may arise from various sources and depend on the nature of the interactions between jurisdictions (e.g. Manski, 1993; LeSage and Dominguez, 2012; Lunberg, 2014). In our context, a potentially relevant source is represented by expenditure externalities, which occur when expenditures in a given jurisdiction also enter the neighbours' utility function. For instance, this is the case of investments in hospital production capacity and quality of care that may respond to the needs not only of the

[2] These transfers are usually aimed at incentivising high quality of care for specific conditions, including chronic diseases and physicians' adherence to clinical guidelines and to cost containment strategies defined at the local level.

residents of the area where they are introduced but also of patients from other jurisdictions (Yu *et al.*, 2013).

Additional externalities can be generated by knowledge spillovers. These stem from the diffusion of hospital clinical practices and technologies, as well as from policies undertaken at the district level and aimed at improving the effectiveness of gatekeeping and at containing avoidable hospital admissions. Moscone *et al*. (2007) suggest that some local authorities may exert a leadership in implementing policy innovations ("demonstrative effect") that improve quality of care and this may give rise to imitation in other jurisdictions. Such knowledge transfer affects the use of hospital services differently across treatments. Moreover, even though we expect information flows to be stronger between contiguous units, the diffusion of best practices is unlikely to be restricted within local neighbourhoods because LHAs are supervised and coordinated by the regional Health Department.

A further rationale for spatial spillovers is fiscal competition among jurisdictions. In our case health jurisdictions do not compete to attract tax base and their mission is to serve the health needs of residents first. However, under fixed price compensation, the system gives jurisdictions an incentive to attract patients from outside as long as DRG tariffs lie above the marginal cost. Since the patients' propensity to shop around for higher quality of care generally decreases with distance and is heterogeneous across treatments, such patterns are likely to differ between complex and basic procedures.

Spillovers may arise also when jurisdictions share common risk factors. Typically, this is the case when similar exogenous features characterise neighbouring jurisdictions, including disease prevalence, or socio-economic and environmental conditions. As long as these common features affect health needs and preferences for specific treatments, they may lead to similar patterns in the demand for hospital services across neighbourhoods.

Finally, spatial dependence can be related to the multi-tier hierarchical structure of the Italian NHS. The vertical and horizontal relations across LHAs and HDs generate interdependencies in planning responsibility that contribute to a considerable local variation in healthcare policies. This is the case for LHA-based policies on hospital care, but also for HD-based policies linking secondary and primary care, whose targets specifically include the containment of inappropriate hospital use.

A frequently overlooked issue in the literature is that spatial clustering in hospital expenditures may vary across treatments, with spillovers potentially differing among procedures in direction and magnitude. In our context, several factors may contribute to such variability. First, the degree of competition among jurisdictions depends on the type of hospitals located in each area. Hospital capacity to deliver basic procedures, including potentially inappropriate treatments, is uniformly distributed over the territory. Consequently, jurisdictions may be incentivised to increase the provision of such services, both to prevent the exit of their residents and to attract patients from neighbouring areas. Patients' outflows generate losses due to cost duplication, since hospital capacity is underused and, at the same time, the jurisdictions of destination have to be compensated for treatments delivered to citizens from other areas. Conversely, the incentives to generate patients' inflows into a jurisdiction arise because hospital tariffs are usually set above the marginal cost of treatment and the receiving destination retains the margin between the tariff and the actual cost.

Given such institutional framework, strategic interactions across hospitals are likely to occur for basic treatments. Providers surrounded by districts with large capacity for treating basic conditions are incentivised to ensure high volumes to meet the health-care needs of their residents in order to contain outflows favoured by neighbours' attraction capacity. On the contrary, when adjacent districts provide relatively low volumes of such hospital services, they deliver care for the most part to their own residents. Consequently, the jurisdiction of reference is freer to implement policies for containing hospital utilization, including the substitution of inpatient care with those outpatient services where minor conditions can be effectively treated and hospitalisation avoided. Therefore, in the case of basic treatments, we expect high (low) expenditures by the residents of one district to be associated to higher (lower) expenditures of neighboring ones.

The scenario differs for complex procedures. Although local authorities keep some discretion in choosing the size and specialisation of their hospitals, these decisions fall mainly under the regulatory power of the regional Department of Health. The purpose of the regulator is to ensure well-balanced access opportunities to all citizens, but also to avoid unnecessary duplications of highly expensive technologies. Because of that, production capacity for complex treatments faces strict planning requirements and concentrates in specialised centres designed to serve more than one district. This reduces hospital competition for complex treatments, thus possibly curbing also spillovers in expenditures as these are ultimately covered by the jurisdiction of origin of the patient. As a consequence, referrals for complex procedures typically respond to the need of ensuring a proper matching between the (high) severity of patients and the availability of adequate technology and human capital in the receiving centre. This is expected to lead to weaker, if any, strategic interactions between neighbouring areas compared to the case of basic treatments: in fact, admissions for complex treatments likely reflect centrally planned decisions that identify the reference centres for the different specialties, resulting from coordination rather than competition among jurisdictions.

The spillovers for complex procedures can be expected not only to be of a smaller intensity compared to those for basic treatments but possibly to differ also in their direction. Indeed, residents in districts with highly qualified centres may find relatively easier access compared to patients in more poorly served areas, because the former may take advantage of proximity and local connections. Despite the fact that specialised centres are committed to serve the needs of several different districts, the residents of the district where the centre is located might enjoy easier access to the facility, thus generating congestion that limits the opportunities for residents from neighboring districts. Therefore, high expenditures for complex treatments experienced by residents from a given district may be associated to lower ones by residents from neighbouring areas.

An additional source of potential differences in spillovers comes from the interaction between primary and secondary care. The large autonomy of Italian HDs in primary and community care gives them the possibility to introduce local programs for improving quality and continuity of care. These programs may include ad hoc financial incentives paid to GPs by HDs and LHAs. In particular, HDs may reward GPs for activities such as comprehensive domiciliary care following acute treatments and direct assumption of responsibilities for chronically ill patients. The literature has shown that such programs have contributed to curb in particular avoidable hospitalisations because of increased prevention and reduced re-hospitalisation rates (Fiorentini et al. 2011). In Emilia Romagna these incentive-based programs vary remarkably across areas in terms of targets, extension and amount of resources invested by local authorities. Moreover, the dissemination of best-practices across districts can be expected to reflect district geographical proximity and/or membership of the same LHA, thus contributing to spillovers in particular for basic conditions that are more sensitive to ambulatory care.

Finally, also the spread of medical knowledge may differ across medical specialties as it is affected by professional networks (Mascia et al. 2014). Some areas are characterized by fairly uniform practices because of the leadership exerted by prominent key players or by agreed clinical guidelines. Conversely, other areas may experience more heterogeneous behavior because of high physicians' discretion in clinical decisions. The differences in the structure of professional links and in the strength of networks across medical specialties may lead to different patterns in the diffusion of clinical practices which may ultimately affect hospitalisations in a way that differs across specialties.

Overall, the empirical strategy should account for both local factors such as patients' cross-border mobility or shared characteristics between contiguous districts and for global spillovers. The latter might be linked to technological investments in hospital care and knowledge transfers; they could also rise in response to policy innovations at the district level, such as the introduction of disease management programs for chronic diseases that contribute to the prevention of avoidable hospitalisations.

4. The data

We use administrative data from the Emilia Romagna Region for the period 2007-2010. The estimating sample covers around 3.7 million citizens (aged 14 or above) followed by around

3,200 GPs operating in 38 Health Districts[3]. The data are provided by the regional Department of Health.

We consider hospitalisations for all residents as tracked in the Hospital Discharge Records. The DRG tariff associated with hospitalisations captures the monetary value of each treatment. We measure district-level expenditures by computing the total monetary value of all the hospitalisations of patients resident in the HD. The information on the tariff attributed to each episode is included in the hospital discharge dataset. The tariff used to compute district expenditures varies with the DRG category attributed to each episode and with the type of hospital that provides the treatment. On average HT and type A hospitals receive larger compensation than type B hospitals in recognition of the higher costs they face. In addition to it, the baseline tariff for each DRG is augmented if the patient experience complications and/or if length of stay at the hospital exceeds DRG-specific thresholds. The availability of tariffs that are adjusted according to the type of provider and case-specific complications allows to proxy estimated expenditures significantly better compared to the use of uniform tariffs based on patient's diagnosis only.

HD hospital expenditures are computed with reference to the amount of resources spent in hospital care for the residents of each district, irrespective of where the treatment is provided. The choice of referring to the residence of the patient rather than to where the patient is hospitalised is consistent with the institutional design of the Italian NHS where health jurisdictions (Regions, LHAs and HDs) are mainly financed using capitation schemes. In each layer, health policymakers use these resources to finance health care for their

[3] Most of the information used in this study is drawn from databases made available by the Regional Department of Health. In particular, we exploit hospital discharge records to compute the dependent variables and use administrative data on hospital personnel and GP activity for the control variables. Finally, we have acquired from the Italian Tax agency and the National Institute of Statistics (ISTAT) information on taxable income and population at the municipality level.

citizens: part is used to cover the services the jurisdiction is directly responsible for, part is transferred to the lower layer. Even when citizens are treated outside their area of residence, the jurisdiction of origin is still financially responsible for them.

In the computation of expenditures, we distinguish between two different types of hospital services. We focus first on hospitalisations that are more sensitive to community and primary care initiatives. They correspond to episodes classified at high risk of potentially inappropriate hospital that could be safely treated in less intensive settings. Such classification is based on a list of 43 DRGs agreed between the Italian Ministry of Health and Regional Governments that has become a recognized standard for the assessment of potentially inappropriate admissions in the Italian NHS[4]. The second group of hospital services encompasses highly complex treatments requiring sizeable technological and human capital investment[5]. While hospitalisations for the 43 DRGs may reflect the effectiveness of district-level policies in containing avoidable admissions, those referring to complex procedures are likely to be influenced by major planning decisions concerning hospital production capacity.

The yearly descriptive statistics for the two dependent variables are reported in Table I.

TABLE I

[4] The list was established by Decree of the Presidency of the Council of Ministers (DPCM 29/11/2001) and included in the "Health Pact" that regulates the institutional relationships between national and regional health authorities. For more details and for the complete list, we refer to the appendix.

[5] The list of highly complex treatments is established by Deliberation n. 1863/2008 of the Regional Government of Emilia Romagna that defines the regional DRG tariffs. The full list of procedures is reported in Appendix A

Potentially inappropriate episodes account for around 7.5% of total expenditures whereas highly complex treatments account for around 40% over the four years[6].

A first set of controls accounts for the characteristics of GPs' practices at the district level. These include the average GP's seniority (*GP_seniority*), the share of male GPs (*share_male_GP*), the density of GPs per 1,000 inhabitants (*num_GPs_1000*), the share of single-handed practices (*share_GP_single*), the share of practices with nursing staff (*share_nurse*) or administrative collaborators (*share_collab*). A second group of regressors captures the HD socio-demographic composition and include shares for age classes (the group 14-35 is taken as reference), the proportion of males (*share_males*) and of foreigners (*share_foreigners*).

To control for heterogeneity in primary care policies among HDs, that generally envisage financial incentives to GPs, we consider the share of specific entries of GPs' top up remuneration on total income. In particular, we include the average share of GPs' income for programs aimed at improving clinical services (*share_inc_clin*), the share of incentives for domiciliary services (*share_inc_domic*) and the share for improvements in practice's organisation (*share_inc_org*).

We add indicators for the presence of a HT (*HD with HT*) and of a type A hospital (*HD type A hosp*). We account for disadvantaged sites whenever the HD is located in partially or totally mountainous areas (*disadvant_area*).

To control for the supply capacity we include the number of hospital ordinary beds per 1,000 residents (*beds_ord_1000*), physicians and nurses employed by the HD

[6] We record a slight downward trend in both types of expenditures, suggesting a generalized containment in ordinary hospital admissions over time.

(*doc_dist_1000, nurses*_1000). Finally, local socio-economic conditions are proxied by per-capita taxable income (*income_HD*) and by the population density of the district *(pop_dens_HD)*. Both outcomes and controls are log-transformed, except for binary variables. Table II reports the descriptive statistics and shows that the covariates are generally characterised by high variability across HDs.

TABLE II

5. The empirical methodology

5.1. Cross-sectional dependence

Standard linear panel data models assume the absence of cross-sectional correlation among the units of observation. Ignoring the potential cross-sectional dependence may produce biased estimates (LeSage and Pace, 2009). The interactions between jurisdictions suggest that spatial spillovers may lead to cross-sectional dependence in hospital expenditures across districts. Figure 1 shows the distribution of both types of HD expenditures averaged over the period 2007-2010: different colors identify the quartiles of the distribution, with darker areas corresponding to higher per-capita expenditures. Spatial clustering emerges for both measures. Potentially inappropriate expenditures are concentrated in the north-east and in the centre-south of the region, while HDs in the centre-north and the south-west display relatively lower spending. The patterns partially differ for complex procedures, with centre-south districts showing relatively low expenditures.

FIGURE 1

To test formally for cross-sectional dependence, we estimate linear fixed-effect (FE) and random-effect (RE) panel data models and perform the Pesaran (2004)'s CD test for cross-sectional dependence [7]. We consider both measures of hospital expenditure as dependent variables and include the controls presented in Table II. The test supports the presence of cross-sectional dependence for inappropriate expenditures, while cross-sectional independence for high-complexity expenditures is not rejected. The average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of residuals is always around 0.5, this signaling possible cross-sectional dependence (de Hoyos and Sarafidis, 2006). Given this evidence, we move to a spatial dependence model analysis.

5.2. The structure of spatial interdependence

A crucial step for estimating spatial models is the identification of neighbouring units. A natural way to define two neighbouring jurisdictions is geographical contiguity. According to such definition, two HDs are neighbours if they have a border in common (*geographical proximity)*. In a multi-tier institutional framework, two or more HDs may also share a common upper layer jurisdiction. Therefore, we might expect interactions to occur among HDs belonging to the same LHA, as they are subjects to the same regulatory constraints and to similar incentives. This feature calls for an alternative definition of contiguity, according to which HDs are neighbours if they belong to the same LHA (*institutional proximity)*, irrespective of whether they have a border in common. The spatial connections can be summarized by a spatial weight matrix $\boldsymbol{W}$ where each cell w_{ij} reflects the intensity of the interaction between unit i and unit j, and $w_{ij} = 0$, so that the matrix has a zero diagonal.

The matrix $\boldsymbol{W}_{Geo}$ based on geographical proximity has spatial weights defined as follows:

$$w_{ij} = \begin{cases} 1, & \text{if districts } i \text{ and } j \text{ share the same border}, \forall i \neq j \\ 0, & \text{otherwise.} \end{cases}$$

[7] We omit here the presentation of the results for the linear FE and RE models with no spatial effects since the focus of the analysis in on spatial dependence. The full set of results is available upon request.

In contrast, the matrix $\boldsymbol{W}_{Inst}$ based on institutional proximity is as follows:

$$w_{ij} = \begin{cases} 1, & \text{if districts } i \text{ and } j \text{ belong to the same LHA}, \forall i \neq j \\ 0, & otherwise. \end{cases}$$

One limitation is that both matrices summarize the links among units by means of a binary variable, thus placing the same weight on all the neighbours of each HD. Instead, one may be willing to account for the decaying intensity of the interactions due to distance. Therefore, we consider two additional matrices ($\boldsymbol{W}_{Geo\ ITD}$ and $\boldsymbol{W}_{Inst\ ITD}$) where the non-zero elements w_{ij} of $\boldsymbol{W}_{Geo}$ and $\boldsymbol{W}_{Inst}$ are weighted by the inverse travel distance (in km) between the centroids of districts i and j. As standard in the literature, all matrices are row-standardized.

Once the structure of spatial interactions has been defined, we evaluate the degree of spatial autocorrelation for the two dependent variables. Table III presents the values for the Moran's I spatial autocorrelation coefficient using the spatial matrices $\boldsymbol{W}_{Geo}$, $\boldsymbol{W}_{Geo\ ITD}$, $\boldsymbol{W}_{Inst}$, $\boldsymbol{W}_{Inst\ ITD}$.

TABLE III

We find significant positive spatial correlation for both measures in each year, this evidence suggesting significant departure from spatial randomness (Gravelle *et al.*, 2014).

5.3. Spatial panel regression models

Alternative models have been proposed to account for spatial dependence. It has been argued that the choice of the specification should reflect the underlying spatial process and the channels that best represent the spatial dynamics of interest [8]. Here, the nature of the

[8] For an extensive survey on the topic see LeSage and Pace (2009).

interactions recommends focusing on specifications that allow for global spillovers through the spatially lagged dependent variable. We therefore consider the Spatial Durbin Model (SDM) and the Spatial Autoregressive Model (SAR)[9].

The panel SDM reads as:

$$\boldsymbol{Y}_t = \rho \boldsymbol{W}\boldsymbol{Y}_t + \boldsymbol{X}_t\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}_t\boldsymbol{\theta} + \boldsymbol{\mu} + \boldsymbol{\alpha}_t\boldsymbol{\iota}_{\boldsymbol{N}} + \boldsymbol{u}_t \qquad (1)$$

where $\boldsymbol{Y}_t$ includes the $N \times T$ observations on the dependent variable, $\boldsymbol{X}_t$ is a matrix of regressors, $\boldsymbol{\mu}$ is a vector of time-invariant district-specific effects, $\boldsymbol{\alpha}_t$ is a vector of time effects and $\boldsymbol{u}_t$ is the vector of spatially uncorrelated disturbances. The $N \times N$ symmetric weight matrix $\boldsymbol{W}$ summarizes the pairwise spatial relationships between the units in the sample.

The spatial autoregressive term $\boldsymbol{W}\boldsymbol{Y}_t$ consists of a weighted average of the values of Y from neighbouring units and is expected to capture endogenous interaction effects (Elhorst, 2010; 2014). Similarly $\boldsymbol{W}\boldsymbol{X}_t$ represents a weighted average of the values of the regressors from neighbours and accounts for exogenous spatial interactions. Spatially lagged regressors also control for the omission of relevant variables (LeSage and Pace, 2009). Under the assumption that $\boldsymbol{\theta} = \boldsymbol{0}$ the SDM in (1) reduces to the SAR:

$$\boldsymbol{Y}_t = \rho \boldsymbol{W}\boldsymbol{Y}_t + \boldsymbol{X}_t\boldsymbol{\beta} + \boldsymbol{\mu} + \boldsymbol{\alpha}_t\boldsymbol{\iota}_{\boldsymbol{N}} + \boldsymbol{u}_t. \qquad (2)$$

The SDM provides consistent estimates even when the true model is a SAR, while the opposite is not true. District and time effects can be treated as fixed or random, therefore we run a robust Hausman test to select the preferred specification. In order to choose

[9] We refer the reader to Appendix C for further discussion on possible alternative specifications of the model.

between SDM and SAR, we run the Wald and LR tests for SDM against SAR ($H_0: \boldsymbol{\theta} = \mathbf{0}$) (Elhorst, 2014)[10].

A parameter of major policy interest is the spatial autoregressive coefficient ρ which measures the strength of spatial dependence among units and whose magnitude and significance can be interpreted straightforwardly. A positive ρ indicates similar patters among neighbours in terms of hospital expenditure, whereas a negative value suggests that districts tend to reduce their expenditure when neighbours' spending rises.

Assessing the change in the dependent variable following a change in the k^{th} regressor is not equally straightforward. Because of global spillovers, a change in the covariate of a specific unit does not affect the outcome of that unit only, but potentially also all the other units indirectly. The $N \times N$ matrix of partial derivatives of $\boldsymbol{Y}$ with respect to the k^{th} regressor is:

$$\left[\frac{\partial \boldsymbol{Y}}{\partial X_{1k}} \quad \cdots \quad \frac{\partial \boldsymbol{Y}}{\partial X_{Nk}}\right]_t = [(\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1}(\beta_k \boldsymbol{I}_N + \theta_k \boldsymbol{W})] \qquad (3)$$

where the term $(\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1} = \boldsymbol{I}_N + \rho \boldsymbol{W} + \rho^2 \boldsymbol{W}^2 + \cdots$ captures global spillovers (LeSage, 2014). LeSage and Pace (2009) argue that the matrix in (3) is a more valid basis to test the existence of spatial spillovers than the coefficients of a spatial model. They define the average of the main diagonal elements of this matrix as *direct effect*, this measure being a summary of a unit's own partial derivatives $\left(\frac{\partial Y_i}{\partial X_{ik}}\right)$, and the average of its off-diagonal elements as *indirect effect*, this providing a summary measure that can be used to test whether spatial spillovers exist (Elhorst, 2010). Both measures account for a feedback effect

[10] All the models are estimated by Maximum Likelihood (ML) in Stata using the user-written command `xsmle` with cluster-robust standard errors. See Belotti *et al.*, (2017) for a detailed discussion.

through the term $(\boldsymbol{I}_N - \rho\boldsymbol{W})^{-1}$. The *total effect* is the sum of direct and indirect effects.

We also move a step ahead with respect to the construction of $\boldsymbol{W}$, with the purpose of summarizing the information conveyed by $\boldsymbol{W}_{Geo}$ and $\boldsymbol{W}_{Inst}$ in a single weight matrix, allowing for different relative weights given to either definition of proximity. Drawing on Pace and LeSage (2002) and Hazir *et al.* (2016), we model spatial dependence by means of a convex combination of the weight matrices $\boldsymbol{W}_{Geo}$ and $\boldsymbol{W}_{Inst}$ (as well as $\boldsymbol{W}_{Geo\ ITD}$ and $\boldsymbol{W}_{Inst\ ITD}$) which assigns different weights to the two alternative structures of spatial dependence.

The convex combination is as follows:

$$\boldsymbol{W} = \alpha_1\boldsymbol{W}_{Geo} + \alpha_2\boldsymbol{W}_{Inst} \qquad (4)$$

$$\alpha_1 + \alpha_2 = 1$$

$$\alpha_1, \alpha_2 \geq 0.$$

Starting from the geographical proximity ($\alpha_1 = 1, \alpha_2 = 0$), we move progressively towards the institutional proximity ($\alpha_1 = 0, \alpha_2 = 1$) by increasing α_2 of 0.1 up to 1 through a gridding procedure. For each combination of α_1 and α_2, we estimate the SDM model in (1) using the row-standardized weight matrix $\boldsymbol{W}$ resulting from (4) and evaluate the log-likelihood. By comparing the log-likelihood of each model, we identify the best performing weight matrix $\boldsymbol{W}$. The values of α_1 and α_2 in the best-fitting combination provide a directly interpretable indication on the relative weights of geographical and institutional proximity in capturing the structure of spatial dependence among HDs.

6. Results

We present here the main empirical results. Since the robust Hausman test always supports the choice of the FE effect specification over the RE for both the SAR and SDM, we focus on FE models[11]. Table IV presents the SAR and SDM estimates of ρ for each proposed specification of the spatial matrix ($\boldsymbol{W}_{Geo}$, $\boldsymbol{W}_{Geo\ ITD}$, $\boldsymbol{W}_{Inst}$, $\boldsymbol{W}_{Inst\ ITD}$)[12].

TABLE IV

For potentially inappropriate expenditures, the estimates of the spatial effects are always positive and statistically significant. The SAR estimates are larger than the SDM ones, especially when proximity is defined on an institutional basis. The coefficients of the SDM range from 0.15 to 0.37, reporting relatively high values for the elasticity of domestic expenditures in response to a change in the expenditures of neighbouring jurisdictions. The estimated effects are in line with the international evidence investigating spatial spillovers in health expenditures using various model specifications[13].

We get fairly different results for highly complex expenditure. The spatially autoregressive coefficient is never significant in the SAR. In the SDM it is negative and (weakly) significant only when $\boldsymbol{W}_{Geo}$ and $\boldsymbol{W}_{Inst}$ are used.

The opposite sign of ρ for the two outcomes indicates that the spatial interactions across districts vary substantially with the treatment. The large and positive effects in potentially

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[11] The full set of RE estimates is available upon request.

[12] In Appendix B, we present several robustness checks based on alternative specifications of the spatial matrix and of the weights used therein. First, we report the estimates for the autoregressive coefficients using straight line instead of travel time distance. Second, we consider a distance weight matrix where we identify neighbours using a criterion based on distance only, no longer conditioning it on sharing a border or the same LHA. Consistently with the literature, we consider distance thresholds of 30 km and 50 km to define the relevant health care market (Gaynor et al. 2012; Longo et al. 2017). For both dependent variables, the results come out as robust to the alternative specifications of the weighting matrices and to the use of different definitions of distance.

[13] For example, the spatial autoregressive coefficient is estimated around 0.35 for Italian LHAs in Atella *et al.*, 2014; 0.24 for US states in Bose, 2015; 0.32 for Spanish regions in Costa-Font nd Pons-Novell, 2007.

inappropriate expenditures suggest that a relatively low amount of resources absorbed by the residents of neighbouring jurisdictions reduces the expenditures of a given HD for its own residents. The presence of neighbours characterized by relatively low expenditures for inappropriate hospitalisation curbs down domestic spending for the same episodes. Restraining the inappropriate use of the hospital seems produce positive spillovers through mimicking by neighbours (demonstrative effect).

Conversely, the fact that the coefficient associated with high complexity expenditures is in general poorly significant indicates that spatial interactions for these types of procedure are absent or at most weak. When significant the sign of the autoregressive coefficient is negative. This is likely to signal dissimilar technological endowments across HDs. Residents from HDs with high capacity to fully provide highly-complex treatments may find easier access than residents in adjacent districts characterized by a lower local endowment of hospital technology.

TABLE V

As for model selection, when testing $H_0\colon \boldsymbol{\theta} = \mathbf{0}$ using the Wald and the LR tests, the SAR is always rejected against the SDM for both outcomes and for any $\boldsymbol{W}$ (Table V). Given such consistent evidence, and considering that spatially lagged covariates also control for omitted relevant variables, we focus on the SDM.

All previous results exploit either the geographical or the institutional definition of contiguity. These definitions are only partially satisfactory, since either fails to identify as neighbours some units among which relevant interactions may actually take place. The geographical definition does not consider links among jurisdictions of the same LHA not sharing a border, while the institutional definition excludes adjacent HDs from different LHAs. To overcome such limitation we estimate the SDM using a spatial weight matrix that results from the convex combination of $\boldsymbol{W}_{Geo}$ and $\boldsymbol{W}_{Inst}$ ($\boldsymbol{W}_{Geo\ ITD}$ and $\boldsymbol{W}_{Inst\ ITD}$) according to equation (4). Table VI presents the values of the log-likelihood and of the weights α_1 and α_2 for the three best and for the worst fitting models.

TABLE VI

When comparing the two types of expenditures, the difference in the best fitting weights is striking. Institutional contiguity alone seems able to capture the relevant spatial connectivity in potentially inappropriate expenditures. In fact, the best fitting model accounts for institutional contiguity only ($\alpha_1 = 0, \alpha_2 = 1$), whereas the fit becomes progressively poorer with decreasing weights attributed to $\boldsymbol{W}_{Inst}$. The worst performing combination is based on geographical proximity only ($\alpha_1 = 1, \alpha_2 = 0$). Differently, for complex treatments the best cases assign a relative larger weight to geographical proximity, with institutional proximity exerting a non negligible but residual role ($\alpha_1 = 0.8, \alpha_2 = 0.2$). These findings are consistent with the conjecture that spillovers for potentially inappropriate conditions are mainly due to institutional links across districts, whereas geographical proximity becomes more relevant for complex procedures: this possibly reflects patients' higher willingness to cross institutional borders in case they can find high quality responses.

It is interesting to notice that for potentially inappropriate expenditures, although the connectivity structure that best fits the data is the one based on institutional links only, this corresponds also to a smaller estimated feedback effect compared to the use of the geographical criterion. Even if this result might appear puzzling, it should be remarked that the weights in the best fitting combination simply indicate that the purely institutional weight matrix better fits the data compared to any combination that assigns a positive weight to geographical contiguity. As such, this finding cannot be interpreted as evidence of more intense interactions giving rise to stronger spillovers among districts. While the choice of the weights addresses the concern of identifying the connectivity matrix most suitable to capture the existing links according to a goodness-of-fit criterion, conversely, the estimated magnitude of ρ captures spillovers intensity once a specific connectivity structure has been chosen. Consistently with this line of reasoning, there is no a priori on the relative magnitude of the estimated autoregressive coefficient ρ when using the best fitting matrix compared to alternative connectivity structures.

To investigate the sources of possible spillovers more deeply, we compute the direct, indirect and total effects. For each dependent variable, we consider the best fitting combination identified by gridding using spatial matrices weighted for inverse distance ($\boldsymbol{W}_{Geo\ ITD}$ and $\boldsymbol{W}_{Inst\ ITD}$) [14].

TABLE VII

For potentially inappropriate hospitalisations, the direct effects presented in Table VII show that the district organisation of primary care significantly affects expenditures of that jurisdiction. A higher share of single handed practices is expected to be associated with higher expenditures. Moreover, in districts where the share of GPs' income for the provision of home-based care is higher, inappropriate expenditures are lower. This confirms that professional networks among GPs and targeted programs for domiciliary care may curb the resources spent for avoidable hospital admissions (Fiorentini *et al.*, 2011). Not surprisingly,

[14] As additional robustness check, we report in Appendix D the results for the second- and third- best fitting convex combinations of the spatial matrices. We take the FE SDM as the reference specification in analogy with the results presented in Table VII and VIII. The available evidence shows that the empirical findings are largely confirmed also when using these alternative weights for the convex combination.

higher shares of residents aged between 51 and 65 and above 65 increase expenditures, with the elasticity associated with the younger age group being twice as large. Supply side conditions play a role as well. In particular, a higher share of hospital beds in the district is associated with larger expenditures. This likely reflects the fact that HD with larger supply of beds are also those specialised relatively more in the delivery complex treatments. Overall, the indirect effects of the other controls are small, with an exception being neighbours' income. A large and significant indirect effect for income signals that the spillover effects are to a large part driven by socio-economic conditions in neighbouring districts.

TABLE VIII

The marginal effects for complex procedures are reported in Table VIII. Also for the best fitting convex combinations of the weight matrices the autoregressive coefficient is non significant, similarly to the results of Table IV. As for the direct effects, we find a significant impact for the share of top-up payments to GPs for home-based care and for the share of residents aged above 65. The negative sign of the latter is in line with the limited propensity to provide highly intensive treatments to the elderly. The indirect effect points to the same direction, thus giving a large and highly significant total effect. As expected, the total effect of the share of residents aged 51-65 is positive, and its magnitude comes mostly from the indirect effect. This evidence suggests that age-related risk factors both in own and neighbouring jurisdictions have a large impact on expenditures for complex procedures.

7. Conclusions

The paper has investigated spatial effects in hospital expenditures for the health districts of Emilia Romagna (Italy) between 2007-10. The decentralised decision-making process of the

NHS allows for remarkable heterogeneity in district policies and patients may easily move out to be treated in neighbouring areas. These dimensions, together with clustering of health-related risk factors, represent possible sources of spatial spillovers. We have focused on two research questions that bear relevant policy implications. First, we have investigated possible differences in spatial spillovers by separately analysing potentially inappropriate hospitalisations and highly complex treatments. Second, we have examined the distinct role of geographical and institutional proximity in generating spatial spillovers.

Interactions largely differ between types of expenditures. We record strong, positive spatial effects in expenditures for potentially avoidable admissions, implying that HDs are benefitted (harmed) by having adjacent jurisdictions with relatively low (high) expenditures for inappropriate hospitalisations. This indicates that jurisdictions promoting policy innovation may favour the transmission of best-practices to neighbouring areas. Differently, expenditures for complex procedures are characterised by spatial effects that are in most cases not significant. We can conclude that, according to our findings, spillovers in expenditures are relevant for basic hospital treatments, such as those for which hospitalisation is potentially avoidable, while the same does not hold for treatments of high complexity. Moreover, in the few circumstances where it is significant, the spatial autoregressive coefficient of per-capita expenditures for complex procedures has a negative sign, thus implying that residents in a jurisdiction surrounded by high-spending areas, receive fewer complex treatments. This pattern may depend on the fact that production capacity for complex treatments tends to be concentrated in given districts in order to exploit economies of scale and of specialisation. Therefore, patients from districts with relatively low technological endowments might experience some restraints in accessing complex procedures compared to those residing in neighbouring areas.

Overall, our results indicate that, when evaluating the performance of local jurisdictions, policymakers should take into account that conditions in surrounding areas can influence expenditure patterns and that spillovers differ across types of treatments. From a policy perspective, two main recommendations can be drawn. On the one side, to contain potentially inappropriate expenditures effort should be devoted to enhancing the diffusion of best-practices following successful local initiatives (e.g. programs for domiciliary care) as they possibly generate positive spillovers. On the other side, policymakers may consider monitoring the actual accessibility of complex treatments for residents in districts with relatively low hospital production capacity.

Our results also provide insights on the role exerted by institution-based and geography-based connections in generating interactions among districts. In fact, spatial dependence in potentially inappropriate expenditure is best captured by interactions occurring among districts belonging to the same upper layer jurisdiction. This supports the view that the transmission of best-practices implemented locally is smoother across jurisdictions that share a common institutional environment.

On the contrary, geographical proximity is relatively more important for complex procedures. An evidence consistent with the idea that local decisions over the provision of specialised procedures are affected relatively more by the choices of geographically adjacent jurisdictions about the composition of supply.

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References

Arbia G, Battisti M, Di Vaio G. 2010. Institutions and geography: Empirical test of spatial growth models for European regions. *Economic Modelling* **27** : 12–21.

Anselin L. 2003. Spatial externalities, spatial multipliers and spatial econometrics. *International Regional Science Review* **26** : 153–166.

Atella V, Belotti F, Depalo D, Piano Mortari A. 2014. Measuring spatial effects in the presence of institutional constraints: The case of Italian Local Health Authority expenditure. *Regional Science and Urban Economics* **49** : 232–241.

Balia S, Brau R, Marrocu E. 2014. What drives patient mobility across Italian regions? Evidence from hospital discharge data in Levaggi R. Montefiori M. (eds) 2014. Health care provision and patient mobility, *Developments in Health Economics and Public Policy* **12** : 133–154.

Baltagi B H, Yen Y-F. 2014. Hospital treatment rates and spillover effects: Does ownership matter?. *Regional Science and Urban Economics* **49** : 193–202.

Bech M, Lauridsen J. 2009. Exploring spatial patterns in general practice expenditure. *European Journal of Health Economics* **10** : 243–254.

Belotti F, Hughes G, Piano Mortari A. 2017. Spatial panel data models using Stata. *The Stata Journal,* forthcoming.

Bose, S. 2015. Determinants of per capita health expenditure in the United States: A spatial panel analysis. *The Journal of Regional Analysis and Policy* **45** : 93–107.

Cappellari L, De Paoli A, Turati G. 2016. Do Market Incentives in the Hospital Industry Affect Subjective Health Perceptions? Evidence from the Italian PPS-DRG Reform. *Journal of the Royal Statistical Society – Series A* **179** : 885–915.

Costa-Font J, Pons-Novell J. 2007. Public health expenditure and spatial interactions in a decentralized National Health System. *Health Economics* **16** : 291–306.

Costa-Font J, Moscone F. 2009. The impact of decentralization and inter-territorial interactions on Spanish health expenditure in Arbia G, Baltagi B. (eds.) *Spatial econometrics: Studies in empirical economics*, Springer: Berlin.

de Hoyos R E, Sarafidis V. 2006. Testing for Cross-sectional Dependence in Panel Data Models. *The Stata Journal* **6** : 482–496.

Dusheiko M, Gravelle H, Martin S, Rice N, Smith P C. 2011. Does better disease management in primary care reduce hospital costs? Evidence from English primary care. *Journal of Health Economics* **30** : 919–932.

Ehlert A, Oberschachtsiek D. 2014. Does managed care reduce health care expenditure? Evidence from spatial panel data. *International Journal of Health Care Finance Economics* **14** : 207–227.

Elhorst J P. 2010. Applied Spatial Econometrics: Raising the Bar. *Spatial Economic Analysis* **5** : 9–28.

Elhorst J P. 2014. Spatial Econometrics. From Cross-Sectional Data to Spatial Panels. *Springer Briefs in Regional Science*. Springer : Berlin.

Fabbri D, Robone S. 2010. The geography of hospital admissions in a National Health Service with patient choice. *Health Economics* **19** : 1029–1047.

Fattore G, Mariotti G, Rebba V. 2013. Review of waiting times policies: Country case studies - Italy in Siciliani L, Borowitz M, Moran V. (eds). Waiting Time Policies in the Health Sector. *OECD Health Policy Studies*.

Fiorentini G, Iezzi E, Lippi Bruni M, Ugolini C. 2011. Incentives in primary care and their impact on potentially avoidable hospital admissions. *European Journal of Health Economics* **12** : 297–309.

Gaynor M, Laudicella M, Propper C (2012) Can governments do it better? Merger mania and hospital outcomes in the English NHS, *Journal of Health Economics,* **31** ; 528–543.

Gravelle H, Santos R, Siciliani L. 2014. Does a hospital's quality depend on the quality of other hospitals? A spatial econometrics approach. *Regional Science and Urban Economics* **49** : 203–216.

Hazir C S, LeSage J P, Autant-Bernard C. 2016. The role of R&D collaboration networks on regional innovation performance. Forthcoming in *Papers in Regional Science*.

Iezzi E, Lippi Bruni M, Ugolini C. 2014. The role of GP's compensation schemes in diabetes care: Evidence from panel data. *Journal of Health Economics* **34** : 104–120.

LeSage J P. 2014. What regional scientists need to know about spatial econometrics. *The Review of Regional Studies* **44** : 13–32.

LeSage J P, Dominguez M. 2012. The importance of modeling spatial spillovers in public choice analysis. *Public Choice* **150** : 525–545

LeSage J P, Pace R K. 2009. *Introduction to Spatial Econometrics*. Taylor & Francis : Abingdon.

Lippi Bruni M, Mammi I, Ugolini C. 2016. Does the extension of primary care practice opening hours reduce the use of emergency services?. *Journal of Health Economics* **50** : 144–155.

Longo F, Siciliani L, Gravelle H, Santos R (2017), Do hospitals respond to rivals' quality and efficiency? A spatial econometrics approach, CHE Research Paper 144, University of York.

Lunberg J. 2014. On the definition of W in empirical models of yardstick competition. *The Annals of Regional Science* **52** : 597–610.

Manski C F. 1993. Identification of endogenous social effects: The reflection problem. *Review of Economic Studies* **60** : 531–542.

Mascia D, Dandi R, Di Vincenzo F (2014) Professional networks and EBM use. A study of interphysician interaction across levels of care, **118**; 24-36.

Moscone F, Knapp M, Tosetti E. 2007. Mental health expenditure in England: A spatial panel approach. *Journal of Health Economics* **26** : 842–864.

Pace R K, LeSage J P. 2002. Semiparametric maximum likelihood estimates of spatial dependence. *Geographical Analysis* **34** : 76–90.

Pesaran M H. 2004. General diagnostic tests for cross section dependence in panels. *Cambridge Working Papers in Economics N. 0435*. University of Cambridge.

Skinner J. 2011. Causes and consequences of regional variations in health care in Pauly M V, McGuire T G, Barros P P. (eds). *Handbook of Health Economics* **2** : 45–93, North Holland.

Yu Y, Zhang L, Li F, Zheng X. 2013. Strategic interaction and the determinants of public health expenditures in China: a spatial panel perspective. *The Annals of Regional Science* **50** : 203–221.

Table I. Descriptive statistics for the outcome variables, district averages, year by year

	Pot_inapp_exp		High_compl_exp	
	Exp. for treatments at risk of inappropriateness *(Euros per capita)*		Exp. for complex treatments *(Euros per capita)*	
Year	Mean	Std. Dev.	Mean	Std. Dev.
2007	47.11	6.23	247.71	23.32
2008	43.63	4.79	243.43	23.03
2009	44.33	4.28	233.54	23.94
2010	42.81	4.58	234.04	22.51
Year	Mean	Std. Dev.	Mean	Std. Dev.
2007-10	44.47	5.23	239.68	23.77
Between		4.44		22.09
Within		2.84		9.03

Table II. Descriptive statistics for the control variables, district averages, years 2007-2010

Variable	Definition	Mean	St. Dev.	Between	Within	Min	Max
GP_seniority	average seniority of GPs in the HD	20.2	1.76	1.52	0.92	14.44	23.74
share_male_GP	HD share of male GPs	71.37	8.87	8.91	0.85	52.83	94.44
num_GPs_1000	Per-capita number of GPs in the HD	0.88	0.06	0.57	0.03	0.74	1.03
share_single_GPs	HD share of single practices	23.06	13.29	12.30	5.33	3.13	71.7
share_nurse	HD share of GP practices with nurse	9.26	9.46	8.42	4.48	0	47.83
share_collab	HD share of GP practices with collaborator	27.36	11.91	10.94	4.96	4	69.57
share_36_50	HD share of patients aged 36-50	27.9	1.58	1.54	0.39	23.33	32.21
share_51_65	HD share of patients aged 51-65	21.21	0.9	0.85	0.31	19.33	24.24
share_over 65	HD share of patients aged over 65	25.48	2.86	2.87	0.28	19.67	32.03
share_males	HD share of male patients	48.2	0.88	0.87	0.28	45.85	49.89
share_foreigners	HD share of foreign patients	7.51	1.97	1.71	1.00	2.86	12.55
share_inc_clin	share GP income for improving clinical services	2.09	2.04	1.99	0.53	0	8.4
share_inc_domic	share GP income for domiciliary services	12.16	3.24	2.88	1.53	4.12	20.07
share_inc_org	share GP income for organisational improvements	3.13	1.28	1.01	0.80	1.52	7.76
HD wih HT	Districts with Hospital Trust (dummy)	0.13	0.34	0.34	0	0	1
HD type A hosp	districts with Type A hospital (dummy)	0.21	0.41	0.41	0	0	1
disadvant_area	disadvantaged area (dummy)	0.24	0.37	0.37	0.00	0	1
ord_beds_1000	Ord. hospital beds in the HD (1000 inhabs.)	2.72	1.58	1.59	0.09	0.01	7.8
doc_1000	Hospital doctors in the HD (1000 inhabs.)	1.78	1.12	1.13	0.07	0.23	4.75
nurses_1000	Per-capita number of hospital nurses in the LHA	6.25	3.87	3.90	0.23	0.85	16.93
Patients_HD	Number of registered patients per HD	97090.75	58400.74	58966.52	1635.93	28526	101896.8
Income_per_cap	HD per-capita taxable income	22642.97	2193.16	2204.20	219.09	17911.9	28719.4
Pop_dens_HD	HD population density (inhabs. per km^2)	310.24	433.32	437.66	5.76	31.04	2677.98

Table III. Moran's I spatial autocorrelation coefficient for the outcome variables and alternative specifications of *W*, year by year

	Pot_inapp				**High_complex**			
year	*W_Geo*	*W_Geo_ITD*	*W_Inst*	*W_Inst_ITD*	*W_Geo*	*W_Geo_ITD*	*W_Inst*	*W_Inst_ITD*
2007	0.251***	0.276***	0.363***	0.400***	0.316***	0.341***	0.364***	0.372***
2008	0.201**	0.255***	0.273**	0.369***	0.265***	0.290***	0.245**	0.256**
2009	0.239***	0.282***	0.207**	0.321***	0.405***	0.448***	0.532***	0.567***
2010	0.241***	0.284***	0.324***	0.408***	0.518***	0.545***	0.696***	0.705***

Table IV. Spatial effects: estimates of the ρ coefficient, SAR and SDM FE models, alternative specifications of *W*, 2007-2010

	Pot_inappr_exp		**High_compl_exp**	
Geographical Contiguity	SAR	SDM	SAR	SDM
W_Geo	0.442	0.302	0.046	-0.193
	(0.000)	*(0.000)*	*(0.697)*	*(0.037)*
W_Geo_ ITD	0.466	0.371	0.058	-0.096
	(0.000)	*(0.000)*	*(0.615)*	*(0.235)*
Institutional Contiguity	SAR	SDM	SAR	SDM
W_Inst	0.432	0.150	0.048	-0.151
	(0.000)	*(0.066)*	*(0.567)*	*(0.097)*
W_Inst_ITD	0.466	0.244	0.071	-0.062
	(0.000)	*(0.000)*	*(0.407)*	*(0.457)*

Table V. Wald and LM tests for model selection: SAR vs SDM

	SAR vs. SDM	**Pot_inappr_exp**	**High_compl_exp**
Geographical Contiguity	*test*	Test statistic (*p-value*)	Test statistic (*p-value*)
W Geo	Wald	33.60 *(0.0205)*	93.45 *(0.0000)*
	LR	31.44 *(0.0361)*	72.43 *(0.0000)*
W_Geo_ ITD	Wald	35.84 *(0.0110)*	74.31 *(0.0000)*
	LR	33.13 *(0.0232)*	60.46 *(0.0000)*
Institutional Contiguity	*test*	Test statistic (*p-value*)	Test statistic (*p-value*)
W_Inst	Wald	77.27 *(0.0000)*	47.07 *(0.0003)*
	LR	68.07 *(0.0000)*	40.84 *(0.0025)*
W_Inst_ITD	Wald	60.88 *(0.0000)*	43.85 *(0.0010)*
	LR	56.03 *(0.0000)*	38.58 *(0.0050)*

Table VI. Convex combination of spatial matrices: values of α_1, α_2 and Log-lik for the 3 best fitting and the worst fitting combinations

	Pot_inappr_exp				High_compl_exp			
	ranking	α_1	α_2	Log-likelihood	ranking	α_1	α_2	Log-likelihood
Geo + Inst	1	0	1	327.4679	1	0.8	0.2	374.6042
	2	0.1	0.9	321.5200	2	0.7	0.3	374.3263
	3	0.2	0.8	321.4231	3	0.9	0.1	373.7200
	.	.	.	.	.	.	.	.
	11	1	0	302.5612	11	0	1	356.1580
Geo + Inst Inverse Travel Distance	1	0	1	323.5631	1	0.8	0.2	367.5171
	2	0.1	0.9	319.5778	2	0.7	0.3	367.1141
	3	0.2	0.8	319.3201	3	0.9	0.1	367.0537
	.	.	.	.	.	.	.	.
	11	1	0	304.6336	11	0	1	355.1628

Table VII. Coefficient estimates and marginal effects: FE SDM for potentially inappropriate expenditures,

$$\boldsymbol{W} = 0 \cdot \boldsymbol{W}_{Geo\ ITD} + 1 \cdot \boldsymbol{W}_{Inst\ ITD}$$

Variables	Main	Wx	Direct	Indirect	Total
GP_seniority	0.212	-0.346	0.182	-0.338	-0.157
share_male_GP	-0.406	1.615	-0.249	1.742	1.493
num_GPs_1000	0.140	0.210	0.165	0.281	0.445
share_single_GPs	0.032**	-0.040	0.029**	-0.036	-0.008
share_nurse	-0.001	-0.001	-0.001	-0.001	-0.002
share_collab	0.065***	0.097	0.076***	0.130	0.206**
share_36_50	0.839	-1.848	0.668	-1.889	-1.221
share_51_65	1.527***	1.061	1.675***	1.648	3.323
share_over 65	0.710**	1.062	0.838**	1.420*	2.258**
share_males	-1.028	-5.745*	-1.648	-6.893*	-8.541*
share_foreigners	0.030	0.098	0.041	0.121	0.162
share_inc_clin	-0.000	0.004	0.000	0.005	0.005
share_inc_domic	-0.178***	-0.006	-0.183***	-0.057	-0.240**
share_inc_org	0.024	-0.052	0.020	-0.053	-0.033
ord_beds_1000	-0.359*	-0.495	-0.419**	-0.669	-1.088*
doc_1000	0.792	-1.156**	0.693	-1.107**	-0.414
nurses_1000	-0.653	1.041*	-0.562	1.013*	0.451
income_per_cap	0.398	4.116***	0.834	4.843***	5.677***
pop_density	-0.637	-1.160	-0.773	-1.512	-2.285
ρ	0.244***		σ^2	0.001***	
Observations	152				
Log likelihood	323.5631				

Table VIII. Coefficient estimates and marginal effects: FE SDM for high-complexity expenditures,

$$\boldsymbol{W} = 0.8 \cdot \boldsymbol{W}_{Geo\ ITD} + 0.2 \cdot \boldsymbol{W}_{Inst\ ITD}$$

Variables	Main	Wx	Direct	Indirect	Total
GP_seniority	0.556*	1.249*	0.523*	1.094*	1.617**
share_male_GP	-0.601	-1.514	-0.560	-1.334	-1.894**
num_GPs_1000	0.173	0.204	0.168	0.170	0.337
share_single_GPs	-0.010	0.032	-0.011	0.031	0.020
share_nurse	-0.001	-0.001	-0.001	-0.001	-0.002
share_collab	0.013	0.121**	0.010	0.110**	0.120**
share_36_50	0.239	0.784	0.218	0.699	0.917
share_51_65	0.329	3.671***	0.227	3.356***	3.582***
share_over 65	-0.525*	-2.017***	-0.470	-1.807**	-2.277***
share_males	1.385	-6.049**	1.559	-5.737**	-4.178
share_foreigners	-0.064	-0.188	-0.059	-0.167	-0.226
share_inc_clin	-0.002	0.008**	-0.002	0.008**	0.006*
share_inc_domic	0.117***	-0.069	0.120***	-0.076	0.044
share_inc_org	-0.026	-0.044	-0.025	-0.037	-0.062**
ord_beds_1000	-0.038	0.081	-0.041	0.079	0.039
doc_1000	0.237	-0.277	0.245	-0.282	-0.036
nurses_1000	-0.271	0.639**	-0.290	0.620**	0.330
Income_per_cap	-0.242	-0.021	-0.242	0.007	-0.235
pop_density	0.269	1.067*	0.240	0.957*	1.197*
ρ	-0.116		σ^2	0.001***	
Observations	152				
Log likelihood	367.5171				

Figure 1. Distribution of HD expenditures, average years 2007-2010

(quartiles, darker colour corresponding to higher spending)