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Measuring spatial effects in the presence of institutional constraints: The case of Italian Local Health Authority expenditure[☆]

Vincenzo Atella [a,b], Federico Belotti [d], Domenico Depalo [c], Andrea Piano Mortari [d,*]

[a] Department of Economics and Finance and CEIS Tor Vergata, Columbia 2, 00133 Rome, Italy
[b] CHP-PCOR Stanford University, 117 Encina Commons, Stanford University, Stanford, CA 94305-6019, United States
[c] Bank of Italy, Nazionale, 91, 00184 Rome, Italy
[d] CEIS Tor Vergata, Columbia 2, 00133 Rome, Italy

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ABSTRACT

Over the last decades spatial econometric models have represented a common tool for measuring spillover effects across different geographical entities (counties, provinces, regions or nations). The aim of this paper is to investigate the issue of measuring spatial spillovers in the presence of institutional constraints that can be geographically defined. In these cases, assuming that spatial effects are not affected by the institutional setting may produce biased estimates due to the composition of twodistinct sources of spatial dependence. Our approach is based on redefining the contiguity structure so as to account for the institutional constraints using two different contiguity matrices: the within matrix, which defines contiguity among units obeying the same institutional setting, and the between matrix, which traces spatial linkages among contiguous units across different jurisdictions. This approach allows to disentangle the two sources of spatial correlation and to easily test for the existence of binding institutional constraints. From the econometric perspective, we extend Lacombe (2004) approach to incorporate the aforementioned institutional constraints in a spatial Durbin model with individual specific slopes, while inference is conducted using a two-way cluster robust variance–covariance matrix controlling for both spatial and time correlations. We apply this methodology to analyze spatial dependence of per-capita public health expenditures in Italyat Local Health Authority level using a balanced panel dataset from 2001 to 2005. Our results show robust evidence of a significant and positive spatial coefficient for the within effect, while the between effect, although significant, is very close to zero, thus confirming the importance and validity of the proposed approach.

1. Introduction

It is widely recognized that sample data collected from geographically close entities are not independent, but spatially correlated, which means that observations of closer units tend to be more similar than further ones (Tobler, 1970).[1] Spatial clustering or geographic-based correlation is often observed for economic and socio-demographic variables such as unemployment, crime rates, house prices, per-capita health expenditures and the alike (Sollé Ollé, 2003; Moscone and Knapp, 2005; Revelli, 2005; Sollé Ollé, 2006; Kostov, 2009; Elhorst and Freret, 2009; Elhorst et al., 2010; Moscone et al., 2012). Theoretical models usually recognize the existence of spatial spillover which declines as distance between units increases; empirically these features can be captured by

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* Corresponding author. Tel.: +39 06 7259 5627.
E-mail addresses: atella@uniroma2.it (V. Atella), federico.belotti@uniroma2.it (F. Belotti), domenico.depalo@bancaditalia.it (D. Depalo), piano.mortari@economia.uniroma2.it (A.P. Mortari).
URL's: http://www.economia.uniroma2.it/atella/ (V. Atella), http://www.econometrics.it (F. Belotti), https://sites.google.com/site/domdepalo/ (D. Depalo), http://www.ceistorvergata.it/area.asp?a=539&oc=817&d=1128 (A.P. Mortari).

[1] It is worth emphasizing that non-spatial structured dependence may also be observed. In these cases, measures of geographical proximity are replaced by measures of similarity allowing to investigate peer effects through social or industrial networks (LeSage and Pace, 2009; Bramoullé et al., 2009).

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means of a weight matrix, attaching higher weights to the nearest neighbors.[2]

The aim of this paper is to investigate the issue of measuring spatial spillovers in the presence of institutional constraints that can be geographically defined. When this occurs, the units of interest may share common borders but obey to different institutional settings. Hence, we expect to observe spatial dependence mainly among neighbors within the same institutional cluster, rather than among neighbors belonging to different clusters. We cast this idea in a theoretical framework where health expenditures of local units are set as a result of a mimicking behavior/yardstick competition among local authorities.

From the econometric perspective, we extend (Lacombe, 2004) approach to incorporate the aforementioned institutional constraints in a Spatial Durbin Model (SDM) with individual specific slopes. Starting from the conventional first-order spatial contiguity matrix,[3] our approach better defines the contiguity structure so as to account for the institutional constraints using two different contiguity matrices: the first one, the within matrix, defines contiguity among units sharing both borders and institutional cluster; the second, the between matrix, traces spatial linkages among contiguous units across different institutional clusters. An important feature of this approach is that it can be directly applied toall those situations where institutional constraints are binding and can be geo-referenced (e.g., Euro membership within the EU, MERCOSUR membership in Latin America or, for example, towns within counties, provinces or regions). This strategy allows us to disentangle the within institutional cluster spatial effect, from the between cluster effect by means of exogenously defined spatial contiguity matrices. Moreover, under the assumption of independence among observational units that do not share common clusters, inference is conducted using a two-way cluster robust variance–covariance matrix, controlling for both spatial and time correlation (Cameron et al., 2011).

We apply this methodology to analyze spatial dependence of per-capita public health expenditures in Italy at Local Health Authority (LHA) level using a balanced panel dataset from 2001 to 2005, a level of analysis never explored before. Given the regional structure of the Italian National Health System (NHS), this case lands itself perfectly to be analyzed through the proposed methodology. Our interest in investigating health expenditures' spatial dependence is due to the relevance of this spendingitem for the Italian National Accounts, especially at regional level.[4]About 70% of the budget for regions with ordinary autonomy and about 40% for those with special autonomy. See the hyperlink "http://www.corteconti.it/export/sites/portalecdc/" "Relazione sulla gestione finanziaria delle regioni, Esercizi 2010–2011" (in Italian).

We find robust evidence of a significant and positive spatial coefficient for the within effect, while the between effect, although significant, is very close to zero. This result confirms the importance and validity of our approach.

The remaining part of this article is organized as follows. Section 2 reviews the related literature. Section 3 briefly describes the institutional setting, discusses the regional and sub-regional health expenditure in Italy and presents some stylized facts. Section 4 briefly sketches our theoretical framework, presents the data and some descriptive statistics, provides the algebraic derivation of the within and between matrices and discuss the economic interpretation of the coefficients involved in our empirical model. Section 6 discusses the empirical findings, highlighting the importance of the institutional setting in explaining spatial correlation across LHAs. Finally, Section 7 offers some concluding remarks.

2. Related literature

This paper finds its roots into the broad literature on spatial econometrics and health care expenditures. To our knowledge the existing literature provides a partial answer to the issue of incorporating institutional constraints into spatial econometric models. (Parent and LeSage, 2008) and (Arbia et al., 2009) have explicitly tackled the problem of "institutionally clustered" data, suggesting the use of a non-conventional spatial weighting matrix which incorporates together distance and "clustering" information. In particular, Parent and LeSage(2008) investigate the pattern of knowledge spillovers arising from patent activity between European regions and tests whether different growth rates are due to differences in technology, transportation costs or geography. Using different specifications of the weighting matrix, the authors model the connectivity structures between regions by relying on technological as well as transportation and geographical proximity. They conclude that a model which combines both geographic and technological proximity and takes into account the asymmetric output gap between contiguous regions fits the data better. Arbia et al.(2009) analyze the growth experiences of European regions, in the period 1991–2004, at NUTS-2 level. In order to take into account institutional differences at national level the authors modify an inverse distance-based spatial matrix using an institutional heterogeneity index based on the linguistic distance between countries. They find that, holding the geographical distance fixed, regions sharing a similar institutional framework tend to converge more rapidly to each other. This implies that institutions play an important role with respect to geographical factors, obtaining further support for the (Rodrik et al., 2004) claim of "primacy of institutions over geography".

Unfortunately, these approaches present practical implementation problems related to the availability of relevant exogenous variables used to appropriately re-weight the distance matrix and to some degree of subjectivity in the selection of these variables. Furthermore, the proposed approach are unable to jointly assess the contribution of the different sources of spatial dependence, since either they are summarized in a single coefficient (Arbia et al., 2009), or they can only be analyzed sequentially (Parent and LeSage, 2008).

Pursuing a different objective, our approach follows (Lacombe, 2004). He studied the effects of Aid to Families with Dependent Children (AFDC) and Food Stamp Payments on female-headed households and female labor-force participation in the US.His goal was to asses the potential bias of different matching techniques meant to reduce the simultaneity bias associated with OLS estimates when latent or unobserved variables vary systematically over geographical regions. He found that OLS estimates of the county effect remain biased even after controlling for potential spatial correlation using different matching techniques and proposes a Spatial Autoregressive Model where the coefficient of within-state and between-state bordering counties are estimated separately. Only recently, Gérard et al.(2010) and Cassette et al.(2012) have recognized the importance of formally taking into account institutional differences in estimating the spatial spillovers, but with a focus on taxes rather than on expenditures.

In terms of health expenditure analysis, the international literature provides plenty of evidence (e.g., Skinner, 2011; Chernew and Newhouse, 2011; Gerdtham and Jonsson, 2000). Italy is not an exception and there is a large body of literature that has explored its determinants, typically at regional level (Levaggi and Zanola, 2003;

[2] Two sources of locational information are generally exploited. First, the location in Cartesian space (e.g., latitude and longitude) is used to compute distances among units. Second, the knowledge of the size and shape of observational units allows the definition of measures of contiguity, e.g., one can determine which units are neighbors in the sense that they share common borders. Thus, the former source points towards the construction of spatial distance matrices while the latter is used to build spatial contiguity matrices. It is worth noting that the aforementioned sources of locational information are not necessarily different. For instance, a spatial contiguity matrix can be constructed by defining units as contiguous when they lie within a certain distance; on the other hand by computing the coordinates of the centroid of each observational unit, approximated spatial distance matrices can be obtained using the distances between centroids. More details are available in (LeSage and Pace, 2009).

[3] Similarly to the time-series framework, spatial contiguity can be extended to higher orders. In spatial contexts the higher order refers to a different contiguity structure based on higher spatial lags. For a detailed discussion see (Anselin, 1988).

[4] About 70% of the budget for Regions with ordinary autonomy and about 40% for those with special autonomy. See the "Relazione sulla gestione _nanziaria delle regioni, Esercizi 2010-2011" (in Italian).

Bordignon and Turati, 2009; Francese and Romanelli, 2011; Giardina et al., 2009; Lo Scalzo et al., 2009; Atella and Kopinska, 2014). The main conclusions reached by these studies are: i) per-capita public health expenditure shows a non-negligible variation across regions and over time; ii) deep cross-regional inequalities in health care expenditure and in the supply and utilization of health care services persist even after adjusting for health needs; iii) such differences are the result of different territorial distribution in socioeconomic factors, supply of health care services, regional specific organizational, managerial structures and inefficiencies. Hence, only a fraction of the observed heterogeneity between regions is the result of differences in health needs. Despite all these studies, to the best of our knowledge this paper is the first attempt to analyze spatial dependence of per-capita public health expenditures in Italy at LHA level.[5]

3. The institutional setting of the Italian National Health System and some stylized facts on health expenditures

The Italian NHS, established in 1978, provides universal coverage free of charge at the point of service, or with some (relatively) light form of co-payment. The system is based on the universalism principle and is funded from general taxation, while patients are free to choose where to be cured from a list of public and private accredited providers.[6]

The system is structured into three levels: national, regional and local. The national level is responsible for designing nation-wide health plans with the aim of ensuring general health objectives. Regional levels have then the responsibility of achieving the objectives posed by the national health plan through the regional health departments, which in turn are responsible for ensuring the delivery of a benefit package (the so called "Essential levels of medical care") through LHAs and a network of public and private accredited providers. At local level, LHAs are run by managers who are responsible to plan health care activities and to organize local supply according to population needs. They also are responsible for guaranteeing quality, appropriateness and efficiency of the services provided and are obliged to guarantee equal access, efficacy of preventive, curative and rehabilitative interventions and efficiency in the distribution of services.

Since its inception in 1978, the system has undergone several reforms aimed at improving management and containing costs. A key feature of this reform process has been the movement towards a more decentralized model, away from the original 1978 idea of an integrated and centralized system which left very few responsibilities to the regional and local levels. In particular, the Legislative Decrees 446/1997 and 56/2000 imposed to transfer the NHS funds from the central to the regional level, thus reinforcing the regional health department's autonomy with the idea of obtaining an alignment between funding and spending powers. In this way regional governments became accountable for their health deficits and were allowed to write them off by increasing local taxes (up to a limit) and by introducing cost-sharing schemes on health care services (mainly on drugs).

The main result of this process was to transform the Italian NHS from a monolithic system to a very heterogeneous network of 21 regional health systems, highly autonomous and with full responsibility. Actually, the high level of heterogeneity existing in the system has also been recognized as an important impairing aspect of the original idea of providing an equal level of care to all Italian citizens.[7]

[5] To our knowledge, Masiero and Gonzalez Ortiz(2013) is the only study based on Italian data that uses spatial techniques. However, its focus is limited to the analysis of the determinants of antibiotic consumption at regional level. At international level, the literature is by far more rich. Some examples are Costa-Font and Pons-Novell(2007), Lauridsen et al.(2010) or Moscone and Knapp(2005).

[6] A more detailed description of the Italian NHS is available in (Lo Scalzo et al., 2009).

[7] Clear examples of the adverse effects of such regional constraints are represented by the different cost-sharing schemes imposed on citizens of different regions or different regulations for the adoption of new innovative drugs or devices, or byconfronting different financial and non-financial incentive schemes for health care providers.

Table 1
Age and sex adjusted LHA expenditures by region (2001–2005).

Region	Mean	CV	N. of LHAs
Piedmont	1.37	0.12	19
Aosta Valley	1.68	0	1
Lombardia	1.42	0.09	15
AP Bolzano	1.99	0.08	4
AP Trento	1.66	0	1
Veneto	1.43	0.09	21
Friuli-Venezia Giulia	1.44	0.05	6
Liguria	1.39	0.08	5
Emilia-Romagna	1.47	0.08	11
Tuscany	1.37	0.08	12
Umbria	1.37	0.06	4
Marche	1.36	0.09	13
Lazio	1.38	0.21	8
Abruzzo	1.44	0.07	6
Molise	1.54	0.09	4
Campania	1.42	0.28	13
Apulia	1.37	0.07	12
Basilicata	1.49	0.07	5
Calabria	1.32	0.14	11
Sicily	1.38	0.09	9
Sardinia	1.36	0.18	8
Italy	1.42	0.14	188

Source: Our calculation on Italian LHA Economic Accounts. Mean values are in thousands of Euro per year.

Within regions, LHAs receive funding from the regional health department and are ultimately responsible for the public health service provision. The rules used by the central government to allocate funds have often changed over the past two decades, mainly because the inspiring principles behind the allocation methods have never been clearly stated. Since 1997 the fund allocation has been based on a weighted (by age and gender) capitation formula that was supposed to take into account the health needs of the local populations, proxied by mortality rates and then by age distributions. In general, under both criteria, older regions got higher funding. If the distribution of health needs across regions is not uniform and as long as the capitation criteria correctly allocate funds, observing significant regional differences in per-capita health expenditure should not be considered a problem. LHA managers are accountable for the financial balance between the funds received and the expenditures on health care services at local level. As a consequence, managers have a certain degree of discretionality to determine how much money they want to spend and how, but they are strictly bounded in this activity by the institutional setting. As LHA managers are appointed by politicians, following a spoil system, these two agents maximize the same utility function. This aspect is extremely important in our context as it will represent a key feature of the theoretical framework we will consider in Section 4.1.

Summarizing, the picture that emerges shows how Italian regions enjoy substantial autonomy within a common legal framework. This peculiar institutional setting becomes relevant in shaping the distribution of health care services provided by each single LHA within and across Italian regions by heterogeneously affecting the quality of care provided and, inevitably, the way in which per-capita expenditure can differ within and between regions.

Based on data obtained from the Italian LHA Economic Accounts, Table 1 reports, for each region and for the country as a whole, the gender and age standardized average LHAs public per-capita health expenditure and its Coefficient of Variation (CV).[8] As expected, within region variation is lower than between (or total) variation, as the CV across

[8] Per-capita health expenditure has been standardized by age and gender as we are interested in exploring patterns of within and total sources of variability that do not depend on the distribution of health care needs.

Italian regions is 0.14 while the CVs of LHAs within the same region is lower with the exception of three out of 21 regions.[9]

These results seem to indicate that different institutional settings play a key role on per-capita health expenditure across the Italian regions. In fact, each single region operates as an independent health system, and within each region LHAs presenta less heterogeneous per-capita health expenditure (once controlled for health needs). This evidence should then warn researchers about the adoption of an econometric strategy that allows to adequately explore the presence of spatial correlation in a context where data are clustered, with the clusters that are heterogenous with respect tosome specific characteristic. In our specific case, observational units (LHAs) are clustered within regions that differ in terms of institutional setting.

4. Theoretical framework and empirical strategy

As a theoretical framework for our empirical analysis, we consider a slightly modified version of the (Sollé Ollé, 2006) model in which yardstick competition on health expenditures (rather than on taxes) yields to a mimicking behavior among neighboring local governments.[10] Our empirical strategy extends (Lacombe, 2004) approach to the panel SDM with individual specific slopes. Furthermore, we explicitly consider the identification issues rose by Bramoullé et al.(2009) for the SDM, and provide a robust inference through two-way clustered standard errors (Cameron et al., 2011).

4.1. Theoretical framework

In what follows, rather than providing the details of the yardstick competition theory, we briefly sketch a theoretical model whose implications arise from the interaction between a principal (the representative voter) and an agent (the local official).

The local official (e.g., LHA manager) appointed by regional politicians (through a spoil system), takes the tax rate as given, and has some discretionary power over health expenditures, which represents our variable of interest. Indeed, the local official can set the expenditure at a level that could ensure a majority of their political party (and implicitly of themselves), to keep extracting rents from their office over next mandate. The voter does not know the optimal level of health expenditure associated with the health services provided because she is unaware of the appropriate costs of health goods and services; however, she can compare health expenditures in her jurisdiction to those in comparable neighbors. In this way the voter may evaluate the appropriateness of this kind of expenditures and then use this information to decide whether or not to re-elect the incumbent government. As a consequence, incumbents are compelled to take into account the voter's comparative behavior in their reaction function and keep the level of health expenditures in line with those in the relevant neighborhood; more precisely, when setting the optimal level of expenditure, local officials equalize the marginal benefit of private interest with the political cost of non-reelection, which in turn depends on loss of votes from lower than expected expenditures.

Differently from the original (Sollé Ollé, 2006) model, we assume that in her voting decision, a voter located in local authority will attach a different weight to the observed health expenditure of the contiguous LHAs within the same region, say α_w, and to those of contiguous LHAs located outside the region (α_b). The straightforward implication of this framework is that, the stronger the institutional constraint and its knowledge by the voter, the lower will bethe value of α_b, implying that the level of health expenditures will be in line with those of the contiguous LHAs within the same region; eventually, under perfect information, $\alpha_b = 0$. The magnitude of these weights represents our testable hypothesis.

4.2. Model specification and estimation

Consistently with the framework described above, our model specification controls for health expenditures' spatial dependence within and between institutional clusters. The spatial contiguity matrix at LHA level has been constructedusing Quantum GIS v.1.6.0[11] starting from the shape file at municipality level.[12] For two municipalities (Rome and Turin), LHAs are smaller than the municipality. Since population totals are collected at municipality level, our solution has summed up the expenditures (adjusted for intra and extra region mobilities) and the population of these LHAs to obtain per-capita expenditures of a new "artificial" LHA.

The resulting spatial matrix is a (188 × 188) first-order contiguity matrix, denoted byW_{all}, whose diagonal elements are equal to zero and each off-diagonal element w_{ij} is equal to 1 if LHAs i and j share a common border.[13] For the purposes of our analysis, this matrix has been partitioned in the following way

$$W_{all} = W_w + W_b, \tag{1}$$

where the element w_{ij}^w of W_w is equal to 1 if LHAs i and j share a common border and belong to the same institutional cluster, while the element w_{ij}^b of W_b is equal to 1 if LHAsi and j share a common border but belong to different clusters.[14]

Since the seminal paper by Cliff and Ord(1968), several models have been proposed for spatially dependent data. A general representation proposed by Manski(1993), extended to account for within and between institutional cluster effects, can be written as

$$\begin{aligned} y_{it} = \alpha + \rho_w \sum_{j=1}^{n} w_{ij}^w y_{jt} + \rho_b \sum_{j=1}^{n} w_{ij}^b y_{jt} + x_{it}\beta + \sum_{j=1}^{n} w_{ij}^w z_{jt}\theta_w \\ + \sum_{j=1}^{n} w_{ij}^b z_{jt}\theta_b + d_t\mu_i + \nu_{it}, \end{aligned} \tag{2}$$

$$\nu_{it} = \lambda_w \sum_{j=1}^{n} m_{ij}^w \nu_{it} + \lambda_b \sum_{j=1}^{n} m_{ij}^b \nu_{it} + \epsilon_{it}, \qquad i = 1, \dots, n, \qquad t = 1, \dots, T, \tag{3}$$

where y_{it} is the per-capita health expenditures of unit i at a given time t, w_{ij}^w, w_{ij}^b, m_{ij}^b and m_{ij}^w represent the (i, j)th elements of the known spatial contiguity matrices W_w, W_b, M_w and M_b,[15] x_{it} is the vector of selected covariates, z_{jt} is the vector of selected spatially lagged covariates (where z_{it} can be equal to x_{it}), $\Psi = (\beta, \rho_w, \rho_b, \theta_w, \theta_b, \lambda_w, \lambda_b)$ is the vector of unknown parameters to be estimated, ϵ_{it} is the idiosyncratic error term, d_t is a $1 \times D$ vector of aggregate time variables (which are treated as

[9] It is worth noting that these regions (Lazio, Campania and Sardegna) are those that in 2006 accrued to more than 70% of the total debt of the Italian NHS and all of them were bailed-out in 2006 and, as a consequence, had to enter a deficit reduction plan in 2007.

[10] Yardstick competition is one out of many possible theoretical models. The most well known alternative, whose reduced form is similar to the one of the yardstick competition, is the so called fiscal competition, which relies on tax base mobility (see (Revelli, 2005)). However, in Italy the tax base is highly stable, invalidating the basic condition for the latter model.

[11] Available at: http://www.qgis.org/.

[12] Available at: http://www.istat.it/it/strumenti/cartografia.

[13] For this study we consider queen contiguity. Among the many possible candidates, a meaningful choice in our case is the one that considers a first-order contiguity matrix. This is because we focus on neighbors within the same regions, hence there would be very few second-order nearest neighbors. Further, the distinction of LHAs within the same regions from those between different regions prevents us from using a distance based matrix or focussing on other weighting variables (e.g., population and income).

[14] For this study, we refer only to first-order contiguous neighbors, but this kind of partitioning can be applied also to higher order contiguity matrices. Itis worth noting that the Valle d'Aosta region and the Autonomous Province of Trento have a single LHA on their territory. In these cases, we set the corresponding w_{ij}^w elements equal to zero.

[15] Notice that, in our case, M_w and M_b are equal to W_w and W_b. However, they could also be different.

non random) and μ_i is a $1 \times D$ vector of LHA-specific slopes on the aggregatetime variables.[16]

As noted in (Manski, 1993), when a spatially lagged dependent variable, spatially lagged regressors and a spatial autocorrelated error term are included simultaneously, the parameters of model (2)–(3) are not identified unless at least one of these interaction effects is excluded. Depending on which of them is dropped, one may obtain different spatial model specifications: a SDM ($\lambda_w = \lambda_b = 0$), a Spatial Durbin Error (SDE) model ($\rho_w = \rho_b = 0$), a Spatial AutoRegressive (SAR) model ($\theta_w = \theta_b = \lambda_w = \lambda_b = 0$), a Spatial Error Model (SEM, $\rho_w = \rho_b = \theta_w = \theta_b = 0$) or a Kelejian and Prucha(1998) model (KPM) ($\theta_w = \theta_b = 0$). As pointedout by LeSage and Pace(2009), the choice of which interaction effect should be excluded (and then implicitly which model is more appropriate to describe the data), should be driven by the research question.

Since ρ_w and ρ_b can be thought of as the empirical counterparts of the weights characterizing the voter's electoral decision (α_w and α_b) and we are interested in estimating unconstrained direct, indirect and total covariates' effects, we believe that the SDM is a more attractive point of departure in this application.[17] Furthermore, as misspecification of the conditional mean (i.e., ignoring spatial dependence in the dependent variable and/or in the covariates) may lead to severely biased estimates, the SDM is the best choice for at least two reasons. First, the SDM allows to obtain unbiased estimates even if the true data generating process is a SAR or a SEM.[18] Second, the inclusion of the spatially lagged regressors could serve as a control for omitted variables, if they are first-order spatially correlated with the included regressors (LeSage and Pace, 2009).

It is worth emphasizing that the exclusion of one of the interaction effects may still not be enough to identify the parameters of interest. Indeed, as shown by Bramoullé et al.(2009), the simultaneous identification of the exogenous and endogenous effects also depends on the structure of the spatial weights matrix. In our case, in order for the spatial effects to be identified, once we adapt Proposition 5 in Bramoullé et al.(2009) to our spatial weight matrix partition, two conditions have tobe met[19]

1. $(\theta_w \neq -\rho_w\beta)$ and $(\theta_b \neq -\rho_b\beta)$;
2. The matrices I, W_w, W_w^2, W_w^3, W_b, W_b^2, and W_b^3 are linearly independent.

The first one is equivalent to test if the model cannot be reduced to a SEM, while the second implies the absence of perfect collinearity among spatially lagged regressors. Under these conditions, it then follows that our SDM can be rewritten in the following way

$$y_{it} = \alpha + \rho_w \sum_{j=1}^{n} w_{ij}^{w} y_{jt} + \rho_b \sum_{j=1}^{n} w_{ij}^{b} y_{jt} + x_{it}\beta + \sum_{j=1}^{n} w_{ij}^{w} z_{jt}\theta_w + \sum_{j=1}^{n} w_{ij}^{b} z_{jt}\theta_b + d_t\mu_i + \epsilon_{it} \quad (4)$$

where the w_{ij}^w and w_{ij}^b come from a row-standardized version of the spatial matrices and $\Psi = (\beta, \rho_w, \rho_b, \theta_w, \theta_b)$.[20]

4.2.1. Estimation

Model (4) can be viewed as a SDM with individual specific slopes. As can be noted, the conventional fixed-effects SDM is obtained when $d_t \equiv 1$. Furthermore, more flexible specifications can be obtained when all cross-sectional units are allowed to have their own trend (Wooldridge, 2005). This enables us to control for LHA unobserved heterogeneity, which can be both time invariant and time-varying according to the specified LHA specific trend.

As far as estimation is concerned, denote y_i the T $T \times 1$ vector of health expenditures for unit i, X_i the $T \times K$ matrix of regressors, WX_i the $T \times (K \times 2)$ matrix of the spatially lagged regressors and with L the $T \times D$ matrix with each row equal to d_t. Then, $\widetilde{y}_i = My_i$, $\widetilde{X}_i = MX_i$ and $\widetilde{WX}_i = MWX_i$ where $M = I_T - L(L'L)^{-1}L$ is the symmetric and idempotent matrix that, depending on the form of d_t, allows for a very general unit-specific de-trending. It is worth noting that, since LHAs are clustered within regions and cannot move to another one, all time-invariant and time-varying (according to a linear or a quadratic trend) unobserved heterogeneity both at LHA and regional level is wiped-out by this general kind of data de-trending. Once data are transformed, Maximum Likelihood (ML) estimation isfeasible by using the log-likelihood function reported in (Lacombe, 2004).

Since we are in a LHA-year panel setting, cluster-robust standard errors (at LHA level) can be crucial in order to conduct valid inference, even after including LHAs and year effects in the model (Kézdi, 2004; Bertrand et al., 2004). Given the nature of our data and the fact that our model specification does not control for spatial autocorrelation in the errors, we consider a double-clustering strategy that allows to take simultaneously into account their potential geographic-based correlation tepCameron11.

More formally, we consider the following two-way clustered variance–covariance matrix

$$\hat{V}\left[\hat{\Psi}\right] = H^{-1}SCSH^{-1} \quad (5)$$

where S is the Jacobian matrix of all first-order partial derivatives of the log-likelihood function with respect to Ψ, H is the Hessian matrix and C is represented by the following $nT \times nT$ block matrix

$$C = J_T \otimes \widetilde{W} \quad (6)$$

where $J_T = \iota_T\iota_T$ is a $T \times T$ matrix with all elements equal to one and $\widetilde{W}$ is the first-order contiguity matrix W_{all} whose diagonal elements are equal to one and each off-diagonal element w_{ij} is equal to 1 if LHAs i and j share a common border.[21]

5. The data

Our empirical analysis is based on data obtained from different sources and refers to 188 LHAs for the period from 2001 to 2005.

Our dependent variable is the per capita LHA total expenditure obtained from the LHA balance sheets (Conti Economici, CE), net of all revenues that accrue from non-LHA residents (either intra or extra region).[22] In this way we control forboth active and passive patient mobilities, thus avoiding potential confounding effects that may arise due to the presence of heterogeneity in the supply of health care services at LHA level. For example, this heterogeneity may stem from the presence of a highly specialized hospital located in a particular LHA which serves

[16] In our case, D determines the shape of LHA fixed effects; if $d_t \equiv (1)$ the model is the standard fixed effect and $D = 1$; if $d_t \equiv (1, t)$ the model is a random trend and $D = 2$; if $d_t quiv(1, t, t^2)$ the model is a random quadratic trend and $D = 3$ and so on.

[17] See LeSage and Pace(2009) and Elhorst(2010) for a detailed discussion on the possibility of estimating unconstrained spatial direct, indirect and total effects when the model is a SDM.

[18] It is possible to write a SEM model in terms of SDM if the process is stationary (Anselin, 1988).

[19] Notice that the stated conditions are sufficient to simultaneously identify exogenous and endogenous effects in the presence of observational unit fixed-effects.

[20] Row-standardization is required to ensure the existence of the $(I_n - \rho_w W_w)^{-1}$ and $(I_n - \rho_b W_b)^{-1}$ matrices when $|\rho_b| < 1$ and $|\rho_w| < 1$ as in Anselin(2003). Furthermore, one may expect that $\rho Wy = \rho_w W_w y + \rho_b W_b y$. While this is true for SAR models with non standardized matrices, it does not necessarily hold for a SDM with row standardized spatial matrices. The reason lies both in the standardization procedure and in the effects of the spatially lagged regressors on y.

[21] We have written a specific Stata program to estimate the model presented in (4) using the two-way clustered variance–covariance matrix in (5). The program is available upon request.

[22] The list of allrevenue categories (with their codes) which have been subtracted from the total health expenditure (defined in the CE as Total Production CostsÓ; code: B9999) in order to adjust for intra or extra region patients' mobility is available from the authors upon request. In order to compute per capita values, we consider regional population data released from the National Statistical Institute, available at http://www.istat.it/en/population-and-households.

Table 2
Summary stats.

Variable	Mean	(Std. dev.)	Min.	Max.
Share aged 0–15	14.928	(2.427)	10.016	23.467
Share aged 16–30	18.136	(2.378)	11.738	25.136
Share aged 31–40	15.978	(1.031)	12.654	18.57
Share aged 41–50	14.012	(0.694)	12.098	15.903
Share aged 51–65	18.287	(1.622)	13.933	22.089
Share aged 66–85	16.777	(2.828)	8.048	24.937
Share aged over 85	1.882	(0.554)	0.487	4.029
Males share	48.663	(0.593)	46.637	50.503
Immigration rate	0.032	(0.021)	0.002	0.124
Income p.c.	9488.133	(2767.768)	4276.795	19,020.002
Female graduate share	0.398	(0.031)	0.337	0.478
Hospital beds (1000 inhab)	4.456	(1.508)	0.159	8.787
Clercks employed p.c.	0.002	(0.001)	0.001	0.005
Nurse employed p.c.	0.008	(0.002)	0.001	0.015
Doctors employed p.c.	0.003	(0.001)	0.001	0.007
Cardiovascular prevalence	0.179	(0.074)	0.021	0.333
Tumor prevalence	0.064	(0.034)	0.007	0.162
Respiratory prevalence	0.043	(0.027)	0.005	0.188
Public hospital trust	0.597	(1.169)	0	10
Center left gov	0.531	(0.499)	0	1

as a hub for patients coming from LHAs in the same region, and also attract patients from other regions.

Concerning the explanatory variables, we consider a number of demand and supply controls. As far as the demand side is concerned, we control for age, gender, presence of immigrants, prevalence of main chronic diseases and average per-capita income. These variables have been computed as population shares at LHA level. In particular, the income variable has been obtained at LHA level from the income tax declaration data of the Italian municipalities provided by the Italian Department of Finance, whileprevalence of chronic diseases has been obtained from the Health Search Database (HSD), a longitudinal observational database run by the Italian College of General Practitioners (SIMG) since 1998 (Mazzaglia et al., 2004). Finally, we have included the share of graduate women at provincial level. Gender, age and education information come from the Italian National Institute of Statistics (ISTAT).

For the supply side, we include the number of health employees distinguishing between doctors, nurses and administrative staff, the number of beds per 1000 inhabitants and the number of public hospital trusts from the Italian Ministry of Health. Finally, in order to control for the role of politics, we have included a dummy variable equal to one in the case of a center-left regional government. The latter comes from the Ministry of Interior. For estimation purposes, all variables have been log-transformed except for the number of hospital trusts. Summary statistics of the selected variables are reported in Table 2.[23]

6. Results

In this section we report the results of the empirical analysis based on model 4. As regressors we consider the vector x_{it}, which contains all variables reported in Table 2, and the vector z_{it}, a sub-vector of x_{it}, which excludes the time dummies.

Our empirical strategy begins by testing whether the data show spatial dependence. Table 3 shows the Moran's I spatial autocorrelation computed using W_{all}, W_w and W_b for each year of the panel. As can be seen, we find evidence of a strong and statistically significant spatial autocorrelation using W_{all} or W_w, and a much lower (and not statistically significant) using W_b. Then, as we exploit the longitudinal dimension of the data, we perform a Hausman test so as to choose between fixed or random-effects, rejecting the consistency of the latter. Furthermore, using the the Hausman-like test proposed in Bartolucci et al.(2013), we reject the null hypothesis of time-invariant unobserved heterogeneity.[24]

Based on this evidence, we first estimate the spatial and time fixed-effects SDM as a benchmark, and then relax the time-invariant assumption by allowing LHA-specific linear trends.[25]

Table 3
Moran's I.

	W_{all}	W_w	W_b
2001	0.128***	0.146***	0.025
2002	0.115***	0.122**	−0.009
2003	0.120***	0.120**	0.070
2004	0.098**	0.118**	0.047
2005	0.061*	0.096**	−0.081

Note: *** is 1% confidence level (CL), ** is 5% CL, * is 10% CL.

6.1. Identification and model selection

As mentioned in Section 4.2, Bramoullé et al.(2009) derived sufficient conditions for the identification of the parameter vector Ψ in Eq. (4). The first condition (i.e., $\theta_w \neq -\rho_w\beta$ and $\theta_b \neq -\rho_b\beta$) implies that the expected expenditures in the i-th LHA are (directly or indirectly) affected by neighboring LHA characteristics. When this condition is violated, it follows that either endogenous and exogenous effects exactly cancel out or that they are confined to the unobserved component. We report the results of this test for a SDM model estimated using only the W_{all} matrix in Table 4 and those for the model with both the W_w and W_b matrices in Table 5. The tables report the Wald statistics for the null hypothesis elicited in the first column (namely whether the model is a SAR, i.e.,$\theta = 0$, or a SEM, i.e.,$\theta = -\rho\beta$) and the LR test for various definition of unobservable heterogeneity using SDM against either a SAR or a SEM model. As can be noted, the results presented in Table 4 are not coherent, unless we use the variance–covariance matrix reported in Eq. (5). The upper-left side of Table 4 shows that both the tests for SAR and SEM specifications cannot be rejected while the likelihood ratio (LR) test always rejects both specifications. On the contrary, when we control for both time and spatial clustering, the results from both Wald and LR testing become coherent, regardless of the fixed-effect specification. This result suggests that, in our case, valid inference may be conducted using time-spatial clustered standard errors. On the other hand, when we estimate the model with both the W_w and W_b, the results of these tests are non-conflicting, independently from the specification of d_t and of the variance–covariance matrix, with the SDM specification being always the preferred one (see Table 5). In our view, this is a first result pointing towards the need for institutional-consistent spatial weights matrices.

As for the second condition in (Bramoullé et al., 2009) (i.e., matrices' linear independence), it can be easily tested by vectorizing each matrix and verifying if the matrix formed by considering the resulting stacked vectors has full rank, as it is in our case for all possible weight matrices. Having selected the SDM as the preferred model, we test whether a specification with two spatial weight matrices is better than the one with a single matrix. For nested models (i.e., SDM with W_w or W_b only versus SDM with both matrices) we use the LR test, while for non nested models (i.e., SDM with W_{all} versus SDM with W_w and W_b) we follow

[23] This table has been produced using the (Terracol, 2001) Stata command.

[24] In our case, this test can be performed comparing the full and pairwise within estimators of model (4). Although, least squares estimation of model (4) may result in severely biased estimates of ρ_w and ρ_b, this bias affects both the full and the pairwise estimators in the same way without altering the power of the test.

[25] We have also estimated a random "quadratic" trend SDM obtaining very similar results with respect to the linear trend specification. Since they show qualitatively the same story, we have chosen the more parsimonious model.

Table 4
Tests for model selection $^{-}W_{all}$.

	Single clustering		Double clustering	
	Test	P-value	Test	P-value
Time invariant				
H_0: $\theta_a = 0$	1.3	0.154	5.8	0.000
H_0:$\theta_a = -\rho_a\beta$	1.2	0.216	2.2	0.007
Random trend				
H_0: $\theta_a = 0$	1.3	0.157	6.1	0.000
H_0:$\theta_a = -\rho_a\beta$	1.2	0.217	2.9	0.000
LR test against SAR model				
Time invariant	37.342	0.007		
Random trend	37.383	0.007		
LR test against SEM model				
Time invariant	31.745	0.033		
Random trend	38.097	0.006		

Table 5
Tests for model selection $-W_w$ and W_b.

	Single clustering		Double clustering	
	Test	P-value	Test	P-value
Time invariant				
H_0: $(\theta_w, \theta_b) = 0$	1.5	0.022	3.4	0.000
H_0: $(\theta_w = -\rho_w\beta, \theta_b = -\rho_b\beta)$	2.1	0.002	6.3	0.000
Random trend				
H_0: $(\theta_w, \theta_b) = 0$	2.3	0.000	6.3	0.000
H_0: $(\theta_w = -\rho_w\beta, \theta_b = -\rho_b\beta)$	1.4	0.049	8.8	0.000
LR test against SAR model				
Time invariant	89.490	0.000		
Random trend	55.828	0.031		
LR test against SEM model				
Time invariant	92.101	0.000		
Random trend	64.840	0.004		

(Burnham, 2004) model selection strategy based on the following modified information criteria.

$$AIC_c = -2\log\left(\ell\left(\hat{\Psi}\right)\right) + 2K + \frac{2K(K+1)}{N-K-1} \tag{7}$$

As shown in Table 6, the single matrix specifications are always nested in the specification with both W_w and W_b.[26]

Table 7 reports the AIC_c for all model specifications: the within-between random trend SDM seems to be the best model. Finally, it is important to highlight that the specifications which include the W_{all} are never chosen, a result that reinforces the need to properly define the contiguity structure in the presence of institutional constraints.

6.2. The spatial effects

It is worth noting that our empirical strategy allows to test the implications of the theoretical framework discussed in Section 4.1. Indeed, we expect that a voter exploiting all available information about the institutional setting, will be mainly influenced by within neighbors rather than by the between ones (i.e.,$\alpha_B \simeq 0$).

The estimated spatial effects are reported in Table 8. When we jointly control for both the within and the between matrices, the empirical results support the model implications, with ρ_w (the empirical counterpart of α_w) that is positive and statistically significant, while ρ_b is negative and statistically significant, although very close to zero. While the former coefficient is in line with our theoretical model, at first glance the latter might seems a bit puzzling. However, it may be due to behaviors that, although not explained by our model, are not in contrast with it. In particular, the negative sign of ρ_b may arise because of some forms of “free riding” between contiguous LHAs belonging to different regions. The promotion of prevention campaigns, investments in new machinery equipment for better diagnostics and surgery procedures, investment in the adoption of evidence-based medicine by physicians, and similar activities tendto increase per capita expenditures in the regions where these activities take place, while potentially inducing beneficial health effects (e.g., shorter waiting times, reduced risk factors, and better diagnostics) also for the citizens of the other regions, especially the contiguous ones.[27]These externalities might induce a free riding behavior, by reducing the incentive of these regions to engage in the same costly strategy. While our data do not allow us to net out these confounding effects, these arguments are consistent with our theoretical model and may plausibly explain the negative sign of ρ_b.

Compared to previous studies, we find that our ρ_w is equal to 0.35 a value which falls in the range of other studies that analyzed health expenditures in a spatial setting, but without controlling for the institutional framework. For example, Costa-Font and Pons-Novell(2007) found a spillover effect of 0.291 in Spain using a spatial error model. Also Barreira(2011), using IV techniques, found even stronger spillover effects (0.43) in the Portuguese context, while Moscone and Knapp(2005) found a lower value (0.12) in the analysis of UK's mental health expenditures.[28]

As shown in Table 8 comparing the spatial coefficient across models characterized by a different definition of contiguity (i.e., models in which the specification of the spatial weight matrix is different), it can be seen that the coefficients obtained using the W_{all} or the W_w matrix alone are very similar in magnitude and both positive and significant, while the estimate of ρ_b using W_b alone is close to zero.

On the other hand, the bottom panel of Table 8 shows the result of the model including both the within and between matrices. Even if the estimated ρs are only slightly different from the previous ones (this is due to the orthogonalityof the W_w and W_b matrices), it is worth emphasizing that the proposed modification of the contiguity structure greatly enriches the informativeness of marginal effects,

Table 6
LR test for matrix partition in SDM.

	Test	P-value
SDM (W_w) ⊂ SDM (W_w and W_b)		
Time invariant	40.37	0.004
Random trend	31.47	0.049
SDM (W_b) ⊂ SDM (W_w and W_b)		
Time invariant	73.64	0.000
Random trend	152.66	0.000

Table 7
Information criterion.

	AIC_c	
	Time invariant	Random trend
W_{all}	−2597.347	−3725.412
W_w and W_b	−2621.971	−3747.234

[26] Since AIC is a large-sample approximation, the last term in (7) represent a second-order bias adjustment needed when N/K is relatively small.

[27] For example, the Calabria's LHAs are characterized by one of the lowest per capita expenditure also because many of their hospitals have obsolete equipments leading to very high patient outflows (see Table 1).

[28] This result may be driven by the fact that the authors analyze a very specific component of health expenditures.

Table 8
Spatial effects.

	Time invariant	Random trend
SDM with single matrix		
ρ_{all}	0.173	0.345***
ρ_w	0.201**	0.371***
ρ_b	−0.063	−0.087***
SDM with double matrix		
ρ_w	0.167	0.350***
ρ_b	−0.036	−0.066***

Note: *** is 1% confidence level (CL), ** is 5% CL, * is 10% CL.

helping to shed light on the determinants of public health expenditures (see Table 10).

6.3. Direct, indirect and total effects

In a spatial econometric model, the effect of an explanatory variable change for a specific unit will affect not only that unit but also its neighbors. Hence, the coefficient β is just a component of the total (marginal) effect, to which the effect of the spatially lagged explanatory variable should be added.

More precisely, for each regressor we have a $N \times N$ matrix of coefficients, indicating how a change in that regressor influences all the units in the sample. This implies that, if K is the number of controls in the model, we have K matrices of dimension $N \times N$ of indirect effects and K vectors of dimension $N \times 1$ of direct effects. The latter are the diagonal elements of the $N \times N$ matrix of total effects and indicate how the dependent variable changes in unit i given the changes in the k^{th} regressor in unit i. Indirect effects are, instead, the off-diagonal elements of the matrix of total effects and indicate how a change in the explanatory variable in unit i affects the dependent variable in unit j through a feedback process (see (Elhorst, 2010)). Furthermore, it should be noted that the estimated direct and indirect effects may go in opposite directions, thus looking only at one of them may not be enough. Finally, given the longitudinal nature of this study, the effects we present should be interpreted as “short-run” effects, whereas LHA fixed-effects are the “long-run” effects.

Direct and indirect effects are reported in Table 9, where the columns 1 and 3 report the average effects for the SDM with time invariant fixed-effects, while the other two columns report the average effects for the SDM with fixed-effects and a unit-specific linear trend. In this specific setting, the specification of the fixed-effects seems to have the greatest impact on the estimated average effects with respect to the single or double matrix specification.[29] Based on Section 6.1, we focus on the random trend specification. Demand side determinants play a greater role for the direct effects. In particular, the younger the population or the higher the share of graduate women, the lower is the health expenditure, whereas coefficients for the supply side are never significant except for the number of public hospital trusts. On the other hand, supply side is more important for the indirect effects. In particular, an increase in the number of public hospital trusts or in the income per capita in nearby LHAs increases the expenditure in the LHAs of interest: both aresymptomatic of a demand induced by the supply side.The expenditure decreases with number of hospital beds, because it is a fixed cost averaged over more individuals.

As for per-capita income, the coefficient in the total effect is positive and significant as expected. Given that income is expressed in logs, we can also infer that public health expenditure is not a luxury good, since the elasticity is lower than 1, reflecting the fact that the Italian NHS offers universal health care coverage, regardless of individual income. This result is also in line with the findings by Costa-Font and Pons-Novell(2007).

[29] Estimate tables have been produced using (Jann, 2005) Stata program.

Table 9
Average direct, indirect and total effects from fixed-effects SDM estimates —$n = 940$.

	W_{all}		W_w and W_b	
	Time invariant	Random trend	Time invariant	Random trend
Direct effects				
Share aged 0–15	0.096	−2.412*	0.120	−2.673**
Share aged 31–40	−1.564**	−1.600**	−1.605**	−1.377**
Share aged 41–50	−1.373**	−0.796	−1.394**	−0.862
Share aged 51–65	−0.377	−0.504	−0.599	−0.567
Share aged 66–85	−0.032	−0.505	0.327	−0.018
Share aged over 85	−0.241	−0.006	−0.205	−0.012
Males share	−5.760***	−3.921	−2.749	−3.496
Clerks employed p.c.	0.032	−0.008	0.040	0.008
Nurse employed p.c.	0.088	0.074*	0.080	0.084
Doctors employed p.c.	0.014	−0.007	0.026	−0.008
Public hospital trust	0.051***	0.053**	0.055***	0.055**
Hospital beds (1000 inhab)	−0.010	−0.000	−0.011	−0.001
Income p.c.	0.215	0.068	0.249	0.151
Immigration rate	−0.041	0.034	−0.076	0.036
Female graduate share	−0.257	0.096	−0.323	−0.360*
Respiratory prevalence	0.005	−0.010	0.000	−0.012
Cardiovascular prevalence	0.018	0.005	0.018	0.007
Tumor prevalence	−0.002	0.014	−0.001	0.013
Center-left gov	−0.026	0.006	−0.014	−0.074**
Indirect effects				
Share aged 0–15	1.326	1.069	0.936	1.226
Share aged 31–40	1.293*	−0.925	1.119*	−1.217
Share aged 41–50	−0.209	−2.875*	−0.365	−1.838
Share aged 51–65	0.974	−1.742*	1.222	−1.329
Share aged 66–85	−0.121	−0.452	0.070	0.078
Share aged over 85	−0.062	−0.443	0.065	−0.369
Males share	−8.380*	11.677*	−3.132	13.915***
Clerks employed p.c.	−0.036	0.025	−0.042	0.084
Nurse employed p.c.	−0.027	0.069	−0.007	0.132
Doctors employed p.c.	0.047	−0.103	0.135	−0.139
Public hospital trust	−0.012	0.061*	0.002	0.061*
Hospital beds (1000 inhab)	−0.038	−0.032	−0.076**	−0.049*
Income p.c.	−0.259	0.375*	−0.044	0.389**
Immigration rate	0.155	0.111	0.145*	0.077
Female graduate share	−0.048	−0.315*	0.147	0.324
Respiratory prevalence	−0.049	−0.048	−0.059	−0.026
Cardiovascular prevalence	0.017	0.031	0.015	0.049
Tumor prevalence	0.048	0.047	0.036	0.023
Center-left gov	0.052**	0.042	0.020	0.117**
Total effects				
Share aged 0–15	1.422	−1.343	1.056*	−1.447
Share aged 31–40	−0.271	−2.525*	−0.486	−2.594*
Share aged 41–50	−1.581*	−3.671**	−1.759**	−2.700*
Share aged 51–65	0.597	−2.247*	0.622	−1.896
Share aged 66–85	−0.153	−0.957	0.398	0.060
Share aged over 85	−0.304	−0.449	−0.140	−0.380
Males share	−14.140**	7.756	−5.881	10.420
Clerks employed p.c.	−0.004	0.017	−0.002	0.092
Nurse employed p.c.	0.061	0.144	0.073	0.216**
Doctors employed p.c.	0.061	−0.110	0.161	−0.147
Public hospital trust	0.039**	0.113**	0.057**	0.116**
Hospital beds (1000 inhab)	−0.048	−0.032	−0.087*	−0.050
Income p.c.	−0.045	0.442*	0.205	0.540**
Immigration rate	0.114	0.145	0.068	0.112
Female graduate share	−0.305**	−0.219	−0.176	−0.036
Respiratory prevalence	−0.043	−0.057	−0.059	−0.037
Cardiovascular prevalence	0.035	0.036	0.033	0.056
Tumor prevalence	0.046	0.061	0.035	0.035
Center-left gov	0.026*	0.048**	0.006	0.043
$W_{all}z$	Yes	Yes	No	No
$W_w z$	No	No	Yes	Yes
$W_b z$	No	No	Yes	Yes
Log-likelihood	1344.89	1910.70	1378.59	1942.58

Note: *** is 1% confidence level (CL), ** is 5% CL, * is 10% CL.

The proposed empirical strategy enables us to distinguish not only between direct, indirect and total effects but also to disentangle the within from the between contribution. This is a natural extension, not yet explored in the literature, that is very helpful to fully appreciate

Table 10
Total effects partition $-n = 940$.

	Within and between	Within only	Between only
Share aged 0–15	−1.447	−2.887*	−1.559
Share aged 31–40	−2.594*	−3.125*	−0.885
Share aged 41–50	−2.700*	−1.631	−1.541*
Share aged 51–65	−1.896	−0.436	−1.634
Share aged 66–85	0.060	−0.421	0.381
Share aged over 85	−0.380	−0.466	0.071
Males share	10.420	6.820	−1.236
Clercks employed p.c.	0.092	0.012	0.067
Nurse employed p.c.	0.216**	0.162	0.118**
Doctors employed p.c.	−0.147	−0.070	−0.061
Public hospital trust	0.116**	0.109**	0.058***
Hospital beds (1000 inhab)	−0.050	−0.039	−0.007
Income p.c.	0.540**	0.576**	0.104
Immigration rate	0.112	0.142	0.008
Female graduate share	−0.036	−0.101	−0.326*
Respiratory prevalence	−0.037	−0.026	−0.020
Cardiovascular prevalence	0.056	0.038	0.018
Tumor prevalence	0.035	0.059	−0.007
Center-left gov	0.043	0.023	−0.065**

Note: *** is 1% confidence level (CL), ** is 5% CL, * is 10% CL.

the usefulness of our approach. Table 10 presents the total effects for a model estimated using both W_w and W_b where the marginal effects have been computed, respectively, setting the between (within) component equal to zero. The negative effect of the younger age shares is mainly due to the spillover coming from neighbors within the same region while the effect of the women's graduate share stems from the between neighbors. Given the fact that resources are transferred from the central government to regions mainly according to their age composition this result is not surprising: the effect of explanatory variables that are already “controlled for” in the capitation formula is expected to be mainly within, while we expected a greater importance of the between effect for those that are not.

Finally, it is worth mentioning that, due to the result of a compensation between a negative and significant direct effect and a positive and significant indirect effect, the total effect of the political dummy is not statistically significant, whenthe effects are computed considering both the within and between contributions (see Table 9 and column 1 of Table 10). Furthermore, when we distinguish between the within and between total effects we observe a negative and significant between total effect. This result was expected since the political dummy is defined at regional level.

7. Conclusions

Despite over the last two decades spatial econometric models have attracted a lot of attention, scholars have neglected the role that institutional constraints can have in the propagation of spatial spillovers. The presence of institutional constraints is a rather common feature when dealing with spatial analyses: it shows up each time we observe geographical entities (e.g., counties, regions, nations) which share common borders, but obey different institutional settings. In all these cases ignoring this feature may induce misleading conclusions in the empirical analysis.

As discussed in this paper, under these circumstances, and if institutions do play a role, spatial effects play a role mainly within entities belonging to the same institutional setting, while the between effect across different institutional settings should be attenuated or totally absent, even if the entities share a common border. In this case, relying only on geographical proximity will then produce biased estimates, due to the composition of two distinct effects. On the other hand, focussing only on one dimension gives only a partial picture.

Our goal with this paper has been to derive a theoretical consistent methodology that partitions the standard contiguity matrix into two matrices (within and between), thus allowing to disentangle the overall spatial effect and to derive interesting testable implications. The empirical analysis has been based on expenditure data from the Italian Local Health Authority from 2001 to 2005, using spatial panel techniques.

As expected, we find robust evidence of a significant and positive spatial coefficient for the within effect, while the between effect, although negative and significant, is very close to zero, thus confirming the importance and validity of our approach.

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