A spatial analysis of inter-regional patient mobility in Italy

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Abstract
Free patient mobility among regions is a stimulus for enhancing healthcare. However, because of scale economies and spatial externalities, jurisdictions may underperform thus challenging the sustainability of regional budgets in decentralised national health systems. Inter-regional patient flows are analysed using 2001-2010 years data on Italian hospital discharges and estimating a dynamic spatial panel model that includes a rich set of push and pull factors and controls for region-pair-specific unobserved heterogeneity. Evidence is provided on scale effects, spatial spillovers (not controlled by regional authorities) and on the role of local supply factors, namely hospital capacity, technology, specialization and performance indicators.

Keywords: inter-regional patient mobility, hospital admissions, decentralised health systems, spatial spillovers, negative binomial gravity model, nonlinear panel data methods

JEL: C23, I11, R23, R50

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1. Introduction

In several national health systems, free patient mobility for hospital care has been encouraged through specific policies with the ultimate aim to gain quality improvements by stimulating competition. This mechanism is expected to work at the regional level especially in decentralised systems, in which hospital care is financed through general taxation and local governments pay for the treatments received by their residents, independently of the location of the healthcare provider. Inter-regional patient mobility may affect the local budgets because of financial losses in the case of reimbursements of hospital admissions outside the region, and gains from non-residents admissions. In this setting, administrators should aim to raise quality, not only to increase citizen satisfaction, but also to restrain outflows of their own enrolees and possibly attract patients from other jurisdictions.

These arguments might not follow, however, where significant asymmetries among competing jurisdictions exist. Regardless of the "effort" made by local policy-makers, some jurisdictions might underperform and experience budget unbalances due to the existence of economies of scale and spatial spillovers among them. If this is the case, patient mobility could complicate the mechanism through which competition works among different locations. From this perspective, the Italian National Health Service (NHS) represents an interesting case of study, because it is a *regionally decentralised* tax-funded system in which patients are entitled to choose any preferred provider of hospital care all over the country.

The NHS is characterised by a high and persistent inter-regional patient mobility (7.5 percent of total admission in 2010) with the geography of hospital admissions favouring flows from southern regions mainly towards central-northern ones: 34.2 percent of total inter-regional flows move in this direction. The current institutional setting is the result of a series of reforms, initiated in 1992, that have introduced universal free patient choice and created 21 separate and autonomous regional health services (RHSs), formally responsible for healthcare organization in their jurisdictions and care delivery for the residents therein. Devolution in healthcare also involved the funding system, through the introduction of a regional tax that partially finances the regional healthcare budgets. Nonetheless, RHSs are subject to central government planning policies, which define the essential levels of care and the overall expenditure ceilings. Free patient choice implies that hospital admissions taking place outside the RHS of enrolment are reimbursed using inter-regional compensation schemes centred on Diagnosis Related Groups (DRG)-based tariffs. This has increased the economic incentive for the regional policy-makers to use patient mobility for attracting financial resources. Decentralisation of the NHS has become fully effective with the constitutional reform approved in 2001, which provided Italian regions with a larger autonomy in the organisation of the healthcare services.

Such configuration of the NHS, common to many European countries such as Italy, Spain, Denmark, Germany and Austria (ADOLPH et al. 2012), can have controversial effects on the efficiency and effectiveness of the healthcare services provided at the regional level, as well as on universalism and equity at the national level, in countries with relevant regional asymmetries. The theoretical literature suggests that free patient choice (under the hypothesis of symmetric jurisdictions) should determine lower, even zero, voluntary inter-regional mobility in the long run, because competition stimulates quality levelling and equal sharing of the market (BREKKE et al. 2010, 2012). However, patient flows across Italian regions have not exhibited any tendency to decrease since the abovementioned constitutional reform. In fact, central-northern regions are net exporters of hospital treatments as their hospitals admit a larger number of patients coming from the South. Concurrently, the compensation of net patient flows has generated additional amounts of financial resources in favour of central-northern regions, and has exacerbated the North-South gradient in the Italian NHS.

The aim of this paper is to enhance the understanding of the phenomenon by providing a comprehensive picture of the patterns of inter-regional patient mobility. More specifically, the analysis focuses on whether and to what extent patient mobility is driven by factors related to policies pursued by the regional health authorities rather than by exogenous factors related to geography, demography and neighbouring- or national-level policies. These issues are addressed by means of an empirical model for inter-regional patient mobility that occurred in Italy after the accomplishment of the decentralisation reforms of the nineties. The analysis makes use of panel data on hospital discharges occurring yearly over the period 2001-2010 in all hospitals, merged with information on the demographic and economic characteristics of Italian regions and on important features of hospital care services in each RHS.

Bilateral Origin-to-Destination (OD) flows between any two regions are analysed by means of a gravity regression model that includes a rich set of push and pull factors. Compared to previous studies, mainly performed on cross-section samples, the longitudinal dimension of the data enables one to estimate a nonlinear conditionally correlated random effects (CCRE) dynamic model that accounts for region-pair-specific unobservable heterogeneity. Moreover, the issue of cross-regional dependence arising from the existence of regional spillovers is addressed by applying recent advances in spatial econometrics (ELHORST, 2014; VEGA and ELHORST, 2015).

Main results suggest that, beside regional population size and income, local supply factors such as hospital capacity and technology endowment, clinical specialization and performance indicators are important drivers of patient mobility. Moreover, geography significantly matters and spatial proximity plays a relevant role in reinforcing inter-regional mobility patterns. Finally, the estimation results are used to illustrate a specific policy scenario relevant to the national and sub-national management of healthcare.

2. Related literature

The theoretical literature has not specifically focused on the analysis of inter-regional patient mobility *per se*, but rather on the effects of patient choice and competition on the behaviour of healthcare providers in the context of regulated prices. Spatial competition models *à la* Hotelling have been used to study patient mobility in decentralized settings in which patients are eligible to receive free care at the point of use (see, e.g., MONTEFIORI, 2005; BREKKE et al., 2010, 2012). These models allow for the simultaneous presence of horizontal (either defined in terms of physical location or healthcare specialization) and vertical (quality) differentiation among jurisdictions. *Ceteris paribus*, the higher the quality gap between providers, the larger the number of patients who seek care in the higher quality region.

While the transitional dynamics in patient mobility may depend on various assumptions, an equilibrium with permanent inter-regional mobility (such as that observed in the data used in this analysis) can be explained only assuming asymmetry between regional systems. LEVAGGI and MENONCIN (2013), consider a context in which regions exhibit different exogenous efficiency levels and are subject to a "soft budget constraint".[1] They find that inefficient regions have an incentive to induce patient flows towards the most efficient regions in exchange for a higher probability of being bailed out. Bailing out is accepted by the efficient regions because they receive the financial benefits related to incoming patients, whose hospital treatments are reimbursed on the basis of a regulated tariff (typically higher than the marginal cost). The overall equilibrium is inefficient and characterised by an excess of patient mobility because of imperfect coordination among government levels. BREKKE et al. (2014) analyse a situation whereby regional jurisdictions differ in their ability to provide healthcare. They indicate that permanent inter-regional mobility, compared to the absence of mobility, might ensure an increase of overall welfare, though with asymmetric effects. There is a benefit for all patients living in the high-performing regions and those moving there for hospital care, and a loss for patients receiving care in the low-performing regions.

The above-mentioned models of bilateral spatial competition have a natural empirical counterpart in terms of gravity models, in which patient flows between pairs of RHSs are influenced by “mass” indicators at origin and destination and depend negatively on the distance between the two “trading” areas. The gravity model has been widely used to analyse patient flows among competing hospitals (CONGDON, 2001; LIPPI BRUNI et al., 2008) and physicians (SCHUURMAN et al., 2010). Much of the extant empirical literature on patient mobility across jurisdictions, however, has focused on the determinants of net patient flows: LEVAGGI and ZANOLA (2004) and CANTARERO (2006) at the regional level, SHINJO and ARAMAKI (2012) at the level of local healthcare areas. FABBRI and ROBONE (2010), instead, estimate a gravity model for bilateral patient flows occurred in 2001 across 171 Italian Local Health Authorities (LHAs), which are accountable for healthcare delivery. They include indicators for technology, presence of hospital trusts and factors characterizing the origin-destination pair. They also account for geographical patterns by including a set of measures based on distances between LHAs and use a spatial filtering technique to purge potential network autocorrelation, which typically characterises migration flow data. The analysis reveals the existence of important scale effects and a poor-rich gradient in patient flows across LHAs.

This study contributes to the current debate on the determinants of patient mobility by analysing their evolution after the accomplishment of the NHS decentralisation and estimating a dynamic panel gravity model for bilateral inter-regional flows, which explicitly accounts for the existence of spatial spillovers.

3. Data and variables

Inter-Regional Patient Flows in the Italian NHS

The analysis is based on administrative data on hospital discharges occurred yearly over the period 2001-2010 in all public and private licensed hospitals of the 21 Italian RHSs. Information on inpatient care is collected by each hospital at the time of discharge and transmitted to the Ministry of Health. Each admission episode is classified using the United States Medicare DRG and the actual length of stay is reported. The data at hand contain valuable information about hospital type, LHA and region where the admission occurred, as well as patient’s LHA and region of residence.

The analysis focuses on deliberate mobility for treatments, which, in principle, is available in each region; thus, data on non-deferrable mobility are discarded.[2]

The unit of analysis is represented by pairs of regions that exchange patients. For each year a 21x21 OD matrix is constructed. Each cell of the matrix contains patient flows obtained by aggregating the number of admissions of patients from each possible region of origin (enrolees in region *i*) in hospitals of each possible region of destination (region *j*). The main diagonal of each matrix is set to zero to exclude intra-regional flows. Thus, 420 bilateral OD patient flows per year are analysed.

Table 1 describes inter-regional flows for all types of admissions (henceforth *Total Flows*), and for specific types classified as *Surgery*, *Medicine* and *Cancers*. *Surgery* and *Medicine* consist of admissions in any surgical and medical DRGs, respectively; the former, entailing higher clinical complexity, are typically reimbursed on the basis of higher tariffs. *Cancers* include all cancer-related admissions, which can be very heterogeneous in terms of clinical complexity and resource intensity and are often associated with long-distance travels toward high-specialized centres.

In the period 2001-2010, an average of 832,410 admission episodes per year occurred in a region different from that of residence. Inter-regional mobility amounts to approximately 7 percent of total admissions. Table 1 also describes the geography of hospital admissions. It shows that patients tend to move mainly from southern to central-northern regions and that approximately 45 percent of total mobility is generated by southern regions.

Table 2 reports four mobility indicators computed at region and macro-region level in the years 2001 and 2010: the *creation rate* (percentage ratio between the outflows of a given region and the total number of patient flows), the *attraction rate* (percentage ratio between the inflows of a given region and the total number of patient flows), the *outflow rate* (percentage ratio between the outflows of a given region and the total number of admissions of the region's enrolees) and the *inflow rate* (percentage ratio between the inflows in a given region and the total number of the region's admissions).

All mobility indicators described in Table 2 exhibit large regional variation, suggesting the existence of clear spatial patterns. On average, the creation rate is higher in the central-northern regions than in the southern ones. Regional disparities, however, are slightly decreasing over time, as described by the coefficient of variation (it moves from 0.62 to 0.59). In 2010, in fact, the regions that create more inter-regional mobility are those most densely populated (i.e., Campania, in the South, Lombardia, in the North and Lazio, in the Centre). With respect to 2001, only Sicilia leaves the group of the four regions that create more mobility. The smallest and least populated regions (Valle d'Aosta, Provincia Autonoma di Bolzano, Provincia Autonoma di Trento, Friuli Venezia-Giulia, Molise) and Sardegna, most likely due to insularity, generate less than 2 percent of total flows, a figure that is very stable over time. It emerges a clear dichotomy between the southern regions (18.2) and the rest of the country (81.8) in the attraction rate for 2010. These figures have basically not changed since 2001. The distribution of the attraction rate is quite dispersed, while the distance between the regions with the highest and lowest rates (Lombardia and Valle d'Aosta) is slightly shorter in 2010. The regions that admit more non-resident patients are Lombardia, Emilia-Romagna and Lazio (with attraction rates of 18.7, 14.6 and 9.8 percent, respectively).

The inflow rate confirms the limited role played by southern RHSs (3.8 in 2010) as destinations for patients seeking care outside the home regions when compared to centre-northern RHSs (9.20). Although to a lesser extent, the reverse is the case when considering the outflow rate. Patient flows are further examined by using the mobility index, which measures the ratio between the inflow and the outflow rates. It takes values larger than 1 when the RHS is a net importer of patients (net exporter of hospital admissions) from other RHS, thus being able to offset the outflows with larger inflows. Figure 1, which depicts the mobility index in 2001 and 2010, confirms the presence of spatial patterns in patient mobility. These are likely due to the influence of demand and supply features of the RHSs at origin and destination and seem to reflect the well-known North-South economic divide, as richer and better equipped regions effectively attract more patients and resources.

Characteristics of Regions at Origin and Destination

The variables that are expected to influence patients' choice, as well as the ability of the RHS to restrain outflows and attract inflows of patients, are distinguished between potential push (at origin) and pull (at destination) factors. Table 3 reports a complete description of all variables used in the econometric analysis.

Patient outflows are expected to be directly proportional to the economic mass of the origin region. *Population* is considered as the mass variable; it indicates the number of enrolees at the RHS and approximates the internal demand for healthcare in each RHS. Bigger regions have a higher internal demand of hospital care, which might induce more variety in the range of specialised health services provided in the area. Furthermore, higher populated regions may exploit economies of scale, leading to cost minimization as well as more and better services. For these reasons, highly populated regions should be able to restrain patient outflows better than small regions.

Per capita Gross Domestic Product (GDP) is included to account for both micro and macro level effects. The former effect is related to the patient ability to travel and seek care outside the region of residence (the hypothesis is that richer individuals have a wider range of hospitals choice, being less constrained by travel and accommodation costs). The macro-level income effect is related to the ability of the RHS to provide efficient and high-quality hospital services (poorer regions would experience outflows of patients towards richer regions). At destination, both *population* and *per capita GDP* are expected to have a positive effect on the number of admissions for extra-regional patients. Among the origin features, two demographic indicators are also included, *population age 0-14* and *population over 65*, that capture the effect of belonging to the frailer population groups on the likelihood of seeking care in extra-regional hospitals.

Another factor that can influence bilateral flows is hospital supply at the regional level. This is measured by the number of *beds in public hospitals* and *in private licensed hospitals* to capture any potential effect of the public-private mix. An excess of hospitals beds is typically considered a signal of bad management, which can translate into a waste of resources, as well as worse quality.[3] Thus, on one side, it is expected that a RHS becomes more inefficient as the number of beds increases, and this should explain larger (smaller) patient outflows (inflows). On the other side, a higher hospital capacity is likely to lower waiting lists, and this should be perceived by patients as an improvement of the regional offer of hospital services leading to smaller (larger) outflows (inflows).

The ‘method of penalties by coefficient of variation’ (MAZZIOTTA and PARETO, 2015) is applied to build a composite *technology endowment index* (TEI). It is obtained from a set of 25 indicators on the number of medical devices available each year in each region.[4] The method, recently applied also by the Italian National Institute of Statistics to measure the infrastructural endowment of the RHSs, is based on the assumption of non-substitutability of the single indicators. To compute the composite index each indicator is rescaled according to population in each region and then standardized. The average of the standardized values of each region is corrected by subtracting a quantity proportional to the coefficient of variation. This ensures that regions which exhibit a strongly unbalanced technological endowment are penalized; the higher the TEI the higher the availability and the comprehensiveness of the technological endowment among the single indicators values. Therefore, regions with a high TEI are expected to restrain patient outflows and increase the inflows.

The *case mix index* (CMI), the *comparative index of performance* (CIP) and an indicator of *concentration of the organizational structure* are also included. These indicators, which describe the distinctive features of each RHS, are computed using all admissions records occurred yearly in the regional hospitals. Because inter-regional patient flows are only a small share of total admissions, any reverse causality issue can be reasonably ruled out.

The CMI allows one to compare the RHSs on the basis of the financial and physical resources allocated to treat all hospital admitted patients. A value greater than 1 indicates a mix of cases more resource-intensive than average. Hence, at the regional level, the CMI can be viewed as an index for specialization in cases with higher resource intensity. It is worth noting that specialization could be either a demand-driven phenomenon, or the result of the interplay between RHS strategies and patient needs. On the one hand, it could be expected that patients are attracted by the RHS that are known for being specialized in highly complex cases. On the other hand, such specialization could induce an increase (reduction) in outflows (inflows) of patients who are forced to seek the less complex care (e.g., because of long waiting lists) in other regions. In this case, the hospital's decision to privilege cases with higher resource intensity might be related to higher profit margins. In this regard, the raw data suggest some convergence in the regional CMI for the period 2001-2010: central-northern regions exhibit initially higher (and decreasing) CMI and higher inflow rates, while southern regions exhibit a lower (and increasing) CMI and lower inflow rates.

The CIP measures the relative performance of the RHS in managing hospital length of stays. A CIP up to value 1 indicates that, assuming equal complexity, hospital stays are shorter (or have the same length) than at the national level, thus suggesting higher (or equal) efficiency relative to the standard. The conventional interpretation would be that inefficiency (higher values of CIP) increases outflows and makes a region less able to attract extra-regional patients. An additional reading of the link between CIP and patient mobility could be that longer hospital stays (for any given case-mix level) are associated with the subjective perception of the patients of a better hospital care quality, in which case the effect would be to decrease outflows at the origin and increase inflows at the destination.

For each region, the indicator of *concentration of the organizational structure* is built by using the Hirschman-Herfindahl index (HHI), where the shares are calculated as the ratio of admissions in a given hospital type over total admissions.[5] The HHI reflects regional differences among organisational strategies about the hospital care network. The effect of higher concentration is more easily understood in terms of reduced variety. At origin, a reduction of variety on the supply side, by limiting the patient choice set, can negatively affect the perceived quality, thus leading to a rise in outflows. Similarly, if the destination region is characterised by a greater concentration, inflows are expected to decrease. By contrast, a higher variety of providers is expected to restrain outflows and increase inflows.[6] Finally, geographical dummies for the three macro-areas of the country (*South, North* and *Centre*) are included. As a matter of fact, historically, Italian regions display strong asymmetries in terms of geographical size, per-capita income, population and accessibility to transport networks.

Region-Pairs Characteristics

Within the gravity model framework, one of the most important determinants of bilateral flows is geographical *distance*. Because it acts as a proxy for transportation and information costs, it is expected to exert an adverse effect on patient mobility.

The distance effect might be moderated by other factors. A measure of *past migration flows* that occurred between each OD pair in the previous five years is also included. This indicator is expected to have a positive impact on patient mobility because past migrations can represent a local source of knowledge about medical services for non-resident patients. A measure of *political similarity* is also included to capture factors such as institutional collaboration in managing hospital care between regions belonging to the same political coalition. Politically closer regions should be more likely to "trade" hospital admissions either because of shared information on best practices in other regions or strategic cooperation in investing in complementary healthcare services, particularly cross-borders.

4. Methodology

The empirical analysis is conducted within a gravity model framework for panel count data. The following exponential functional form for the conditional mean of the process is adopted:

$$\mathrm{E}\left[\mathbf{Y}_{\mathrm{ijt}}|\mathbf{X}_{\mathrm{t}},\alpha_{\mathrm{ij}}\right]=\alpha_{\mathrm{ij}}\ \exp\left(\mathbf{X}_{\mathrm{it}}\beta_{\mathrm{o}}+\mathbf{X}_{\mathrm{jt}}\beta_{\mathrm{d}}+\mathbf{X}_{\mathrm{ijt}}\beta_{\mathrm{od}}+\mathbf{dist}_{\mathrm{ij}}\gamma_{\mathrm{od}}\right) \tag{1}$$

where the subscript *i* refers to the region of Origin, *j* to the region of Destination and *t* to time, with $t = 2001, \dots, 2010$. The observations in each year refer to pairs of OD regions, $ij = 1, \dots, 420$. $\mathbf{Y}_{\mathrm{ijt}}$ is the number of admissions of patients resident in region *i* who seek hospital care in region *j* at time *t*. The matrices $\mathbf{X}_{\mathrm{it}}$ and $\mathbf{X}_{\mathrm{jt}}$ include the variables describing the most salient features of the regions at origin and destination, respectively. The matrix $\mathbf{X}_{\mathrm{ijt}}$ includes the variables that represent the distinctive traits of each region pair. The variable

$\mathbf{dist}_{ij}$ captures the geographical distance between regions in each OD pair. The term α_{ij} is the individual pair effect.

The estimation of model (1) requires addressing the methodological challenges posed by the estimation of *short* panel count data models when cross-section dependence, overdispersion, unobservable heterogeneity and serial correlation are possibly present. For consistency of the estimators, estimation of (1) based on the Poisson density requires cross-section independence and strict exogeneity of the regressors, while serial correlation could be allowed for as long as the dynamics is correctly specified by an adequate number of lagged terms. In what follows, it is explained how each feature of the data is tackled to ensure the use of consistent estimators.

Flow data are typically characterised by cross-section dependence induced by correlation in space (GRIFFITH and JONES, 1980; LE SAGE and PACE, 2008 and 2009). The latter arises because flows of a given origin are influenced by the features of the neighbouring regions. Analogously, flows towards a specific destination respond also to features of the nearby destinations. The traditional gravity model is underspecified as it relies just on a function of the OD distance to clear spatial correlation and insure cross-section independence. In this analysis the existence of spatial spillovers is explicitly addressed for both methodological and substantive economic motives. As emphasised in LE SAGE and PACE (2009), overlooking spatial spillover may result in biased and inconsistent estimators. Moreover, the existence of spatial spillovers posits unavoidable challenges to regional policy makers and RHS managers, as will be discussed in detail in the results section of the paper.

ELHORST (2014) and VEGA and ELHORST (2015) propose a very flexible approach to deal with spatial spillovers, which can be straightforwardly applied also in the case of nonlinear count data models.[7] Following their Spatial Lag of X (SLX) model approach, spatial dependence is addressed by including spatial lags of the explanatory variables, which are computed by pre-multiplying a given regressor by the row-standardized matrix of the inverse distance (in kilometres) between any two regions. The resulting matrix ($\mathbf{WX}_{it}$ or $\mathbf{WX}_{jt}$) is the weighted average of the neighbouring regions values, with weights declining as a function of distance. When spatial lags are included, the effect of a given variable becomes more complex: its total effect can be decomposed into a *direct* component, due to changes occurred in a region's own variable, and an *indirect* or *spillover* one, caused by changes in the same variable taking place in neighbouring regions, at origin or destination. It is worth noting that in the SLX specification spillovers are local in nature. Moreover, differently from other widely applied spatial specification (such as the spatial autoregressive one) in the SLX model the ratio between the direct and the indirect effect is not constrained to be the same across the explanatory variables.

With regard to overdispersion, the usual approach based on the adoption of a negative binomial-type 2 (NB) density is followed. Overdispersion is often due to unobservable heterogeneity, the treatment of which is intrinsically intertwined with how the individual α_{ij} terms are actually specified. For inter-regional patient flows, the term α_{ij} may be seen as the unobservable propensity of the origin *i* patients to seek care in a given destination *j*. In the case of a single cross-section, controlling for heterogeneity only relies on observed attributes, and the estimators may be inconsistent due to unobservable factors. However, by exploiting the longitudinal feature of the data, it is possible to propose a model that allows for correlation between unobservable effects and observed regressors. In panel data models, this is typically done by using the standard fixed-effect (FE) estimator. However, for counts in which overdispersion is addressed using the NB density, a conditional FE estimator does not exist, as demonstrated by ALLISON and WATERMAN (2002). The unconditional FE estimator, consisting in including indicator variables for all region-pairs, is not feasible due to the incidental parameter problem (IPP) when *T* is short and *N* is large, as it is the case for sample used in this study. Besides, in NB models such estimator is problematic because the fixed effects are built into the distribution of the gamma heterogeneity, not the mean as in Poisson models, and the IPP leads to underestimated standard errors (HILBE, 2011). The only feasible model is a (beta-distributed) random effects model, which assumes independence between the regressors and the unobservable effects. This would be a strong assumption, because it would imply that the unobservable term α_{ij} depends neither on the characteristics of each region nor on those of the region pair.

A way to relax this assumption is to assume that exogenous regressors and the unobservable effect are *conditionally* correlated. This approach, originally developed by MUNDLAK (1978) and CHAMBERLAIN (1982) in the context of linear panel models, can be seen as a way to combine the fixed and random effects approaches to obtain some of the virtues of each. In fact, in the context of model (1), it handles correlation between the pair-specific unobserved effect, α_{ij}, and the time-varying regressors. More specifically, the resulting conditionally correlated random effect (CCRE) model specifies α_{ij} as a function of the time-averages of all time-varying exogenous regressors. Therefore, the unobservable effects are assumed to be correlated with the time-averages of region-pair regressors, $\bar{\mathbf{X}}_{ij} =$

$1/T\sum_{t=1}^{T}\mathbf{X}_{ijt}$, as well as origin and destination variables, $\bar{\mathbf{X}}_i$ and $\bar{\mathbf{X}}_j$, and spatial lags of the same variables. The multiplicative form of the individual terms in (1) allows one to account for the correlation between individual effects and the regressors by simply augmenting the conditional mean with the complete set of their time-averaged counterparts. Hence, the CCRE-NB model can be estimated using a standard random effect (RE) estimator. Besides overcoming the strong assumption that α_{ij} are independent of regressors, this model also allows to estimate the coefficients of the time-invariant regressors (e.g. geographical distance), which would be removed in a standard FE model by construction.

Lastly, in order to account for possible serial correlation, year dummies, which are supposed to capture the effect of macro shocks common to all the region pairs, are included along with the first lag of the dependent variable. Thus, the final model is a dynamic CCRE-NB specification.[8] Having a short panel, the effect of the initial conditions might be important: any correlation between them and the individual pair effect (α_{ij}) is ruled out by employing the *conditional* approach proposed in WOOLDRIDGE (2005), which rests on the MUNDLAK correction and entails specifying the α_{ij} terms as a function, not only of the $\bar{\mathbf{X}}_{ij}$, $\bar{\mathbf{X}}_i$ and $\bar{\mathbf{X}}_j$ but also of the initial period value of the dependent variable.[9] The final specification of the conditional mean of the inter-regional patient count flows is:

$$E\left[\mathbf{Y}_{ijt}|\mathbf{X}_t,\alpha_{ij}\right]=\alpha_{ij}\exp\left(\mathbf{Y}_{ij,t\text{-}1}\gamma+\mathbf{X}_{it}\beta_o+\mathbf{X}_{jt}\beta_d+\mathbf{X}_{ijt}\beta_{od}+\mathbf{dist}_{ij}\gamma_{od}+\mathbf{WX}_{it}\beta_{ow}+\mathbf{WX}_{jt}\beta_{dw}+\theta_t\right) \quad (2)$$

with $\alpha_{ij}=\exp\left(\mathbf{Y}_{ij,0}\delta+\bar{\mathbf{X}}_i\lambda_o+\bar{\mathbf{X}}_j\lambda_d+\bar{\mathbf{X}}_{ij}\lambda_{od}+\mathbf{W}\bar{\mathbf{X}}_i\phi_{ow}+\mathbf{W}\bar{\mathbf{X}}_j\phi_{dw}+\varepsilon_{ij}\right)$

and where $\mathbf{Y}_{ij,t-1}$ is the one period lagged dependent variable and $\mathbf{Y}_{ij,0}$ its initial period value, θ_t is a vector of year dummies and ε_{ij} is a pure random term, that may be seen as unobservable heterogeneity uncorrelated with the regressors. The other terms are the same as in (1).

The specification reported in (2), which simultaneously accounts for the main features of patients flow count data - overdispersion, unobservable heterogeneity, cross regional and serial correlation - and includes a comprehensive set of pull and push factors, is expected to provide an accurate representation of the conditional mean of the response variable.

5. Results

Total Inter-Regional Patient Flows

This section presents the results of the gravity model for the total inter-regional bilateral patient flows occurred in the period 2001-2010, using a quasi-balanced panel of observations.[10] Table 4 compares results that are obtained by estimating a static RE model, a CCRE model that relaxes the assumption of independence between the regressors and the unobservable effects, and the dynamic version of the CCRE model, as reported in equation (2).

Before discussing in detail the estimated effects, models are compared on the basis of the Likelihood Ratio (LR) tests, reported at the bottom of Table 4. The first one tests the joint significance of the coefficients of the time-averages of the regressors and their spatial lags included in the CCRE (DEBARSY, 2012). The null hypothesis is strongly rejected, meaning that the model should include individual fixed effects to better address unobservable heterogeneity. For this reason, the RE estimation results displayed in the first column of Table 4 are not discussed in detail. The LR-test in the last column of the table tests the joint significance of the dynamic component ($\boldsymbol{y}_{ij,t-1}$ and $\boldsymbol{y}_{ij,0}$) coefficients. The rejection of the null hypothesis provides strong evidence of correlation between the individual pair terms and the time-varying regressors, this leads to the conclusion that the dynamic CCRE fits the data better than the static CCRE.[11] It is worth noting that the squared correlation between actual and fitted values slightly decreases in the dynamic CCRE model with respect to its static counterpart (0.503 vs. 0.583). This is reasonably due to the loss in degrees of freedom as explained by CAMERON and TRIVEDI (2013). The lagged dependent variable has a highly significant coefficient, confirming the existence of inertia in patient flows. Although for count data a positive autocorrelation coefficient implies an explosive dynamics, its magnitude – only slightly greater than zero – coupled with the negative coefficient of the initial value term, entails a very mild persistence. This result might be an issue for the long-run financial sustainability of the current decentralised setting of the Italian NHS, especially when relevant geographical and economic factors affecting patients mobility are not under the direct control of the regional governments.

Turning to the discussion of the estimated effects of the dynamic CCRE, reported in the third column of Table 4, it is worth noting that because the explanatory variables are log-transformed, the estimated coefficients can be interpreted as *direct* elasticities or *indirect* (spillovers) elasticities for the spatially lagged terms.[12] In terms of significance of the regressors, moving from the static to the dynamic version of the CCRE specification leads to the loss of explanatory power of population and the direct effect of concentration of the organizational structure (HHI). GDP per capita has a positive and significant effect only at destination, suggesting that patient flows are attracted by regions that are supposed to offer better and more efficient hospital care. A 10 percent increase in GDP per capita increases inflows of about 7.6 percent.

The RHSs supply factors, represented by the number of beds, the TEI, the CMI, the CIP and the HHI, are highly significant. A greater capacity of public hospitals discourages outflows and increases inflows at destination: the coefficient at destination is particularly sizeable when compared to the analogous coefficient at origin. The effect of a 10 percent increase in this covariate entails a reduction of 1.1 percent in outflows and an increase in inflows of 8.2 percent. In light of this result, the national policies that promote hospital bed rationing to enhance the economic efficiency of the NHS have important effects in terms of inter-regional mobility. In this regard, Section 6 will illustrate the simulation of a specific policy scenario derived by setting the total number of beds in each RHS at the recommended national target.

The CMI exhibits a positive and significant coefficient at origin, thus specialisation in treatments with higher resource intensity is associated with higher outflows. At the same time, the negative coefficient at destination indicates that inflows are discouraged. These results are expected when the specialization in more resource-intense cases is associated with a reduction in the provision of less resource-intense care, in which the RHS could have no strategic advantage to specialize. A higher CIP (indicating lower efficiency) negatively affects patient flows at both locations. However, this result is not consistent with a unique interpretation: it seems to indicate that less efficient RHSs are less attractive, but also more capable to restrict outflows. In the latter case, inefficiency in managing length of stay might be associated with a perception of better quality in hospital care, which reduces outflows, as argued in section 3. It is worth noting that, at least when focusing on total flows, the regional technological endowment and the hospital organizational structures do not play any significant role in shaping inter-regional patient flows.

The cross-region dependence arising from local externalities is accounted for by origin and destination spatially lagged terms. The coefficients of such variables can be interpreted as indirect effects resulting from a change in a given variable occurring in the focal region's neighbours. The spatial lag of GDP per capita is significant only at destination, where it exhibits a negative coefficient. This could indicate that richer neighbouring RHS, expected to provide more efficient and effective health treatments, compete with the focal RHS in attracting patients. Relevant spillover effects are related to hospital capacity: outflows towards a specific region increase with the number of beds in public hospitals in the neighbouring

RHSs, whereas they are slightly crowded out by a higher number of beds in private hospitals in the same RHSs. The technology endowment of proximate regions plays a relevant role at origin, determining an increase in outflows. Conversely, the spatial lags of the CMI and HHI indicators at origin reduce the outflows, meaning that neighbouring RHSs offering less diversified and less specialized hospital services are not viewed as attractive alternatives. Similarly, the negative effect of the spatially lagged CIP indicator suggests that efficient RHSs have an advantage over inefficient neighbouring regions. At destination, a symmetric (positive and significant) effect for the spatially lagged term of the HHI is found. This indicates that the ability to attract non-resident patients is enhanced from being located close to less diversified RHSs.

Among the determinants at the region-pair level, geographical distance, which is fundamental in explaining spatial patterns in patient mobility, exhibits the expected adverse on inter-regional flows. On the contrary, political similarity between regions is effective in enhancing bilateral patient flows, confirming the hypothesis that politically aligned regions are more likely to exploit complementary healthcare services and share information on the extra-regional availability of healthcare services. Conversely, past migration flows are not associated with any significant effect.

Finally, the model also includes the South and North dummies. The former, being significantly negative at destination, signals the low attractiveness of southern RHSs.

Specific Inter-Regional Patient Flows

Table 5 reports the estimation results for the models estimated for different types of admissions classified as *Surgery*, *Medicine* and *Cancers*, using the same dynamic CCRE specification used for total patient flows as in Table 4.

Differently from the general model, where the mass variables have a marginal role in explaining OD patient flows, population, along with GDP per capita, has significant direct and indirect effects. As the size of the population increases, the number of admissions outside the region of residence for *Surgery*, for which patients are likely to require more complex and resource intensive care than patients admitted in medical DRGs, significantly increases. By contrast, the ability to attract cancer patients from other regions decreases. Turning to GDP per capita, a 10 percent increase makes surgical patients outflows decrease by approximately 4 percent, while medicine and cancer patient inflows increase by 8.5 and 12.2 percent, respectively. Moreover, evidence of spillover effects is found: the proximity of smaller RHSs helps in containing outflows in all the three cases considered and in attracting inflow in the

Medicine and *Cancers* model. Richer neighbouring regions discourages surgery outflows and all types of inflows.

The number of beds in public hospitals is particularly important to attract inflows in all models. The corresponding elasticity, which is about 0.76 in the *Medicine* model, increases with complexity and it is closer to unit in *Cancers* model. The capacity of private hospitals significantly reduces surgical patients outflows only. Indirect effects of hospital capacity are present in all models and highly significant particularly for *Cancers*, where an increase of 10 percent in the number of beds of private hospitals in proximate regions leads to more outflows (1.4 percent) and lower inflows (-2.7 percent). A corresponding increase in the public hospitals leads to a decrease in outflows of 9.7 percent and an increase of inflows of 47 percent. Differently from total patient flows, the technology indicator plays a central role in the *Cancers* model, where inflows increase of approximately 16 percent for a 10 percent higher TEI. A higher TEI in the proximate regions has the effect of increasing surgical patients outflows.

The positive effect of the CMI at origin and the symmetric negative effect at destination discussed when interpreting the general model, are found for *Surgery* and *Medicine*, respectively. Also the negative spillover effect at origin is confirmed in the same models. The spatially lagged CMI has a positive effect for *Medicine* at destination, meaning that a given destination can more easily attract extra-regional patients when its surrounding regions are relatively specialized in resource-intensive treatments. As a push factor, the CIP is statistically significant only in the model for *Medicine*. As a pull factor, it keeps its significance in all models and exhibits the largest effect for *Surgery*. A 10 percent higher level of this inefficiency index for the proximate RHSs increases inflows in the *Medicine* and *Cancers* models (about 34 and 82, respectively) but has a negative effect on surgical patient inflows.

Finally, the HHI is a significant push and pull factor for *Surgery*: as concentration in the organisational structure increases, the outflows increase and the inflows decrease. This variable also entails relevant negative indirect effects at origin in all models and positive indirect effects in the *Medicine* and *Cancers* models. For example, cancer patient outflows (inflows) decrease (increase) up to 24 (47) percent when the HHI in the proximate regions increase of 10 percent, suggesting that regions with less diversified hospital services are not viewed as attractive alternative destinations.

The signs of the geographical dummies confirm the general spatial patterns of the OD patient flows discussed in Section 3. Moreover, for *Surgery* and to a lesser extent for *Medicine*, the North dummy is negative and significant at destination, suggesting that surgical patients inflows are lower in northern regions than in central ones. The distance effect is greater for *Cancers*, probably because of the length of specific treatments that often require multiple daily admissions in hospital. Political similarity seems to be relevant for both Surgery and Medicine.

Overall, the results discussed above depict a very comprehensive picture of the patient inter-regional flows in Italy by highlighting how the effects of some key variables vary according to the RHS being seen as an origin rather than a destination and how such effects are amplified or moderated by neighbouring RHSs.

6. A Post-estimation policy scenario

Estimation results can be used to evaluate *ex ante* the effect that either national or regional policies, affecting some determinants of bilateral OD flows, might have on inter-regional patient mobility. As an example, here the focus is on hospital capacity, which has repeatedly been the target of bed rationing policies decided by the central government to improve the cost-efficiency of the NHS. Namely, the proportional change and the net change in outflows, as well as in inflows, is calculated by using patient mobility data in 2010 and estimates from the general model for total flows.

Because the gravity model specifically distinguishes between regional characteristics at origin and destination as potential determinants of OD patient flows, it is necessary to consider simultaneously the proportionate change in flows generated by changes in a covariate at origin and at destination. The proportionate change in total outflows from origin *i* is computed as:[13]

$$\frac{\Delta\mathrm{E}(\mathbf{Y}_{\mathrm{i}}|\mathbf{X})}{\mathbf{Y}_{\mathrm{i}}} = \frac{1}{\mathbf{Y}_{\mathrm{i}}}\sum_{\mathrm{j}\neq\mathrm{i}}^{\mathrm{j}=21} \Delta\mathrm{E}\big(\mathbf{y}_{\mathrm{ij}}|\mathbf{X}\big) = \frac{1}{\mathrm{Y}_{\mathrm{i}}}\sum_{\mathrm{j}\neq\mathrm{i}}^{\mathrm{j}=21} \beta_{\mathrm{ok}}\frac{\Delta\mathbf{x}_{\mathrm{ik}}}{\mathbf{x}_{\mathrm{ik}}}\mathbf{y}_{\mathrm{ij}} + \frac{1}{\mathbf{Y}_{\mathrm{i}}}\sum_{\mathrm{j}\neq\mathrm{i}}^{\mathrm{j}=21} \beta_{\mathrm{dk}}\frac{\Delta\mathbf{x}_{\mathrm{jk}}}{\mathbf{x}_{\mathrm{jk}}}\mathbf{y}_{\mathrm{ij}},$$

where $\mathbf{Y}_{\mathrm{i}} = \sum_{\mathrm{j}\neq\mathrm{i}}^{\mathrm{j}=21} \mathbf{y}_{\mathrm{ij}}$. After some algebra this is equal to:

$$\frac{\Delta\mathrm{E}(\mathbf{Y}_{\mathrm{i}}|\mathbf{X})}{\mathbf{Y}_{\mathrm{i}}} = \beta_{\mathrm{ok}}\frac{\Delta\mathbf{x}_{\mathrm{ik}}}{\mathbf{x}_{\mathrm{ik}}} + \beta_{\mathrm{dk}}\sum_{\mathrm{j}\neq\mathrm{i}}^{\mathrm{j}=21}\frac{\Delta\mathbf{x}_{\mathrm{jk}}}{\mathbf{x}_{\mathrm{jk}}}\omega_{\mathrm{ij}},$$

where the parameter at destination β_{dk} multiplies the weighted average of the relative variations of the covariate at destination, using as weights the share of outflows to a given destination $\omega_{ij} = \mathbf{y}_{ij}/\mathbf{Y}_i$. Similarly, one could derive the expression for the proportionate change in total inflows at destination *j*.

Table 6 displays results from the scenario that would follow if each RHS modifies the total number of beds to adjust to the most recent bed-population ratio target recommended by the central Government (3.7 beds *per* 1,000 inhabitants).[14] The 2010 data indicate a relevant regional variability in the bed-population ratio, with the indicator ranging from 3.5 (Campania) to 5.4 (Molise). Direct and indirect effects are calculated using the elasticities of *beds in public hospitals* at origin and destination, and those of the corresponding spatial lags (last column Table 4). Seventeen out of twenty-one regions should cut beds by a proportion included in the range 4.5 – 31.0 percent (see column *required adjustment*). This would lead to an overall reduction of patient mobility of 9 percent (66892 admission episodes) in a year. This figure is largely affected by the direct effects of adjustment to the national benchmark in each region (both on outflows and inflows), whereas the indirect effects accounts for approximately 32.5 percent of the total effect. Looking at the single regions, seven of them suffer a loss in terms of net mobility. For example, the southern region of Campania, with an increase of 8.5 per cent in negative net mobility (from -55,310 to -59,988 patients). Conversely, the central region of Lazio, for example, would experience a consistent increase in its positive net mobility (about 83 percent). This exercise could be extended for the calculation of the monetary reimbursement associated with patient flows for each region.

7. Discussion and Conclusions

Free patient mobility might represent a tool for enhancing the effectiveness and efficiency of local healthcare services. However, it may also constitute a challenge for local governments in decentralised tax-funded healthcare systems, where local authorities, while responding to centrally defined standards, are fully responsible for the organisation and the purchase of healthcare services. This risk crucially depends on the ultimate nature of the patterns of inter-regional patient flows.

This study examined the determinants of inter-regional patient mobility in a decentralised context using Italy as a case of study. A gravity model for bilateral OD patient flows was estimated on longitudinal data from hospital discharges that occurred over the period 2001-2010. A number of methodological issues related to the estimation of short panel models for count data featuring simultaneously cross-section dependence, overdispersion, unobservable heterogeneity and serial correlation were specifically addressed.

Main findings obtained from models estimated for total flows, and specifically for *Surgery*, *Medicine* and *Cancers*, indicate that RHSs in the richest regions attract more patients, in particular for surgical treatments. The regional characteristics that best explain an RHS ability to attract non-resident patients are the number of beds and the performance indicator, whereas the technological endowment significantly explains *Cancers* inflows. At origin, surgical patient outflows are higher in regions with a larger population and hence a higher internal demand and lower in regions with a higher hospital capacity. Surgical patient outflows are particularly responsive to the availability of beds in private hospitals and the diversification of the organisational structure in the RHS of origin. More importantly, the results indicate that neighbouring regions' supply factors, specialisation and performance indicators generate significant local externalities, which largely explain OD patient flows.

From a practitioner's perspective, the empirical model proposed in this study can also be considered a useful policy analysis tool, which can be promptly applied to shed light on the potential consequences of health policy interventions on patient mobility based on managing specific factors. By way of example, a post-estimation analysis offering a better interpretation of the hospital capacity effect on patient mobility is presented. The implementation of the national policy on hospital beds rationing generates a reduction in patient choice, as approximated by inter-regional mobility, of about 9 percent, with large geographical variation in the distribution of the financial gains and losses associated with patient flows.

The econometric analysis has also detected a mildly explosive dynamic in inter-regional patient mobility over time. This result, coupled with the significant role played by factors not directly controlled by regional policy-makers and RHS managers (such as population, GDP per capita and spatial spillovers), might induce a polarisation between the group of the richest, most populated and best performing regions, which are increasingly capable of attracting patients, and the group of the weakest regions, with growing outflows and severe financial and organizational problems.

These considerations call for a thorough assessment of the long-run sustainability of the current decentralised NHS. RHS budget autonomy could not be entirely consistent with free patient choice. This opens a more general discussion on whether and to what extent the health financing system would require the introduction of appropriate equalising compensation schemes aimed at neutralising the financial consequences of mobility and, eventually, to pledge universalism and equity in healthcare.

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TABLE 1: Inter-Regional Mobility Flows by Type of Admission and by Origin and Destination Macro-Areas

	2001	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Total Flows	839,719	836,460	832,831	854,333	858,934	859,413	840,259	828,624	794,028	779,498
Share of *Total Flows* over total admissions	6.8	6.8	6.8	6.9	7.0	7.0	7.2	7.2	7.2	7.3
Specific inter-regional flows										
Surgery	341,141	349,738	354,197	375,845	380,051	390,071	391,777	395,961	381,764	378,821
Medicine	480,715	468,556	459,902	458,969	459,803	452,003	430,735	414,133	412,264	400,677
Cancers	84,223	83,080	82,405	84,086	86,326	85,253	84,341	81,958	81,532	79,524
Geographical distribution of inter-regional flows (percentages)										
From Southern originis	44.96	44.05	43.86	43.88	43.82	43.59	43.23	42.96	43.20	43.45
From Central origins	18.23	18.82	18.82	19.13	19.04	19.06	19.40	19.53	19.53	19.73
From Northern origins	36.81	37.13	37.32	36.99	37.14	37.35	37.37	37.51	37.28	36.82
From Southern origins to Southern destinations	11.49	11.59	11.48	11.56	11.69	11.70	11.54	11.08	10.72	10.92
From Southern origins to Central destinations	14.22	13.65	13.77	13.85	14.12	13.85	13.70	14.12	14.43	14.51
From Southern origins to Northern destinations	19.25	18.81	18.61	18.48	18.01	18.04	18.00	17.76	18.04	18.02
From Northern origins to Southern destinations	3.11	3.26	3.32	3.19	3.11	3.13	2.94	2.86	2.46	2.83
From Northern origins to Central destinations	3.90	3.80	3.83	3.82	3.87	3.95	4.08	4.16	4.32	4.27
From Northern origins to Northern destinations	29.80	30.07	30.17	29.98	30.17	30.28	30.34	30.48	30.49	29.73
From Central origins to Southern destinations	4.36	4.96	5.02	5.23	5.32	5.30	5.04	4.69	4.27	4.46
From Central origins to Central destinations	6.52	6.33	6.32	6.39	6.29	6.22	6.36	6.46	6.71	6.63
From Central origins to Northern destinations	7.35	7.53	7.48	7.51	7.43	7.53	8.00	8.37	8.55	8.64

Note: Flows for Surgery, Medicine do not sum up to Total Flows because admissions in long-term and rehabilitation wards and admissions of healthy babies born at the hospital are excluded. Flows for Cancers include admissions in surgical and medical DRGs of patients diagnosed with a tumor.

TABLE 2: Patterns of Inter-Regional Patient Mobility (Percentages)

	2001					2010				
Regions	**Creation rate**	**Attraction rate**	**Outflow rate**	**Inflow rate**	**Mobility index**	**Creation rate**	**Attraction rate**	**Outflow rate**	**Inflow rate**	**Mobility index**
Piemonte	7.66	5.91	8.00	6.29	0.79	6.37	5.43	6.62	5.70	0.86
Valle d'Aosta	0.60	0.22	20.23	8.49	0.42	0.63	0.25	20.43	9.26	0.45
Lombardia	9.27	20.53	3.88	8.20	2.11	8.79	18.74	4.19	8.52	2.04
Provincia Autonoma Bolzano	0.56	0.80	4.83	6.74	1.40	0.52	0.87	4.11	6.76	1.65
Provincia Autonoma Trento	1.71	1.36	14.45	11.82	0.82	1.77	1.18	15.19	10.69	0.70
Veneto	4.89	8.57	4.45	7.54	1.70	6.14	7.87	6.27	7.89	1.26
Friuli Venezia-Giulia	1.79	2.23	6.98	8.53	1.22	1.81	2.64	7.18	10.11	1.41
Liguria	4.66	5.01	10.05	10.72	1.07	4.95	4.78	11.25	10.92	0.97
Emilia-Romagna	5.66	11.78	5.52	10.84	1.96	5.84	14.62	5.83	13.43	2.30
Toscana	4.34	7.85	5.34	9.26	1.73	5.02	8.96	6.49	11.02	1.70
Umbria	2.00	3.43	9.26	14.91	1.61	2.37	3.09	11.70	14.75	1.26
Marche	3.72	3.17	9.96	8.62	0.87	3.74	3.56	10.82	10.36	0.96
Lazio	8.18	10.19	6.35	7.79	1.23	8.61	9.79	6.57	7.42	1.13
Abruzzo	3.84	4.00	9.59	9.95	1.04	5.05	3.36	16.09	11.32	0.70
Molise	1.85	1.78	22.34	21.75	0.97	1.56	2.43	18.33	25.89	1.41
Campania	10.81	3.03	7.41	2.19	0.30	10.27	3.17	6.98	2.26	0.32
Puglia	6.98	4.71	6.07	4.18	0.69	7.48	3.73	6.76	3.48	0.52
Basilicata	3.78	1.44	23.40	10.42	0.45	2.92	1.97	21.04	15.21	0.72
Calabria	7.47	1.68	13.52	3.39	0.25	7.46	1.06	16.24	2.67	0.16
Sicilia	8.37	1.80	6.31	1.42	0.23	6.82	1.90	6.16	1.80	0.29
Sardegna	1.84	0.52	4.28	1.25	0.29	1.88	0.58	4.86	1.56	0.32
South	44.96	18.96	8.08	3.57	0.44	43.5	18.2	8.57	3.78	0.44
Centre	18.23	24.6	6.78	8.95	1.32	19.7	25.4	7.50	9.46	1.26
North	36.81	56.41	5.70	8.48	1.49	36.82	56.39	6.13	9.09	1.48
Centre-North	55.04	81.04	6.02	8.61	1.43	56.55	81.79	6.55	9.20	1.41
min.	0.60	0.22	3.88	1.25	0.23	0.52	0.25	4.11	1.56	0.16
max.	10.81	20.53	23.40	21.75	2.11	10.27	18.74	21.04	25.89	2.30
range	10.21	20.31	19.52	20.50	1.89	9.75	18.49	16.93	24.33	2.14
coefficient of variation	0.62	0.99	0.60	0.55	0.57	0.59	0.98	0.53	0.61	0.58
std. dev.	2.96	4.74	5.77	4.58	0.57	2.82	4.68	5.40	5.51	0.58
mean	4.76	4.76	9.63	8.30	1.01	4.76	4.76	10.15	9.10	1.01
coefficient of variation	0.62	0.99	0.60	0.55	0.57	0.59	0.98	0.53	0.61	0.58

Notes: the *creation rate* is the percentage ratio between the outflows of a given region and the total number of patient flows. The *attraction rate* is the percentage ratio between the inflows of a given region and the total number of patient flows. The *outflow rate* is the percentage ratio between the outflows of a given region and the total number of admissions of the region's enrolees. The *inflow rate* is the percentage ratio between the inflows in a given region and the total number of the region's admissions.

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TABLE 3: Descriptive Statistics, Variable Definitions and Data Sources (Years 2001-2010)

Variable	**mean**	**st. dev.**	**min**	**max**	**Definition**	**Primary source**
Total inter-regional flows	1981.9	3936.5	0	39196	hospital admissions of patients from Origin region *i* in Destination region *j*	Hospital discharge data - Ministry of Health
Surgery inter-regional flows	890.3	1919.0	0	19250	hospital admissions with surgical DRGs of patients from Origin region *i* in Destination region *j*	Hospital discharge data - Ministry of Health
Medicine inter-regional flows	1056.6	2025.1	0	19485	hospital admissions with medical DRGs of patients from Origin region *i* in Destination region *j*	Hospital discharge data - Ministry of Health
Cancer inter-regional flows	198.3	467.2	0	4909	hospital cancer-related admissions of patients from Origin region *i* in Destination region *j*	Hospital discharge data - Ministry of Health
Population	2805617	2374442	119546	9917714	resident population in a region (annual average)	ISTAT
GDP per capita	23950	5889	14831	33464	regional per capita GDP (euros), constant values (2005)	ISTAT
Population aged 0-14 (%)	13.88	1.69	10.66	18.51	share of the population aged 0-14 years old	ISTAT
Population aged over 65 (%)	20.23	2.68	14.28	26.82	share of the population aged 65 years old or over	ISTAT
Beds in public hospitals	10260.6	8666.5	453	40771	number of hospital beds in public hospitals in each region	NHS statistical yearbook
Beds in private licensed hospitals	2411.6	2670.5	0	9729	number of hospital beds in private licensed hospitals in each region	NHS statistical yearbook
Technology endowment index -TEI	99.21	4.43	88.61	123.81	composite index calculated using 25 medical devices available in each region	NHS statistical yearbook
Case mix index - CMI	0.997	0.064	0.892	1.119	ratio between the average weight of admissions in a specific region and the average weight of admissions in the whole NHS	Own calculations on Hospital discharge data
Comparative index of performance - CIP	1	0.112	0.821	1.768	ratio between the case-mix standardised average length of stays in each region and the national average	Own calculations on Hospital discharge data
Organisational structure - HHI	0.471	0.196	0.184	1	Hirschman-Herfindahl index for market concentration in each region	Own calculations on Hospital discharge data
South	0.381	0.486	0	1	1 if Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna or Sicilia	Own caclulations
North	0.429	0.495	0	1	1 if Liguria, Lombardia, Piemonte, Valle d'Aosta, Emilia-Romagna, Friuli-Venezia Giulia, PA Trento, PA Bolzano or Veneto	Own caclulations
Centre	0.190	0.393	0	1	1 if Toscana, Umbria, Marche or Lazio	Own caclulations
Past migration flows	3967	6320	8	47318	residential changes of citizens from Origin *i* to Destination *j* in the 5 previous years (stock)	ISTAT
Political similarity	0.55	0.50	0	1	1 if the regional governments of Origin *i* and Destination *j* share the same political orientation	Own calculations
Distance	469.0	248.3	54.5	1125.5	distance in Km between the centroids of Origin *i* and Destination *j*	Own calculations

TABLE 4: Estimated models for Total Inter-Regional Patient Flows in Italy (2001-2010)

Dependent Variable y_{ijt}: Patient flows to Destination j from Origin i						
Negative Binomial models	**RE**		**CCRE**		**Dynamic CCRE**	
Origin characteristics			*direct effects*			
Population	0.654	***	0.463	*	0.368	
GDP per capita	-0.341	**	-0.172		-0.200	
Population aged 0-14 (%)	0.004		0.020		0.007	
Population aged over 65 (%)	0.007		-0.002		-0.007	
Beds in public hospitals	-0.132	**	-0.095	*	-0.112	**
Beds in private licensed hospitals	-0.013	*	-0.008		-0.008	
Technology endowment index -TEI	0.188		0.171		0.120	
Case mix index - CMI	0.250		0.311	*	0.345	**
Comparative index of performance- CIP	-0.179	*	-0.252	***	-0.254	***
Organisational structure - HHI	0.070	**	0.075	**	0.024	
South	-0.631	***	0.098		0.411	
North	0.356	***	-0.276		-0.352	
Spatial lags			*indirect effects*			
Population	0.400		1.847		2.278	
GDP per capita	-3.751	***	-3.308	***	-1.825	**
Beds in public hospitals	-0.445	*	-0.327		-0.218	
Beds in private licensed hospitals	-0.038	**	-0.043	**	0.003	
Technology endowment index - TEI	1.861	***	2.106	***	1.534	***
Case mix index - CMI	-4.080	***	-3.856	***	-2.760	**
Comparative index of performance CIP	-1.052		-0.724		-1.170	**
Organisational structure - HHI	-0.696	***	-0.910	***	-0.849	***
Destination characteristics			*direct effects*			
Population	-0.506	***	-0.077		0.124	
GDP per capita	0.450	***	0.656	***	0.761	***
Beds in public hospitals	1.031	***	1.030	***	0.823	***
Beds in private licensed hospitals	0.010		0.007		0.007	
Technology endowment index -TEI	0.102		0.008		0.030	
Case mix index - CMI	-0.920	***	-0.899	***	-0.714	***
Comparative index of performance- CIP	-0.995	***	-1.128	***	-0.654	***
Organisational structure - HHI	-0.003		-0.093	***	-0.015	
South	-0.287	***	-1.452	***	-0.966	**
North	0.040		-0.392	*	-0.270	
Spatial lags			*indirect effects*			
Population	-0.591	*	2.690	**	0.882	
GDP per capita	-0.556		-3.591	***	-2.041	**
Beds in public hospitals	0.333		0.278		0.484	**
Beds in private licensed hospitals	-0.104	***	-0.062	***	-0.067	***
Technology endowment index - TEI	-1.135	**	0.434		-0.300	
Case mix index - CMI	-0.493		-0.832		0.664	
Comparative index of performance CIP	0.353		-0.895		0.355	
Organisational structure - HHI	2.298	***	1.437	***	1.737	***
Origin-Destination characteristics						
Distance	-0.258	***	-0.088		-0.263	***
Past migration flows	0.194	***	0.040		0.034	
Political similarity	0.007	**	0.008	**	0.011	***
Lagged patient flows (y_{t-1})					0.00005	***
Initial patient flows (y_0)					-0.00008	***
Log Likelihood	-21156		-21026		-20818	
Squared correlation between actual and fitted flows	0.498		0.583		0.503	
LR-test (degrees of freedom 36)			259.39		327.640	
(p-value)			(0.000)		(0.000)	

Notes: Number of regional units: 21; total number of region-pairs: 420; total number of observations: 3760
The variables Population, GDP per capita, Beds, TEI, CMI, CIP, Distance and Past migration flows are log-transformed
All models include a constant and time dummies (year 2002 is the reference year)
CCRE models include time averages of the time-varying exogenous covariates
Level of significance: *** 1%, ** 5%, * 10%

TABLE 5: Estimated Models for Inter-regional Patient Flows for Cancers, Surgery and Medicine in Italy (2001-2010)

Dependent Variable y_{ijt}: Patient flows to Destination j from Origin i			
Negative Binomial Dynamic CCRE model	**Surgery**	**Medicine**	**Cancers**
Origin characteristics		*direct effects*	
Population	0.798 **	0.064	0.126
GDP per capita	-0.410 *	-0.095	-0.586
Population aged 0-14 (%)	-0.009	0.018	-0.029
Population aged over 65 (%)	-0.007	0.004	0.032 *
Beds in public hospitals	-0.057	-0.083	-0.163
Beds in private licensed hospitals	-0.025 **	0.002	-0.014
Technology endowment index -TEI	0.152	0.021	-0.223
Case mix index - CMI	0.626 ***	-0.099	0.348
Comparative index of performance- CIP	-0.141	-0.178 *	-0.228
Organisational structure - HHI	0.109 ***	-0.024	0.074
South	-0.945	1.777 *	2.484 **
North	-0.265	-0.524 *	-0.828 ***
Spatial lags		*indirect effects*	
Population	3.799 **	0.657	9.422 ***
GDP per capita	-3.134 ***	0.175	1.558
Beds in public hospitals	-0.572 **	0.381	-0.966 *
Beds in private licensed hospitals	-0.009	0.001	0.114 **
Technology endowment index - TEI	2.270 ***	0.492	0.098
Case mix index - CMI	-3.324 **	-2.668 **	3.745
Comparative index of performance CIP	-0.961	-1.308 **	-1.171
Organisational structure - HHI	-0.794 ***	-0.659 **	-2.444 ***
Destination characteristics		*direct effects*	
Population	-0.260	-0.227	-1.280 **
GDP per capita	0.606 ***	0.854 ***	1.218 ***
Beds in public hospitals	0.791 ***	0.765 ***	0.981 ***
Beds in private licensed hospitals	0.008	0.003	-0.023
Technology endowment index -TEI	-0.059	0.041	1.589 ***
Case mix index - CMI	-0.060	-1.304 ***	-0.237
Comparative index of performance- CIP	-0.783 ***	-0.546 ***	-0.667 ***
Organisational structure - HHI	-0.095 *	-0.012	-0.053
South	-0.543	-1.283 ***	-1.783 ***
North	-0.663 ***	-0.320 *	0.926 ***
Spatial lags		*indirect effects*	
Population	0.620	-2.423 *	-8.726 **
GDP per capita	-2.250 *	-2.577 **	-15.857 ***
Beds in public hospitals	0.632 **	0.007	4.710 ***
Beds in private licensed hospitals	-0.030	-0.121 ***	-0.275 ***
Technology endowment index - TEI	-1.736 **	-0.402	3.302 *
Case mix index - CMI	-0.365	2.606 **	-3.001
Comparative index of performance CIP	-2.642 ***	3.452 ***	8.166 ***
Organisational structure - HHI	0.234	2.403 ***	4.738 ***
Origin-Destination characteristics			
Distance	-0.238 ***	-0.391 ***	-0.767 ***
Past migration flows	0.014	0.043	0.084
Political similarity	0.008 *	0.008 ***	-0.009
Lagged patient flows (y_{t-1})	0.00005 ***	0.00005 ***	0.00003 ***
Initial patient flows (y_0)	-0.0001 ***	-0.00006 ***	-0.00002 ***
Log Likelihood	-18099	-19332	-14257
Squared correlation between actual and fitted flows	0.399	0.581	0.821
LR-test (degrees of freedom 36)	278.49	315.710	292.82
(p-value)	(0.000)	(0.000)	(0.000)

Notes: Number of regional units: 21; total number of region-pairs: 420; total number of observations: 3760
The variables Population, GDP pc, Beds, TEI, CMI, CIP, Distance and Past migration flows are log-transformed
All models include a constant and time dummies (year 2002 is the reference year), and time averages of the time-varying exogenous covariates
Level of significance: *** 1%, ** 5%, * 10%

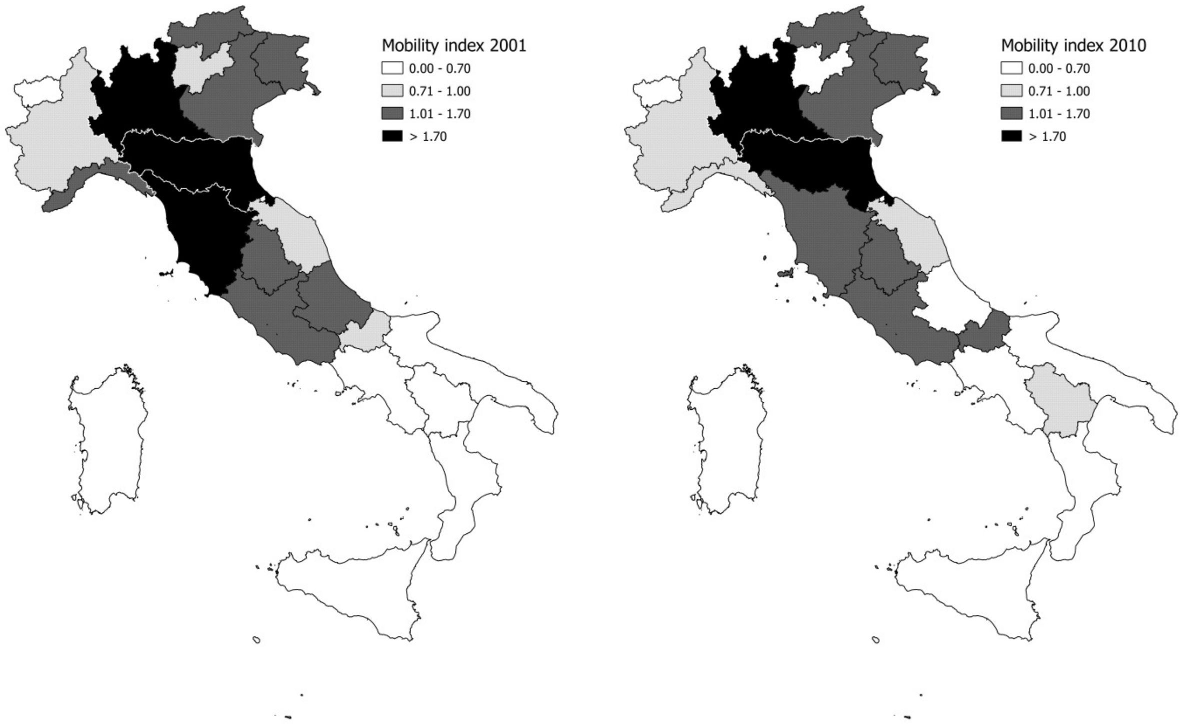
TABLE 6: Estimated Effects of the Implementation of the National Target on the Bed-Population Ratio (Reference Year: 2010)

	2010 baseline values					**Direct effects**		**Indirect effects**		**Total effects**				
	Beds per 1,000 inhabitants	Required adjustment (%)	Outflows	Inflows	Net mobility	Total change in outflows (a)	Total change in inflows (b)	Total change in outflows (c)	Total change in inflows (d)	Total change in outflows (a+c)	Total change in inflows (b+d)	Net change (b+d) - (a+c)	Net mobility at benchmark	% change in net mobility
Piemonte	4.2	-12.7	49623	42318	-7305	-4481	-3282	-1328	-1380	-5809	-4662	1147	-6158	-15.7
Valle d'Aosta	4.2	-11.0	4914	1952	-2962	-383	-164	-140	-65	-523	-229	295	-2667	-10.0
Lombardia	4.3	-14.5	68533	146076	77543	-7064	-9102	-1950	-4370	-9014	-13472	-4459	73084	-5.7
Provincia Autonoma Bolzano	4.2	-12.4	4017	6804	2787	-352	-688	-118	-205	-471	-893	-422	2365	-15.2
Provincia Autonoma Trento	4.7	-21.1	13778	9213	-4565	-2066	-641	-440	-262	-2506	-902	1604	-2961	-35.1
Veneto	3.9	-6.1	47885	61321	13436	-2078	-5101	-1101	-2299	-3179	-7400	-4221	9215	-31.4
Friuli Venezia-Giulia	4.2	-11.9	14138	20577	6439	-1197	-918	-471	-489	-1667	-1407	260	6699	4.0
Liguria	4.3	-14.5	38595	37297	-1298	-3984	-2261	-1105	-1253	-5088	-3513	1575	277	-121.3
Emilia-Romagna	4.5	-17.1	45545	113980	68435	-5517	-6135	-1371	-3130	-6888	-9266	-2378	66057	-3.5
Toscana	3.9	-4.5	39104	69833	30729	-1243	-3813	-925	-2596	-2167	-6408	-4241	26488	-13.8
Umbria	3.6	3.4	18450	24099	5649	449	-2025	-460	-811	-11	-2836	-2825	2824	-50.0
Marche	4.1	-9.9	29145	27776	-1369	-2041	-1686	-814	-731	-2854	-2417	437	-932	-31.9
Lazio	4.5	-17.4	67078	76341	9263	-8299	-1630	-2240	-1192	-10539	-2822	7717	16980	83.3
Abruzzo	4.0	-8.0	39395	26220	-13175	-2236	-2872	-926	-768	-3162	-3640	-478	-13653	3.6
Molise	5.4	-31.0	12187	18967	6780	-2688	-295	-366	-220	-3055	-515	2539	9319	37.5
Campania	3.5	6.2	80023	24713	-55310	3527	-1915	-1569	-805	1958	-2720	-4678	-59988	8.5
Puglia	3.9	-5.5	58335	29042	-29293	-2263	-954	-1845	-417	-4108	-1371	2737	-26556	-9.3
Basilicata	3.7	0.5	22759	15329	-7430	88	-120	-644	-157	-556	-277	279	-7151	-3.8
Calabria	3.9	-5.2	58166	8247	-49919	-2167	-351	-1823	-95	-3990	-446	3543	-46376	-7.1
Sicilia	3.7	0.0	53139	14843	-38296	-2	-846	-1659	-358	-1661	-1204	457	-37839	-1.2
Sardegna	4.2	-11.3	14689	4550	-10139	-1178	-377	-424	-114	-1602	-492	1111	-9028	-11.0

Note: the required adjustment is calculated with respect to the value of 3.7 for the bed-population ratio, which corresponds to the latest recommendations from the central government.

FIGURES

FIGURE 1: Spatial Pattern of Inter-Regional Patient Mobility. Mobility Index in 2001 and 2010.



Notes

[1] The hypothesis of exogenous differences in efficiency levels is consistent with the evidence of the heterogeneous performance of Italian local health authorities, which follow the traditional North-South divide (e.g. BALDI and VANNONI, 2015).

[2] Non-deferrable mobility is due to the accidental presence of an individual in a region different from that of residence, or as the outcome of central planning on the location of some highly specialized treatments, such as transplants. Therefore, the admissions classified in three Major Diagnostic Categories (MDC) related to “Injuries, Poison and Toxic Effect of Drugs”, “Multiple Significant Trauma” and “Burns” and in all the DRG related to transplants were excluded. Admissions in the first two MDCs most likely represent unavoidable mobility given that the choice to seek care outside the origin region is hardly attributable to a deliberate decision of the patient but rather to the occasional presence in another region. The provision of specialised hospital treatments for burns and transplants is centrally planned and provided at an inter-regional scale. For a similar reason, admissions episodes occurring in two hospitals located in Lazio, “Bambin Gesù”, which delivers highly specialised neonatal care and treatments for children with rare diseases, and “Smom”, which delivers rehabilitation and neuro-rehabilitation services, were also excluded.

[3] For this reason, the Italian government is used to set national targets on the bed-population ratio. Because targets have changed repeatedly over time, it is not possible to build an indicator of efficiency based on the distance between the observed number of beds and the national target for each of the years considered.

[4] The devices considered are those reported in the yearbooks of the Italian NHS: automated immunochemistry analyser, linear accelerator in radiotherapy, immunoassay analyser, anaesthesia machine, ultrasound imaging system, haemodialysis delivery system, computerised gamma camera, differential haematology analyser, analogue x-ray system, surgical light, monitor, mobile x-ray system, computerized axial tomography (CT), magnetic resonance imaging, medical imaging table, continuous ventilator system, digital angiography systems, hyperbaric chamber, computerised gamma camera, mammogram, positron emission tomography (PET), integrated PET-CT, operating table, and two types of panoramic radiography machines.

[5] In Italy, there are eight types of RHS-financed hospital care providers. In 2010, approximately 34% of public hospitals are run by LHAs (approximately 24% of total inter-regional flows); 10.2% are autonomous public enterprises (13.6% of inter-regional flows); 4.6% are scientific institutes for research, hospitalization and healthcare (17% of inter-regional flows) and 2.2% are medical school hospitals (16% of inter-regional flows). Private licensed hospitals represent approximately 45% of the total number of providers, and have the same share of flows attributed to the LHA public hospitals. Research centres, classified hospitals and LHA-qualified institutes account for 0.2, 2.3 and 1.6% of total providers, respectively.

[6] Some degree of homogeneity in the organisational structure of hospital care might entail some advantages, e.g., in terms of higher efficiency due to the exploitation of economies of scale and more effective financial planning. However, these effects are not expected to offset the benefits arising from higher variety.

[7] Note that the Poisson or negative binomial estimation procedure has not yet been developed for the Spatial Autoregressive model (LE SAGE and THOMAS-AGNAN, 2015). Moreover, the Spatial Error Model specification is not considered because it rules out spillover by construction.

[8] On the basis of a preliminary analysis, it was found that additional lags were not significant.

[9] Note that when the lagged dependent variable is included, the strict exogeneity assumption no longer holds; in this case, it is necessary to resort to sequential exogeneity (WOOLDRIDGE, 2010).

[10] Because of under-reporting, records for the Sardinian patient flows in 2009 were dropped.

[11] The reported dynamic CCRE specification, which specifies the individual pair terms α_{ij} as a function of the averages of both time-varying origin and destination characteristics and region-pairs regressors (see (2)) outperforms, in terms of the LR-test, the two more parsimonious specifications which only include one set of average terms at a time.

[12] Being the model dynamic, by interpreting the coefficients as direct and indirect effects implies focusing on short-run effects.

[13] For the sake of simplicity, the time subscript and the unobservable α_{ij} are omitted from the equations.

[14] The hospital capacity of the private licensed hospitals is not considered in the calculations because of their minor impact on mobility with respect to public hospitals, as indicated by the coefficients reported in Table 4, third column.