Inter-regional patient mobility in a decentralized health care system

Silvia Balia

Department of Economics and Business; CRENoS - Università di Cagliari. Via S. Ignazio 78, 09123 Cagliari, Italy, email: silvia.balia@unica.it, tel: +390706753706

Rinaldo Brau

Department of Economics and Business; CRENoS - Università di Cagliari. Via S. Ignazio 17, 09123 Cagliari, Italy, email: brau@unica.it; tel: +390706753315

Emanuela Marrocu - corresponding author

Department of Economics and Business; CRENoS - Università di Cagliari. Via S. Ignazio 78, 09123 Cagliari, Italy, email: emarrocu@unica.it; tel: +390706753714

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Abstract

Inter-regional patient mobility, measured as Origin-Destination patient flows between any two regions, is analysed within a dynamic spatial panel data framework, using 2001-2010 data on Italian hospital discharges. The aim is to assess the effects of the main determinants of patient flows, distinguishing between the impacts of regional health policies and those exerted by exogenous factors (geography, size, neighbouring regions, national policies). Empirical results indicate that the main drivers of mobility are regional income, hospital capacity, organisational structure, performance and technology. Moreover, neighbouring regions' supply factors, specialisation and performance largely affect mobility by generating significant local externalities.

Keywords:

inter-regional patient mobility, hospital admissions, decentralised health systems, spatial spillovers, non-linear panel data methods, Italy

JEL:

C23, I11, H70, R23

1. INTRODUCTION

In several national health services (NHS), patient choice for hospital care, and the resulting patient mobility, has been encouraged through specific policies that have created financial incentives for providers to compete among them and have also led to improvements in the quality of care (Beckert, Christensen & Collyer, 2012; Gaynor, Moreno-Serra & Propper, 2013). There is a large empirical literature on the relationship between quality and hospital competition, and recent contributions suggest that positive effects on quality emerge where reforms towards patient choice are in place (Propper, 2012; Gravelle, Santos & Siciliani, 2014; Bloom, Propper, Seiler & Van Reenen, 2015).

In the last decades, many countries have also implemented decentralisation reforms by giving to sub-national governments some degree of autonomy in the provision of public services. In decentralised healthcare systems, free patient mobility among regions contributes to stimulate inter-jurisdictional competition (IC). The advantages of IC are numerous. In line with the "first-generation" perspective of fiscal federalism, patient mobility helps to maximise social welfare through an easier match between residents' preferences and services and to foster innovation in service supply at the local level. As highlighted in more general terms by Oates (1999), in a situation with imperfect information and learning-by-doing opportunities, there are potential gains from experimentation with a variety of policies: when a jurisdiction defines an effective way of providing a specific public service, other jurisdictions may improve their performance by simply adopting similar solutions. Consistently with the "second-generation" literature (Oates, 2005; Weingast, 2009), decentralisation is a suitable mechanism for limiting politicians' opportunistic behaviour in settings with asymmetric information between voters and elected representatives. In this perspective, free patient mobility makes operational the yardstick competition mechanism by enabling voters to directly compare local services to those provided in other jurisdictions (Besley & Case, 1995).

IC can also present relevant drawbacks. It might determine higher inequity in the quality of care and access to services at the country level, because service provision depends on autonomous decisions of local governments. Free patient mobility can help mitigating such problems. Concerns also regard inefficiency of local governments in dealing with the dysfunctional effects due to competition in the supply of public services. While in traditional models (e.g. Brown & Oates, 1987; Wildasin, 1991), mobility usually determines an under-provision of public goods because costs are borne by the destination jurisdiction, in the healthcare sector mobility leads to over-provision of care when hospitals are financed through general taxation and local governments pay for their residents' treatments independently of the provider's location. In such sub-optimal equilibrium, quality improvements are mainly related to the accountability mechanism, which makes local policy-makers responsible for both financial losses and gains deriving from patient mobility.

Other concerns refer to external factors that can characterise a decentralised setting: unexploited economies of scale, especially when sub-national jurisdictions are very small in terms of population size; income disparities across regions, because with free mobility low-income regions can experience higher provision costs; the emergence of non-internalized spillover effects among neighbouring jurisdictions, on both the demand and production sides, which can lead to local governments inefficiency in terms of expenditure increases or of low quality. However, there is also evidence of positive spatial spillovers among competing hospital care providers (Gravelle et al., 2014), which could lead to quality improvements also at the jurisdiction level. In healthcare, when significant asymmetries among competing jurisdictions exist, the drawbacks may overcome the advantages of IC. Regardless of the "effort" made by local policy-makers, some jurisdictions might underperform and experience budget unbalances. If this is the case, patient mobility could complicate the mechanism through which IC works.

From this perspective, the Italian NHS represents an interesting case of study because it is a *regionally decentralised* tax-funded system, in which patients are entitled to choose any hospital care provider all over the country. The NHS is characterised by a high and persistent inter-regional patient mobility (7.5% of total admission in 2010) with the geography of hospital admissions favouring flows from southern regions towards central-northern ones: 34.2% 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). Devolution in healthcare also involved the funding system, through the introduction of regional taxation that partially finances regional healthcare expenditures. 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 RHSs with a larger autonomy in the organisation of the healthcare services (hospital capacity, technological endowment, hospital network organisation, variety and specialisation of the local supply).

Decentralisation of NHSs is common to many European countries such as Italy, Spain, Sweden, Denmark, Germany and Austria (Adolph, Greer & da Fonseca, 2012). Free choice reforms have been implemented in Italy, Sweden and England. In light of the theoretical debate mentioned above, the combination of decentralisation with free patient mobility can have controversial effects on the efficiency and effectiveness of the healthcare provided at the regional level, as well as on universalism and equity at the national level. One of the standard predictions of IC models is 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 (e.g., Brekke, Cellini, Siciliani & Straume, 2012). However, according to our data (see the Appendix A in the Supplemental online material), 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, suggesting that quality differences have been persistent over the observed period. 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 main features of inter-regional patient mobility in a NHS, where IC is stimulated by free patient choice and inter-regional full-cost reimbursements. More specifically, our research questions concern whether and to what extent patient mobility is driven by factors related to policies pursued by the regional health authorities, rather than by exogenous internal factors, such as geography and demography, or exogenous external factors, such as neighbouring regions- or national-level policies.

These issues are addressed by means of an empirical model for inter-regional patient mobility occurring yearly over the period 2001-2010 in all hospitals, after the accomplishment of the decentralisation reforms. Compared to previous analysis, mainly performed on cross-section samples, the longitudinal dimension of the dataset used in this study allows to estimate a dynamic spatial conditionally correlated random effects (CCRE) model that accounts for region-pair-specific unobservable heterogeneity.

Main results suggest that local supply factors, such as hospital capacity and technology endowment, clinical specialization and performance indicators are important drivers of patient mobility, and regional population size and income also play an important role. Geography significantly matters and spatial proximity plays a relevant role in reinforcing inter-regional mobility patterns. The novel evidence provided in this study offers a valuable contribution to the ongoing debate on the effects of decentralisation of NHSs and patients' empowerment through free mobility. Moreover, as reported in the online Appendix B, the estimation results are exploited 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 analysed inter-regional patient mobility *per se*, but rather 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 (Montefiori, 2005; Brekke et al., 2012). These models allow for both horizontal (either defined in terms of physical location or healthcare specialization) and vertical (quality) differentiation among jurisdictions.

Consistently with the general results on IC outlined in the Introduction, the expected effects of free patient mobility on quality are mixed. With self-interested providers, the expected positive effect crucially depends on whether more patient choice increases providers' marginal profit from quality (see Brekke, Gravelle, Siciliani & Straume, 2014a for a survey).

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. When regions exhibit different exogenous efficiency levels and are subject to a “soft budget constraint”, inefficient regions have an incentive to induce patient flows towards the most efficient regions in exchange for a higher probability of being bailed out (Levaggi & Menoncin, 2013).[1] 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. According to Brekke, Levaggi, Siciliani and Straume (2014b), if regions differ in their ability to provide healthcare, 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 therein, and a loss for patients receiving care in the low-performing regions. The size of the loss for the latter regions and the maximisation of total welfare crucially depend on an adequate setting of transfer prices, which at the optimum should not cover the total cost of the treatments. Finally, Brekke, Levaggi, Siciliani and Straume (2016) consider a framework with three representative constituencies differing in per-capita income and responsible for the cost of residents' extra-regional care. They show that: i) reducing the barriers to free patient mobility determines an incentive for medium-low income regions to reduce quality;[2] ii) increasing income disparities between regions increases the inter-regional quality difference.

The aforementioned theoretical results give scope to testing the relevance of regional income gaps, efficiency differences between RHSs that can be measured through performance indicators and geographical factors, in addition to size effects (economies of scale) and spatial spillovers already stressed by the IC literature.

The above-reviewed models of bilateral spatial competition have a direct empirical counterpart in terms of gravity models, in which patient flows between any two RHSs are driven by the socio-economic variables of the origin and destination regions, by factors influencing the RHS's ability to restrain outflows and attract inflows, and depend negatively on the geographical distance between those regions. The gravity model has been widely used to analyse patient flows among competing hospitals (Congdon, 2001; Lippi Bruni, Nobilio & Ugolini, 2008) and physicians (Schuurman, Berube & Crooks, 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) and Fabbri and Robone (2010) at the level of local healthcare areas.

This study aims to contribute to the current debate on decentralisation of NHSs and patients' empowerment through free inter-regional mobility by assessing the effects of the wide range of factors suggested by the existing theoretical and empirical literature reviewed above. The next sections illustrate the econometric framework and how the main determinants of bilateral patient flows have been operationalized.

3. METHODOLOGY

In order to assess the determinants of regional bilateral patient flows, the empirical analysis is conducted within a gravity framework for panel count data. The following exponential functional form for the conditional mean of the process is adopted:

$$E\left[Y_{ijt}|X_t,\alpha_{ij}\right]=\alpha_{ij}\exp\left(X_{it}\beta_o+X_{jt}\beta_d+X_{ijt}\beta_{od}+\mathrm{dist}_{ij}\gamma_{od}\right) \quad (1)$$

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 $\mathbf{dist}_{\mathrm{ij}}$ 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 & Jones, 1980; Le Sage & 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 account for spatial spillovers, which can be straightforwardly applied also in the case of non-linear count data models.[3] 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 ($\mathbf{WX}_{\mathrm{it}}$ or $\mathbf{WX}_{\mathrm{jt}}$) 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 allow 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 (Allison & 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. 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) in the context of linear panel models, can be seen as a way to combine the FE and random effects (RE) 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 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.

Finally, 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 $\mathbf{Y}_{ijt}$. Thus, the final model is a dynamic spatial CCRE-NB specification.[4] 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 $\overline{\mathbf{X}}_{ij}$, $\overline{\mathbf{X}}_{i}$ and $\overline{\mathbf{X}}_{j}$ but also of the initial period value of the dependent variable.[5] The final specification of the conditional mean of the inter-regional patient count flows is:

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

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

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, spatial and serial correlation - and includes a comprehensive set of explanatory variables, is expected to provide an accurate representation of the conditional mean of the response variable.

4. DATA AND VARIABLES

Data sources

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 contain valuable information about hospital type, Local Health Authority (LHA) and region where the admission occurred, as well as patient's LHA and region of residence.

National Statistical Office (ISTAT), NHS Statistical Yearbook and Hospital discharge data are used to build a unique database of demographic and economic characteristics of the Italian regions and features of the hospital care services in each RHS.

The dependent variable

The unit of analysis is represented by pairs of regions that exchange patients. Given that in Italy there are 21 regions, in each year there are 420 observations on bilateral OD patient flows. The dependent variable is 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*).

In building the dependent variable, data on non-deferrable mobility is discarded. The remaining patient flows represent potentially avoidable mobility, because this depends on the patient's deliberate choice to seek hospital care in another RHS.[6]

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% of total admissions. Approximately 45% of total mobility is generated by southern regions as patients tend to move mainly from southern to central-northern regions. The online Appendix A reports a detailed description of the inter-regional flows for all types of admissions (henceforth *Total Flows*), and for specific types classified as *Surgery*, *Medicine* and *Cancers*. Distinguishing between these three types of admissions is relevant because the dynamics of patient mobility and the extent to which the various factors affects the ability of a region to restrain outflows and to attract inflows of patients varies with different economic incentives and with hospital specialization.

Explanatory variables

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 factors related to policies pursued by the regional health authorities and exogenous factors, both internal and external with respect to the focal RHS, as suggested by the theoretical and empirical literature. Table 1 reports a complete description of all variables used in the econometric analysis.

[Table 1 about here]

Patient outflows are expected to be directly proportional to *Population* at origin. It is measured by 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 locally. 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 in the availability and distribution of health services. Italian RHSs should meet the target, set by the central government, on the beds-population ratio to be considered efficient by the Ministry of Health. An excess of hospitals beds, relative to own population, is considered a signal of bad management, which can translate into a waste of resources, as well as lower quality.[7] Given its population, a RHS is expected to become less efficient as the number of beds increases, and this should explain larger (smaller) patient outflows (inflows). On the other hand, a higher hospital capacity is likely to lower waiting lists, and this should lead to an improvement of the regional service provision yielding smaller (larger) outflows (inflows).

The ‘method of penalties by coefficient of variation’ (Mazziotta & Pareto, 2016) is applied to build a composite *technology endowment index* (TEI), that uses 25 indicators on the number of medical devices available each year in each region.[8] 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 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.

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 average. The conventional interpretation would be that inefficiency (higher values of CIP) increases outflows and makes a region less able to attract extra-regional patients. However, it is important to consider that because patients might perceive longer stays as an insurance against bad health at home after admission, they might associate better quality to RHSs that exhibit higher values for CIP and make their decisions accordingly. This would lead to lower outflows and higher inflows. This interpretation depends on the fact that patients measure healthcare quality with error, particularly in the absence of public data on true quality (Montefiori, 2005), and do not only consider clinical quality but all aspects of the hospital experience (Romley & Goldman, 2011).

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.[9] 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. By contrast, a higher variety of providers is expected to restrain outflows and increase inflows.[10]

Finally, geographical dummies for the three macro-areas of the country (*South, North* and *Centre*) are included to account for the persistent asymmetries – in terms of geographical size, per-capita income, population and transport accessibility – among the Italian regions.

Region-Pairs Characteristics

Within the gravity model, 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.

5. RESULTS

Table 2 reports the results of the gravity model for total (first three columns) and specific types of admissions (last three columns) for inter-regional bilateral patient flows occurred in the period 2001-2010. The first three columns report results 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 (equation 2). The models are compared on the basis of the Likelihood Ratio (LR) tests, reported at the bottom of Table 2. 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 individual fixed effects should be included to account for unobservable heterogeneity. The LR-test in the third 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 is more adequate than its static counterpart.[11] 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 a non-stationary 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 decentralised Italian NHS, especially when relevant geographical and economic factors affecting patient mobility are not under the direct control of the regional governments.

[Table 2 about here]

The estimated effects of the dynamic CCRE, reported in the third column of Table 2, are computed following the approach in Le Sage and Thomas-Agnan (2015). Because the explanatory variables are log-transformed, they 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% increase in GDP per capita increases inflows of about 7.4%.

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 effect at destination is particularly sizeable when compared to the analogous effect at origin. The effect of a 10% increase in this covariate entails a reduction of 1.1% in outflows and an increase in inflows of 7.8%. In light of this result, the national policies that promote hospital bed rationing to enhance the NHS efficiency have important effects in terms of inter-regional mobility. In this regard, the Online

Appendix B reports the simulation of a specific policy scenario derived by setting the total number of beds in each RHS at the recommended national target (3.7 beds *per* 1,000 inhabitants). The estimated model predicts a reduction of 8.2% in patient mobility.

The CMI exhibits a positive and significant effect at origin, thus specialisation in treatments with higher resource intensity is associated with higher outflows. At the same time, the negative effect 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. The result at origin is consistent with the interpretation that patients observe signs of better quality in RHS that have relatively longer length of stays. At destination, the result is consistent with the fact that the CIP is capturing the overall efficiency and quality levels of the RHS. 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 impacts of such variables can be interpreted as indirect effects resulting from changes in each 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 effect. 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 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 the geography of 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. 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.

Models for specific types of admissions classified as *Surgery*, *Medicine* and *Cancers*, show that population and GDP per capita have significant direct and indirect effects. As population increases, the number of admissions outside the origin region 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% increase makes surgical patient outflows decrease by approximately 4%, while medicine and cancer patient inflows increase by 8.1 and 11.6%, respectively. Moreover, evidence of spillover effects is found: the proximity of smaller RHSs helps in containing outflows in all specific models and in attracting inflows in the *Medicine* and *Cancers* model. Richer neighbouring regions discourage *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 0.73 in the *Medicine* model, increases with complexity and it is close 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 for *Cancers*, where an increase of 10% in the number of beds of private hospitals in proximate regions leads to more outflows (1.1%) and lower inflows (-2.6%). A corresponding increase in the public hospitals leads to a decrease in outflows of 9.2% and an increase of inflows of 45%. Differently from total patient flows, the technology indicator plays a central role in the *Cancers* model, where inflows increase of approximately 15% for a 10% higher TEI. A higher TEI in the proximate regions has the effect of increasing surgical patient 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. At origin the CIP is statistically significant only in the model for *Medicine*; at destination it keeps its significance in all models and exhibits the largest effect for *Surgery*. A 10% increase in the CIP of the proximate RHSs increases inflows in the *Medicine* and *Cancers* models (about 33 and 78, respectively) but has a negative effect on surgical patient inflows. The HHI is a significant 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, suggesting that regions with less diversified hospital services are not viewed as attractive alternative destinations.

The distance effect is greater for *Cancers*, probably because treatments often require multiple daily hospital admissions. Political similarity seems to be relevant for both *Surgery* and *Medicine*.

Overall, the results discussed above depict a very comprehensive picture of patient inter-regional mobility in Italy by highlighting how the effects of some key variables vary according to the admission type, the RHS being a *sender* or a *receiver* of patients and the features of neighbouring RHSs.

6. DISCUSSION AND CONCLUSIONS

Free patient mobility might represent a tool for enhancing the effectiveness and efficiency of local healthcare services. 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 services. This risk crucially depends on the characteristics 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 indicate that the most effective determinants of inter-regional patient mobility, besides exogenous factors such as regional income and population, are supply-side features of the RHSs, namely number of beds, the diversification of the RHS organizational structure and the comparative index of performance. The technological endowment enhances the regions' ability to attract non-resident patients for cancer treatments. The role of supply factors, coupled to the persistence of inter-regional mobility, challenges the validity of the simplest IC theoretical competition models, while it fits well with models that assume persistent heterogeneity between regional systems. More importantly, the results indicate that neighbouring regions' supply factors, specialisation and performance indicators generate significant local externalities, which largely explain OD patient flows. These novel empirical findings call for advances in the theoretical bilateral spatial competition models, in order to account for neighbouring regions' characteristics.

The econometric analysis has also detected a mild non-stationary dynamics 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. Notwithstanding the limits of the analysis presented in this paper, these findings could be reasonably extended to other decentralised economic settings characterised by relevant income and efficiency gaps where free patient choice is part of the economic agenda.

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. According to the theoretical literature on IC, a typical "pigouvian solution" is in principle available in terms of subsidies (i.e.

intergovernmental grants, see Wildasin, 1991), usually combined to interventions on prices (e.g. tax rates constraints, see Zodrow & Mieszkowski, 1986). Similarly, the literature on inter-regional patient mobility has emphasised the role of transfer pricing schemes (Levaggi, Moretto & Pertile, 2014; Brekke et al., 2014b, 2016). These schemes have been introduced in Germany, Denmark, Norway, Spain, where fixed costs are not included in the DRG tariffs. However, this could relax the incentive compatibility constraint to which local politicians are subject when IC is not moderated by national compensation schemes. Therefore, each country defines its preferred institutional arrangement depending on its history and the orientation of the political debate.

The empirical application proposed in this paper presents some limitations which will be addressed in future research. One of the most important limitations is that, because of lack of data, it was not possible for the period under investigation to include outcome indicators that are usually used to proxy quality within the health economics literature. Future developments also include the extension of the analysis to financial flows associated with mobility and the study of welfare and inequality effects of patient mobility in a decentralised context.

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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 (Baldi & Vannoni, 2017).

[2] More precisely, the model yields this result when considering the medium and low income regions together. Considering them separately, the only region that certainly reduces quality is the medium income one, whereas for the low-income region the effect is indeterminate.

[3] Note that the Poisson or negative binomial estimation procedure has not yet been developed for the Spatial Autoregressive model (Le Sage & Thomas-Agnan, 2015). Moreover, the Spatial Error Model specification is not considered because it rules out spillover by construction.

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

[5] 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).

[6] 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. See the online Appendix A for a detailed account of the excluded admissions.

[7] Because population is already included in the regression model, the absolute number of beds is used in place of the beds-population indicator. Furthermore, because targets have changed repeatedly over time, it is not possible to build an indicator based on the distance between the observed number of beds and the national target for each of the years considered.

[8] 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.

[9] In Italy, there are eight types of RHS-financed hospital care providers: public hospitals, autonomous public enterprises, scientific institutes for research, hospitalization and healthcare, medical school hospitals, private licensed hospitals, research centres, classified hospitals and LHA-qualified institutes.

[10] 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.

[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 outperforms, in terms of the LR-test, the two more parsimonious specifications which only include one set of average terms at a time.

[12] Because the model is dynamic, interpretation focuses on short-run effects.

Table 1. Descriptive statistics, variable definitions and data sources (Italy, 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 calculations
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 calculations
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 2. Estimated models for total and specific inter-regional patient flows in Italy (2001-2010)

Dependent Variable y_{ijt}: Patient flows to Destination j from Origin i						
	Total flows			Specific types of flows		
				Surgery	Medicine	Cancers
Negative Binomial models	RE	CCRE	Dynamic CCRE	Dynamic CCRE		
Origin characteristics	direct effects					
Population	0.623 ***	0.441 *	0.350	0.760 **	0.061	0.120
GDP per capita	-0.325 **	-0.164	-0.190	-0.390 *	-0.090	-0.558
Population aged 0-14 (%)	0.004	0.019	0.007	-0.009	0.017	-0.028
Population aged over 65 (%)	0.007	-0.002	-0.007	-0.007	0.004	0.030 *
Beds in public hospitals	-0.126 **	-0.090 *	-0.107 **	-0.054	-0.079	-0.155
Beds in private licensed hospitals	-0.012 *	-0.008	-0.008	-0.024 **	0.002	-0.013
Technology endowment index -TEI	0.179	0.163	0.114	0.145	0.020	-0.212
Case mix index - CMI	0.238	0.296 *	0.329 **	0.596 ***	-0.094	0.331
Comparative index of performance- CIP	-0.170 *	-0.240 ***	-0.242 ***	-0.134	-0.170 *	-0.217
Organisational structure - HHI	0.067 **	0.071 **	0.023	0.104 ***	-0.023	0.070
South	-0.601 ***	0.093	0.391	-0.900	1.692 *	2.366 **
North	0.339 ***	-0.263	-0.335	-0.252	-0.499 *	-0.789 ***
Spatial lags	indirect effects					
Population	0.381	1.759	2.170	3.618 **	0.626	8.973 ***
GDP per capita	-3.572 ***	-3.150 ***	-1.738 **	-2.985 ***	0.167	1.484
Beds in public hospitals	-0.424 *	-0.311	-0.208	-0.545 **	0.363	-0.920 *
Beds in private licensed hospitals	-0.036 **	-0.041 **	0.003	-0.009	0.001	0.109 **
Technology endowment index - TEI	1.772 ***	2.006 ***	1.461 ***	2.162 ***	0.469	0.093
Case mix index - CMI	-3.886 ***	-3.672 ***	-2.629 **	-3.166 **	-2.541 **	3.567
Comparative index of performance CIP	-1.002	-0.690	-1.114 **	-0.915	-1.246 **	-1.115
Organisational structure - HHI	-0.663 ***	-0.867 ***	-0.809 ***	-0.756 ***	-0.628 **	-2.328 ***
Destination characteristics	direct effects					
Population	-0.482 ***	-0.073	0.118	-0.248	-0.216	-1.219 **
GDP per capita	0.429 ***	0.625 ***	0.725 ***	0.577 ***	0.813 ***	1.160 ***
Beds in public hospitals	0.982 ***	0.981 ***	0.784 ***	0.753 ***	0.729 ***	0.934 ***
Beds in private licensed hospitals	0.010	0.007	0.007	0.008	0.003	-0.022
Technology endowment index -TEI	0.097	0.008	0.029	-0.056	0.039	1.513 ***
Case mix index - CMI	-0.876 ***	-0.856 ***	-0.680 ***	-0.057	-1.242 ***	-0.226
Comparative index of performance- CIP	-0.948 ***	-1.074 ***	-0.623 ***	-0.746 ***	-0.520 ***	-0.635 ***
Organisational structure - HHI	-0.003	-0.089 ***	-0.014	-0.090 *	-0.011	-0.050
South	-0.273 ***	-1.383 ***	-0.920 **	-0.517	-1.222 ***	-1.698 ***
North	0.038	-0.373 *	-0.257	-0.631 ***	-0.305 *	0.882 ***
Spatial lags	indirect effects					
Population	-0.563 *	2.562 **	0.840	0.590	-2.308 *	-8.310 **
GDP per capita	-0.530	-3.420 ***	-1.944 **	-2.143 *	-2.454 **	-15.102 ***
Beds in public hospitals	0.317	0.265	0.461 **	0.602 **	0.007	4.486 ***
Beds in private licensed hospitals	-0.099 ***	-0.059 ***	-0.064 ***	-0.029	-0.115 ***	-0.262 ***
Technology endowment index - TEI	-1.081 **	0.413	-0.286	-1.653 **	-0.383	3.145 *
Case mix index - CMI	-0.470	-0.792	0.632	-0.348	2.482 **	-2.858
Comparative index of performance CIP	0.336	-0.852	0.338	-2.516 ***	3.288 ***	7.777 ***
Organisational structure - HHI	2.189 ***	1.369 ***	1.654 ***	0.223	2.289 ***	4.512 ***
Origin-Destination characteristics						
Distance	-0.258 ***	-0.088	-0.263 ***	-0.238 ***	-0.391 ***	-0.767 ***
Past migration flows	0.194 ***	0.040	0.034	0.014	0.043	0.084
Political similarity	0.007 **	0.008 **	0.011 ***	0.008 *	0.008 ***	-0.009
Lagged patient flows (y_{t-1})			0.00005 ***	0.00005 ***	0.00005 ***	0.00003 ***
Initial patient flows (y_0)			-0.00008 ***	-0.0001 ***	-0.00006 ***	-0.00002 ***
Log Likelihood	-21156	-21026	-20818	-18099	-19332	-14257
Squared correlation, actual and fitted flows	0.498	0.583	0.503	0.399	0.581	0.821
LR-test (degrees of freedom 36)		259.39	327.640	278.49	315.710	292.82
(p-value)		(0.000)	(0.000)	(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 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

The effects are computed following the approach in Le Sage and Thomas-Agnan (2015)

Level of significance: *** 1%, ** 5%, * 10%

Appendix A

Inter-Regional Patient Flows in the Italian NHS

The unit of analysis is represented by pairs of regions that exchange patients. For each year a 21x21 Origin-Destination (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, the dependent variable is given by the 420 bilateral OD admissions flows per year.[1]

Admissions considered as non-deferrable, i.e. those for which the patient has no choice as far the location where the treatment has to take place, where discarded.[2]

Table A1 describes inter-regional flows for all types of admissions (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. In 2010, admissions for surgical patients are 48.6 percent of total flows and they have increased by 19.6 percent with respect to 2001. Medical admissions instead count for 51.4 percent of total flows and they have decreased of about 10.2 percent in a decade. 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. Cancer-related admissions are a smaller and quite stable quota of total flows (10.2 percent in 2010, with a rise of 1.7 percent in the last decade).

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

[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 specialized 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 specialized neonatal care and treatments for children with rare diseases, and “Smom”, which delivers rehabilitation and neuro-rehabilitation services, were also excluded.

Table A2 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 exhibit large regional variation, suggesting the existence of spatial correlation. On average, the creation rate is higher in the central-northern regions than in the southern ones. Regional disparities seem to be slightly decreasing over time, as indicated by the coefficient of variation, which decreases from 0.62 to 0.59. However, it is worth noting that such a modest decrease (a change of just 0.03) is hardly relevant in economic terms for the whole population of 21 regions considered in this study. In 2010 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 A1, which depicts the mobility index in 2001 and 2010, confirms the existence of spatial correlation 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.

Table A1 - 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

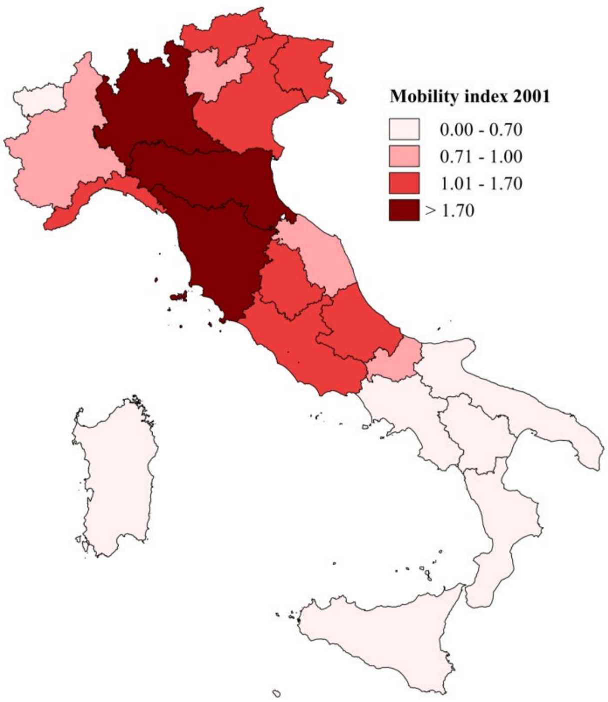
Note: Flows for Surgery, Medicine do not sum up to Total Flows because admissions in long-term and rehabilitation wards and admissions of healthy babies born at the hospital are excluded. Flows for Cancers include admissions in surgical and medical DRGs of patients diagnosed with a tumor.

Table A2 - 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
minimum	0.60	0.22	3.88	1.25	0.23	0.52	0.25	4.11	1.56	0.16
maximum	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.

Figure A1 - The Geography of Inter-Regional Patient Mobility. Mobility Index, 2001 and 2010



Appendix B

A post-estimation policy scenario

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.

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, are calculated by using patient mobility data in 2010 and estimates from the general model for total flows (column 3 of Table 2 in the article).

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:[3]

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

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

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

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 $\omega_{ij} =$

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

y_{ij}/Y_i. Similarly, one could derive the expression for the proportionate change in total inflows at destination *j*.

Table A3 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).[4] 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 (third column of Table 2 in the article). 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 8.2 percent (63707 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. This is the case for the southern region of Campania that exhibits an increase of 8.1 per cent in negative net mobility (from -55,310 to -59,765 admission episodes). Conversely, the central region of Lazio, for example, would experience a consistent increase in its positive net mobility (about 80 percent). This exercise could be extended for the calculation of the monetary reimbursement associated with patient flows for each region.

[4] 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 the third column of Table 2 in the article.

Table B1 - 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	-4268	-3126	-1264	-1314	-5532	-4440	1092	-6213	-15.0
Valle d'Aosta	4.2	-11.0	4914	1952	-2962	-365	-156	-133	-62	-499	-218	281	-2681	-9.5
Lombardia	4.3	-14.5	68533	146076	77543	-6727	-8669	-1857	-4162	-8584	-12831	-4246	73297	-5.5
Provincia Autonoma Bolzano	4.2	-12.4	4017	6804	2787	-336	-655	-112	-195	-448	-850	-402	2385	-14.4
Provincia Autonoma Trento	4.7	-21.1	13778	9213	-4565	-1967	-610	-420	-249	-2387	-859	1527	-3038	-33.5
Veneto	3.9	-6.1	47885	61321	13436	-1979	-4858	-1048	-2189	-3028	-7047	-4020	9416	-29.9
Friuli Venezia-Giulia	4.2	-11.9	14138	20577	6439	-1140	-874	-448	-466	-1588	-1340	247	6686	3.8
Liguria	4.3	-14.5	38595	37297	-1298	-3794	-2153	-1052	-1193	-4846	-3346	1500	202	-115.6
Emilia-Romagna	4.5	-17.1	45545	113980	68435	-5254	-5843	-1306	-2981	-6560	-8824	-2265	66170	-3.3
Toscana	3.9	-4.5	39104	69833	30729	-1183	-3631	-881	-2472	-2064	-6103	-4039	26690	-13.1
Umbria	3.6	3.4	18450	24099	5649	427	-1929	-438	-772	-10	-2701	-2691	2958	-47.6
Marche	4.1	-9.9	29145	27776	-1369	-1944	-1606	-775	-697	-2718	-2302	416	-953	-30.4
Lazio	4.5	-17.4	67078	76341	9263	-7904	-1552	-2134	-1136	-10037	-2688	7350	16613	79.3
Abruzzo	4.0	-8.0	39395	26220	-13175	-2129	-2735	-882	-732	-3011	-3466	-455	-13630	3.5
Molise	5.4	-31.0	12187	18967	6780	-2560	-281	-349	-210	-2909	-491	2418	9198	35.7
Campania	3.5	6.2	80023	24713	-55310	3359	-1824	-1494	-766	1865	-2590	-4455	-59765	8.1
Puglia	3.9	-5.5	58335	29042	-29293	-2155	-909	-1757	-397	-3912	-1306	2607	-26686	-8.9
Basilicata	3.7	0.5	22759	15329	-7430	84	-114	-614	-150	-530	-263	266	-7164	-3.6
Calabria	3.9	-5.2	58166	8247	-49919	-2064	-335	-1736	-90	-3800	-425	3375	-46544	-6.8
Sicilia	3.7	0.0	53139	14843	-38296	-2	-805	-1580	-341	-1582	-1146	435	-37861	-1.1
Sardegna	4.2	-11.3	14689	4550	-10139	-1122	-359	-404	-109	-1526	-468	1058	-9081	-10.4

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.