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FREE PATIENT MOBILITY IS NOT A FREE LUNCH. LESSONS FROM A DECENTRALISED NHS

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Free patient mobility is not a free lunch. Lessons from a decentralised NHS

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Abstract
Patient mobility is a crucial phenomenon in contexts of hospital competition based on quality and driven by patient choice. This study examines inter-regional patient mobility in the Italian National Health Service, a regionally decentralised tax-funded system in which in-patient hospital services are provided free at any point of use in the whole country, using administrative data on hospital discharges from 2001 to 2010 in all public and private accredited hospitals. The aim is to understand whether mobility patterns might have consequences for the efficiency and effectiveness of the healthcare provided at the regional level, as well as universalism and equity in healthcare. We specify a gravity model for Origin-Destination (OD) flow data that distinguishes between emissiveness (at Origin) and attractiveness (at Destination) factors affecting bilateral flows. We exploit the longitudinal dimension of the data and estimate a negative binomial conditionally correlated random effects (CCRE) dynamic model that allows for region-pair-specific unobservable heterogeneity. Total and specific types of flow (surgical, medical, acute and cancer-related admissions) are modelled, accounting for the correlation between unobserved region-pair effects and time-variant covariates and their spatial lags. Our main findings indicate that RHSs in the richest regions attract more patients from other regions and that the most effective pull factors are the number of beds and diversification of the organisational structure. We also find that the ability of a RHS to attract patients who reside in other regions decreases with the concentration of the organizational structure. Finally, we have detected a mildly explosive dynamics in inter-regional patient mobility over time, which could have implications for the long-run sustainability of the overall national-regional health system.

Keywords: hospital admissions, gravity model, decentralised health systems, spatial dependence, negative binomial regression, nonlinear panel data methods
Jel classification: I1, C23, I18, H75, H77

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1. Introduction

The Italian National Health Service (NHS) is a regionally decentralised tax-funded system in which patients are entitled to choose a preferred provider of hospital care in the whole country. The current setting is the result of a series of reforms, initiated in 1992, that have introduced universal free patient choice and created twenty-one separate and autonomous regional health services (RHSs) that are formally responsible for healthcare organization in their jurisdictions and provision of care for the residents therein but subject to central government planning policy (which defines 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 Diagnosis Related Groups (DRG)-based tariffs. Decentralisation in healthcare services also involved the funding system through the introduction of a regional tax that partially covers the regional healthcare budgets. This decentralised setting has become fully effective with the constitutional reform approved in 2001, which provided Italian regions with a larger autonomy in the administration and organisation (e.g., hospital accreditation) of the healthcare services.

Because Italy can be described as a country with a persistent North-South economic divide, such configuration of the NHS 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. The Italian NHS is characterised by a high and persistent inter-regional patient mobility (7.5 per cent of total admission in 2010) with the geography of hospital admissions favouring flows from southern regions mainly towards central-northern ones: 34.2 per cent of total inter-regional flows move in this direction.

The economic importance of patient mobility lies in the fact that, in a context of fixed-prices, it generates an incentive for providers to compete on quality improvements (see, e.g., Gaynor and Town, 2012). When patients are allowed to seek care outside their jurisdictions, local health systems have an incentive to raise quality to attract patients from other jurisdictions and restrain outflows of their own enrollees. This makes the issue of inter-regional mobility increasingly important in the current debate on the effects of decentralization in the healthcare sector. Free patient mobility is consistent with both the "first generation" literature on Fiscal Federalism (which focuses on the capability of decentralised settings to maximize social welfare) and the "second-generation" literature, in which the hypothesis of benevolent social planners is abandoned and decentralisation is mainly regarded as a suitable mechanism for limiting politicians' opportunistic behaviour (Oates, 2005; Weingast, 2009). In line with both approaches, local policy makers should care about patient mobility, either because few patient outflows and high attractiveness indicate citizen satisfaction with the regional health systems or because inflows lead to more financial resources accruing to the regional healthcare budget, whilst outflows are accompanied by a financial loss related to the reimbursement of the hospital admission of patients outside their region of residence. By making local policy makers accountable for their behaviour, a complete decentralisation of the healthcare services could effectively induce them to decrease their demand of central funds, thus lessening the "soft budget constraint" problem.1 These arguments might not follow, however, when significant asymmetries between competing jurisdictions are present (a situation particularly relevant for Italy). Regardless of the "effort" made by local policy makers, some jurisdictions might underperform in equilibrium due to the existence of relevant economies of scale and the presence of spatial spillovers among jurisdictions. If this is the case, the mechanism through which competition between RHSs works in the presence of inter-regional patient mobility could be very complex.

Nonetheless, the evolution of patient mobility provides important indications for assessing whether decentralisation has been successfully improving the performance of the healthcare services in a context of asymmetric jurisdictions. In fact, a high performing regional healthcare service should be able to attract inflows and restrain outflows of patients. The theoretical literature suggests that in the case of symmetric jurisdictions, free patient choice 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*, 2008, 2010, 2012a, b). This has not been the case for Italy, where patterns of patient flow across regions have not exhibited any significant tendency to decrease over the last decade. In fact, central-northern Italian regions are confirmed as net exporters of hospital treatments in the sense that their hospitals admit a larger number of patients coming from the South. This fact has translated into additional amounts of financial resources, generated by the compensation of net patient flows, in favour of Northern regions, and has exacerbated the North-South gradient in the Italian NHS.

This fact seems to be in contrast with the positive effects that the decentralization process should have had. Hence, it is interesting to determine whether and to what extent patient mobility is driven by factors mainly unrelated with the policies pursued by the local health authorities. This paper addresses this issue by means of an empirical model for inter-regional patient mobility that has characterized the Italian NHS after the accomplishment of the decentralisation reforms of the nineties. Beyond the Italian case, the importance of our research question relates to the general appropriateness of a decentralised institutional setting in which regions bear the cost of care freely chosen by their residents and provided by any hospital in the country.

For the purpose of our analysis, we use time series data on hospital discharges occurring yearly over the period 2001-2010 in all public and private accredited hospitals of the twenty-one Italian RHSs. Using numerous sources of official and administrative data, we have enriched the dataset by collecting information on the demographic and economic characteristics of Italian regions and on important features of hospital care services in each RHS. We analyse bilateral Origin-to-Destination (OD) flows between regions by means of a gravity regression model that takes into account the overdispersed count nature of data. Because inter-regional patient flows depend on characteristics of both origin and destination, we have selected variables that are expected to influence patient choice about the hospital at which to seek care as well as the ability of the RHS to attract inflows and restrain outflows of patients. We exploit the longitudinal dimension of the data and estimate a nonlinear

[1] "Soft budget constraint" refers to the inefficient use of public funds by irresponsible local authorities accompanied by a request of additional financial resources so as to meet centrally defined targets. See Kornai *et al* (2003). For an application to the healthcare service in Italy see Bordignon and Turati (2009).

conditionally correlated random effects (CCRE) dynamic model that allows for correlation between the unobservable region-pair-specific characteristics and the observed regressors (Mundlak, 1978; Wooldridge, 2005). We also address the issue of cross-regional dependence by including spatial lags of some explanatory variables. Our estimated models provide us with a useful tool for analysing specific what-if scenarios that are relevant to the health authorities for the national and sub-national management of services, as illustrated in the last section of the paper.

Overall, we find compelling evidence of a permanent North-South gradient in mobility. The results suggest that hospital capacity, performance, population size and income in the regions are among the most important drivers of patient mobility. Conditionally on the exogenous variables considered, inter-regional patient mobility does not exhibit any significant decreasing trend. Finally, spatial proximity plays a relevant role in reinforcing patient mobility patterns across regions.

2. Related Literature

The theoretical literature in health economics 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 (see Brekke *et al.* 2014a). Within a given area, when prices are fixed, patient choice should lead to higher quality in healthcare services because providers can only modify quality levels to attract more patients, with the ultimate goal of maximising revenues or profits. Remarkably, this behaviour is not limited to private providers because even public ones have to face the financial consequence of their decisions, being partly subject to the financial targets that require them, at minimum, to break even.

Spatial competition models *à la* Hotelling have provided a useful framework used in several papers to study patient mobility in decentralized settings in which patients are eligible to receive free care at the point of use.[2] These models allow for the simultaneous presence of horizontal (whether defined in terms of physical location or healthcare specialization) and vertical differentiation (quality) among jurisdictions. Ceteris paribus, the higher the quality gap between different providers is, the higher the number of patients who decide to seek care in the higher quality region in absolute terms. While the transitional dynamics in patient mobility may depend on various assumptions, an equilibrium with permanent inter-regional mobility (such as that observed in our data) can be explained only by abandoning the hypothesis of symmetry between regional systems. This is the case of Levaggi and Menoncin (2008, 2013), who consider a context in which regions exhibit different exogenous efficiency levels and are subject to a "soft budget constraint". 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 found to be inefficient and is characterised by an excess of patient mobility because of an imperfect coordination among government levels. In addition, Brekke *et al.* (2014b) analyse a situation whereby regional jurisdictions differ in their ability to

[2] See, for example, Montefiori, 2005; Brekke *et al.*, 2008, 2010, 2012a, b; Siciliani *et al*, 2013).

provide healthcare. They indicate that permanent inter-regional mobility ensures an increase of overall welfare with asymmetric effects, namely, a benefit for all patients living in the “high-skill” regions and those moving there for hospital care – since decentralisation creates more incentives to improve quality – and a loss for patients receiving care in the “low-skill” regions.

In our opinion, the above-mentioned models of bilateral spatial competition have a natural empirical counterpart in terms of gravity models, whereby patient flows between pairs of regional health services are influenced by ‘mass’ indicators at origin and destination and depend negatively by the distance between the two “trading” areas. The gravity model has been widely used to analyse patient flows among competing hospitals (e.g., Congdon, 2001; Lippi Bruni *et al*, 2008) and physicians (Schuurman *et al*, 2010).

Much of the extant empirical literature on inter-regional mobility has focused on the determinants of net patient flows. Levaggi and Zanola (2004) estimated a pooled regression model for net patient migration of each Italian region to the rest of the country in the period 1995-1997, for which the main explanatory variables are per-capita regional income, the share of elderly population, beds- and hospitals-to-population ratios. This approach has been subsequently adopted by Cantarero (2006) to study inter-regional patient mobility in Spain in the period 1996-1999. More recently, Shinjo and Aramaki, (2012) have analysed the determinants of net patient flows in Japan using cross-sectional data available at the local level (Secondary Healthcare Service Areas). Though a larger set of variables was potentially available to the authors, the significant explanatory factors were essentially those considered by Levaggi and Zanola.

Patient mobility across local healthcare services is studied also by Fabbri and Robone (2010). As opposed to the aforementioned studies and consistently with standard gravity models, they focus on bilateral patient flows, namely, hospital admissions that occurred in 2001, across Italian Local Health Authorities (LHAs). They estimate a Poisson pseudo-maximum likelihood model to address two issues that are typical of the log gravity equation, that is, zero flows and heteroscedasticity in the error term. The model includes new variables to explain flows at both origin and destination (e.g., technology indicators and presence of hospital trusts), factors characterizing the origin-destination pair, such as geographical distance and contiguity, and a set of “spatial factors” based on distances between LHAs to account for the potential presence of network autocorrelation, which typically characterizes migration flow data. The analysis reveals the existence of important scale effects and that, ceteris paribus, the gradient of patient flows is from poorer to richer LHAs and from the South to the North, particularly for the most severe cases.

Beyond the gravity framework, it is worth mentioning a few recent works about patient mobility in Italy. In a study of regional cross-border mobility, Brenna and Spandonaro (2014) suggest that private hospital accreditation policies function as a strategic tool to attract patient flows. This result is supported also by Fattore et al. (2014), who study the determinants inter-regional mobility for patients treated for aortic valve substitution and shed light on the potential consequences on equity in the access to care to the detriment of the poorest regions located in South Italy. Analogous to previous papers, however, the latter works do not exploit the longitudinal dimension of patient mobility data.

3. Data and variables

3.1 Inter-regional patient flows in the Italian NHS

We use the time series of data on hospital discharges that occurred yearly over the period 2001-2010 in all public and private accredited hospitals of the 21 Italian RHSs.[3] Information on in-patient care is collected by each hospital at the time of discharge and regularly transmitted to the Ministry of Health. Each admission episode is classified using the US Medicare DRG and the actual length of stay is reported.[4] The data at hand also contain valuable information about the type of hospital, the corresponding LHA and the region where the admission has occurred, as well as the LHA and the region of residence of the patient.

Inter-regional mobility is by its very nature intrinsically heterogeneous. For example, the location of some admissions is determined by the incidental presence of an individual outside his or her region of residence. In this case, we can refer to it as non-deferrable or unavoidable mobility. Other inter-regional flows are the natural outcome of central planning of some highly specialized treatments, such as transplants. Our focus is instead on deliberate mobility for treatments, which, in principle, should be available in the region of residence.[5]

The unit of analysis is represented by pairs of regions that exchange patients. For each year, we construct a 21x21 Origin-Destination (OD) matrix that describes patient flows by aggregating the number of admissions of patients from each possible region of origin (enrolees in region *i*) in public or private accredited hospitals of each possible region of destination (region *j*). The main diagonal of each matrix is set to zero to exclude intra-regional flows. This leaves us with 420 bilateral OD patient flows per year.

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[3] As reported in Table 1, in the year 2010, approximately 34 per cent of public hospitals are run by LHAs (approximately 24 per cent of total inter-regional flows); 10.2 per cent are autonomous public enterprises (13.6 per cent of total inter-regional flows); 4.6 per cent are scientific institutes for research, hospitalization and healthcare (17 per cent of total inter-regional flows) and 2.2 per cent are medical school hospitals (16 per cent of total inter-regional flows). Private accredited hospitals represent approximately 45 per cent of the total number of providers, and they have the same share of flows attributed to the LHA public hospitals. The other typologies of providers are research centres, classified hospitals and LHA-qualified institutes, and they account for 0.2, 2.3 and 1.6 per cent of total providers in the same year, respectively.

[4] Version 10 of the Medicare DRG is used for admissions in years 2001-2005; Version 19 is instead used for years 2006-2008; for years 2009-2010, the most recent Version 24 is used.

[5] In view of that, we have excluded 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. 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. We have also excluded 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" (rehabilitation and neuro-rehabilitation services) because the Italian NHS considers the cost of admissions in these extra-regional hospitals as part of the home production of each RHS, thus reducing incentives to compete in the same areas of healthcare.

As reported in Table 2, in the time interval considered, an average of 832,410 admission episodes per year occurred in a region different from that of residence. Each year, the share of total admissions that can be referred to as inter-regional mobility amounts to approximately 7 per cent, increasing from 6.8 per cent in 2001 to 7.3 in 2010. Simple calculations on the statistics reported in Table 2 indicate that many flows are classified as *Acute* admissions. This figure tends to decrease over time, moving from 72.5 per cent in 2001 to 66.5 per cent in the most recent year, 2010.[6] Total flows can be further divided into *Surgery* and *Medicine* flows. In 2010, approximately 41 per cent of these inter-regional flows refer to *Surgery* (admissions are typically more complex and are compensated on the basis of tariffs, which are known to be, on average, higher than for *Medicine*). This figure has increased by 20 per cent since 2001, while mobility for admissions in medical DRGs has decreased by approximately 10 per cent in the same time span. In the econometric analysis, we will analyse total inter-regional flows as well as subgroups of flows for *Acute*, *Surgery*, *Medicine* and cancer-related procedures and treatments (*Cancers*).

The most recent picture of the geography of hospital admissions reflects a country in which citizens tend to move mainly from southern to central-northern regions. OD flows in this direction count for 32.5 per cent of total inter-regional flows, while OD flows in the opposite direction represent only a small fraction (7 per cent). Approximately 44 per cent of total inter-regional flows are generated by southern regions (338,693 admission episodes). Approximately 18 per cent of total flows are from regions in the South to regions in the North (140,429 admission episodes), while only 2.8 per cent of flows are from the North to the South (22,029). Flows between northern origins and destinations represent approximately 29.7 per cent of total inter-regional mobility, while this figure is only 11 per cent in the case of flows between southern origins and destinations.

A closer reading of the indicators describing inter-regional mobility indicates that there is large variation between Italian regions. Table 3 reports the creation and attraction rates; the outflow and inflow rates are calculated using hospital admission episodes in 2001 and 2010.[7] The table indicates that the regional contribution to patient mobility might be correlated with spatial proximity. Both the creation and attraction rates exhibit some spatial pattern. On average, the creation rate is higher in the central-northern regions than in the southern ones. Regional disparities are slightly decreasing from 2001 to 2010 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: Campania, in the South, generates approximately 10.3 per cent of total flows, followed by Lombardia (North, 8.8 per cent) and Lazio (Centre, 8.6 per cent). With respect to 2001, only Sicilia leaves the group of the four regions that create more mobility with a decrease of 1.5 percentage points in its creation rate. The smallest and least populated regions (Valle d'Aosta, P.A Bolzano, P.A. Trento, Friuli

[6] *Acute* admissions require at least one night spent at the hospital and exclude long-term and rehabilitation wards and admissions of healthy babies born at the hospital.

[7] The creation rate is the percentage ratio between enrolees of region *i* admitted in hospitals of other regions and total number of patient flows in Italy; the attraction rate is the percentage ratio between non-enrolees admitted in hospitals of region *j* and the total number of patient flows in Italy. The inflow rate is the percentage ratio between non-enrolees admitted in region *j* (inflows) and total number of admissions in region *j*. The outflow rate is the percentage ratio between enrolees of region *i* admitted in other regions (outflows) and total number of admissions of enrolees of region *i*.

Venezia-Giulia and Molise) and Sardegna, most likely due to insularity, generate less than 2 per cent of total flows, a figure that is very stable in the whole 2001-2010 period. If we look at the attraction rate in the macro geographical areas in 2010, we find a clear dichotomy between the southern regions (18.2) and the rest of the country (81.8). These figures have basically not changed with respect to 2001. The distribution of the attraction rate is quite dispersed with a persistently high coefficient of variation, 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 per cent, respectively). Since 2001, however, Lombardia and Lazio have slightly decreased their attraction rate while the Emilia-Romagna has gained approximately 3 percentage points.

We further examine patient flows in each region using the mobility index. This index measures the ratio between the inflow rate and the outflow rate and 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. The maps reported in Figure 1 indicate a clear North-South gradient and suggest that spatial proximity might play a role in explaining inter-regional patient mobility. For the majority of regions in the Centre-North of Italy, the mobility index is larger than 1 (larger than 2 for Lombardia and Emilia-Romagna), and from 2001 to 2010, Liguria and Abruzzo have moved from the group of net exporters of hospital admissions to that of net importers. All southern regions display indexes equal to or lower than 0.7 (the only exception being Molise, which has an index of 1.41 in 2010). Spatial patterns in hospital admissions, which are likely due to the influence of demand and supply features of the RHSs at origin and destination, seem to reflect the well-known North-South economic divide, as richer and better equipped regions effectively attract more patients and resources.

3.2 Characteristics of regions at origin and destination

We have collected information about the demographic and economic characteristics of each Italian region and about important features of the regional hospital care services. This allows us to build a wide range of indicators that we will employ in the econometric analysis. Because inter-regional patient flows depend on characteristics of both origin and destination regions, we have selected a set of variables that are expected to influence patient choice about the hospital at which to seek care as well as the ability of the RHS to attract inflows and restrain outflows of patients. In the following, we distinguish between potential emissiveness (at Origin) and attractiveness (at Destination) factors. The complete description of all variables is reported in Table 4.

Patient outflows are expected to be directly proportional to the economic "mass" of the origin region: gross domestic product (GDP) and population. The first mass variable, *per capita GDP*, may pick up 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 high-quality hospital services (hence, poorer regions would experience outflows of patients towards richer regions). The second mass variable, *population,* indicates the number of enrolees to the RHS and approximates the internal demand for healthcare. 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. At destination, both *per capita GDP* and *population* are expected to have a positive effect on the number of admissions for patients who reside in other regions. The explanation is that RHSs in richer regions can provide more efficient and effective healthcare services, and RHSs in bigger regions are characterised by a larger variety of specialized care than smaller regions. Among the origin features, we also include two demographic indicators, *population age 0-14* and *population over 65*, that capture the effect of belonging to the frailer groups of the population on the likelihood of seeking care in extra-regional hospitals.

Other factors that can influence outflows and inflows are indicators of hospital supply such as the number of beds and the level of technology endowment at the regional level. We use two variables for the number of beds in each region (*beds in public hospitals* and *in private licensed hospitals*) to capture any potential effect of the public-private mix. The weakness of these indicators is that they do not capture quality of care. In fact, an excess of beds in hospitals is typically considered a signal of bad management, which can translate into a waste of resources, as well as worse quality.[8]Thus, on one side, we could expect that as the number of beds increases, the region becomes more inefficient, and this should explain larger (smaller) patient outflows (inflows). On the other side, a higher endowment of beds 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). To measure the endowment of medical equipment at the RHS level, we build a *technology endowment index* (TEI) given by the weighted sum of 16 medical devices available each year in each region, whereby the weights are the relative prices calculated by Finocchiaro Castro *et al.* (2014) using data provided by the Italian Observatory of Prices and Technologies (Osservatorio Prezzi e Tecnologie).[9] A better endowment is expected to restrain patient outflows and increase the inflows.

We also included the *case mix index* (CMI) and the *comparative index of performance* (CIP) indicators. These indicators, calculated on acute admissions with stays longer than one day and reported in the yearly report on hospitals activity based on the discharges database, are

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[8] For this reason, the Italian government has being setting national targets on the optimal number of beds (per 1.000 inhabitants) either through recommendation of the Ministry of Health or through the annual documents of the Department of Treasury or the spending reviews. This implies that targets can change frequently even within the same years, thus preventing us from building an indicator of efficiency based on the distance between the observed number of beds and the national target for each of the years considered.

[9] The Observatory of Prices and Technologies stopped working in 2005; therefore, we do not have more recent information. We believe that this does not represent a problem because it is reasonable that relative prices have been stable over time. Relative prices are calculated using constant values at 2000 and the magnetic resonance imaging price is the numeraire. 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, computed axial tomography, magnetic resonance imaging, medical imaging table, and continuous ventilator system. For further details, see the Appendix A in Finocchiaro Castro *et al* (2014).

used by the Italian Ministry of Health to assess the efficiency of the RHS.[10] The CMI compares the RHSs on the basis of the resources used to treat the mix of patients in the hospitals and is calculated as the ratio between the average weight of admissions in a specific region and the average weight in the whole NHS.[11] A CMI higher than 1 indicates a greater clinical complexity compared to the national benchmark. Hence, it can be viewed as an index for specialisation in more complex cases. Specialization could be either an essentially demand-driven phenomenon or the result of the interplay between RHS strategies and patient needs. On the one hand, we could expect that patients are attracted by the RHS, which are known for being specialized in highly complex treatments. On the other hand, specialisation in highly complex cases 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 perform more treatments and procedures in DRGs with high clinical complexity can be related to the capacity to provide care with a higher profit margin independently of quality. The raw data, indeed, suggest some convergence in the regional CMI for the period 2001-2010: central-northern (and richer) 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 and is calculated as the ratio between the case-mix standardised average length of stays in each region and the national average. A CIP lower than (or equal to) 1 indicates that, assuming equal complexity, hospital stays are shorter (or have the same length) than at the national level, thus suggesting higher (or at least 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 patients from other regions. An additional reading of the link between CIP and patient mobility could be that longer hospital stays (for any given level of case-mix) are associated with the subjective perception of the patients of a better quality of hospital care, in which case the effect would be to decrease outflows at the origin and increase inflows at the destination.

For each region, we also build an indicator of the *concentration of the organizational structure* using the Hirschman-Herfindahl index, $HHI = \sum_{i=1}^{H} s_i^2$, where s_i is the market share of hospital type i (calculated in terms of admissions in a hospital type over total admissions) and H is the number of types of hospitals.[12] The HHI can take values ranging from $1/H$ (low concentration) to 1 (high concentration), reflecting differences between regional 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

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[10] Stays are typically longer in the long term and rehabilitation wards and neonatal care units. We have decided, however, to use all admissions present in the database to capture the complete specialisation and performance patterns.

[11] The average weights are the weighted sums of all admissions (at the regional or national level), for which the weights are DRG-specific and reflect the average amount of financial and physical resources necessary for each DRG.

[12] In the Italian regions we can have a maximum of eight types of hospitals who are financed by the RHS to produce care; a detailed description is reported in footnote 3.

concentration, inflows are expected to decrease. By contrast, a higher variety of providers is expected to restrain outflows and increase inflows.[13]

Finally, we include geographical dummy variables (*South, North* and *Centre*) both as origin and destination characteristics to distinguish between regions located in the three main geographic areas and capture the North/South economic divide.

3.3 Region-pairs characteristics

Inter-regional patient flows also depend on the characteristics of the specific region-pair. 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 hospital treatment exchanges. We further investigate whether such effects are moderated by other factors.

The first indicator is the *distance* in kilometres between each origin and destination region. This variable is expected to have a negative impact on patient mobility. Moreover, it is expected to account for spatial correlation among the observational units. Our model also includes *past migration flows,* as measured by the residential changes that occurred between each pair of OD regions in the previous five years. This indicator is expected to have a positive impact on patient mobility because past migrations can represent a source of knowledge for patients seeking healthcare. People who have migrated may provide their relatives and friends with valuable information on the medical services available in their region of residence and in the contiguous ones. Moreover, patients are also more likely to seek care in hospitals located in regions where relatives or friends migrated because they can provide informal support before, during and after the hospital stay. This is particularly important when treatments require long stays. For all these reasons, past migration flows also account for spatial correlation in patient mobility. We finally introduce a *political similarity* dummy variable, which equals 1 if the regional governments share the same political orientation (i.e., the same coalition won elections). An important aspect in the understanding of bilateral patient flows in the Italian NHS is whether regions belonging to the same political coalition can foster institutional collaboration in managing hospital care We expect that politically closer regions are more likely to trade hospital admissions either because of shared information on the adoption of best practices in other regions or because political similarity may help strategic cooperation in investing in complementary healthcare services, particularly cross-borders, and exploit economies of scale.

We finally include two indicators built using the share of admission episodes in surgical DRGs for each region pair. The first indicator is the share of surgical admission episodes of patients resident in origin i that occurred in region j over the total amount of surgical episodes delivered to non-resident patients in that destination region. It can be considered as a measure of *relative attractiveness* because higher shares would indicate that the destination region is more attractive for patients from that specific origin region, which could be defined as the preferred "trading" partner for surgery, than from any other region. OD flows are expected to increase with the attractiveness of surgery. The second indicator is calculated for each region pair as the share of surgical admission episodes of patients resident in origin i

[13] We cannot exclude that some degree of homogeneity in the organisational structure of hospital care may also entail some advantages, e.g., in terms of higher efficiency due to the exploitation of economies of scale and more effective planning of the RHS. However, we do not expect that these effects offset the benefits arising from higher variety.

that occurred in region *j* over the total number of surgical episodes that occurred outside the origin region and can be viewed as a measure of *relative loyalty*. Because surgical DRGs typically involve treatments with higher complexity than medical DRGs, we expect that the fraction of surgical admissions, from a specific origin, drives patient mobility to the same destination also for less complex treatments. Both attractiveness and loyalty mechanisms might be based on microlevel learning (at destination) and communication (at origin) of patients sharing their experiences with treatments received in specific destinations within family and friends networks.

4. Methodology

The empirical analysis of inter-regional patient flows is conducted within a gravity model framework for panel count data. We adopt the exponential functional form for the conditional mean of the process, which we specify as follows:

$$E\left[y_{ijt}|\boldsymbol{X}_t, \alpha_{ij}\right] = \alpha_{ij}\exp\left(X_{it}\beta_o + X_{jt}\beta_d + X_{ijt}\beta_{od} + \gamma_{od}dist_{ij}\right) \qquad (1)$$

where the subscript *i* refers to the region of origin, *j* to the region of destination and *t* to time, with *t*= 2001, …, 2010. The observations in each year refer to pairs of Origin-Destination (OD) regions, *ij*= 1, 2, ..., *N*=420. $\boldsymbol{y_{ijt}}$ is the number of admissions of patients resident in region *i* who seek hospital care in region *j* at time *t*. The matrix $\boldsymbol{X_{it}}$ includes the variables that describe the most salient features of the region of origin, whereas $\boldsymbol{X_{jt}}$ comprises the analogous variables observed at the destination region. The matrix $\boldsymbol{X_{ijt}}$ includes those variables that are supposed to describe the distinctive traits of each region pair. The variable $dist_{ij}$ captures the geographical distance between regions in each OD pair. The term $\boldsymbol{\alpha_{ij}}$ 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. It is worth recalling that 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, we explain how we tackle each feature of the data to ensure the use of a consistent estimator.

Flow data are typically characterized by cross-section dependence induced by correlation in space (Griffith and Jones, 1980; Le Sage and Pace, 2008, 2009). The latter arises because flows of a given origin are usually influenced by the features of the neighbouring regions, and analogously, flows towards a specific destination respond also to features of the nearby destinations. In our analysis, spatial dependence is tackled by including spatial lags of some relevant 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 (WX_{it} or WX_{jt}) is the weighted average of the neighbouring regions values, with weights declining as a function of distance. Moreover, we account for spatial dependence by including regressors featuring spatial characteristics, such as geographical distance. These are past migration flows and the relative attractiveness, relative loyalty and political similarity indicators described in the previous section.[14]

With regard to overdispersion, we follow the usual approach with count data models and adopt a negative binomial-type 2 density. However, it is worth noting that 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 in the presence of unobservable factors. For this reason, by exploiting the longitudinal feature of our dataset, we 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 Negative Binomial (NB), a conditional FE estimator does not exist, and an unconditional FE estimator is not feasible due to the incidental parameter problem (IPP) when *T* is short and *N* is large, as is the case for our sample.[15] Moreover, in such a model, contrary to what is implied by FE estimation, the coefficients of the time-invariant regressors are identified (Hilbe, 2011 and Cameron and Trivedi, 2013). On the other hand, the unconditional FE-NB, which would consist in including indicator variables for all region-pairs, is problematic because in NB models 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 (see Hilbe, 2011). Apparently, the only feasible model is a (beta-distributed) random effects (RE) model, which assumes independence between the regressors and the unobservable effects. This is a strong assumption in our case 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 possible way to relax this assumption is to assume that exogenous regressors and the unobservable effect are *conditionally* correlated. This approach was originally developed by Mundlak (1978) and Chamberlain (1982) in the context of linear panel models and 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 our model, 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, in our gravity model for bilateral flows, the unobservable effects are assumed to be correlated with the time-averages of regressors describing pair characteristics, $\bar{X}_{ij} = 1/T \sum_{t=1}^{T} X_{ijt}$, as well as origin and destination traits, $\bar{X}_i$ and $\bar{X}_j$, in addition to spatial lags of the same variables. The multiplicative form of the individual terms in (1) allows us to account for the correlation

[14] Fabbri and Robone (2010) argue that past inter-regional migration is one of the most relevant factors that can generate network correlation in patient flows.

[15] In fact, Allison and Waterman (2002) demonstrate that the “conditional FE-NB” implemented in commercial econometric software is not a “true” FE model because the conditional mean absorbs in the intercept a term that includes both the unobservable effect and the overdispersion parameter, so that they cannot be identified separately.

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. While overcoming the strong assumption that α_{ij} are independent of regressors, this model has also the advantage of allowing for the estimation of the coefficients of the time-invariant regressors (namely, geographical distance), which would be removed in a standard FE model by construction.[16]

Finally, we address the possible serial correlation issue, which in patient flows may be induced by an inertia type of phenomena. To account for this aspect of the data, we include year dummies, which are supposed to capture the effect of macro shocks common to all the region pairs, and the first lag of the dependent variable, making the model a dynamic CCRE-NB specification.[17] Given that we have a short panel, we also account for the effect of the initial conditions. To rule out any correlation between them and the individual pair effect (α_{ij}), we employ 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 $\bar{X}_{ij}$, $\bar{X}_i$ and $\bar{X}_j$ but also of the initial period value of the dependent variable.[18] The final specification of the conditional mean of the inter-regional patient count flows is:

$$E\left[y_{ijt}|X_t, \alpha_{ij}\right] = \alpha_{ij}\exp\left(\gamma y_{ij,t-1} + X_{it}\beta_o + X_{jt}\beta_d + X_{ijt}\beta_{od} + \gamma_{od} dist_{ij} + WX_{it}\beta_{ow} + WX_{jt}\beta_{dw} + \theta_t\right) \quad (2)$$

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

where $y_{ij,\,t-1}$ is the one period lagged dependent variable and $y_{ij,0}$ its initial period value, the terms pre-multiplied by the spatial weight matrix W are the spatial lags of the explanatory variables, the barred term are averages of time-varying regressors, □ is a vector of year dummies and □ is a pure random term, which may be viewed as unobservable heterogeneity not correlated with the regressors. All the other terms are the same as in (1).

It is worth noting that consistency of the estimators rests on the assumption that the conditional mean is correctly specified. We believe that such an assumption is reasonably satisfied because the highly parameterized specification we propose is adequate to simultaneously account for the main features of our flow count data, i.e., overdispersion, unobservable heterogeneity, cross regional and serial correlation.[19]

[16] This approach is computationally equivalent to the adoption of a "hybrid" model, described in Allison (2005), which consists in estimating a NB-RE model including all the deviations from the individual-specific means and the means of all time-varying covariates.

[17] In preliminary analysis, we investigate the dynamic structure of the model, and we found that no additional lags of dependent variable and regressor lags were significant.

[18] It is worth noting 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).

[19] For a comprehensive discussion on the estimation issues for panel count data models, refer to Cameron and Trivedi (2013), Hilbe (2011) and Wooldridge (2010).

5. Results

To analyse the main determinants of inter-regional patient flows in Italy, we estimate dynamic CCRE-NB models by applying the following estimation strategy: First, we consider a very parsimonious specification, which includes as main explanatory variables only population and GDP per capita at both origin and destination, as well as geographical distance. We then proceed by augmenting the model to include RHS demand and supply factors and those characteristics that are unique with respect to each pair of regions. Finally, we propose a general specification also accounting for possible externalities produced by neighbouring regions at both origin and destination. The general specification is then estimated with respect to specific flows of patients, namely, those related to acute, surgery, medicine and cancer admissions. This analysis by subsample is expected to unveil possible differences in the estimated effects, thus allowing for a deeper understanding of how the role played by the various determinants changes according to the type of hospital admission.[20]

The main results of the estimated models are presented in Table 5. In the baseline model, reported in the first column, the population coefficient is positive and highly significant both at origin and destination.[21] The higher magnitude of the coefficient of the receiving region indicates that population is more effective as a pull rather than a push factor. This is also the case for GDP per capita, which exhibits a positive and significant coefficient only at destination. This evidence, as anticipated in section 3, seems to suggest that patient flows are attracted by regions that are supposed to offer more diversified, efficient and effective hospital care as their level of population and income increase. As expected, geographical distance has an adverse effect on patient flows; the greater the distance is, the higher the travel and the information costs. The lagged dependent variable has a highly significant coefficient that indicates the existence of inertia in patient flows. Although for count data a positive autocorrelation coefficient would imply an explosive/non-stationary dynamics, its magnitude – only slightly greater than zero – coupled with the negative coefficient of the initial value terms entails a very mild persistence, which therefore is not an issue for our empirical models (Cameron and Trivedi, 2013).

The baseline model is augmented by introducing a number of regional demand and supply factors along with the characteristics that pertain to the origin-destination pair of regions. As origin demand factors, we include the percentages of population in the age groups 0-14 years and over 65 years. The latter term proves to be not significant (it is significant only when considering flows for cancer-related admissions, as indicated in the last column of Table 7), while the first one is positive and highly significant, thus indicating that outflows increase with the share of the youngest patients in the population; this is reasonable because, when sick, they need very specific and advanced treatments. It is worth noting that when the two new population terms are included, the level of population has no explanatory power at origin.

Supply factors are taken into account by considering the number of beds (both in public and in private hospitals), the technological endowment, the case mix index, the comparative

[20] It is worth noting that because of misreporting, we drop observations related to the Sardinian patient flows in 2009 due in all estimated models.

[21] The result at origin, which seems to contradict our hypothesis described in section 3, is likely due to a misspecification problem of the baseline model and, in fact, is not confirmed once the gravity equation is correctly specified with the inclusion of the relevant covariates at origin and destination.

index of performance and the concentration index of the organizational structure. A greater hospital capacity, as represented by a higher availability of beds, discourages outflows and increases inflows at destination, where the coefficient of the public component is particularly sizeable (0.647) when compared to the one associated with the region of origin (-0.081). Hence, the national policies that promote hospital bed rationing to enhance the economic efficiency of the NHS have important effects in terms of inter-regional patient flows. In this regard, Section 6 will illustrate the simulation of a specific scenario deriving from setting the number of beds at the recommended national target. The indicator of technological endowment does not exhibit any effect either at the origin or destination on total patient flows. When the attention is focused on specific flows (i.e., those for cancer treatments), the level of technology is very relevant, as emphasized in section 5.1.

The comparative index of performance (CIP) does not affect patient flows at the origin, whereas its significantly negative coefficient at destination indicates that less efficient RHS are less attractive. The case mix index (CMI) exhibits a positive and significant coefficient at origin, suggesting that a higher degree of complexity in the treatments increases outflows; at the same time, the negative coefficient at destination indicates that inflows are discouraged. These results may be reasonable because the specialization in more complex cases may be associated with a reduction in the provision of less complex care, in which the RHS could have no comparative advantage to specialize. We will see in Table 7, in fact, that this effect is particularly important for *Surgery* flows, typically more complex than *Medical* flows. A similar reasoning applies when considering the HHI index for concentration of the organizational structure, which tends to enhance outflows at origin and reduce inflows at destination. Thus, a RHS that favours one or few specific types of hospital, leading to a concentration of admissions therein, is likely to be seen as a system that offers a less diversified range of hospital services.

In model (2), for both origin and destination regions, we also include two dummy variables, North and South, to account for the long lasting divide between the two macroareas of the country, as detailed in the introduction and in Section 3. All else being equal, northern RHSs exhibit less intense outflows (the coefficient at origin is equal to -0.189), being at the same time very attractive as destinations (the coefficient at destination is 0.513). Conversely, for southern regions, the unattractiveness effect prevails (-0.848).

Focusing on the determinants at the region-pair level, we find evidence that all of them are effective in enhancing patient flows. Thus, they act as moderating factors of the adverse effects exerted by spatial distance, which remains highly significant even after the inclusion of the other region-pair indicators. It is worth highlighting that the five region-pair indicators are also expected to account for OD spatial dependence.

Both *relative attractiveness* and *relative loyalty* indicators are positive and highly significant. Being based on the information available on surgical admission in other regions, they indicate that a specific destination RHS is not only preferred by the surgery patients of the associated origin region but also by all other types of patients of the same origin seeking less complex healthcare. Patients tend to trust more those destination RHS (thus becoming "loyal") chosen by surgery patients from the same origin region because they benefit from the information about the quality of the destination RHS provided at origin and feel reassured by emulating the choices of these more care-demanding, co-regional citizens.

Our hypothesis on the role of past migration, described in Section 3, is also confirmed by the model, i.e., past migrants coming from the same patient origin represent a beneficial source of knowledge on the health services provided in the destination RHS, thus reducing the information costs and the degree of uncertainty faced by potential patients. Moreover, relatives and friends migrated in a given destination make this more attractive because they can provide informal support before, during and after the hospital stay.

Finally, political similarity between regions in each pair represents another factor that enhances bilateral patient flows, confirming our hypothesis that politically aligned regions are more likely to exploit complementary healthcare services and share information on the extra-regional availability of healthcare services.

In the specification reported in column (3) of Table 5, we augment model (2) by including the spatial lagged terms for some specific variables of both origins and destinations, namely, GDP per capita, bed availability, technology endowment, CMI, CIP and concentration indicators. Such spatial lagged variables are expected to account for cross-region dependence arising from local externalities due to neighbouring regions. The spatial lag of GDP per capita is significant only at destination, where it exhibits a significant negative coefficient. This could indicate that neighbouring RHS are considered more favourite destinations because when their level of income increases, they are expected to provide more efficient and effective health treatments. The technology endowment of proximate regions at destination does not seem to play any relevant role, whereas at origin, it determines an increase in outflows, so that being surrounded by RHSs offering supposedly more advanced and varied medical technologies makes the own health system much less competitive and unable to restrain patient flows. Conversely, the spatial lags of the CMI and HHI indicators at origin reduce the outflows, meaning that neighbouring RHSs that are little diversified in the range of the hospital treatments provided are not viewed as attractive alternative destinations. Similarly, the negative effect of the spatially lagged CIP indicator on outflows suggests a benefit for relatively more efficient RHSs from the higher inefficiency in the neighbouring regions. At destination, we find symmetric (positive and significant) effects for the spatially lagged term of the HHI and CMI. These coefficients indicate, respectively, that the ability to attract non-resident patients is enhanced from being located close to less diversified RHSs and that, all things being equal, a given destination can more easily attract extra-regional patients (most likely the less complex cases) when its surrounding regions are relatively specialized in high complex treatments. In general, the inclusion of the lagged spatial variables do not substantially modify the estimates for the non-spatially lagged regressors. The most noteworthy exception is the coefficient of population at origin, which finally shows the expected and significant negative coefficient. This provides some evidence that increases in the number of potential patients allow the RHS to take advantage of economies of scale with effects on efficiency and, ultimately, on outflows. Furthermore, we find that a higher CIP at origin significantly leads to a reduction in outflows.

Due to the inclusion of geography-related covariates in model (3), the significance and often the sign of the geographical dummies with respect to model (2) is affected. At origin, the South dummy becomes significant and captures the difficulties of movement of people residents in regions located in the South of Italy with respect to the Centre. The North dummy remains significant, and its sign confirms that people move more easily from regions located in the North than from the Centre. At destination, only the lower appeal of southern RHSs is confirmed.

Overall, a comparison of the models reported in Table 5 indicates that the most general model outperforms the other two models in terms of goodness-of-fit, as it exhibits the higher square correlation between observed and fitted values (0.887 vs. 0.840 or 0.686). The better performance of the third specification is confirmed by the lowest value found for the

Akaike and the Bayesian information criteria, which, as is well known, combine the increase in model fitting with a penalization for the inclusion of additional covariates. The LR test for the joint significance of the Mundlak correction terms, reported at the bottom of Table 5, is highly significant in all estimated models, providing evidence of correlation between the individual pair terms and the time-varying regressors.

5.1 *Robustness and subsample analysis*

We have performed a robustness check on the set of Mundlak correction terms. Table 6 compares our preferred specification (first column) with two models that include a set of correction terms computed for time-varying variables observed only at origin and destination (second column) or only for the region pairs (third column). The LR tests yields the strongest rejection for the first model, thus confirming the appropriateness of modelling the individual pair effects as a function of origin, destination and origin-destination time-averaged regressors.

Table 7 complements our analysis by displaying the results from separate regression models estimated on four broad categories of admissions described in section 3.1. The results reported in Table 7 differ from those of the model estimated for total inter-regional flows (model 3 in Table 5) in the role that some origin and destination characteristics have in explaining bilateral flows. In particular, GDP per capita finally plays an important role as push factor for at least two types of flows, *Surgery* and *Cancers*, indicating that richer regions significantly reduce these types of outflows. The RHSs that have a higher technology endowment index significantly restrain outflows and attract more patients from other regions for cancer-related admissions. The spatial lags of this variable indicate that well-endowed neighbouring RHSs increase the ability of the focal region to attract flows for cancer-related admissions while reducing the attractiveness of surgery in the focal region. At origin, being surrounded by well-endowed neighbouring RHSs reinforces the outflows for all types of admissions considered with the exception of *Cancers*, for which the effect moves in the opposite direction. An additional important result refers to the spatial lag of per capita GDP that exhibits a negative and significant coefficient at origin for *Acute* and, in particular, for *Surgery*. The richer the neighbouring regions are, the larger the incentives for the focal RHS to restrain outflows for surgical treatments. As for the number of beds, estimates indicate that the hospital capacity of the private licensed providers is an important feature for origin RHSs that want to restrain outflows for surgery and cancers, while a better endowment of beds in public hospitals has a favourable effect on restraining flows out of the residence region for all *Acute* admissions and *Medicine*.

6. Simulation of policy scenarios

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. We specifically focus on hospital capacity because of existing bed rationing policies decided by the central government, as well as on the technology endowment indicator, which more likely depends on the RHS policies. Because these covariates are log-transformed, the estimated parameters are elasticities. We calculate the proportional change and the net change in outflows, as well as in inflows, using patient mobility data in 2010 and estimates from model 3 of Table 5 and the *Cancers* model of Table 7.

Because our gravity equation specifically distinguishes between regional characteristics at origin and destination as potential determinants of outflows, we need to consider simultaneously the proportionate change on outflows generated by changes in a covariate at origin and at destination. For example, if we are interested in the effect of a 10% increase in the number of beds in public hospitals in a specific region, the effect on the inter-regional flow between origin *i* and destination *j* will be the outcome of two (potentially opposing) partial effects: a decrease of 0.95% in outflows due to bed variation at origin *i* and an increase in outflows of 7.4% due to bed variation in destination *j*, which yields a total net change in outflows y_{ij} (inflows y_{ji}) of 6.5%.

This calculation can be extended to measure the proportionate change in total inter-regional flows of origin *i*: [22]

$$\frac{\Delta E(Y_i|X)}{Y_i} = \frac{1}{Y_i}\sum_{j\neq i}^{j=21} \Delta E(y_{ij}|X) = \frac{1}{Y_i}\sum_{j\neq i}^{j=21} \beta_{ok}\frac{\Delta x_{ik}}{x_{ik}} y_{ij} + \frac{1}{Y_i}\sum_{j\neq i}^{j=21} \beta_{dk}\frac{\Delta x_{jk}}{x_{jk}} y_{ij} \tag{4}$$

where $Y_i = \sum_{j\neq i}^{j=21} y_{ij}$. After some algebra this is equal to:

$$\frac{\Delta E(Y_i|X)}{Y_i} = \beta_{ok}\frac{\Delta x_{ik}}{x_{ik}} + \beta_{dk}\sum_{j\neq i}^{j=21}\frac{\Delta x_{jk}}{x_{jk}}\omega_{ij} \tag{5}$$

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 $\omega_{ij} = y_{ij}/Y_i$. Similarly, one could derive the expression for the proportionate change in total inter-regional flows of destination *j*. The results are reported in Tables 8-9, describing the effects of two hypothetical scenarios deriving from the adjustment to a specific value in all RHSs in the indicators of the number of beds in public hospitals and the TEI, respectively.

The exercise reported in Table 8 simulates the scenario that would follow if each RHS modified the number of beds in the public hospitals to adjust to the most recent bed-population ratio recommended by the central Government (3.7 beds *per* 1,000 inhabitants).[23] Although the Ministry of Health has repeatedly issued strong recommendations to equalise this ratio across all RHSs, the 2010 data still indicate a relevant regional variability, with the indicator ranging from 3.5 (Campania) to 5.4 (Molise). The effort required of the RHSs to reach the benchmark of 3.7 (secondo column of the table) is very high for many of them. Seventeen of twenty-one regions have to cut beds by between 4.5 and 31 per cent. This would lead to an overall reduction of patient mobility of approximately 7.6 per cent (59,207 admission episodes) in a year. If we look at the single regions, we see that eight of them suffer a loss in terms of net mobility. For example, Emilia Romagna, with a 6.1 (11.9) decrease in outflows (inflows), should lose the "theoretical" monetary value associated with

[22] For the sake of simplicity, in the following, we omit reporting the time subscript and the unobservable α_{ij}.

[23] In our calculation, we do not consider the hospital capacity of the private licensed hospitals because of their minor impact on patient mobility with respect to public hospitals, as indicated by the coefficients reported in Table 5, model 3.

the DRG of approximately 10,833 admission episodes. All the other regions (particularly those located in the Centre and South of Italy), would gain from the additional amount of financial resources potentially received as compensation of net mobility. In each region, the reduction in outflows is mainly driven by bed rationing in all other destination regions: The general effect of bed rationing at origin, in fact, is to increase the outflows. The reduction in inflows, conversely, mainly depends on own hospital bed variation, which indeed reduces the ability of a region to attract extra-regional patients. These results are expected because the estimated elasticities reveal that the RHSs find an important pulling force in hospital beds.

Table 9 presents another simulation exercise that employs the estimated elasticities of the technology indicator and its spatial lags in the model for Cancers (first column of Table 7). Our estimates detect strong direct and indirect pull effects, suggesting that some regions might be induced to undertake strategic investments in technology to meet the expectations of local demand. We find that, in the absence of a national benchmark on the optimal technology endowment-population ratio, lack of coordination between RHSs and central governments could induce quite strong effects both at the regional and national level. As an example, we simulate of a hypothetical scenario whereby all RHSs reach a TEI-population ratio equal to the 95th percentile of the distribution (corresponding to Liguria) in 2010, by estimating both direct and indirect effects on mobility. The former are calculated using the elasticities of the covariates at origin and destinations, whereas the latter are calculated using the elasticities of the corresponding spatial lags. If all RHSs were better equipped, there would be a total increase in outflows of 1.28 times. This figure is largely affected by the indirect effects (both on outflows and inflows), the direct effect leading to a smaller change of approximately 27 per cent. For the majority of the RHSs, the total (direct plus indirect) effect on net mobility is positive and quite large, meaning that increasing the number of technological machines fosters inter-regional mobility. The deriving financial flows related to net mobility might provide an incentive to redirect the regional supply of services in favour of extra-regional patients. We can see that single regions are affected differently by the variation in the TEI. For Lombardia, which in 2010 had below average endowment, for example, despite the doubling of outflows, we estimate the largest gain (approximately 11245 admissions). The regions that lose more in this hypothetical scenario are located in the South, while the multiplicative effect of the TEI mainly concerns the northern regions, which already have the highest attraction rates.

7. Discussion and conclusions

Patient mobility can be considered a tool for enhancing the effectiveness and efficiency of a local healthcare system. However, it may also constitute a challenge for local governments in the regionally decentralised tax-funded healthcare systems in which there is free patient choice and the local authority, though responding to centrally defined standards, acts as purchaser of the healthcare services. When inter-regional patient mobility is a long-lasting phenomenon, financial flow imbalances across regions may challenge the sustainability of regional budgets, with non-negligible consequences on the real achievement of universalism and equity of healthcare provision.

In this paper, we examine the determinants of inter-regional patient mobility in Italy by estimating a gravity model for bilateral Origin-Destination patient flows using longitudinal data from hospital discharge records that occurred among Italian regions over the period 2001-2010. Our econometric approach addresses all the methodological issues entailed by the estimation of short panel models for count data featuring simultaneously cross-section dependence, overdispersion, unobservable heterogeneity and serial correlation. We thus estimate dynamic conditionally correlated random effects negative binomial models for the total number of patient flows and specific types of admissions (surgical, medical, acute and cancer-related), which are supposed to respond differently to changes in some features of the RHSs, both at origin and destination.

For many variables, the estimated coefficients are in line with the effects expected on the basis of the arguments presented in section 3. Our findings indicate that RHSs in the richest regions attract more patients from other regions and that the most effective pull factors are the number of beds and the diversification of the organisational structure. We also find that the ability of a RHS to attract patients who reside in other regions decreases with the concentration of the organizational structure, which tends to reduce inflows at destination because of the narrow variety of hospital services offered in a RHS that favours only one or a few specific types of hospital. We find that at origin, patient flows are held back in regions with a larger population, presumably because they can take advantage of scale economies and provide a larger offer of health treatments. Moreover, a reduction in outflows is also due to a higher efficiency in managing length of stays and by hospital capacity. The latter, as measured by the number of beds, discourages outflows and increases inflows at destination. This result should be interpreted with caution in the current context of centrally defined policies aimed at improving the economic efficiency of the NHS and in each RHS by rationing the number of available beds. The geographical indicators capture the difficulties of the movement of patients from southern regions with respect to those from central regions. As expected, patients from regions located in the North move more easily than those from the Centre. Other things being equal, the RHSs located in South Italy are far less appealing as destinations.

We address cross-section dependence in the data by including variables that characterize the unique traits of the OD region pairs, such as geographical distance (found to discourage mobility), relative attractiveness and relative loyalty indicators based on the share of surgical admissions and past migration flows (with enhancing effects due to information and support networks), as well as by including spatial lags of some key explanatory variables. In particular, we find that spatial lags of the efficiency indicators detect the existence of local externalities from proximate regions, operating through learning and communication processes, which negatively affect the outflows and positively affect the inflows of patients.

The analysis by type of admission has unveiled a few remarkable differences in the estimated effects of some key indicators. The technology endowment behaves as a pull factor for cancers and, more generally, medical admissions and also as a push factor for cancer-related admissions. A larger capacity of the public hospitals seems to help restraining outflows for acute and medicine admissions, while the hospital capacity of the private licensed providers appears to be more important for origin RHSs that aim to restrain outflows for surgery and cancers.

We have used estimation results to calculate the effect of changes in a few variables that are relevant to the local and central policy makers. Beyond the specific cases illustrated in this work, our empirical approach can be used to shed light on the potential consequences of health policy interventions on patient mobility based on managing specific covariates in the model.

Our econometric analysis has also detected a mildly explosive dynamic in inter-regional patient mobility over time. This result could have serious implications for the long-run sustainability of the overall NHS in Italy. More specifically, the estimated dynamics are likely to induce a polarisation between the group of performing regions, which are increasingly capable of attracting more patients, and the group of the weakest regions, with growing outflows and severe financial and organizational problems.[24] These considerations call for a thorough assessment of the sustainability of the current healthcare system. RHS budget autonomy and the claim of increasing national healthcare quality levels are not entirely consistent with free patient choice. This opens a more general discussion, which is beyond the scope of our paper, 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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[24] Even the safeguard of the principle of free patient choice at the national level could be at risk, as exemplified by a recent decree (April 2013) by means of which Campania - the region with the highest financial burden related to inter-regional mobility - has unilaterally introduced the requirement of a prior authorization for the extra-regional reimbursements for some treatments characterized by low complexity and high risk of inappropriateness.

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Tables

Table 1. Percentage distribution of hospitals and share of admissions of non-resident patients by type of provider in 2010

	Percentage distribution of hospitals	**Share of admissions of non resident patients**
Autonomous public enterprises	10.2	13.6
LHA's public hospital	34.0	24.3
Medical school hospitals	2.2	16.1
Scientific institutes for research, hospitalization and healthcare	4.6	16.7
Classified hospitals	2.3	2.6
Private accredited hospitals	44.8	24.2
LHA-qualified institutes	1.6	1.9
Research centres	0.2	0.6

Table 2. 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 number of inter-regional flows	839719	836460	832831	854333	858934	859413	840259	828624	794028	779498
Share of inter-regional flows over total admissions	6.8	6.8	6.8	6.9	7.0	7.0	7.2	7.2	7.2	7.3
Subgroups of inter-regional flows										
Surgery	341141	349738	354197	375845	380051	390071	391777	395961	381764	378821
Medicine	480715	468556	459902	458969	459803	452003	430735	414133	412264	400677
Acute	608722	590382	573196	573637	568811	566048	556415	542095	525175	518669
Cancer	84223	83080	82405	84086	86326	85253	84341	81958	81532	79524
Geographical distribution of inter-regional flows										
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	43.61	49.59	50.23	52.26	53.25	53.05	50.43	46.94	42.69	44.56
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	55.04	7.53	7.48	7.51	7.43	7.53	8.00	8.37	8.55	8.64

* 2009 under-reports inflows in Sardinia

Table 3. Patterns of inter-regional patient mobility

Regions	2001 Creation rate	2001 Attraction rate	2001 Outflow rate	2001 Inflow rate	2010 Creation rate	2010 Attraction rate	2010 Outflow rate	2010 Inflow rate
Piemonte	7.66	5.91	8.00	6.29	6.37	5.43	6.62	5.70
Valle d'Aosta	0.60	0.22	20.23	8.49	0.63	0.25	20.43	9.26
Lombardia	9.27	20.53	3.88	8.20	8.79	18.74	4.19	8.52
P.A. Bolzano	0.56	0.80	4.83	6.74	0.52	0.87	4.11	6.76
P.A. Trento	1.71	1.36	14.45	11.82	1.77	1.18	15.19	10.69
Veneto	4.89	8.57	4.45	7.54	6.14	7.87	6.27	7.89
Friuli Venezia-Giulia	1.79	2.23	6.98	8.53	1.81	2.64	7.18	10.11
Liguria	4.66	5.01	10.05	10.72	4.95	4.78	11.25	10.92
Emilia-Romagna	5.66	11.78	5.52	10.84	5.84	14.62	5.83	13.43
Toscana	4.34	7.85	5.34	9.26	5.02	8.96	6.49	11.02
Umbria	2.00	3.43	9.26	14.91	2.37	3.09	11.70	14.75
Marche	3.72	3.17	9.96	8.62	3.74	3.56	10.82	10.36
Lazio	8.18	10.19	6.35	7.79	8.61	9.79	6.57	7.42
Abruzzo	3.84	4.00	9.59	9.95	5.05	3.36	16.09	11.32
Molise	1.85	1.78	22.34	21.75	1.56	2.43	18.33	25.89
Campania	10.81	3.03	7.41	2.19	10.27	3.17	6.98	2.26
Puglia	6.98	4.71	6.07	4.18	7.48	3.73	6.76	3.48
Basilicata	3.78	1.44	23.40	10.42	2.92	1.97	21.04	15.21
Calabria	7.47	1.68	13.52	3.39	7.46	1.06	16.24	2.67
Sicilia	8.37	1.80	6.31	1.42	6.82	1.90	6.16	1.80
Sardegna	1.84	0.52	4.28	1.25	1.88	0.58	4.86	1.56
South	44.96	18.96	8.08	3.57	43.5	18.2	8.57	3.78
Centre	18.23	24.6	6.78	8.95	19.7	25.4	7.50	9.46
North	36.81	56.41	5.70	8.48	36.82	56.39	6.13	9.09
Centre-North	55.04	81.04	6.02	8.61	56.55	81.79	6.55	9.20
min.	0.60	0.22	3.88	1.25	0.52	0.25	4.11	1.56
max.	10.81	20.53	23.40	21.75	10.27	18.74	21.04	25.89
range	10.21	20.31	19.52	20.50	9.75	18.49	16.93	24.33
coefficient of variation	0.62	0.99	0.60	0.55	0.59	0.98	0.53	0.61

Table 4. 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
Acute inter-regional flows	1338.8	2611.6	0	25069	hospital acute admissions 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
GDP pc	23950	5889	14831	33464	regional per capita GDP (euros), constant values (2005)	ISTAT
Population	2805617	2374442	119546	9917714	resident population in a region (annual average)	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	300.01	258.42	11.69	1160.18	weighted sum of sixteen medical devices available in each region	NHS statistical yearbook and Osservatorio Prezzi e Tecnologie
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
Relative attractiveness - Surgical Admissions (%)	5	9.79	0	79.9	share of surgical admission episodes of patients resident in Origin *i* occurred in Destination *j* over the total amount of surgical episodes delivered to non resident patients in that Destination region	Own calculations on Hospital discharge data
Relative loyalty - Surgical Admissions (%)	5	10.28	0	76.9	share of surgical admission episodes of patients resident in Origin *i* occurred in Destination *j* over the total number of surgical episodes occurred outside the Origin region	Own calculations on Hospital discharge data
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 5. Dynamic panel models for inter-regional patient flows in Italy (2001-2010)

Dependent Variable y_{ijt}: Patient flows to Destination *j* from Origin *i*			
Negative Binomial CCRE models	**1**	**2**	**3**
Origin characteristics			
GDP pc	-0.245	-0.145	-0.199
Population	0.726 ***	-0.091	-0.326 **
Population aged 0-14 (%)		0.024 ***	0.032 ***
Population aged over 65 (%)		0.004	0.005
Beds in public hospitals		-0.081 **	-0.095 **
Beds in private licensed hospitals		-0.009 *	-0.012 **
Technology endowment index -TEI		-0.011	0.011
Case mix index - CMI		0.362 ***	0.319 ***
Comparative index of performance- CIP		-0.062	-0.252 ***
Organisational structure - HHI		0.182 ***	0.019
South		-0.006	-1.387 ***
North		-0.189 **	0.398 **
Spatial lag - GDP pc			-1.011
Spatial lag - Technology endowment index - TEI			0.128 **
Spatial lag - Case mix index - CMI			-2.686 ***
Spatial lag - Comparative index of performance CIP			-1.076 **
Spatial lag - Organisational structure - HHI			-1.642 ***
Destination characteristics			
GDP pc	0.646 ***	0.933 ***	0.928 ***
Population	1.403 ***	1.296 ***	0.683 ***
Beds in public hospitals		0.647 ***	0.743 ***
Beds in private licensed hospitals		0.012	0.010
Technology endowment index -TEI		0.006	-0.006
Case mix index - CMI		-0.984 ***	-0.83 ***
Comparative index of performance- CIP		-0.518 ***	-0.559 ***
Organisational structure - HHI		-0.501 ***	-0.227 ***
South		-0.848 ***	-1.710 ***
North		0.513 ***	0.196
Spatial lag - GDP pc			-1.814 ***
Spatial lag - Technology endowment index - TEI			-0.026
Spatial lag - Case mix index - CMI			1.089 *
Spatial lag - Comparative index of performance CIP			0.738
Spatial lag - Organisational structure - HHI			3.770 ***
Origin-Destination characteristics			
Distance	-0.396 ***	-0.375 ***	-0.428 ***
Relative attractiveness - Surgical Admissions (%)		0.017 ***	0.017 ***
Relative loyalty - Surgical Admissions (%)		0.017 ***	0.015 ***
Past migration flows		0.055 ***	0.055 ***
Political similarity		0.006 *	0.010 ***
Lagged patient flows (y_{t-1})	0.00007 ***	0.00003 ***	0.00002 ***
Initial patient flows (y_0)	-0.00007 ***	-0.00005 ***	-0.00004 ***
Log Likelihood	-21379.5	-20663.9	-20538.7
Squared correlation between actual and fitted flows	0.686	0.840	0.887
Akaike's information criterion	42803	41451.86	41241.40
Bayesian information criterion	42940.11	41838.26	41752.43
LR-test for Mundlak correction (p-value)	58.65	384.79	421.63
	(0.0000)	(0.0000)	(0.0000)

Negative Binomial CCRE models are conditionally correlated random effects models. Number of regional units: 21; total number of region-pairs: 420; total number of observations: 3760. All specifications include a constant and the variables Population, GDP pc, Beds, Technology endowment index, Case mix index, Comparative index of performance, Distance and Past migration flows are log-transformed. The spatially lagged variables are obtained by pre-multiplying the relevant variable by the row-standardized inverse distance matrix. All specifications also include time averages of the time-varying exogenous covariates and time dummies (year 2002 is the reference year). All models include fixed effects at region-pair level, origin level and destination level. Level of significance: *** 1%, ** 5%, * 10%

Table 6. Robustness analysis for the Mundlak correction - Dynamic panel models for inter-regional patient flows in Italy (2001-2010)

Dependent Variable y_{ijt}: Patient flows to Destination j from Origin i			
Negative Binomial CCRE models	**pair FE and O&D FE**	**pair FE**	**O&D FE**
Origin characteristics			
GDP pc	-0.199	-0.252 **	-0.274 **
Population	-0.326 **	0.140 **	-0.385 **
Population aged 0-14 (%)	0.032 ***	0.013 *	0.022 ***
Population aged over 65 (%)	0.005	0.001	0.007
Beds in public hospitals	-0.095 **	-0.097 **	-0.088 **
Beds in private licensed hospitals	-0.012 **	-0.013 ***	-0.015 **
Technology endowment index -TEI	0.011	0.009	0.012
Case mix index - CMI	0.319 ***	0.294 **	0.356 ***
Comparative index of performance- CIP	-0.252 ***	-0.216 ***	-0.180 ***
Organisational structure - HHI	0.019	-0.025	0.047
South	-1.387 ***	-0.363 ***	-2.036 ***
North	0.398 **	0.123	0.657 ***
Spatial lag - GDP pc	-1.011	-1.722 ***	-0.941
Spatial lag - Technology endowment index - TEI	0.128 **	0.130 **	0.117 **
Spatial lag - Case mix index - CMI	-2.686 ***	-2.682 ***	-1.962 ***
Spatial lag - Comparative index of performance C	-1.076 **	-1.402 ***	-0.421
Spatial lag - Organisational structure - HHI	-1.642 ***	-1.627 ***	-1.208 ***
Destination characteristics			
GDP pc	0.928 ***	0.567 ***	0.861 ***
Population	0.683 ***	-0.567 ***	0.524 ***
Beds in public hospitals	0.743 ***	0.764 ***	0.749 ***
Beds in private licensed hospitals	0.010	-0.011	0.012
Technology endowment index -TEI	-0.006	0.006	0.005
Case mix index - CMI	-0.830 ***	-0.760 ***	-0.824 ***
Comparative index of performance- CIP	-0.559 ***	-0.551 ***	-0.528 ***
Organisational structure - HHI	-0.227 ***	0.022	-0.198 **
South	-1.710 ***	-0.217 **	-1.473 ***
North	0.196	0.144 *	0.402 **
Spatial lag - GDP pc	-1.814 ***	-1.697 ***	-1.631 **
Spatial lag - Technology endowment index - TEI	-0.026	0.054	-0.006
Spatial lag - Case mix index - CMI	1.089 *	-0.611	1.129
Spatial lag - Comparative index of performance C	0.738	1.243 ***	0.812 *
Spatial lag - Organisational structure - HHI	3.770 ***	4.272 ***	3.884 ***
Origin-Destination characteristics			
Distance	-0.428 ***	-0.405 ***	-0.392 ***
Relative attractiveness - Surgical Admissions (%)	0.017 ***	0.017 ***	0.017 ***
Relative loyalty - Surgical Admissions (%)	0.015 ***	0.015 ***	0.016 ***
Past migration flows	0.055 ***	0.082 ***	0.160 ***
Political similarity	0.010 ***	0.009 ***	0.008 ***
Lagged patient flows (y_{t-1})	0.00002 ***	0.00003 ***	0.00002 ***
Initial patient flows (y_0)	-0.00004 ***	-0.00005 ***	-0.00002 ***
Log Likelihood	-20538.7	-20642.580	-20666.760
Squared correlation between actual and fitted flows	0.887	0.850	0.900
Akaike's information criterion	41241.40	41393.150	41489.510
Bayesian information criterion	41752.43	41729.690	41975.620
LR-test for Mundlak correction (p-value)	421.63	207.760	256.120
	(0.0000)	(0.0000)	(0.0000)

Negative Binomial CCRE models are conditionally correlated random effects models. Number of regional units: 21; total number of region-pairs: 420; total number of observations: 3760. All specifications include a constant and the variables Population, GDP pc, Beds, Technology endowment index, Case mix index, Comparative index of performance, Distance and Past migration flows are log-transformed. The spatially lagged variables are obtained by pre-multiplying the relevant variable by the row-standardized inverse distance matrix. All specifications also include time averages of the time-varying exogenous covariates and time dummies (year 2002 is the reference year). The model "pair FE and O&D FE" includes fixed effects at region-pair level, origin level and destination level. The model "pair FE" includes fixed effects at region-pair level only. The model "O&D FE" includes fixed effects at the origin and destination level only. Level of significance: *** 1%, ** 5%, * 10%

Table 7. Dynamic panel models for inter-regional patient flows in Italy (2001-2010) for categories of admissions

Dependent Variable y_{ijt}: Patient flows to Destination *j* from Origin *i*				
Negative Binomial CCRE models	**Cancers**	**Acute**	**Surgery**	**Medicine**
Origin characteristics				
GDP pc	-0.860 **	-0.163	-0.381 ***	-0.061
Population	-0.951 *	0.259	-0.431 **	-0.088
Population aged 0-14 (%)	0.018	0.015	0.028 ***	0.028 ***
Population aged over 65 (%)	0.043 **	-0.002	0.005	0.007
Beds in public hospitals	-0.001	-0.173 ***	-0.041	-0.108 **
Beds in private licensed hospitals	-0.029 *	-0.010	-0.024 ***	-0.002
Technology endowment index -TEI	-0.123 ***	0.002	0.016	0.011
Case mix index - CMI	0.026	0.078	0.451 ***	-0.049
Comparative index of performance- CIP	-0.159	-0.146 *	-0.062	-0.221 **
Organisational structure - HHI	0.158	-0.001	0.114 *	-0.023
South	-0.408	-1.565 ***	-2.479 ***	-1.027 **
North	0.032	0.490 ***	0.423 **	0.362 **
Spatial lag - GDP pc	-0.631	-2.204 ***	-1.822 ***	-0.142
Spatial lag - Technology endowment index - TEI	-0.387 **	0.124 *	0.173 ***	0.140 *
Spatial lag - Case mix index - CMI	-0.002	-2.309 ***	-2.501 ***	-3.435 ***
Spatial lag - Comparative index of performance C	0.637	-1.141 **	-0.473	-1.64 ***
Spatial lag - Organisational structure - HHI	-3.994 ***	-1.709 ***	-1.453 ***	-1.501 ***
Destination characteristics				
GDP pc	2.397 ***	0.306 *	0.712 ***	1.23 ***
Population	-0.012	1.401 ***	0.468 ***	0.491 **
Beds in public hospitals	0.673 ***	0.908 ***	0.606 ***	0.755 ***
Beds in private licensed hospitals	0.028	0.006	0.014 *	0.013
Technology endowment index -TEI	0.265 ***	-0.011	-0.007	0.022
Case mix index - CMI	-0.231	-0.243 *	-0.231 **	-1.263 ***
Comparative index of performance- CIP	-1.205 ***	-0.148 *	-0.612 ***	-0.601 ***
Organisational structure - HHI	-1.076 ***	-0.557 ***	-0.273 ***	-0.242 **
South	-0.671 *	-0.371	-1.880 ***	-2.353 ***
North	0.447 ***	0.770 ***	-0.071	0.140
Spatial lag - GDP pc	-12.571 ***	-0.841	-1.364 *	-1.837 *
Spatial lag - Technology endowment index - TEI	0.940 ***	0.031	-0.243 ***	0.055
Spatial lag - Case mix index - CMI	0.494	-0.851	0.432	4.987 ***
Spatial lag - Comparative index of performance C	2.351	0.493	-1.359 ***	2.379 ***
Spatial lag - Organisational structure - HHI	4.694 ***	3.285 ***	1.175 ***	4.371 ***
Origin-Destination characteristics				
Distance	-0.701 ***	-0.363 ***	-0.638 ***	-0.404 ***
Relative attractiveness - Surgical Admissions (%)	0.015 ***	0.018 ***	0.035 ***	0.001
Relative loyalty - Surgical Admissions (%)	-0.004	0.012 ***	0.024 ***	0.004 ***
Past migration flows	0.036	0.063 **	0.080 ***	0.051 *
Political similarity	-0.009	0.007 *	0.007 **	0.009 **
Lagged patient flows (y_{t-1})	0.00003 ***	0.00002 ***	0.00001 ***	0.00004 ***
Initial patient flows (y_0)	-0.00003 *	-0.00004 **	-0.00001	-0.00007 ***
Log Likelihood	-14287.219	-19759.443	-17394.267	-19338.099
Squared correlation between actual and fitted flows	0.910	0.740	0.921	0.770

Negative Binomial CCRE models are conditionally correlated random effects models. Number of regional units: 21; total number of region-pairs: 420; total number of observations: 3760. All specifications include a constant and the variables Population, GDP pc, Beds, Technology endowment index, Case mix index, Comparative index of performance, Distance and Past migration flows are log-transformed. The spatially lagged variables are obtained by pre-multiplying the relevant variable by the row-standardized inverse distance matrix. All specifications also include time averages of the time-varying exogenous covariates and time dummies (year 2002 is the reference year). All models include fixed effects at region-pair level, origin level and destination level. Level of significance: *** 1%, ** 5%, * 10%

Table 8. Estimated effects of the implementation of the national target on the bed-population ratio (reference year: 2010)

	2010 baseline values				Changes in outflows			Changes in inflows			Net mobility
Regions	Beds *per* 1,000 inhabitants	Required adjustment (%)	Outflows	Inflows	Own region change (a)	Other regions change (b)	Total change (%)	Own region change (c)	Other regions change (d)	Total change (%)	(c+d) - (a+b)
Piemonte	4.24	-12.7	49623	42318	602	-4872	-8.6	-3997	441	-8.4	714
Valle d'Aosta	4.16	-11.0	4914	1952	52	-467	-8.5	-159	22	-7.0	278
Lombardia	4.33	-14.5	68533	146076	949	-5767	-7.0	-15747	1223	-9.9	-9705
P.A. Bolzano	4.22	-12.4	4017	6804	47	-367	-8.0	-624	92	-7.8	-213
P.A. Trento	4.69	-21.1	13778	9213	278	-965	-5.0	-1445	86	-14.7	-671
Veneto	3.94	-6.1	47885	61321	279	-4902	-9.7	-2784	685	-3.4	2524
Friuli Venezia-Giulia	4.20	-11.9	14138	20577	161	-880	-5.1	-1822	123	-8.3	-979
Liguria	4.33	-14.5	38595	37297	535	-3092	-6.6	-4026	304	-10.0	-1166
Emilia-Romagna	4.46	-17.1	45545	113980	741	-3523	-6.1	-14440	824	-11.9	-10833
Toscana	3.87	-4.5	39104	69833	167	-3535	-8.6	-2321	512	-2.6	1560
Umbria	3.58	3.4	18450	24099	-60	-1502	-8.5	613	272	3.7	2447
Marche	4.10	-9.9	29145	27776	274	-2734	-8.4	-2034	227	-6.5	652
Lazio	4.48	-17.4	67078	76341	1115	-3145	-3.0	-9878	219	-12.7	-7630
Abruzzo	4.02	-8.0	39395	26220	300	-3887	-9.1	-1556	386	-4.5	2416
Molise	5.37	-31.0	12187	18967	361	-808	-3.7	-4376	40	-22.9	-3890
Campania	3.48	6.2	80023	24713	-474	-8052	-10.7	1139	257	5.7	9922
Puglia	3.91	-5.5	58335	29042	304	-5130	-8.3	-1178	128	-3.6	3776
Basilicata	3.68	0.5	22759	15329	-12	-1163	-5.2	62	16	0.5	1254
Calabria	3.90	-5.2	58166	8247	291	-4208	-6.7	-321	47	-3.3	3642
Sicilia	3.70	0.0	53139	14843	0	-4867	-9.2	-1	114	0.8	4980
Sardegna	4.17	-11.3	14689	4550	158	-1412	-8.5	-382	51	-7.3	922
Total			779498	779498			-7.6			-7.6	0

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.

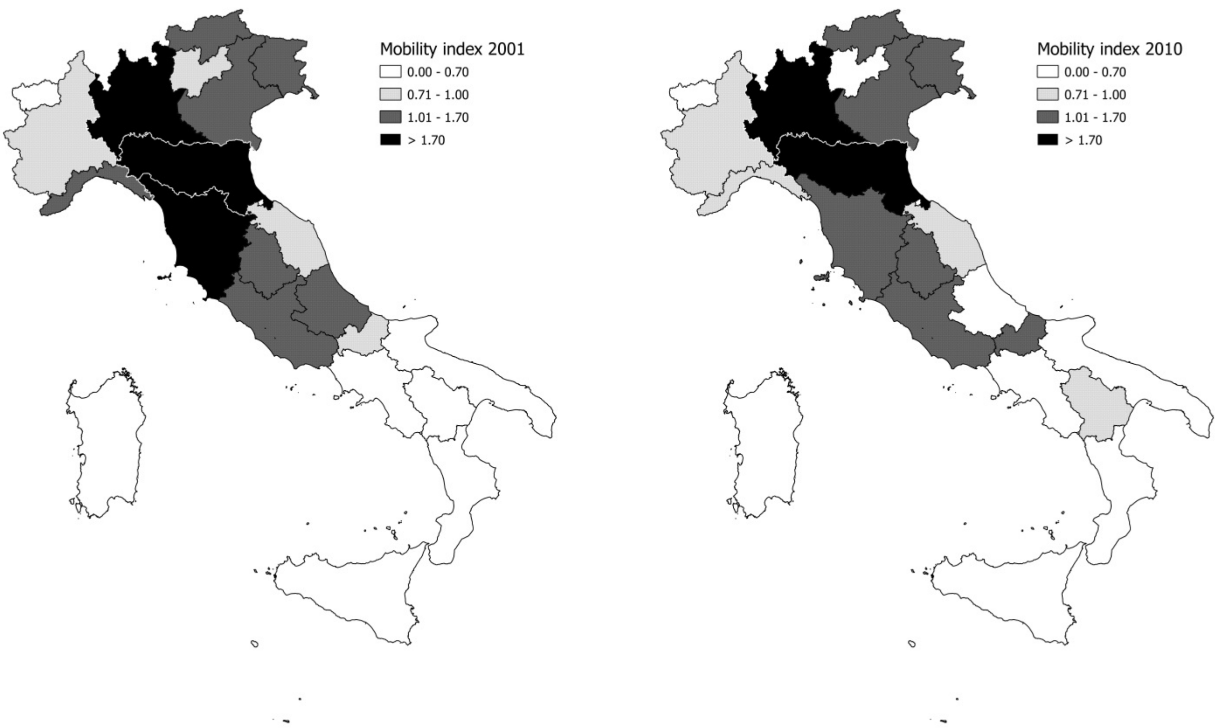
Table 9. Estimated effects of the implementation of the same technology endowment-population ratio (reference year: 2010)

	2010 baseline values				**Direct effects**		**2010 baseline values**		**Indirect effects**		**Total effects**		
Regions	TEI *per* 1,000,000 inhabitants	Required adjustment (%)	Outflows	Inflows	Total change in outflows (%)	Total change in inflows (%)	lagged CIP	Required adjustment (%)	Total change in outflows (%)	Total change in inflows (%)	**Total change in outflows (%)**	**Total change in inflows (%)**	**Net mobility**
Piemonte	108.8	34.2	5225	2628	46	33	310.1	18.4	106	157	152	190	-2950
Valle d'Aosta	137.2	6.4	328	113	14	71	425.4	23.6	126	260	140	330	-85
Lombardia	117.0	24.8	4137	20849	59	21	294.4	19.1	165	77	224	98	11245
P.A. Bolzano	126.9	15.0	321	383	27	61	356.8	21.3	126	219	153	280	579
P.A. Trento	115.4	26.5	1156	377	45	78	387.8	21.3	122	308	167	386	-480
Veneto	116.8	25.0	5285	5445	32	34	297.2	19.6	94	126	126	160	2047
Friuli Venezia-Giulia	125.5	16.3	957	4224	34	16	360.4	20.1	151	56	185	72	1273
Liguria	146.0	0.0	3202	3039	0	37	422.6	21.1	118	156	118	192	2053
Emilia-Romagna	111.2	31.3	3984	9801	51	32	376.6	16.9	130	104	181	135	6064
Toscana	141.2	3.4	3491	6610	5	24	357.2	20.6	103	131	108	156	6522
Umbria	118.7	23.0	1348	2064	45	22	361.7	16.5	154	100	198	122	-161
Marche	123.4	18.3	2712	1565	28	63	325.9	17.4	104	181	133	243	215
Lazio	131.4	11.1	5233	10343	20	19	298.6	17.6	124	73	144	92	2005
Abruzzo	114.5	27.4	4026	1175	38	33	349.6	15.1	105	168	143	201	-3398
Molise	196.2	-25.6	1236	2173	-36	22	383.7	16.5	91	79	55	101	1502
Campania	133.4	9.4	11748	1347	9	43	282.4	17.9	69	182	78	225	-6101
Puglia	106.1	37.5	7172	3451	44	16	299.6	14.6	94	55	138	71	-7431
Basilicata	140.3	4.1	2035	2472	6	21	393.1	20.2	88	78	95	100	536
Calabria	107.0	36.4	7221	466	42	36	364.6	16.2	88	142	130	178	-8577
Sicilia	142.3	2.6	6845	821	3	76	338.4	18.7	80	198	83	274	-3443
Sardegna	126.3	15.6	1862	178	18	71	379.8	17.2	87	229	105	299	-1416
Total			79524	79524	27	27			101	101	128	128	0

The required adjustment is calculated with respect to the 95th percentile of the TEI-population ratio distribution reported in the first column.

Figures

Figure 1. Spatial pattern of inter-regional patient mobility. Mobility index in 2001 and 2010.



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