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Monetary flows for health mobility: The Italian NHS from a network perspective*

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Abstract

This study investigates the dynamics of healthcare mobility in Italy, where citizens have the freedom to access medical treatment across regions. More than half a million patients, primarily from the Southern regions, engage in healthcare mobility, resulting in a total expenditure of €3.7 billion in 2019. Leveraging a unique dataset spanning from 2002 to 2019, this research examines financial transactions, utilizes network analysis, and identifies influencing factors through a gravity model. Socioeconomic disparities and the availability of specialized services are key drivers of this mobility. Regions with higher healthcare quality and the presence of private licensed hospitals attract a larger number of patients. This study offers valuable insights into the intricacies of interregional healthcare mobility, which can inform healthcare policy and promote regional equity considerations.

Keywords: Italian health system; network analysis; gravity model; decentralisation.

JEL Classification: H75, I14, I18.

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1 Introduction

In Italy, healthcare is a constitutionally guaranteed fundamental service aimed at providing a range of services uniformly across the country on the basis of centrally defined essential levels of assistance (Livelli Essenziali di Assistenza or LEA). Operationally, the Italian National Healthcare Service (NHS), like in many other European countries, is a tax-funded system whose provision is mostly decentralized by regions, offering patients the freedom to choose healthcare providers. It includes 20 autonomous Regional Health Services (RHS), allowing patients to receive free of charge healthcare in either public or licensed private health structures across the country (Adolph et al., 2012). In particular, the NHS ensures healthcare services for citizens registered with the local healthcare agencies in their own region of residence. Nevertheless, citizens have the right to receive healthcare services in facilities located in other regions, a possibility that gives rise to interregional healthcare mobility (henceforth referred to as "regional mobility" in our analysis).¹ Since the provision of health services is of regional competence, the funding mechanism envisages a reimbursement for healthcare provided to patients moving outside their own region of residence, which is based on an interregional compensation scheme based on Diagnosis-Related Group (DRG-based) national tariffs. Consequently, the inter-regional mobility of patients may raise concerns about both the efficiency and the territorial equity of healthcare provision, especially when – as in the Italian case – there are significant differences across regions in the initial endowment of economic resources, social backgrounds, and transport infrastructures. In Europe, patient mobility within the same country is not as pronounced. Other cases of healthcare mobility are present, for example in Spain, although not in such high numbers, where there are bilateral agreements

¹Our study focuses on regional mobility, which excludes both intraregional mobility (between different facilities within the same region) and cross-border mobility (services provided abroad).

between different regions to ensure healthcare for their own citizens (Cantarero, 2006; Perna et al., 2022). Even though healthcare mobility gives the right to citizens to access care without territorial constraints, some of this mobility is unintentional and undesirable, as it is driven by regional disparities in both the quantity and quality of healthcare services. Thus, it occurs that health mobility is intertwined with important social and territorial issues, which make migration of patients not attributable to a beneficial Tiebout (1956) "vote-with-your-feet" effect, where individuals move to areas offering better services at the same cost. On the contrary, inter-regional mobility may become a state of necessity, driven by temporary needs, and aimed at accessing services not available in the region of residence, without involving a willingness to permanently migrate to other regions. To offer insight into the potential significance of inter-regional mobility, it's worth mentioning that in Italy, this phenomenon involves more than half a million patients, predominantly hailing from the Southern regions, seeking medical treatment in regions other than their own. Italy has seen numerous studies concentrating on individual patients and the various health factors influencing this mobility. The monetary counterpart of inter-regional flow of patients has been characterised by a steadily increasing overall trend and currently amounts to about 3.7 billion of euros in the last year of our analysis (2019). To this respect, Italy is an interesting case study, as the last decade has been characterized by a deep financial crisis, exacerbating the economic differences between the North and the South (Lagravinese, 2015) with unavoidable effects also on the demand and supply of health. Indeed, inequalities in terms of per capita GDP, education and occupation rates have started to increase again with non-negligible effects on available healthcare resources, on the quality of uneven healthcare services, and on the living conditions of citizens (Barra et al., 2022; Lagravinese et al., 2019). Furthermore, starting from 2002, the Italian healthcare system has been decentralized, transferring significant powers to regions, but due to infrastructural and income disparities, there is a noticeable trend of patients relocating from the Southern to the Northern regions, especially when specialized services are not available (or available at low quality) in their own region. In Italy, early research into this phenomenon included the study conducted by Levaggi and Zanola^{*} (2004). Their empirical results indicate that quality plays a substantial role in driving mobility in the country, with income serving as a determining factor for the level of service quality provided. More recently, the focus has shifted to patient data using Hospital Discharge Records. In detail, according to the research by Balia et al. (2018), the primary factors driving this mobility include regional income, hospital capacity, organizational structure, performance, and technology. Moreover, Balia et al. (2020) conducted a study using Italian hospital discharge records (SDO) related to admissions for digestive system cancer treatments for patients residing in Sardinia and Sicily. Their findings suggest that mobility is more pronounced among younger patients and those with a higher level of education. Additionally, the choice of hospital is significantly influenced by factors that represent the attractiveness of the hospital, with discernible distinctions between local and distant healthcare providers. Bruni et al. (2021) using Italian patient-episode level data on elective Percutaneous Transluminal Coronary Angioplasty procedures over the years 2008–2011. Their results support that a higher propensity for mobility can be attributed to a younger age of patients and a lower perceived quality of residential facilities. In recent years, several empirical studies have shown a significant correlation between mobility flows and actual/perceived quality (Berta et al., 2021; Berta, Vinciotti and Moscone, 2022). Moreover, Beraldo et al. (2023) employed a quasi-experimental strategy to assess the impact on patient migration of programs for reorganization, regualification and improvement of the regional healthcare system, finding that outbound mobility was about 24-31% higher in those regions where a lower quality was detected and a stricter implementation of such plans was needed. As just shown, the majority of the recent empirical works have analyzed intra-regional mobility using individual patient data based on DRGs (Diagnosis-Related Groups). To our knowledge, no one has utilized the monetary flows between different regions. Monetary flows, while more aggregated than patient data, offer immediate insights into territorial disparities and play a crucial role in resource allocation at the regional level. For these reasons, our work aims to contribute to the literature on healthcare mobility among Italian regions in two main ways. First, we analyse monetary flows between Italian regions over a lengthy period (2002-2019), collecting a non-public domain database. Second, we use these monetary flows to estimate a comprehensive network of regional patient outflows and inflows for various healthcare services. To the best of our knowledge, this is the first application of network analysis to interregional patient mobility in the healthcare sector. Furthermore, we identify the determinants of monetary flows by employing a comprehensive gravity model with spatial interactions to capture dependency relations across regions.

The remainder of this paper is organized as follows: Section 2 provides information on the institutional framework, Section 3 describes the dataset used, Section 4 presents the empirical analysis and the results, and Section 5 concludes our study.

2 Institutional setting

The National Health Service (NHS) was established in 1978² to replace the numerous health insurance funds with a single public national health fund, financed through sickness contributions and central government tax revenue. The NHS was designed as a multi-layered system to ensure universal access to a comprehensive set of services

²Law 833/1978.

on an equal basis. The organization involved the Central Government (CG), the Regional Government (RG), and a number of local health authorities (LHAs), with the CG allocating funds to each RG to guarantee territorial equity in the provision of services. For a long time, this system caused a misalignment between expenditure and funding responsibilities, a problem that the reforms of the '90s and 2001^3 attempted to solve through the introduction of quasi-markets and fiscal decentralization. The underlying idea was to shift the balance of power in favour of the RGs by splitting providers from purchasers of services and increasing efficiency through free mobility and competition for patients, with the general taxation supplementing regional taxation to cover local financial needs. With regard to the activities of the layers involved in this process, the reforms provided for exclusive power of the CG in defining the essential levels of care to be offered to all citizens, and exclusive responsibility of RGs for the organization and administration of healthcare; finally, LHAs were intended to be financially accountable for the services delivered to their resident population (Turati, 2013). In compliance with the principle of free choice, patients are allowed to choose any provider within the Italian territory. As a consequence of this possible choice, payments for out-of-region care give rise to financial transactions between regions of residence and destination on the basis of a conventional flat rate. The latter includes the running and full costs of care, with the regions experiencing high outflows paying for both the treatments supplied to their outgoing patients and the fixed costs of their public services. As a positive mobility balance represents net gains, each region has a strong incentive to limit outflows and attract inflows. In this paper, we estimate that, in Italy, 80% of volume and financial flows are represented by hospital acute

³Legislative Decrees 502/1992, 517/1993, and 229/1999, Constitutional Law 3/2001.

care⁴. Its provision is completely free of charge for patients⁵ and largely relies on public production supplemented by private licensed hospitals (PLHs). In turn, PLHs are allowed to treat patients on behalf of the NHS and be refunded by the LHA (and thus the RG) the patient is enrolled to. However, different contractual schemes apply to public and private licensed hospitals. While the former is constrained to ceilings on the number of total admissions, but are reimbursed ex-post for any cap overshoot, the latter receive no coverage for budget loss but restrictions apply only to resident patients. It follows that PLHs face an incentive to attract out-of-region patients to finance excess production (Brenna and Spandonaro, 2015). After more than two decades, both mobility and regional financial empowerment have not had the desired effects. In the long run, free patients' choice should determine zero voluntary interregional mobility, as competition should stimulate quality levelling and ensure fair market sharing (Brekke et al., 2014, 2016; Gravelle et al., 2014). Instead, the Italian NHS is characterized by high and persistent interregional mobility; this is despite the attempts by the CG to limit it by including exit and attraction rates in the evaluation criteria of regional health performance used to allocate funds among regions (Fabbri and Robone, 2010). As shown in Figures A.1 and A.2 in the Appendix, patient flows even increase between 2002 and 2019, with a clear north/centre-south gradient especially for destination inflows. With regard to the financial responsibility, the transition to a regionally organized NHS has gone through a period of lack of cost-containment incentives, leading to large budget deficits in many regions. As a result, Financial Recovery Plans $(FRP)^6$ were introduced in 2004 for regions with significant budget shortfalls to limit access to public national health funds and force

⁴Authors' own elaborations of the data available for analysis.

⁵Specifically, the provision is free of charge under the presentation of a physician referral and for emergency cases.

⁶Law 311/2004, Law 296/2006.

such RGs to define consolidation paths. FRP must contain measures to ensure a balanced health budget and measures to rebalance the delivery of LEA. They remain effective for three years and are renewed if the associated goals are not achieved. In this last case, a commissioner may be engaged to set up more constraining plans including tax increases combined with CG transfers cuts (Beraldo et al., 2023). Table A.1 in the Appendix shows the regions and years under FRP, as well as any periods with commissioner.

3 Data and descriptive statistics

To analyse interregional monetary flows resulting from patient mobility, we made a formal request to the Ministry of Health, which provided us with the matrix of credits and debits for hospital care among Italian regions from 2002 to 2019. From an economic perspective, active mobility represents a credit item for the regions, while passive mobility represents a debit item. Each year, the region that provides the healthcare service to non-residents is reimbursed by the citizen's region of residence. Since some regional characteristics are not available separately for the autonomous provinces of Trento and Bolzano, the corresponding data are aggregated to obtain a single value for the whole region (Trentino Alto Adige). We thus obtain a sample of 20 regions and 380 pairs per year, for a total of 6840 observations. Figure 1 introduces an overall picture of these dynamics by showing the total monetary flows and the interregional per capita compensation network of the Italian NHS, this latter variable in order to take into account the fact that the total amount of compensation can be affected by population size and growth. In real terms, the import and export of patients between regions resulted in an average monetary flow of more than 3.5 billion euros, showing a significant increasing trend over years, especially since 2012 (in 2019,

3.7 billion euros). Looking at these data in terms of population, the consistent decline in per capita spending stopped as population growth came to a halt in 2014. Since then, the related value has increased by about 100 euros per inhabitant (in 2019, 1,775 euros).

figure 1 around here

Patient mobility can depend on various factors. While many have been analysed in previous studies, others, such as the Institutional Quality Index (IQI), exposure to Financial Recovery Plans (FRP), and Caesarean section (C-section) rate, represent a novel aspect and may provide new insights into healthcare mobility. The three panels in the table 1 report origin-destination factors, demographic and economic characteristics of the region (contextual factors), and some of the most relevant attributes of the regional health system (RHS factors), respectively. The variables in the last two panels are taken into account for both origin (O-regions) and destination regions (D-regions). Exclusively for descriptive purposes, to highlight notable distinctions between the regions of departure and destination, we present in Table 1, O-regions in the first (Q1) and fourth (Q4) quartiles of the outflow distribution, along with the D-regions in the first (Q1) and fourth (Q4) quartiles of the inflow distribution⁷. The geographical distance, expressed in kilometres, is the most critical origin-destination factor. Considered as a proxy for transportation, accommodation, and information costs (Balia et al., 2018; Bruni et al., 2021), it is expected to exert an adverse effect on origin-destination (OD) monetary flows. Regarding contextual factors, population and GDP reflect the size of the region and are larger for Q4 than Q1 regions, favouring outflows at the origin and inflows at the destination. A possible explanation for

⁷Origin regions in Q1: Sardinia, Molise, Trentino-Alto Adige, Friuli Venezia Giulia, Aosta Valley. Origin regions in Q4: Apulia, Calabria, Lazio, Liguria, Lombardy. Destination regions in Q1: Aosta Valley, Basilicata, Calabria, Sardinia, Trentino-Alto Adige. Destination regions in Q4: Emilia Romagna, Lazio, Lombardy, Tuscany, Veneto.

increased outflows for bigger O-regions may be saturation of RHS, while increased inflows for bigger D-regions may be due to a greater variety of healthcare services provided locally, in turn induced by a larger population (Balia et al., 2018). While overall regional population reflects the internal demand for healthcare, the share of over-65 residents approximates the need for care of the frailest population group. As for the share of high educated residents⁸, no large changes in the share of the elderly are observed between regions of different quantiles. Instead, employment rate and household income are higher in Q1 than in Q4 O-region, as well as in Q4 than Q1 Dregions, with higher household wealth associated to greater ability to retain patients at origin and attract patients at destination. Finally, the Institutional Quality Index is a composite indicator ranging from 0 to 1 proposed by Nifo and Vecchione (2014) to measure the quality of governance in Italian regions⁹. This index is structured following a hierarchy framework into five dimensions: voice and accountability, government effectiveness, regulatory quality, rule of law, and control and corruption. As expected, the most able regions to retain patients (Q1 O-regions) and those most able to attract patients (Q4 D-regions) are those with higher institutional quality. With respect to RHS factors, higher public healthcare expenditures (HCE) per capita are observed for Q1 O-regions, but no relevant differences are detected among D-regions by quartile. Caesarean section rates are used to measures the appropriateness of healthcare provision (Baicker et al., 2006; De Luca et al., 2021). C-section, in fact, is not recommended in the absence of clinical reasons or complications because it is more invasive, riskier, and more expensive than delivering naturally. Not surprisingly, greater appropriateness characterises those regions most capable of retaining patients and those most capable of attracting them. The Comparative Index of Performance (CIP) and

⁸High educated residents are those with a tertiary or doctoral degree.

 $^{^{9}}$ Since data on IQI are only available for years after 2004, a linear interpolation is performed for missing data.

the Case-Mix Index (CMI) represent two important indexes for the evaluation of the regional hospital care (Ciarrapico et al., 2023). CIP is an efficiency measure and is calculated as the ratio between the average standardized case-mix hospital stay of a given region and the national average hospital stay. No great variations in the CIP are observed by quartile at either origin or destination. It is probably due to the major burden of public hospitals, which exhibit unchanged average hospital stays. Q4 D-regions offer instead two more days of inpatient stay than Q1 D-regions. CMI allows for a comparison of the complexity of the case mix treated and is obtained as the ratio between the average weight of the inpatient admission of a given region and the average weight of the inpatient admission in the national case mix. As in the previous case, there are no relevant differences by quartile. The technology endowment index (TEI) is a composite indicator of the availability and comprehensiveness of the regional technological endowment ¹⁰ (Balia et al., 2018). Its interquartile trend seems to depend on the size of the regions in the two groups, as it is greater in Q4 than in Q1 at both origin and destination. Finally, to assess the concentration of the RHS organizational structure we consider the percentage of beds in PLHs out of the total number of beds and percentage of discharges from specialized facilities out of the total number of hospital discharges¹¹. The share of private beds does not differ much by quartile at the destination, while it is higher in regions with higher outflows, a result that will be overturned when several confounding factors will be taken into account in Section 4.1.1. In contrast, the share of discharges in specialized institutions does

¹⁰The devices used for the computation are: automated immunochemistry analyser, linear accelerator in radiotherapy, immunoassay analyser, anaesthesia machine, ultrasound imaging system, haemodialysis delivery system, computerized gamma cam-era, differential haematology analyser, analogue X-ray system, surgical light, monitor, mobile X-ray system, computerized axial tomography (CT), magnetic resonance-imaging (MRI), medical imaging table, continuous ventilator system, digital angiography systems, hyperbaric chamber, mammogram, positron emission tomography(PET), integrated PET-CT, operating table, and two types of panoramic radiography machines.

¹¹As specialized inpatient facilities we consider University Hospitals, Scientifically-Oriented Inpatient Facilities, and Research Facilities.

not vary at origin, while at destination it is much higher in the regions most able to attract patients.

Table 1 around here

4 Empirical analysis

In order to analyse patient mobility, the empirical analysis is divided into two parts. The first part is developed through the Network Analysis to investigate monetary flows between regions. The second part uses network indices to estimate a gravity model to examine the determinants of mobility.

4.1 Network Analysis

Our network analysis is based on the interregional compensation schemes from 2002 to 2019 provided by the Ministry of Health¹². In terms of value, this implies that an exporting (or debtor) region refunds money to the region that receives the "foreign" patient (importing or creditor region). The flow of money then corresponds to a flow of patients multiplied by the cost of specific healthcare services. In other words, being a creditor region in value terms is equivalent to importing patients from other regions. The latter will therefore be debtor regions, exporting patients to the rest of Italy. Over time, regional heterogeneity has fostered quality differentials which have nourished a high and persistent interregional patient mobility. Mobility patterns are traditionally characterised by patient flows from southern regions towards hospitals located in very distant regions of central-northern Italy, despite the related costs of travelling. Our work aims to deepen this characterisation applying the complex

¹²As some data are not available at a disaggregated level, the two autonomous provinces of Trento and Bolzano are considered as a single regional health service (i.e., Trentino-Alto Adige).

network theory which has become popular in the field of international trade (An et al., 2014; Cappelli et al., 2023; De Andrade and Rêgo, 2018; Fan et al., 2014; Tokito et al., 2016; Zhang et al., 2014). The interregional health mobility network is conceptualised using complex network theory, where regions represent the nodes (or vertices) and healthcare expenditures between regions the connections (or edges). Complex network theory allows using specific indicators for analysing the structural characteristics of our network. In traditional analysis of complex networks, one of the most important problems is related to the identification of the importance of nodes, that – in our case – are represented by regions. This importance can be assessed considering the number of connections a node has to other nodes and the related flow of money. In this regard, the weighted degree represents the trade intensity of a regions with other regions, taking into consideration not only the number of connections but also the related amount of value.

There exists an exporting-based network, considering the outgoing edges, and an importing-based network, based on the incoming links. If we look at the outgoing edges, then we are estimating the weighted out-degree centrality, representing the export side of the network. If n denotes the number of regions in our problem, the weighted out-degree centrality of region/node i can be defined as follows:

weighted-in-degree_j =
$$\sum_{i=1}^{n} w_{ij}$$
 (1)

where w_{ij} is the weight of the link between regions *i* and *j*. The weighted outdegree centrality captures the outreach of a region to the community. A high weighted out-degree centrality indicates that region i exports a lot, aiming to reach all other regions with a certain pervasiveness (all regions are practically connected, but the weight indicates how pervasive the influence of i is). The weighted out-degree centrality, then, captures the level of engagement a region i initiates with members of the community. If a region is characterised by a high weighted out-degree, this implies that it is exporting a lot of money (i.e., patients) to many regions. In this regard, the weighted out-degree centrality identifies those regions whose inhabitants are most dependent on other regions for healthcare. On the contrary, if we look at the incoming links, then we are analysing the weighted in-degree centrality, which displays the import side of the network: importing money from one region is equivalent to importing patients. Consequently, the weighted in-degree centrality represents those regions that are attractive to patients of other regions in terms of healthcare. Formally, being n the overall number of regions, the weighted in-degree centrality of region/node j can be defined as follows:

weighted-in-degree(weighted_in_degree_j) =
$$\sum_{i=1}^{n} w_{ij}$$
 (2)

In the context of a network or graph, w_{ij} represents the weight of the link between node *i* and node *j*. This weight can signify various types of relationships, such as distances, costs, strengths, or other quantitative measures between the nodes. The weighted in-degree centrality measures the number of links – and their amounts – others have initiated with region j. Regions with high weighted in-degree centrality gain attention to their markets among the regions participating in the exchange. Weighted in-degree centrality, thus, captures the community's engagement with them. Those with high weighted in-degree centrality scores can be considered as market hubs since others have exported to them. The complex network can be displayed in several ways, such as a chord diagram. A chord diagram is a visual representation that depicts the relationships and connections between different nodes (or – in our case – regions). Individual nodes are represented by circular segments arranged along the circumference of a circle. The circle serves as a frame of reference for visualising the relationships between them. Interconnections between regions are represented by lines called chords (hence the name of the diagram). These chords connect two or more circular segments, indicating the interactions between the corresponding regions. The thickness or width of the chords is proportional to the magnitude or strength of the relationship being represented. In this regard, we show the interregional compensation scheme of the Italian NHS according to four different dimensions: (i) absolute real values of money flows between regions (Figure 1); (ii) absolute real values of money flows between regions adjusted for distance (Figure 2)¹³; (iii) absolute real values of money flows between regions adjusted for population (Figure 3)¹⁴; (iv) absolute real values of money flows between regions adjusted for distance and population (Figure 4)¹⁵. In order to make the graphical representation of the network more exhaustive, each figure takes into account both the import (weighted in-degree) and export (weighted out-degree) side and macro-regions have been marked by a different colour: northern regions are dark grey, central regions light grey and southern regions and islands light blue¹⁶. It is important to underline that both sides are representing the same network, highlighting the two sides of the mobility pattern. The length of the segment along the circle identifies the weight of a certain region on the overall network. Without adjusting the real flows of money, the export side of the network identifies the southern macro-region as the main exporter of patients (Figure 2). From this point of view, the North represents the most important destination of all Italian

¹³For each pair of regions, the real values of the money flow are multiplied by the distance between the corresponding centroids (a centroid represents the geometric center of all the points in a geometric shape): as distance increases so does the weight that a given money flow has on the entire network.

¹⁴The export of patients depends not only on distance but also on the number of inhabitants of a given region. For this reason, we divide the export value by the population of the region of origin. In this way, we normalise the network by the population size of the different regions.

¹⁵Since the previous aspects can potentially play a joint role, we adjust the money flows by multiplying them by distance and dividing them by population.

¹⁶Table A.3 in the Online Appendix shows the NUTS statistical codes used in the Figures.

patients, while northern regions export their patients without leaving their macro borders. Focusing on the import side, Lombardy (ITC4) increased its ability to attract patients from other regions over time to the detriment of the central regions and Liguria (ITC3). Southern regions and islands tend to receive patients from adjacent regions with the exception of Abruzzo (ITF1) that is an attractor of patients from Lazio (ITI4). The same characterisation applies to the central regions which mutually import patients among them. Once we adjust our network for the distance between different centroids, it becomes even clearer how southern and island regions contribute to overall patient exports (Figure 3). This aspect highlights the importance that healthcare in the Centre but especially in the North plays in satisfying the care needs of southern and island regions. Over time Lazio increased the propensity to export patients to more distant health providers in northern regions. Adjusting our network by taking into consideration the population size of exporting regions, the North is characterised by a high propensity to export patients (Figure 4). In any case, these exports are concentrated among northern regions. Finally, considering the distance between regional centroids and population of exporting regions allows to better understand how the interregional compensation network of the Italian NHS works. Most export flows go from the South to the North and the Centre seems to play a role as an intermediary, receiving some of the patients from the South and exporting their patients to the North (Figure 5). The import/export details for each region are reported in Table A.1 in the Online Appendix.

Figures 2,3,4,5 around here

4.1.1 Analysis of the determinants

To analyze the determinants of Origin-Destination (OD) monetary flows for health mobility between pairs of Italian regions, we estimate a random effect (RE) gravity model where the outcome of interest is specified as follows:

$$Y_{OD,t} = \alpha_0 + \alpha_1 \text{DIST}_{OD,t} + \sum_{i=O,D} \beta_i X_{i,t} + \sum_{i=O,D} \gamma_i Q_{i,t-1} + \delta_{OD} + \tau_t + \epsilon_{OD,t}$$
(3)

At time t, Y_{OD} is the OD monetary flow representing outflows for the origin region O and inflows for the destination region D. The outcome of interest and all regressors are expressed in logarithms, except binary and percentage variables. DIST_{OD} is the OD distance in kilometers. X_i , with i = O, D, is the set of contextual factors reported in table 2 that include population, population over 65, the percentage of high education, employment rate, household income, per capita GDP, Institutional Quality Index, and a dummy variable for Special-Statute Regions. Q_i comprises Regional Health Service (RHS) quality indicators, considered with a time lag of one year to avoid endogeneity issues. They are the C-section rate, the Comparative Index of Performance, the Case-Mix Index, the Technology Endowment Index, the percentage of beds in LPHs out of the total number of beds, the percentage of discharges from specialized facilities over the total number of discharges, and two binary variables for undergoing FRP with and without commissioner. The regressors in X_i and Q_i are the same for both origin and destination regions. δ_{OD} and τ_t capture OD-pair random effects and time fixed effects, respectively, and ϵ_{OD} is the error term.

Table 2, around here

Compared to the fixed effect (FE) model, this specification has the advantage of allowing the impact of time-invariant determinants to be observed. However, ODpair random effects are assumed to be uncorrelated with the variables included in the regression, a strong restriction in health economics analyses (Jones, 2000). To relax this assumption, we perform Mundlak correction and model the OD-pair random effects as a linear function of all time-varying regressors averaged over time. This results in a Conditional Random Effect (CRE) model, that has been proven to yield equivalent FE and RE estimators (Mundlak, 1978). In this way, we are able to control for an unrestricted number of unobserved variables, such as past migration flows (Balia et al., 2018; Berta, Martini, Spinelli and Vittadini, 2022), political similarity between origin and destination regions, and social capital characteristics at the local level (Ciarrapico et al., 2023).

A further econometric problem is given by the independence among observations assumed in the RE and CRE models. When monetary flows interact spatially, the model produces biased estimates. Controlling for OD distance, in fact, is inadequate in the presence of spill-overs from neighboring regions. To capture dependency relations, we rely on a CRE Spatial Durbin Model (CRE-SDM) and include a spatial lag of the dependent and independent variables. In the presence of omitted variables correlated with regressors, this approach leads to unbiased estimates and allows valid inferences to be drawn about the effects of interest (LeSage and Pace, 2008). Our final specification is given by:

$$Y_{\text{OD},t} = \alpha_0 + \alpha_1 \text{DIST}_{\text{OD},t} + \sum_{i=O,D} \left(\beta_i X_{i,t} + \gamma_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_{i,t-1} \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_i \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_i \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_i \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_i \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_i \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_i \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i Q_i \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i X_i \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \nu_i W_i X_i + \eta_i W_i X_i \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \mu_i W_i X_i + \eta_i W_i X_i \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \mu_i W_i X_i + \eta_i W_i X_i \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \mu_i W_i X_i + \eta_i W_i X_i \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \mu_i W_i X_i + \eta_i W_i X_i \right) + \sum_{i=O,D} \left(\chi_i W_i Y_i + \mu_i W_i X_i + \eta_i W_i X_i \right) + \sum_{i=O,D} \left(\chi_i W_i X_i + \eta_i W_i X_i \right) + \sum_{i=O,D} \left(\chi_i W_i X_i + \eta_i W_i X_i \right) + \sum_{i=O,D} \left(\chi_i W_i X_i + \eta_i W_i X_i \right) + \sum_{i=O,D} \left(\chi_i W_i X_i + \eta_i W_i X_i \right) + \sum_{i=O$$

 $\delta_{\rm OD} + \tau_t + \epsilon_{{\rm OD},t}(4)$ With

$$\delta_{\text{OD}} = \sum_{i=O,D} \left(\zeta_i \bar{X}_i + \theta_i \bar{Q}_i \right) + \sum_{i=O,D} \left(\psi_i W_i \bar{Y}_i + \phi_i W_i \bar{X}_i + \lambda_i W_i \bar{Q}_i \right) + \mu_{\text{OD}}$$
(5)

where the bar symbol indicates the variables averaged over time for Mundlak correction¹⁷. W is a row-standardized spatial weight matrix of inverse OD distances, whose elements are equal to zero when O = D and below the inverse of the median distance¹⁸. It follows that the strength of the interaction decreases as the distance between neighboring regions increases and cancels beyond the median distance. As neighboring regions include both origin and destination neighbors, we build an originspecific matrix (W_O) and a destination-specific matrix (W_D) and multiply each of them by the corresponding Y_i , X_i , and Q_i . Setting $Z_i = Y_i$, X_i , Q_i and $\Omega_i = \chi_i$, ν_i , η_i , $\Omega_O W_O Z_O$ captures origin-based spatial dependence relations using an inverse-distance weighted average of Z_O of origin O neighbors. In practice, forces in Z_O leading to monetary outflows from neighbors of origin region O to destination region D may produce spill-over effects and determine part of the outflows from origin region O to destination region D. Similarly, $\Omega_D W_D Z_D$ captures destination-based interactions between inflows of region D and forces in Z_D of neighbors¹⁹. For all models, we apply the RE maximum likelihood estimator.

¹⁷To preserve estimation efficiency, time averages are included only for variables for which a positive share of variance is explained within the OD pair (Mundlak, 1978).

¹⁸Instead of inverse distances, the matrix of spatial weights could contain ones for neighbouring regions and zeros otherwise. We chose the first option so as not to exclude from the analysis the two Italian island regions, Sardinia and Sicily.

¹⁹A third type of dependence may be reflected in the matrix $W = W_O \cdot W_D$, capturing origindestination dependence and any relation between neighbors of the origin O and neighbors of the destination D (LeSage and Pace, 2008). We include $\xi W Y_{OD,t}$ in our preferred specification, but the parameter ξ is not statistically significant.

4.2 Results

Table 3 shows the results estimated according to the specifications described in the previous section: RE (model 1), CRE (model 2), CRE-SDM (model 3). As described by the likelihood ratio (LR) tests reported at the bottom of the table, the coefficients of time-averaged variables included in model 2 are jointly statistically significant, as are the spatial lags added in model 3. This provides strong evidence that the CRE-SDM model is more suitable than the CRE model, that in turns perform better than the RE specification. For an easier visualization of the table, we divide the results into five blocks. One relates only to the OD-pair variable, distance, while the others are for the direct and indirect effects of origin- and destination-region variables separately. As the dependent variable and regressors are log-transformed, we interpret the coefficients as direct or indirect elasticities. Largely unchanged across models, OD monetary flows decrease with increasing distance. Regarding the direct effects of origin-region characteristics, a small subset of factors remains statistically significant in model 3. A 10% increase in GDP causes a reduction of 3.15% in monetary outflows. High GDP can be conceived as a proxy for region overall wealth, translating into highquality healthcare and an increased ability to retain patients. Lower outflows are also observed for SSRs, with the related dummy included to avoid bias from comparing regions with different independence levels, especially on the financing side (Bordignon et al., 2020). Further investigations reveal that our result is mainly driven by northern SSRs (Friuli Venezia Giulia, Trentino South Tyrol, and Valle d'Aosta). As their health systems are financed mostly from their own revenues with no recourse to the national health fund, the CG has limited power to direct and constrain their health legislation, effectively expanding their autonomy and making them subject to less effective cost-containment policies (Balduzzi et al., 2018). This could lead to greater

supply of healthcare services and, consequently, greater ability to retain patients. Another factor influencing monetary outflows is hospital supply. This is measured as the percentage of beds in PLHs to total beds to capture the effect of public-private mix in the availability and distribution of health services. We find that a 10% increase in the share of PLH beds reduces outflows by about 4.07. A possible explanation is that, in the high-complexity and more expensive segment, the licensed private sector has market shares of more than 40%, especially in broadly distributed specialties such as orthopaedics, oncology, and cardiac surgery (Petracca et al., 2016). Also, in regions where private providers are strong competitors to their public counterpart, patients select hospitals by quality and penalize facilities farther away (Martini et al., 2022). Then, in line with Beraldo et al. (2023), we find that regions under FRP with commissioner face larger monetary outflows than those with no restrictions and oversight. The reason is that such regions experience greater restrictions and reductions in the resources available for healthcare. With regard to spill-overs from neighbours, origin regions are more able to retain patients when they are located close to regions with high CIP, and thus higher inefficiencies, and fewer discharges from specialized facilities. Surprisingly and in contrast to the results found in the other blocks, high percentages of PLH beds in neighbouring regions are associated with higher patient retention of the origin region, a finding that is not immediately interpretable. Further investigations show that this result is driven by outflows directed toward northern regions and indicate that patients prefer not to move to the North if nearby regions offer extensive private healthcare services. Furthermore, especially in the North, the regions with a higher percentage of private hospital beds are Veneto and Lombardy, which border, among other regions, with Emilia-Romagna. The latter, however, has the highest percentage of public hospital beds. These three regions, regardless of the healthcare system adopted, report a higher quality of healthcare service compared to other Italian regions. This result suggests that if the public healthcare service works properly, it is not strictly necessary to relocate to other regions. Differently from the above findings, at destination several factors keep their statistical significance in model 3, although only the GDP of nearby regions generates spill-over effects, with the ability to attract patients increasing with proximity to low-wealth regions. The use of monetary data as the outcome of interest allows new insights into destination variables. Results can be interpreted not only as the ability to attract out-of-region patients, but also as reflections of the mechanisms through which regions generate revenue from mobility. Consistently with some previous evidence (Balia et al., 2020; Brenna and Spandonaro, 2015), our findings point to specialization as the main determinant of monetary inflows. Specifically, a 10% increases in technology levels and discharges from specialized facilities results in increased inflows of 1.0% and slightly more than 1.2%, respectively. The largest effect is found for the share of PLH beds, where a 10% rise leads to a 12.2% increase in inflows. As mentioned above, PLHs have a large market shares in high-complex sectors. It follows that, for a given number of incoming patients, monetary inflows rise due to the higher cost of care offered in these types of hospitals. Moreover, as described in Section 2, PLHs are more likely to face incentives to attract patients. Mechanisms of attraction are found in reduced waiting times and increased length of admissions (Berta, Martini, Spinelli and Vittadini, 2022; Berta, Vinciotti and Moscone, 2022), with both factors requiring more hospital beds. Insights into mobility for specialization are also offered by the CMI coefficient, which reflects the heterogeneity of care offered in each destination region. It is negatively correlated with monetary inflows, suggesting that the ability to attract and generate revenue from mobility is not determined by the supply of care for a wide range of diseases, but rather by the provision of highly specialized care for specific conditions for which patients are willing to travel. This is confirmed by the results on cancer

and surgery found by (Balia et al., 2018). Among other RHS factors, being under FRP with commissioner and CIP also drive monetary inflows, both presenting a negative correlation. Regarding contextual characteristics, a 10% increase in population leads to reduced monetary inflows of nearly 17.5%, probably due to a saturation of the RHS and a patients' preference for short waiting times (Bruni et al., 2021). The finding on the over-65 population, positively associated with inflows, also relates to the productive capability of the health system. If attractiveness depends on the supply of specialized care and the latter is usually directed to younger groups, regions with larger elderly cohorts have lower domestic demand for these types of care and shorter waiting lists, favouring inflows. In line with the above findings, SSRs present a negative coefficient, a result mainly driven by southern regions . Finally, a 10%increase in IQI, which summarizes different dimensions of the quality of institutional environment, causes an increase in inflows of about 1.16%. This is not surprising, as institutional quality has been found to positively affect public sector performance (Alesina and Tabellini, 2007, 2008; Mauro, 1998). Specific to the healthcare field, De Luca et al. (2021) find that high institutional quality reduces inappropriateness of hospital services. In turn, this could lead to higher patient inflows.

Table 3, around here

5 Conclusions

Patient mobility is particularly relevant both in economic and social terms, as it impacts regional financial resources and, at the same time, involves only citizens with higher incomes who can independently move to facilities with better services. The results of our study indeed demonstrate that greater mobility occurs between regions with lower income levels and regions with higher income levels. In Italy, this phenomenon of patient mobility involves every year more than half a million patients (mostly from Southern regions to Northern regions) who seek medical care in regions different from their place of residence. This factor, in addition to indicating a perceived low quality in the regions of origin, significantly diminishes the resources available to these regions. In fact, since the right to healthcare is universally guaranteed in Italy, each citizen can independently decide in which facility to receive treatment. However, this implies that at the end of the year, the services provided outside the region are funded by the regions of residence. This financing process only exacerbates the differences between poor and wealthy regions. It should come as no surprise that healthcare mobility, especially hospital admissions, intersects with significant social issues and is strongly influenced by them. One of the most important influencing factors is certainly related to the trust placed in hospital facilities. Trust in hospital facilities shows interesting social and territorial differences. For example, the disparity in hospitalization rates between different geographical areas of the country cannot solely be attributed to organizational and structural issues. This is a trend that has intensified over the years, leading to an increasing gap between the North and South of the country. The healthcare system's financing system should also be reconsidered. The current financing system should be rethought in order to reduce disparities and enable consistent care across the entire national territory. The primary taxes (the surtax on central personal income tax (RPIT) and for the regional tax on productive activities (RTPA)) that currently fund the Italian healthcare system appear to respond differently to the economic cycle, favouring the wealthier regions, especially those in the north (Lagravinese et al., 2018). The behaviour of regional taxes and monetary flows for health mobility may increase the Italian North-South gap. The data available since 2002 have also shown us that mobility has not stopped over time. Despite the healthcare reform that decentralized the healthcare system on a regional basis, granting more powers to the regions has not dampened the mobility phenomenon. Indeed our findings have clearly shown how financial flows are almost always unidirectional, with substantial resources moving from the South to the North, and involving the same Southern regions that should retain these resources to make the healthcare system more suitable for the needs of their citizens. At this point, after more than twenty years since the federal reform, it is necessary to consider whether it makes sense to maintain a decentralized system that generates such a significant regional imbalance. Or, alternatively, whether it would be desirable to undergo a phase of re-centralization of powers and greater control over performance at the central level.

References

- Adolph, C., Greer, S. L. and da Fonseca, E. M. (2012), 'Allocation of authority in european health policy', Social Science & Medicine 75(9), 1595–1603.
- Alesina, A. and Tabellini, G. (2007), 'Bureaucrats or politicians? part i: a single policy task', American Economic Review 97(1), 169–179.
- Alesina, A. and Tabellini, G. (2008), 'Bureaucrats or politicians? part ii: Multiple policy tasks', *Journal of Public Economics* 92(3-4), 426–447.
- An, H., Zhong, W., Chen, Y., Li, H. and Gao, X. (2014), 'Features and evolution of international crude oil trade relationships: A trading-based network analysis', *Energy* 74, 254–259.
- Baicker, K., Buckles, K. S. and Chandra, A. (2006), 'Geographic variation in the appropriate use of cesarean delivery: do higher usage rates reflect medically inappropriate use of this procedure?', *Health Affairs* 25(Suppl1), W355–W367.
- Balduzzi, R., Davide, P. et al. (2018), 'La specialità che c'è, ma non si vede. la sanità nelle regioni a statuto speciale', *CORTI SUPREME E SALUTE* (1), 155–180.
- Balia, S., Brau, R. and Marrocu, E. (2018), 'Interregional patient mobility in a decentralized healthcare system', *Regional Studies* 52(3), 388–402.
- Balia, S., Brau, R. and Moro, D. (2020), 'Choice of hospital and long-distances:
 Evidence from italy', *Regional Science and Urban Economics* 81, 103502.
- Barra, C., Lagravinese, R. and Zotti, R. (2022), 'Exploring hospital efficiency within and between italian regions: new empirical evidence', *Journal of Productivity Anal*ysis 57(3), 269–284.

- Beraldo, S., Collaro, M. and Marino, I. (2023), 'Patient migration as a response to the regulation of subnational healthcare budgets', *Regional Studies* pp. 1–13.
- Berta, P., Guerriero, C. and Levaggi, R. (2021), 'Hospitals' strategic behaviours and patient mobility: Evidence from italy', *Socio-Economic Planning Sciences* 77, 101030.
- Berta, P., Martini, G., Spinelli, D. and Vittadini, G. (2022), 'The beaten paths effect on patient inter-regional mobility: An application to the italian nhs', *Papers in Regional Science* 101(4), 945–977.
- Berta, P., Vinciotti, V. and Moscone, F. (2022), 'The association between hospital cooperation and the quality of healthcare', *Regional Studies* **56**(11), 1858–1873.
- Bordignon, M., Coretti, S., Piacenza, M. and Turati, G. (2020), 'Hardening subnational budget constraints via administrative subordination: The italian experience of recovery plans in regional health services', *Health economics* **29**(11), 1378–1399.
- Brekke, K. R., Levaggi, R., Siciliani, L. and Straume, O. R. (2014), 'Patient mobility, health care quality and welfare', *Journal of Economic Behavior & Organization* 105, 140–157.
- Brekke, K. R., Levaggi, R., Siciliani, L. and Straume, O. R. (2016), 'Patient mobility and health care quality when regions and patients differ in income', *Journal of health economics* 50, 372–387.
- Brenna, E. and Spandonaro, F. (2015), 'Regional incentives and patient cross-border mobility: evidence from the italian experience', *International journal of health policy and management* 4(6), 363.

- Bruni, M. L., Ugolini, C. and Verzulli, R. (2021), 'Should i wait or should i go? travelling versus waiting for better healthcare', *Regional Science and Urban Economics* 89, 103697.
- Cantarero, D. (2006), 'Health care and patients' migration across spanish regions', The European Journal of Health Economics 7, 114–116.
- Cappelli, F., Carnazza, G. and Vellucci, P. (2023), 'Crude oil, international trade and political stability: Do network relations matter?', *Energy Policy* **176**, 113479.
- Ciarrapico, A. M., Cosci, S. and Mirra, L. (2023), 'Social capital and patients' mobility in italy', *Regional Studies* 57(5), 907–919.
- De Andrade, R. L. and Rêgo, L. C. (2018), 'The use of nodes attributes in social network analysis with an application to an international trade network', *Physica* A: Statistical Mechanics and its Applications 491, 249–270.
- De Luca, G., Lisi, D., Martorana, M. and Siciliani, L. (2021), 'Does higher institutional quality improve the appropriateness of healthcare provision?', *Journal of Public Economics* 194, 104356.
- Fabbri, D. and Robone, S. (2010), 'The geography of hospital admission in a national health service with patient choice', *Health Economics* 19(9), 1029–1047.
- Fan, Y., Ren, S., Cai, H. and Cui, X. (2014), 'The state's role and position in international trade: A complex network perspective', *Economic Modelling* 39, 71–81.
- Gravelle, H., Santos, R. and Siciliani, L. (2014), 'Does a hospital's quality depend on the quality of other hospitals? a spatial econometrics approach', *Regional science* and urban economics 49, 203–216.

- Jones, A. M. (2000), Health econometrics, *in* 'Handbook of health economics', Vol. 1, Elsevier, pp. 265–344.
- Lagravinese, R. (2015), 'Economic crisis and rising gaps north-south: evidence from the italian regions', Cambridge journal of regions, economy and society 8(2), 331– 342.
- Lagravinese, R., Liberati, P. and Resce, G. (2019), 'Exploring health outcomes by stochastic multicriteria acceptability analysis: An application to italian regions', *European Journal of Operational Research* 274(3), 1168–1179.
- Lagravinese, R., Liberati, P. and Sacchi, A. (2018), 'The growth and variability of regional taxes: an application to italy', *Regional Studies* **52**(3), 416–429.
- LeSage, J. P. and Pace, R. K. (2008), 'Spatial econometric modeling of origindestination flows', Journal of Regional Science 48(5), 941–967.
- Levaggi, R. and Zanola*, R. (2004), 'Patients' migration across regions: the case of italy', Applied economics 36(16), 1751–1757.
- Mauro, P. (1998), 'Corruption and the composition of government expenditure', Journal of Public economics 69(2), 263–279.
- Mundlak, Y. (1978), 'On the pooling of time series and cross section data', Econometrica: journal of the Econometric Society pp. 69–85.
- Nifo, A. and Vecchione, G. (2014), 'Do institutions play a role in skilled migration? the case of italy', *Regional Studies* 48(10), 1628–1649.
- Perna, R., Cruz-Martínez, G. and Fuentes, F. J. M. (2022), 'Patient mobility within national borders. drivers and politics of cross-border healthcare agreements in the spanish decentralized system', *Health Policy* 126(11), 1187–1193.

- Petracca, F., Ricci, A. et al. (2016), Gli ospedali privati accreditati: struttura, attività e attrazione di mobilità interregionale, *in* 'Rapporto OASI 2016', Egea, pp. 201– 223.
- Tiebout, C. M. (1956), 'A pure theory of local expenditures', Journal of political economy 64(5), 416–424.
- Tokito, S., Kagawa, S. and Nansai, K. (2016), 'Understanding international trade network complexity of platinum: The case of japan', *Resources Policy* 49, 415–421.
- Turati, G. (2013), The italian servizio sanitario nazionale: a renewing tale of lost promises, in 'Federalism and decentralization in European health and social care', Springer, pp. 47–66.
- Zhang, H.-Y., Ji, Q. and Fan, Y. (2014), 'Competition, transmission and pattern evolution: A network analysis of global oil trade', *Energy Policy* 73, 312–322.

Origin-destination factors				
	Mean	Median	Min	Max
Distance (Km)	469	433	55	1,546
	Conte	extual factors		
	Origin		Destin	nation
	Q1	Q4	Q1	Q4
Flowsª (× €1,000)	57,822	309,070	33,484	458,749
Pop. (× 1,000 inhab.)	862	5,382	1,066	5,569
Over 65 (%)	21.21	18.97	19.92	21.58
High edu. (%)	2.40	3.45	2.03	3.63
Empl. rate (%)	60.40	50.66	55.36	64.39
Household incomeª (€)	34,233	32,312	32,160	38,624
GDP ^a (× €1 million)	23,426	147,361	23,962	184,356
IQI	0.6344	0.3912	0.5037	0.7186
	RI	HS factors		
	Origin		Destination	
	Q1	Q4	Q1	Q4
Public HCE per capitaª (€)	1,931	1,727	1,830	1,769
C-section rate (%)	32.58	42.23	35.70	29.71
Public hospital stay (days)	7.49	7.00	7.27	7.35
Private hospital stay (days)	4.67	5.32	4.18	6.12
CIP	1.06	1.01	1.05	1.02
СМІ	1.00	0.96	0.97	1.04
TEI	2,508	12,178	2,579	15,208
Private beds (%)	13.43	25.68	16.69	17.79
Specialized (%)	14.96	15.21	6.23	19.00

Table 1 – Summary statistics by origin-destination flow quantile

Note: The table shows summary statistics of contextual and regional health service (RHS) factors for the first (Q1) and fourth (Q4) quartiles of OD per-capita monetary flow distribution. Origin regions in Q1: Sardinia, Molise, Trentino-Alto Adige, Friuli Venezia Giulia, Aosta Valley. Origin regions in Q4: Apulia, Calabria, Lazio, Liguria, Lombardy. Destination regions in Q1: Aosta Valley, Basilicata, Calabria, Sardinia, Trentino-Alto Adige. Destination regions in Q4: Emilia Romagna, Lazio, Lombardy, Tuscany, Veneto. GDP: Gross Domestic Product; IQI: Institutional Quality Index; Public HCE: Public healthcare expenditures; CIP: Comparative Index of Performance; CMI: Case-Mix Index; TEI: Technology Endowment Index.

^a Data are deflated using the 2010 GDP deflator provided by EUROSTAT (2010).

Table 2. List of variables.

Contextual factors					
Population	Overall population	2002- EUROS 2019	STAT		
Population over 65	Population over 65 relative to the total population	2002- EUROS 2019	STAT		
High education (%)	Ratio of individuals with tertiary or doctoral education to total population	2002- EUROS 2019	STAT		
Employment rate (%)	Ratio of employed to total population	2002- EUROS 2019	STAT		
Household income (€)	Regional average household income	2003- 2019			
GDP	Regional per capita gross domestic product	2002- EUROS 2019	TAT		
IQI	Institutional Quality Index	2004-Nifo at20192004	nd Vecchione,		
	RHS factors				
Public HCE (€)	Public healthcare expenditures	2002- ISTAT 2019 All	– Health for		
C-section rate (%)	Ratio of caesarean sections to total deliveries	2002- Ministr 2019	ry of Health		
Public hospital stay (days)	Average inpatient stay in public hospitals	2002- Ministr 2019	ry of Health		
Private hospital stay (days)	Average inpatient stay in private licenced hospitals	2002- Ministr 2019	ry of Health		
CIP	Comparative Index of Performance: Ratio between the average standardized case-mix hospital stay of a given region and the national average hospital stay	2002- Ministr 2019	ry of Health		
СМІ	Case-Mix Index: Ratio between the average weight of the inpatient admission of a given region and the average weight of the inpatient admission in the national case mix	2002- Ministr 2019	ry of Health		
ΤΕΙ	Technology Endowment Index: Composite indicator of the availability and comprehensiveness of the regional technological endowment	2002- Ministr 2019	ry of Health		
Private beds (%)	Ratio of beds in private hospitals to total beds	2002- Ministr 2019	ry of Health		
Specialized (%)	Ratio of discharges from specialized hospitals to total discharges	2002- Ministr 2019	ry of Health		

Note: The table shows the variables used in the analysis along with their description, period of availability, and data source. GDP: Gross domestic product. IQI: Institutional Quality Index. HCE: Healthcare expenditures. C-section: Caesarean section. CIP: Comparative Index of Performance. CMI: Case-Mix Index. TEI: Technology Endowment Index.

Table 3 – Estimation results

RE CRE→ CRE→DM OD variable -1.2907*** (0.081) -1.3582*** (0.079) -1.3892*** (0.078) Origin variables – Direct effects -1.2907*** -1.2907*** -1.2907*** (0.079) -1.3892*** (0.078)	3)
Distance -1.2907*** (0.081) -1.3582*** (0.079) -1.3892*** (0.078)	3)
	3)
Origin variables – Direct effects	
Population1.8818***(0.16)1.2733***(0.23)0.1867***(0.34))
Over 65 -0.2646* (0.14) 0.2656* (0.14) 0.0549 (0.19))
GDP -0.7268*** (0.11) -0.4337*** (0.12) -0.3252** (0.14))
IQI -0.0466*** (0.015) -0.0267* (0.016) -0.0056 (0.02))
SSR -0.1766 (0.12) -0.8046 ^{***} (0.19) 0.6440^{**} (0.32))
C-section _{t-1} (%) 0.0015 (0.0016) 0.0005 (0.0016) -0.0016 (0.002)	2)
CIP_{t-1} 0.0523 (0.11) 0.0494 (0.12) 0.0113 (0.13))
CMI t-1 -0.2223^{***} (0.12) -0.2180^{*} (0.13) -0.1680 (0.14))
TEI t-1-0.0180 (0.036) -0.0276^* (0.036) -0.0674 (0.042)	2)
PrivateBeds _{t-1} (%)-0.0966 (0.14) -0.3343^{**} (0.15) -0.4184^{**} (0.16))
Specialized _{t-1} (%) 0.0620 (0.051) 0.0464 (0.051) -0.0330 (0.055)	5)
FRP-0.0144(0.013)0.0193(0.013)0.0013(0.014))
FRP - Commissioned 0.0505*** (0.018) 0.0382** (0.018) 0.0660*** (0.02))
Origin variables – Indirect effects	
Y -0.0256 (0.17))
Population 0.1191 (0.41))
Over 65 0.1258 (0.38))
GDP -0.0334 (0.28))
IQI 0.0822 (0.077)	')
SSR -1.7390 (1.9)	
C-section _{t-1} (%) 0.0039 (0.0048	8)
CIP t-1 -0.8476^* (0.46))
CMI t-1 -0.4938 (0.35))
TEI t-1 0.0028 (0.14))
PrivateBedst-1 (%) -1.8381*** (0.52))
Specialized _{t-1} (%) 0.5381^{***} (0.2)	
-0.0024 (0.037)	')
FRP - Commissioned -0.0196 (0.055)	5)
Destination variables – Direct effects	
Population-1.3292***(0.16)-1.6809***(0.23)-1.6915***(0.24))
Over 65 1.9628*** (0.14) 1.9489*** (0.14) 1.9791*** (0.14))
GDP 0.3117*** (0.11) -0.0798 (0.12) -0.1126 (0.13))
IQI 0.1264*** (0.015) 0.1175*** (0.016) 0.1208*** (0.016)	5)
SSR -0.1804 (0.12) -0.3724*** (0.19) 0.4724** (0.21))

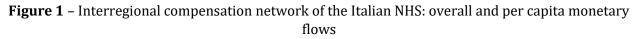
C-section _{t-1} (%)	-0.0037**	(0.0016)	-0.0025	(0.0016)	-0.0023	(0.0017)
CIP _{t-1}	-0.4888***	(0.11)	0.5027***	(0.12)	0.5051***	(0.12)
CMI t-1	0.0833	(0.12)	-0.1966	(0.13)	-0.2189*	(0.13)
TEI t-1	0.1309***	(0.036)	0.1129***	(0.036)	0.1064	(0.036)
PrivateBedst-1 (%)	1.2156***	(0.14)	1.2164***	(0.15)	1.2071***	(0.15)
Specialized _{t-1} (%)	0.1234**	(0.051)	0.1319***	(0.051)	0.1294**	(0.051)
FRP	-0.0282**	(0.013)	-0.0201	(0.013)	-0.0186	(0.013)
FRP - Commissioned	-0.0793***	(0.018)	-0.0739***	(0.018)	-0.0750***	(0.018)
	Destination variables – Indirect effects					

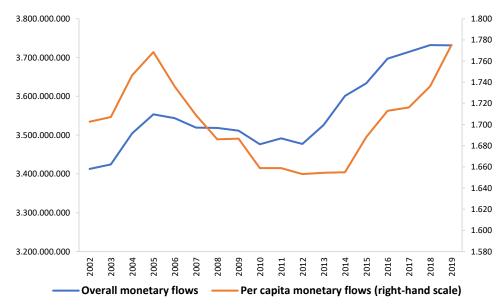
Y					0.0322	(0.031)
Population					0.0651	(0.18)
Over 65					0.1030	(0.21)
GDP					-0.2498*	(0.14)
IQI					0.0418	(0.068)
SSR					-0.0458	(0.095)
C-section _{t-1} (%)					0.0005	(0.0028)
CIP _{t-1}					0.3971	(0.54)
CMI t-1					-0.3007	(0.45)
TEI t-1					0.0051	(0.0015)
PrivateBedst-1 (%)					-0.6421	(0.47)
Specialized _{t-1} (%)					0.1652	(0.21)
FRP					0.0793	(0.078)
FRP - Commissioned					-0.0971	(0.078)
Time FE	~		\checkmark		✓	
Time-averaged X	×		✓		✓	
Constant	-4.2131***	(1.2)	3.1011	(1.9)	5.6112	(2.4)
σ_{δ}	0.9102***	(0.035)	0.8300***	(0.03)	0.7941***	(0.029)
σ_ϵ	0.2292***	(0.0021)	0.2284***	(0.0021)	0.2273***	(0.0021)
ρ	0.9404***	(0.0348)	0.9296***	(0.0049)	0.9242***	(0.0053)
Log-likelihood	-713.05		-656.93		611.78	
LR test			112.25***		90.30***	
Ν	6,460		6,460		6,460	

The table shows the effects of the regressors included in Xi and Qi estimated while controlling for time fixed effects (FE) and Origin-Destination (OD) pairs random effects (RE) and according to different specifications: RE, Correlated Random Effects (CRE), CRE Durbin Spatial Model (CRE-SDM). GDP: Gross Domestic Product; IQI: Institutional Quality Index; SSR: Special-Statute Region; FRP: Financial Recovery Plan; CIP: Comparative Index of Performance; CMI: Case-Mix Index; TEI: Technology Endowment Index.

 σ_{δ} : standard deviation of δ_{OD} ; σ_{ϵ} : standard deviation of $\epsilon_{(OD,t)}$; ρ : fraction of variance due to δ_{OD} . LR: likelihood ratio. Standard errors in parentheses.

* p<0.1, ** p<0.05, *** p<0.01





Note: monetary flows are expressed in real terms *Source*: own elaborations on Ministry of Health data

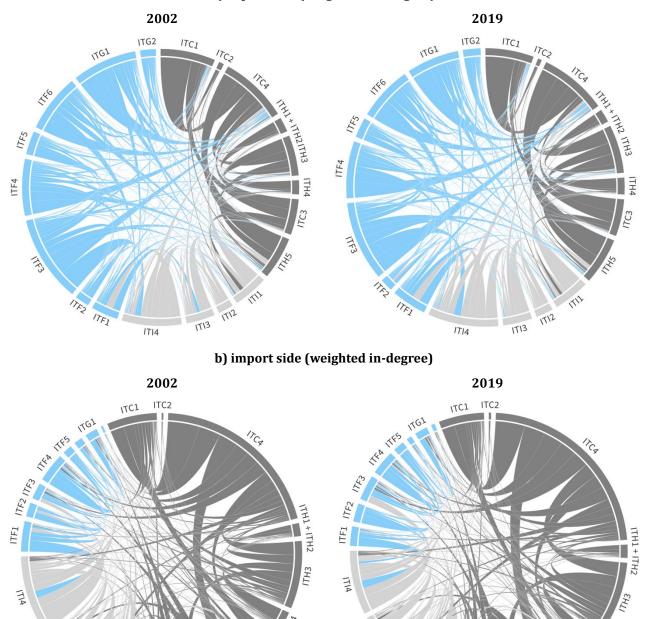


Figure 2- Chord diagram: Interregional compensation network of the Italian NHS

a) export side (weighted out-degree)

Note: each figure takes into account both the import (weighted in-degree) and export (weighted out-degree) side and macro-regions have been marked by a different colour: northern regions are dark grey, central regions light grey and southern regions and islands light blue. Both sides are representing the same network, highlighting the two sides of the mobility pattern. Table A.3 in the Online Appendix shows the NUTS statistical codes used in the Figure.

1711

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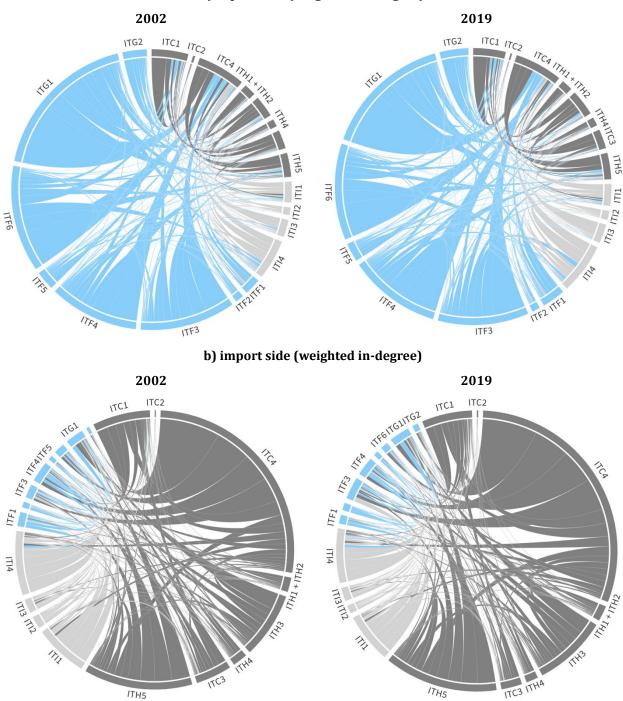


Figure 3 – Chord diagram adjusted for distance: Interregional compensation network of the Italian NHS

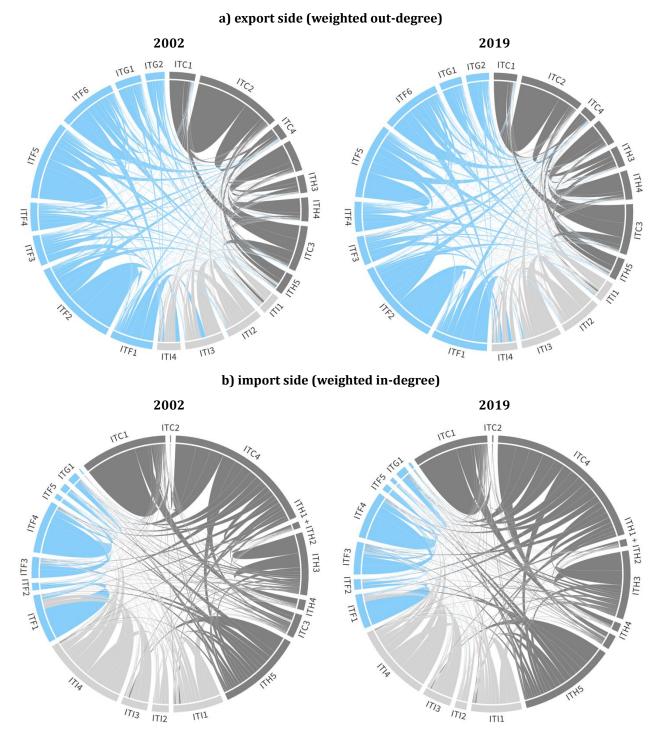
a) export side (weighted out-degree)

Note: each figure takes into account both the import (weighted in-degree) and export (weighted out-degree) side and macro-regions have been marked by a different colour: northern regions are dark grey, central regions light grey and southern regions and islands light blue. Both sides are representing the same network, highlighting the two sides of the mobility pattern. Table A.3 in the Online Appendix shows the NUTS statistical codes used in the Figure.

ITH5

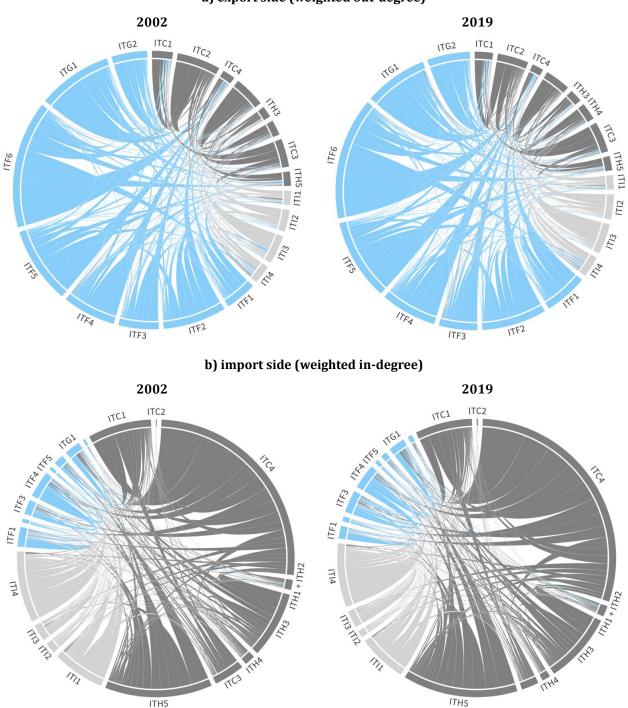
ITH5

Figure 4 – Chord diagram adjusted for population: Interregional compensation network of the Italian NHS



Note: each figure takes into account both the import (weighted in-degree) and export (weighted out-degree) side and macro-regions have been marked by a different colour: northern regions are dark grey, central regions light grey and southern regions and islands light blue. Both sides are representing the same network, highlighting the two sides of the mobility pattern. Table A.3 in the Online Appendix shows the NUTS statistical codes used in the Figure.

Figure 5 – Chord diagram adjusted for distance and population: Interregional compensation network of the Italian NHS



a) export side (weighted out-degree)

Note: each figure takes into account both the import (weighted in-degree) and export (weighted out-degree) side and macro-regions have been marked by a different colour: northern regions are dark grey, central regions light grey and southern regions and islands light blue. Both sides are representing the same network, highlighting the two sides of the mobility pattern. Table A.3 in the Online Appendix shows the NUTS statistical codes used in the Figure.

Appendix

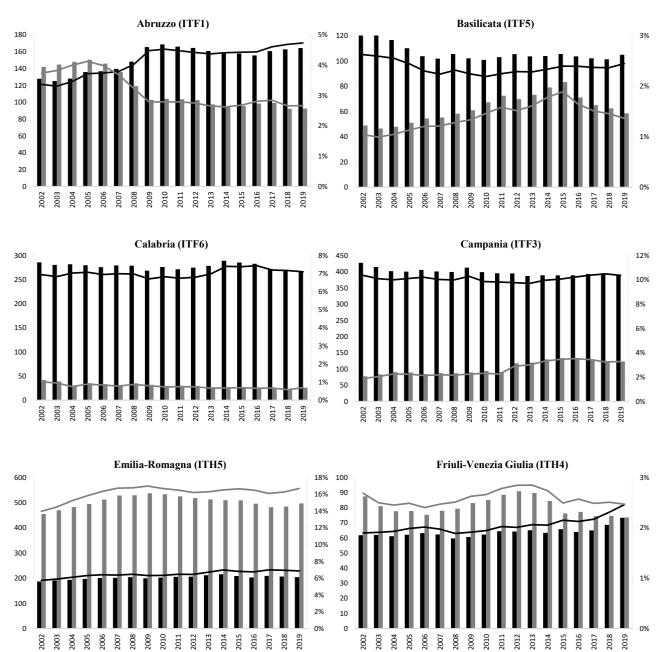
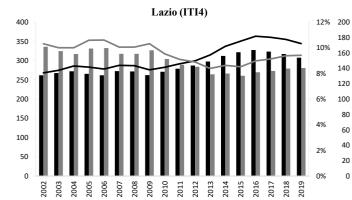
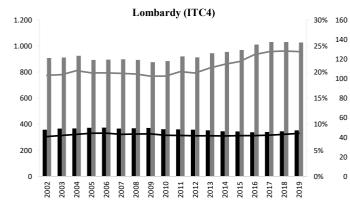
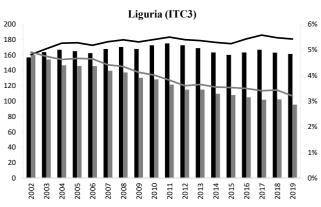
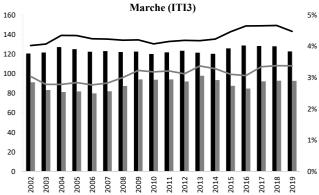


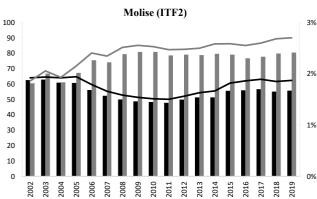
Figure A1 – Interregional compensation exports and imports of the Italian NHS

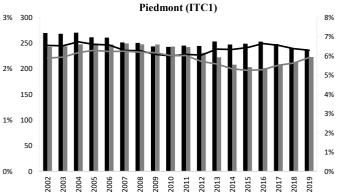


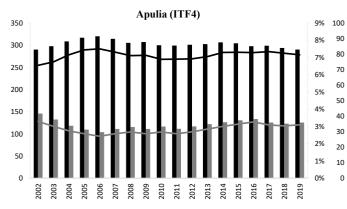


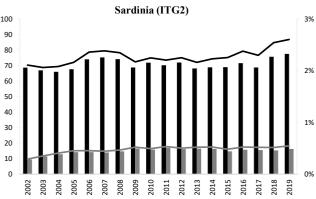




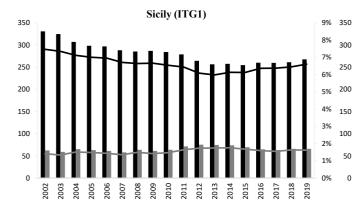


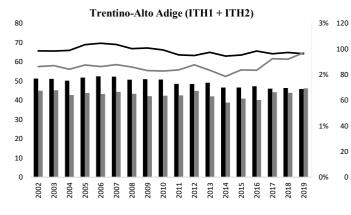


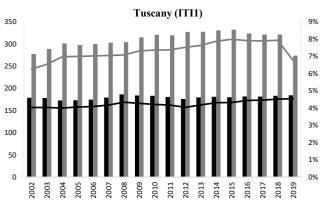


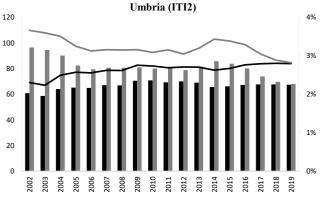


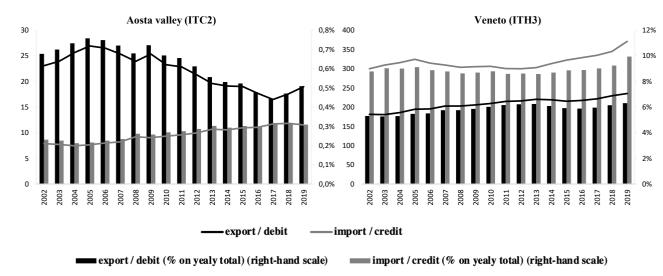
250 2% 200 150 1% 100











Note: export and import values are expressed in million euros and in real terms.

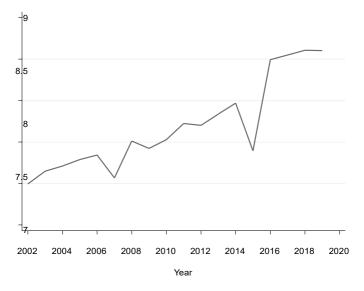


Figure A.2. Percentage of out-of-region to total admissions by year. Source: Ministry of Health.

(a) Origin regions

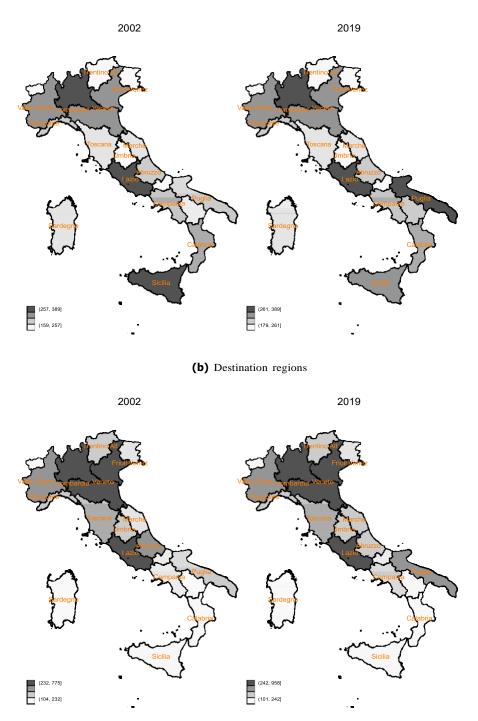


Figure A.3. Geographic distribution of unconditional total monetary flows of Italian region in 2002 and 2019. Increasing colour intensity corresponds to increasing values of origin total monetary outflows (panel a) and destination total monetary inflows (panel b). The distribution of monetary flows $\times \notin 1$ million is divided into the four quartile-bounded groups listed in the legends.

Table A.1. Regions and years under FRP.

	Years	Years with commissioner
Abruzzo	2007-2019	2007-2016
Apulia	2010-2019	
Calabria	2009-2019	2010-2019
Campania	2007-2019	2009-2019
Lazio	2007-2019	2008-2019
Liguria	2007-2009	
Molise	2007-2019	2009-2019
Piedmont	2010-2015	
Sardinia	2007-2009	
Sicily	2007-2019	

Note: The table shows the regions and the years under financial recovery plans (FRP) and the years with commissioner, if any. Source: Ministry of Health.

NUTS 1	NUTS 2	Code
	Piedmont	ITC1
	Aosta Valley	ITC2
	Liguria	ITC3
	Lombardy	ITC4
Northern Italy	Trentino-Alto Adige	ITH1 + ITH2
	Veneto	ITH3
	Friuli-Venezia Giulia	ITH4
	Emilia-Romagna	ITH5
	Tuscany	ITI1
Central Italy	Umbria	ITI2
	Marche	ITI3
	Lazio	ITI4
	Abruzzo	ITF1
	Molise	ITF2
	Campania	ITF3
Southern and Insular Italy	Apulia	ITF4
	Basilicata	ITF5
	Calabria	ITF6
	Sicily	ITG1
	Sardinia	ITG2

Table A.2 – Legend: NUTS statistical regions of Italy

Note: NUTS 1 represents the groups of regions, while NUTS 2 represents the regions (Trentino-Alto Adige includes the two autonomous provinces of Trento and Bolzano).