



FULL ARTICLE

The beaten paths effect on patient inter-regional mobility: An application to the Italian NHS

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Abstract

We study inter-regional migration flows due to hospital admissions and focus on the impact of migration beaten paths. We estimate a gravity model applied to Italian data for the period 2010–2016. We find that beaten paths have a positive effect on inter-regional patient flows, with estimated elasticity equal to +0.32%. Therefore, family and social ties among people living in the region of origin and destination for hospital admissions may explain the concentration of health migration (HM) in some regions. Moreover, the beaten path effect is stronger for private hospitals. We also find that HM patients are more sensible to hospital quality than those admitted in local hospitals.

KEYWORDS

hospital ownership, migration beaten paths, patient inter-regional mobility

JEL CLASSIFICATION

C32, C53, L93

1 | INTRODUCTION

The migration of patients to hospitals in other regions is becoming increasingly important. For example, Balia et al. (2018) estimates that in Italy the inter-regional migration of patients is equal to 7.4% of annual hospital

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admissions, i.e., about 87,000 people. Similar evidence is provided for Spain (Cantarero, 2006), and the United States (Werden, 1990). Clearly, health migration (HM) is a problematic aspect of patient mobility. In fact, it creates (1) inequality between patients (Fattore et al., 2014) and (2) huge transfers of resources between different regions and territorial areas of the same country (Ferretti et al., 2020).¹ However, some previous contributions (Balía et al., 2018, 2020; Cantarero, 2006; Fattore et al., 2014; Levaggi & Zanola, 2004) have investigated HM, but they have not considered the importance of some typical factors of migratory phenomena, which may explain why the flows of patients from some regions of origin are concentrated in some regions of destination.

The migration literature has indeed highlighted the importance of beaten paths (Rodríguez-Pose, 2020), i.e., factors such as kinship, ethnicity, or friendship as local attractors. Having a community of friends and acquaintances in the destination regions reduces the costs of mobility² and at the same time increases the expected benefits of migration. Therefore, beaten paths may be relevant in the context of HM. This is the goal of this paper: to provide some empirical evidence on the impact of beaten paths on HM. To the best of our knowledge, this is the first paper to focus mainly on beaten paths, to shed more light on their effects on HM.

HM is a profoundly different type of migration from that which characterizes populations moving to higher-income or safer countries. It is a short-term migratory flow,³ with the return to the region of origin after the intervention and re-education period. In addition to involving patients, HM involves family members usually engaged in informal care activities (Maplethorpe et al., 2015; Vlachantoni et al., 2015). This implies finding accommodation and temporarily adapting to the life in the destination region.

HM means that some regions are net importers and others are net exporters, because, as shown by Cantarero (2006) and Levaggi and Zanola (2004), both the origin and the destination regions have push and pull determinants, i.e., factors that cause in- and out-migration to occur.⁴ Regarding the latter, the number of patients moving from one region is clearly related to the quality of the health care offered both in the region of origin and in the region of destination, to the distance, and to the mobility costs. The desire for better health care is what drives patients to HM, as shown by Levaggi and Zanola (2004) and Balía et al. (2020). On the contrary, the long distance and the lack of knowledge and social relations in the region of destination may offset the decision to move away from the region of origin. Therefore, considering push effects, at the heart of HM there is the trade-off between the greater benefits deriving from higher hospital quality, and the greater costs because of mobility. If we consider instead regions of destination, suppliers may attract patients. For instance, in social insurance health system as in UK or in Italy, different hospital types (e.g., public or private) may have different incentives toward attracting extra-regional patients.⁵

This work analyzes these issues and the impact of beaten paths on HM by studying the patient inter-regional mobility in Italy during the period 2010–2016 using a gravity model to investigate the flows region of origin vs hospital of destination. The considered medical disciplines are cardiology, oncology, and orthopedics, in which the highest

¹The problems of equity are due to the fact that HM involves both monetary costs (health care costs are covered by the NHS, but mobility and ancillary charges are borne by patients and family members) and non-monetary, relationship, and environmental costs. Cergas (2017) and Ferretti et al. (2020) show, for instance, that in Italy the richest Northern region (Lombardy) receives annually about €1 billion of revenues from other regions for payments regarding extra-regional patients. At the opposite, one of the most populated Southern regions (Campania) pays about €0.4 billion annually for extra-regional mobility of its patients. Clearly, these payments shift resources between regions, generating further discrimination if they occur in favor of richer regions.

²In fact, it increases the level of information, reduces the cost of accommodation, and facilitates integration into the local context.

³The report on the Italian health care system Cergas (2017) shows an average hospital length of stay of a patient in HM of about 7 days. In cases of long-term treatment, the length of stay can reach 30 days.

⁴For instance, during the period 2010–2016 in Italy, and considering only elective admissions for cardiology, oncology, and orthopedics treatments, Lombardy is the most relevant exporter, with a total net flow of immigration (i.e., the difference between immigrants and emigrants) equal to 84,862 patients, accounting for the 26.4% of local admissions (i.e., patients living in the same region as the admission hospital). Emilia-Romagna (+18,630 patients), Tuscany (+16,610 patients), and Veneto (+10,693 patients) are also relevant net exporters. On the contrary, Calabria is a net importer (−20,707) that accounts for the highest percentage of health emigrants over local admissions (about 76%): it means that for every patient living in that region admitted in a local hospital, there is almost another one that is admitted outside the region. Similarly for Campania: it is a net importer (−27,969), and about one in every three patients seeks admission outside the region (health emigrants account for almost 30% of local admissions).

⁵Berta et al. (2021) show that Italian hospitals might have financial incentives to shorten strategically the waiting times of extra-regional patients. This will attract higher in-migration flows and, in turn, higher reimbursement.





flows of HM are involved (Fattore et al., 2014). Moreover, admissions for these types of treatment are mainly elective, and therefore their HM flows have underlying patients' choices.⁶

To explore these issues, we design an econometric model based on count data. As HM flows derive from a selected sample of patients, we consider both intra- and extra-regional patient flows to study the impact of beaten paths on inter-regional mobility. Moreover, our model takes into account possible endogeneity of factors affecting inter-regional mobility such as hospital quality and waiting time, as well as potential spatial autocorrelation.

If the empirical analysis confirms that beaten paths are a significant positive determinant of HM, this would imply that destination regions where past inter-regional population migration is higher are currently net inter-regional patient exporter. This would be a signal that where family and social ties are strong it is easier to obtain admission in hospitals outside the region of residence, despite the relevant monetary and non-monetary mobility costs.⁷ Beaten paths may be regarded as shadow factors reducing the barriers to access to good quality care, and limiting the possible impact of discrimination due to income for the population living in low health quality regions. These findings, if confirmed, may have some important health policy implications, because beaten paths may then reduce the incentives for net patient importer regions to improve the health quality level of their health care systems.

Beaten paths may then explain why, differently from the prediction of some contributions (Besley & Case, 1995a; Oates, 2005; Weingast, 2009), even in the long run we observe regional quality disparities in regional health care systems. These papers affirm that asymmetries in the quality of health services induce mobility but also competition between regions, and the latter should reduce the quality gap. The pressure exerted by the populations of low-quality regions should push regional governments to invest in health expenditure and improve the efficiency of the local health care sector. However, there is no evidence of a reduction in HM. Chun (2008) and Berta et al. (2021), for example, show that in Italy inter-regional transfers for HM are constantly increasing. Beaten paths, by reducing the costs of HM, can decrease the pressure on regional governments for a better health quality on the part of local populations, who can instead, through family and social ties, afford treatments in better hospitals even if they live at a very far distance.

The paper is organized as follows: Section 2 reviews the relevant literature, and highlights the main features of our contribution sector. Section 3 presents the Italian institutional background, Section 4 outlines the empirical methods and the econometric challenges we face, Section 5 describes the data sources and some descriptive statistics on HM and beaten paths in Italy, and Section 6 provides our empirical results. Lastly, Section 7 concludes the paper and discusses some policy implications.

2 | RELATED LITERATURE

Our paper is related to two streams of research: (1) inter-regional patient mobility and (2) migration flows. Patient mobility has been investigated both with theoretical and empirical contributions. Brekke et al. (2014) presents a model with patient mobility between two regions, with different levels of ability to provide high-quality health care.⁸ This implies that the high-skill region will provide higher-quality health care, and this is the source of patient mobility. They compare two regimes: (1) no patient mobility and (2) patient mobility with a transfer system. They show that only if the transfer payment scheme covers the marginal costs, then there is a welfare improvement with patient mobility. However, in equilibrium there is still regional quality asymmetry. Brekke et al. (2016) publish a theoretical

⁶Given that official statistics on Italian migration flows by origin and destination between regions are not available for the periods after World War II, we estimate a model of Italian inter-regional population migration. We use the results to predict backwards the origin-destination regional flows for the years not covered by official statistics. In this way, it is possible to fully capture the impact of beaten paths.

⁷There are no health costs for HM in Italy. All treatments are covered by public health expenditure if they are provided under the essential levels of assistance (*livelli essenziali di assistenza*) decided by the national government.

⁸They design a Hotelling model with two regions where health care is financed through taxation. Patients receive care for free but incur in mobility costs.





model that highlights some effects of cross-border patient mobility. They study its effects on the health quality and welfare in three regions, differing in income distribution.⁹ Again they use a location model (*à la* Salop in this case) and have a *status quo* regime where the richer regions have better health quality. This induces patient mobility from the poorest region. Using decreasing variations in non-monetary mobility costs, Brekke et al. (2016) show that patient inter-regional mobility increases the health quality gap between rich and poor regions. These theoretical contributions suggest that health quality differences and socioeconomic asymmetries may explain patient long distance mobility, and that regional quality gaps may persist in the long run.

On the contrary, the theoretical contributions on inter-jurisdictional competition have shown that patient mobility may stimulate low health quality regions to increase it (Besley & Case, 1995b; Oates, 2005; Weingast, 2009). Gravelle et al. (2014) argue that positive spatial spillovers may lead to health quality improvements in all competing regions. Balia et al. (2018) state that inter-regional patient mobility may generate both negative effects (because it may lead low-quality regions to further reduce their quality) and positive outcome (because it stimulates the average quality level through competition).

These models have provided the background for empirical analyses on patient inter-regional mobility, mainly using a gravity model in which patient flows between two local areas are functions of economic and demographic variables both at the origin and destination regions, of mobility barriers, and of regional policies. Levaggi and Zanola (2004) study the Italian case and investigate the impact of regional health quality, and find that it is a determinant of HM. However, they use income and health expenditure as proxies of quality, while it should be measured by a specific indicator related to risk-adjusted health outcomes. Cantarero (2006) studies the Spanish case and finds, like Levaggi and Zanola (2004), that quality is a determinant of flows, but again uses some proxies for hospital quality. Lippi Bruni et al. (2008) investigate flows within an Italian region of patients for coronary angioplasty and find that destination information is an important factor. This preliminary insight points out the importance of social ties in the patient's destination location, because they might increase the information level. Fabbri and Robone (2010) analyze patient flows among local health authorities (LHA) in Italy in 2001. They show that the greater the size of the LHA, the higher the patient attraction, i.e., HM is determined by economies of scale in the destination regions, a sort of learning-by-doing effect in achieving better quality levels. Fattore et al. (2014) point out that, despite the full coverage of health care costs by the Italian NHS, HM can hide problems of socioeconomic discrimination in the use of good quality care. For instance, they find that individual characteristics such as age and morbidity are determinants of HM. These insights may reveal a barrier to access to good health for elderly and for patients in bad health status. Balia et al. (2020) analyze the mobility of patients residing in the two main Italian island regions and find that it mainly concerns the younger and more educated population groups, and that hospital's quality matters even if it is located at a great distance from the patient's residence.

Unfortunately, there are no income individual data for patient admissions in Italy, but Fattore et al. (2014) argue that the significance of age and the substantial economic and relational resources involved with HM suggest that there might be a disadvantage for people living in net importer regions, which are mainly located in the poorer Southern part of Italy.¹⁰ This would imply that low-income patients, even if theoretically they have access to top quality treatments because health care costs are covered by the NHS, in reality face high barriers to access to care outside their region, due to the high non-health care monetary costs associated with HM.

The second stream of literature connected to our contribution is that of migratory flows (Massey & Arango, 2005; Partridge et al., 2008; Pissarides & McMaster, 1990), in particular the contributions that study the territorial concentration of flows (DaVanzo, 1983). Many studies highlight the importance of economic factors, so that migration flows are mainly directed toward high-income regions (Bodvarsson et al., 2015; Greenwood, 1997). Recently, however, the focus has also shifted toward factors such as quality of life, social capital, and the likelihood of progress in the world of work (Biagi et al., 2011; Faggian & McCann, 2009). Finally, some contributions highlight

⁹They have a rich region, a middle income level region, and a poor region.

¹⁰In Southern Italy, the per capita income is about 60% of the Northern Italy one.





the role of social relations and networks existing in immigration regions (Rodríguez-Pose, 2020). In this case the migratory flows follow the beaten paths (Biagi & Dotzel, 2018; DaVanzo, 1983). According to this trend, the local networks formed for past immigration significantly lower the costs of mobility, psychological effects, and information barriers (Bodvarsson et al., 2015). These costs are particularly high in inter-regional patients' mobility.¹¹

Our contribution shares some features of both literature streams. It is related to the empirical literature on inter-regional patient mobility, using a gravity model but, differently from previous contributions, focuses on patient flows from the region of origin to the hospital of destination. Patient inter-regional mobility is indeed the result of a decision to leave a region to be admitted to a specific hospital. Therefore, flows in our model are related to region-hospital pairs. Moreover, a further difference with the empirical contributions on the inter-regional mobility of patients is the inclusion of a risk-adjusted measure of hospital clinical quality, given by the objective indicators provided by Piano Nazionale Esiti (health outcomes evaluation plan, PNE: <https://pne2017.agenas.it>). This program of quality evaluation is run by a national public agency (AGENAS)¹² and provides hospital-specific indicators of process and health outcomes.¹³

With regard to the literature on migration flows, our contribution highlights the impact of beaten paths on HM, a phenomenon not satisfactorily studied before. The innovative contribution of the paper lies precisely in providing a bridge between a particular migratory flow such as the inter-regional mobility of patients, and a typical feature of the largest migratory movements between countries.

3 | INSTITUTIONAL BACKGROUND

In Italy, since 1978, NHS provides universal health coverage (Ferré et al., 2014). The NHS is financed through national and regional taxation as well as patient copayments in case of specialist visits, medical examinations, and provision of drugs.¹⁴ As mentioned before, the Italian government establishes some essential levels of health care (LEA) that must be provided to everyone in every Italian region. The organization and supply of these LEA treatments are fully delegated to each regional government, which manages the regional health system. Each year the Italian government allocates specific health funds to each region, according to a per capita system.

The supply side related to hospital admissions is not uniform across the Italian regions. In some regions it is composed only by public hospitals, and in others, by public hospitals and licensed not-for-profit and for-profit private hospitals. Each hospital receives from the regional government a reimbursement, for each patient admitted, through a system of LHA, acting as third-party payer.¹⁵ The reimbursement is based on a mix of per-case payment and a prospective payment system based on diagnosis-related groups (DRG). Licensed private hospitals admit patients free of charge and receive a reimbursement from the LHA where the patient is enrolled as well as the public hospitals.

Patients are enrolled in a specific regional LHA according to their residence. However, they are free to choose any Italian hospital. If a patient chooses a hospital outside its LHA but still within its region of residence, the LHA pays the reimbursement to the chosen hospital. If the patient is admitted in a hospital outside its region of residence, then the hospital receives a reimbursement from the region of origin of the patient according to a national DRG-based tariff.

¹¹The possibility of being admitted to a hospital outside the region where family members, friends, or acquaintances have migrated in the past allows to reduce information costs, the psychological costs of being away from home, and often also the monetary costs of accommodation.

¹²AGENAS-Agenzia Nazionale per i Servizi sanitari regionali is a public agency that provides scientific, economic, and statistical support to the Italian Ministry of Health.

¹³Risk adjustments take patient's age, gender, and a large set of comorbidities into account. The health quality indicators are ratios in which the numerator is the number of cases that experienced a bad health outcome in a given period after a specific treatment. The denominator is the total number of patients admitted in the same period for that treatment. Previous contributions have used proxies for hospital's quality (with the exception of Balia et al. (2020)).

¹⁴Copayments levels consider individual or family income, the presence of chronic pathologies, etc. Poor individuals and patients with chronic diseases are exempted from copayment.

¹⁵Each LHA has about 600,000 people to assist. The number of LHAs in each region varies depending on the regional population. The hospital receives the reimbursement from the LHA where it is located.





Under this regime, the regions that import more patients than they export (i.e., net exporter regions) receive additional financial resources; on the contrary, regions that export more patient than they import (i.e., net importer regions) suffer from a drain on financial resources. Net importer regions, on top of sustaining the costs for the organization of their regional health system, that it is usually designed to serve the entire regional population, have to pay the additional costs for inter-regional mobility. This situation may create financial problems in low health quality regions, where a high percentage of patients choose to be admitted in other, high health quality, regions.

Aware of these problems, and of the incentive for regions with high health quality to attract an increasing number of extra-regional patients, the Italian government has tried to limit HM by including inter-regional flows in the evaluation criteria of regional health performances. The latter are used to allocate the funds transferred by the Italian government to the various regions (Fabbri & Robone, 2010). However, these policies are based only on regional disparities in financial flows for health; they do not consider the costs of mobility that patients, and their families, involved in HM, have to sustain. This is why our work aims to highlight the effect of the beaten paths in HM. Family and social relationships with people who in the past have emigrated from the patient's region of origin and are permanently established in the destination region where the admission hospital chosen by the patient is located can substantially reduce the costs of mobility. These family relationships can also be the cause of inter-regional mobility beyond consideration of hospital quality. It can be a simple informal transmission of information in the context of the social relationship, or even the links of some hospital doctors with the regions of origin.

The eventual confirmation of the importance of the beaten paths for HM would open up important health policy considerations. On one hand, by reducing the costs of mobility, they limit income effects that can prevent access to good quality care for the poorest part of the population. On the other hand, they might reduce the incentives for the national and the regional governments of net importer regions to improve the health quality level.

4 | EMPIRICAL METHODS

We analyze the impact of beaten paths on HM by designing an econometric model for patient inter-regional mobility based on a region-hospital gravity model for count data, with region-level fixed effects to control for all possible time-invariant unobserved factors related to patients flows.¹⁶ We take hospital quality, capacity, ownership, as well as possible differences among hospitals in urban or rural areas into account.

We start by defining a random utility model considering a patient k living in one of the 21 Italian regional health systems i , who decides to be hospitalized choosing among $j = 1, \dots, J$ available hospitals, which are all located in Italy.¹⁷ This choice is aimed at maximizing patient k 's utility function defined as:

$$U_{kijrt} = u_{kijrt} + \epsilon_{kijrt} = b_{kijrt} - c_{kijrt} + \epsilon_{kijrt}, \quad (1)$$

where k, i, j, r , and t are subscripts respectively for individual, region of origin, hospital destination, region of destination, and time. If the region of destination of the hospital of admission is different from that of origin, this choice is part of the inter-regional patient flow between region i and r . The utility U is a balance between observable benefits b and costs c of hospitalization. In addition, ϵ_{ijrt} is an error term that accounts for unobservable determinants of utility.

Under the assumptions that each individual chooses the hospital that maximizes her utility, that errors are independently and identically distributed, with type one extreme value distribution (McFadden, 1973), the probability that the patient k living in the region i chooses the hospital j located in the region r is equal to:

¹⁶Our unit of observation is the flow of patients from a region to a specific hospital, given that at the heart of HM flows there is the choice of patients in a hospital, not of just the region of hospitalization. Therefore, we consider push and pull factors at the regional and hospital levels.

¹⁷Italy has 992 public or publicly accredited hospitals (Italian Ministry of Health, 2021).





$$P(d_{kijrt} = 1) = \frac{\exp(u_{kijrt})}{\sum_{z=1}^J \exp(u_{kizrt})}, \quad (2)$$

where d_{kijrt} is equal to 1 if the hospital j located in the region r is chosen at time t by patient k living in region i , and 0 otherwise. By multiplying the probability $P(d_{kijrt} = 1)$ by the population of region i that may be hospitalized at time t , denoted as W_{it} , we obtain y_{ijrt} , i.e., the expected flow of patients to be admitted in hospital j , given by Equation (3):

$$y_{ijrt} = P(d_{kijrt} = 1) \times W_{it}. \quad (3)$$

Assuming that this expected flow is equal to the observed one and using Equations (1)–(2), we can rewrite Equation (3) as follows:

$$y_{ijrt} = \exp(\ln(W_{it}) + b_{ijrt} - c_{ijrt} - \ln(M_{it}))\eta_{ijrt}, \quad (4)$$

where M_{it} corresponds to the multilateral resistance term (Anderson & Van Wincoop, 2003) and η_{ijrt} makes the flows of patients subject to stochastic disturbances, with $E(\eta_{ijrt}) = 1$. η_{ijrt} is assumed to be uncorrelated with the independent variables. The benefits for the patients in Equation (1) are defined as follows:

$$b_{ijrt} = \beta_0 + \beta_1 \ln(WT_{ijt}) + \beta_2 \text{Private}_j + \beta_3 \ln(\text{GDPDest}_{rt}) + \beta_4 \ln(\text{HospitalBeds}_{jt}) + \beta_5 \text{Quality}_{jt}, \quad (5)$$

where WT_{ijt} indicates waiting times, HospitalBeds_{jt} the bed capacity of hospital j at time t , Private_j is a dummy variable equal to 1 if the hospital is private, and GDPDest_{rt} is the per capita income in the destination region, as a proxy for both the standard of life and the investment in the regional health care sector. Last, Quality_{jt} is an indicator of hospital quality provided by the PNE.¹⁸

The costs of choosing hospital destination j in a region r are defined as:

$$c_{ijrt} = \alpha_0 + \alpha_1 \ln(\text{Dist}_{ij}) + \alpha_2 \ln(\text{HotelBeds}_{jt}) + \alpha_3 \text{Urban}_j + \alpha_4 \ln(\text{BeatenPath}_{ir}), \quad (6)$$

where Dist_{ij} is the distance between the patient and the hospital (computed as the road distance between region i 's centroid and hospital j address), HotelBeds_{jt} is a measure of the accommodation capacity in the destination region, which can be important for relatives and caregivers who could follow the patient. Urban_j is dummy variable equal to 1 if the hospital is located in an urban zone. BeatenPath_{ir} is our main interest variable, capturing the beaten path effect.¹⁹ It is given by the integral of migration flows from region i to region r from year 1969 until year 2010. We consider also a different specification of beaten paths: four separated decades, i.e., 1969–1979, 1980–1989, 1990–1999, 2000–2010, to observe whether the effect is consistent over time and if it is stronger in some specific time interval.

Last, as highlighted by the gravity model literature (Anderson & Van Wincoop, 2003), inter-regional flows may be affected by a mass variable given by the population in the region of origin (PopOrig) and of destination (PopDest), as in Fabbri and Robone (2010), by the share of elderly in the region of origin (ShareOver65Orig , i.e., the percentage of people with 65 years old and more), and in the region of destination (ShareOver65Dest), because it may limit

¹⁸Each quality indicator (see Table A1 in the Appendix) has been standardized by subtracting its mean and then dividing the result by its standard deviation. The whole sample composite hospital quality measures have been calculated by averaging all the obtained standardized indicators. Clinical area-specific quality measures have been calculated with the same method using relevant measures for each clinical area. As the PNE indicators are rates of undesired outcomes such as mortality, the sign of the obtained composite measure has been reversed to favor the interpretation as quality.

¹⁹As discussed by Fabbri and Robone (2010), omitting the effect of beaten paths may induce network autocorrelation given that hospital flows directed from a given region of origin to contiguous hospitals can be affected by the presence of relatives or friends in the destination region.



extra-regional hospitalization (Levaggi & Zanola, 2004), and by time-invariant regional differences (e.g., culture, public administration, organization of the health care system, different structure of academic activities, and so forth) that may affect mobility costs. These factors are denoted as multilateral resistance terms, and we take them explicitly into account using fixed effects. The latter are given by a dummy that is region of origin specific (R_i) and another dummy that is region of destination specific (C_r). We also add an interaction variable between private hospitals and beaten path, i.e., $Private \times BeatenPath$, to capture a possible pull effect of private hospitals in attracting extra-regional patients. If we substitute in Equation (4) the expression for benefits (Equation (5)) and costs (Equation (6)), we obtain the following equation:

$$\begin{aligned} Y_{ijrt} = & \exp(\beta_0 + \beta_1 \ln(WT_{ijrt}) + \beta_2 Private_{ij} + \beta_3 \ln(GDPDest_{rt}) + \beta_4 \ln(HospitalBeds_{jt}) + \\ & + \beta_5 Quality_{jt} + \lambda_1 R_i - \alpha_0 - \alpha_1 \ln(Dist_{ij}) - \alpha_2 \ln(HotelBeds_{jt}) - \alpha_3 Urban_{jt} + \\ & - \alpha_4 \ln(BeatenPath_{ir}) - \lambda_2 C_r + \gamma_1 \ln(PopDest_{rt}) + \gamma_2 \ln(PopOrig_{it}) + \\ & + \gamma_3 \ln(ShareOver65Dest_{rt}) + \gamma_4 \ln(ShareOver65Orig_{it}) + \\ & + \gamma_5 Private_{ij} \times \ln(BeatenPath_{ir})) \eta_{ijrt}. \end{aligned} \quad (7)$$

Table 1 shows the description of dependent and independent variables, and the sources of data. As dependent variable we consider different specifications: to total flow from region i to hospital j and the per treatment flow, i.e., cardiology, oncology, and orthopedics. By applying the model to the different treatments, we can observe if there are trends that are specific to a single type of admission. Regarding data sources, flows are obtained from patients' hospital discharge charts (*schede di dimissione ospedaliera*—SDO) provided by the Italian Ministry of Health, quality indicators from PNE, hospital's ownership and location is provided by the Ministry of Health, variables related to per capita GDP, and hotels' capacity are provided by the Italian national institute of statistics (Istat-Istituto Nazionale di Statistica). Past origin–destination regional migration flows are provided by Istat for the period 1995–2019.²⁰ However, as shown by Ballarino and Panichella (2015), more than 2 million individuals moved from Southern to Northern Italy during the period 1950–1970, out of 46 million (about 5% of the Italian population), to settle down permanently. Therefore, the time series starting from 1995 does not capture the most relevant inter-regional migration phenomenon. Consequently, using data from the period 1995–2019, we estimate a model to predict backwards the origin–destination regional migratory flows for the period 1969–1994, to have a complete series.

Introducing Mig_{ijt} , the migration flow from region i to region j in year t , and following Hejduková and Kureková (2020), we have the following simple model for internal migration²¹:

$$\begin{aligned} Mig_{ijt} = & \exp(\alpha_0 + \alpha_1 \ln(TotMigOut_{i,t-k}) + \alpha_2 \ln(TotMigIn_{j,t-k}) + \alpha_3 \ln(GDP_{it}) + \\ & + \alpha_4 \ln(GDP_{jt}) + \alpha_5 \ln(Dist_{ij}) + \alpha_6 \ln(Pop_{it}) + \alpha_7 \ln(Pop_{jt}) + \lambda_i + \theta_j), \end{aligned} \quad (8)$$

where GDP_{it} and GDP_{jt} are, respectively, the per capita income in regions i and j , Pop_{it} and Pop_{jt} are regional populations, $Dist_{ij}$ is the distance between region i and j , λ_i and θ_j are region fixed effects to capture any other time-invariant push or pull factors. $TotMigOut_{i,t-k}$ is the total number of migrants leaving region i in period k before t . This variable, which has been available as an official statistic since the beginning of the twentieth century, represents the total of all people who have left the region.²² The data do not indicate for which destination. However, it is a relevant predictor of the flow of migrants from region i to region j . Similarly, $TotMigIn_{j,t-k}$ gives the total number of people who entered region j in period $t - k$. We consider, in testing the model, several lags of migration flows: $k = 1, \dots, 9$,

²⁰This time interval is different from that adopted in the existing literature regarding past migration. For instance, Balia et al. (2018) use the stock of migration in the five previous years and investigate its effect on inter-regional patient flows over the 2001–2010 time interval.

²¹As the dependent variable can have some 0 values, we estimate a PPML model. Details motivating this empirical method are provided in the section “Identification.”

²²The source is Istat.





TABLE 1 Description and source of variables

Variable	Description	Data source
<i>Dependent variables</i>		
Total flows	Number of patients from region i admitted to hospital j at time t	SDO
Total flows (cardiology)	Number of cardiology patients from region i admitted to hospital j at time t	SDO
Total flows (oncology)	Number of cancer patients from region i admitted to hospital j at time t	SDO
Total flows (orthopedics)	Number of patients from region i admitted to hospital j at time t for hip and knee replacement	SDO
<i>Hospital variables</i>		
$Quality_{jt}$	Composite indicator for hospital j 's quality at time t	PNE
$HospitalBeds_{jt}$	Number of hospital beds in hospital j at time t	Ministry of Health
WT_{jt}	Average waiting time in hospital j at time t	SDO
$Private_j$	Dummy = 1 if hospital j is private, = 0 Public	Ministry of Health
$Urban_j$	Dummy = 1 if hospital j is located in a urban area, = 0 Rural	Ministry of Health
<i>Regional variables</i>		
GDP_{rt}	GDP per capita for the region of destination r at time t	Istat
$HotelBeds_{rt}$	Number of hotel beds in the region of destination r at time t ($\times 100,000$)	Istat
$PopOrig_{it}$	Population in region of origin i at time t	Istat
$ShareOver65Orig_{it}$	Share of population 65+ in region of origin i at time t	Istat
$PopDest_{rt}$	Population in region of destination r at time t	Istat
$ShareOver65Dest_{rt}$	Share of population 65+ in region of destination r at time t	Istat
<i>Origin-destination pair variables</i>		
$BeatenPath_{ir}$	Number of citizens migrated from region i to region r in 1969–2010	Istat
$Distance_{ij}$	Travel distance from region i to hospital j	Google maps

i.e., up to a decade before the year t . The results are shown in Table A3 in the Appendix at the end of the paper. The goodness-of-fit is rather high, i.e., the model can explain about 84% of the origin–destination migration flows.

4.1 | Identification

A major challenge of our identification strategy is the potential problem of selection in our data. As our aim is to study the determinants of HM, we have to consider that extra-regional flows are a selected sample. Therefore, for instance, if we estimate a positive and significant β_5 coefficient in Equation (7) using a sample including only extra-regional flows, we cannot infer that extra-regional mobility is driven by quality. Indeed, this might occur because both intra-regional and extra-regional flows are determined by hospital quality. If we want to take into account the impact of hospital quality on extra-regional flows, we must also evaluate the impact of quality on intra-regional mobility and compare the estimated coefficient for internal flows to the coefficient estimated for external flows. Thus our sample includes all the flows from each Italian region to each hospital. As such, we use intra-regional flows as control group and estimate Equation (9).





$$\begin{aligned}
 y_{ijrt} = & \exp(\beta_0 + \beta_1 \ln(WT_{ijrt}) + \beta_2 Private_{ij} + \beta_3 \ln(GDPDest_{rt}) + \beta_4 \ln(HospitalBeds_{jt}) + \\
 & + \beta_5 Quality_{jt} + \beta_6 Extra_{ir} \times Quality_{jt} + \lambda_1 R_i - \alpha_0 - \alpha_1 \ln(Dist_{ij}) + \\
 & - \alpha_2 \ln(HotelBeds_{jt}) - \alpha_3 Urban_{ij} - \alpha_4 \ln(BeatenPath_{ir}) - \alpha_5 Extra_{ir} - \lambda_2 C_r + \\
 & + \gamma_1 \ln(PopDest_{rt}) + \gamma_2 \ln(PopOrig_{it}) + \gamma_3 \ln(ShareOver65Dest_{rt}) + \\
 & \gamma_4 \ln(ShareOver65Orig_{it}) + \gamma_5 Private_{ij} \times \ln(BeatenPath_{ir})) \eta_{ijrt}.
 \end{aligned} \quad (9)$$

In this setting, the main coefficients of interest are α_4 and γ_5 . These coefficients capture the beaten path effect. If α_4 is positive and significant, the presence of past migrations from the origin region to the destination region is a pull factor for the destination hospitals. If γ_5 is positive, the pull effect of migration beaten paths is stronger for private hospitals. Furthermore, β_5 and β_6 identify the impact of hospital quality on HM flows. If β_6 is positive and significant, this would mean that quality is more important for patients involved in HM than for those admitted in local regional hospitals. We also include in our model *Extra*, a binary variable indicating whether the flow is extra-regional: its attached coefficient (α_5) is expected to be negative and offsets the expected extra-regional mobility to a lower level than intra-regional mobility.

Another major challenge of modeling patient mobility is the possible endogeneity of *Quality_{jt}*. Indeed, hospitals with higher quality may attract more patients and such increased flows would lead to quality improvements due to learning-by-doing (Gutacker et al., 2016). This simultaneity induces a bias in the estimation of both β_5 and β_6 . To overcome such issue, we follow (Gutacker et al., 2016) and lag the hospital quality indicators by 1 year. This approach avoids the simultaneity bias because demand for health care is likely to be based on past levels of quality rather than the current ones and present flows cannot influence past quality.

Furthermore, waiting times may also be endogenous. Even if our main interest is not to estimate the impact of waiting time on extra-regional mobility, a bias in β_1 can also lead to a bias in β_5 and β_6 , as quality and waiting time may be correlated with the same hospital-level unobservables. The main reason is that flows and waiting time are simultaneously determined: patients may choose hospitals with lower waiting times, and increased demand may increase waiting time due to limited capacity (Gutacker et al., 2016). To prevent this issue, we follow the strategy of Gutacker et al. (2016) and Riganti et al. (2017) using lagged waiting time, as current variations in flows at time t cannot affect the waiting time at period $t - 1$.

Another econometric issue regards the nature of our data. To estimate Equation (9), we adopt a Poisson Pseudo Maximum Likelihood (PPML) estimator to deal with several possible drawbacks (i.e., heteroskedasticity, higher efficiency, presence of many zeros in the dependent variable) of log-linearizing Equation (9) and estimating it by OLS (Santos Silva & Tenreiro, 2006).²³ Because we apply a PPML estimator to our data, the logarithmic transformation of Equation (9) yields that the natural logarithm of patient flows y_{ijrt} is equal to the exponent of the expression on the right-hand side of the equation. Therefore, after the transformation, we have a log-linear equation for some coefficients (e.g., *Quality*, *Private*) and a log-log relation for others, such as *BeatenPath*. This implies that the estimated coefficients of the variables in logarithm are elasticities of patient flows with respect to variations of the independent variables.

A further econometric challenge in the estimation of Equation (9) is the residual correlation that may occur due to unobserved hospital-level factors, such as reputation. Indeed, hospitals with higher reputations than their competitors may attract more patients and lead to less attractiveness of the nearby hospitals, and this effect may decrease with distance. In this case spatial autocorrelation would be negative. To test the degree of spatial autocorrelation in the residuals, we adopt the Jacqmin-Gadda (JG) test (Fabbri & Robone, 2010; Jacqmin-Gadda et al., 1997). This test generalizes the test based on Moran's I in the context of generalized linear models. Specifically, Moran's test cannot

²³As showed by Manning and Mullahy (2001), when the log-scale error term in a model is heteroskedastic, the OLS estimates are biased. Santos Silva and Tenreiro (2006) show that PPML based on the assumption that conditional variance $V[y|x]$ is proportional to the conditional mean $E[y|x]$ is likely to be more efficient than OLS estimators. PPML can deal with the presence of zeros in the dependent variable (Santos Silva & Tenreiro, 2011). Finally, the PPML estimator based on the Poisson assumption for the dependent variable is valid even when y_{ijrt} is not strictly an integer, as shown by Gourieroux et al. (1984).





be applied in our framework, as our sample is large and the PPML model is heteroskedastic (Jacqmin-Gadda et al., 1997; Oden, 1995). Let us define $\mathbf{W}$, a 841×841 spatial weight matrix, which entries are the inverse distances between hospitals and $\hat{\phi}$, the vector of the expected flows from Equation (9). Under the null hypothesis of uncorrelated residuals, the JG test statistic is described in Equation (10). The standardized T statistic is asymptotically normally distributed. The expected value and standard error of T are outlined in Jacqmin-Gadda et al. (1997).

$$T = (\mathbf{y} - \hat{\mathbf{y}})' \mathbf{W} (\mathbf{y} - \hat{\mathbf{y}}). \quad (10)$$

If the null hypothesis of uncorrelated residuals is rejected, we adopt the spatial filtering as a correction (Griffith, 2007). Spatial filtering consists of using a set of eigenvectors of the transformed spatial weight matrix $\mathbf{M}$ (Equation (11), $\mathbf{i}$ is a vector of ones) as proxies of those unobservables affected by spatial patterns (Chun, 2008). According to Griffith (1996), each eigenvector represents a distinct spatial pattern characterized by some degree of autocorrelation. The set of eigenvectors is chosen through a step-wise forward selection process. Eigenvectors of the matrix $\mathbf{M}$ are ordered according to the corresponding eigenvalue and are retained into Equation (9) if they increase the JG-test p -value. This is repeated until the p -value is greater than 0.6.

$$\mathbf{M} = \left(\mathbf{I} - \frac{\mathbf{i}\mathbf{i}'}{n} \right) (\mathbf{W} + \mathbf{W}') \left(\mathbf{I} - \frac{\mathbf{i}\mathbf{i}'}{n} \right). \quad (11)$$

We may also face origin–destination unobservable heterogeneity affecting patients' propensity to move from their region to a hospital in another region. This implies using region pairs fixed effects. Therefore, as a robustness check, we estimate Equation (9) introducing origin–destination fixed effects. Last, some previous papers (Fabbri & Robone, 2010; Levaggi & Zanola, 2004) use population and the share of elderly at the origin and destination as mass variables in the gravity model. This is our last robustness check.

5 | DATA AND DESCRIPTIVE STATISTICS

We rely upon hospital discharge records (SDO) including admissions for cancer, cardiology, and orthopedics between 2010 and 2016 in both public and private hospitals (publicly accredited) in Italy. Excluding emergency admissions, our sample comprises only elective patients; therefore, the patient flows we are studying are derived from patient choice. For each admission, the SDO record includes patient's demographic characteristics, region of residence, information about diagnoses, and the procedures she receives during hospitalization.²⁴ Patient flows are obtained upon aggregation of each hospitalization at the level of region of origin–destination hospital-year. We integrate the SDO records with publicly available hospital-quality indicators disclosed by PNE. The indicators are shown in Table A1 in the Appendix.

5.1 | Patient and hospital characteristics

Table 2 describes the patients in our sample that consists of 1.8 million hospital admissions in cardiology (10.8%), oncology (42.6%), and orthopedics (46.6%). The average patient age of admission is approximately 67 years. The oldest patients were hospitalized for orthopedics, whereas the youngest were hospitalized for cancer. On average, 60% of the patients are female. Cardiology waiting time is on average 27 days, whereas for oncology patients average waiting time is 23 days. Orthopedics has an average waiting time of 79 days. The combination of these data

²⁴Both procedures and diagnoses are coded according to the International Classification of Disease (ICD 9 CM).





TABLE 2 Descriptive statistics: patients' characteristics, waiting times, length of stay, region of residence-admission

		Whole sample	Cardiology	Oncology	Orthopedics
Age	mean	66.67	67.98	63.51	69.19
	sd	11.94	11.70	13.05	10.17
	median	69	70	65	71
	min	18	18	18	18
	max	107	97	106	107
Female	mean	0.596	0.360	0.622	0.625
	sd	0.491	0.480	0.485	0.484
Waiting time	mean	49.78	27.47	22.91	78.71
	sd	70.27	44.81	24.96	88.64
	min	0	0	0	0
	max	486	324	174	486
Length of stay	mean	8.17	13.27	6.82	8.23
	sd	5.36	7.57	5.53	3.59
	min	1	4	1	3
	max	58	58	35	25
Region of residence					
North	mean	0.520	0.498	0.517	0.528
	sd	0.500	0.500	0.500	0.499
Center	mean	0.196	0.177	0.193	0.202
	sd	0.397	0.382	0.394	0.402
South	mean	0.284	0.325	0.291	0.270
	sd	0.451	0.468	0.454	0.444
Region of admission					
North	mean	0.571	0.555	0.568	0.578
	sd	0.495	0.497	0.495	0.494
Center	mean	0.192	0.177	0.191	0.196
	sd	0.394	0.381	0.393	0.397
South	mean	0.237	0.268	0.241	0.226
	sd	0.425	0.443	0.428	0.418
Observations	number (%)	1,840,730 (100%)	198,672(10.8%)	784,920 (42.6%)	857,138 (46.6%)

leads to an average waiting time of approximately 50 days. Overall, 52% of the patients are enrolled in the Northern region health care systems, 19.6% in the Center, and 28.4% in the South of Italy. However, 57.1% of patients are admitted in hospitals located in Northern regions and 23.7% of the patients are hospitalized in Southern hospitals. The share of patients admitted in Northern hospitals is higher than the share of patients residing in Northern regions, whereas the opposite occurs for Southern regions. This descriptive finding gives a preliminary evidence of the degree of mobility in Italy. The share of patients hospitalized in Central Italy is instead very similar to the share of patients residing in the same area, suggesting that in such an area the net mobility is very low. Similar patterns can be observed across all medical disciplines.





Table 3 presents the hospital characteristics. In the whole sample, 49% of the hospitals are located in urban areas. Moreover, private ownership is related to approximately 32% of hospitals in Italy. In terms of hospital capacity, cardiology has the largest size (on average 663 beds), whereas orthopedics has the smallest size (362 beds). Cancer procedures are delivered by hospitals having on average 458 beds.

Summary statistics for risk-adjusted hospital quality indicators are reported in Table A2 in the Appendix at the end of the paper. They cover different dimensions per treatment. The PNE indicators published by public agency AGENAS are: mortality rates in cardiology and oncology; in orthopedics readmission rates (i.e., the patient is readmitted for the same treatment within a month from the initial surgery). Average mortality for cardiology procedures ranges from 2.43% (acute myocardial infarction) to 3.42% (heart valve replacement). Mortality related to cancer procedures is heterogeneous among types of cancer. Lung cancer surgery has the lowest mortality (1.52%); however, we observe a hospital characterized by a very high mortality rate (81.28%). Surgery related to colon cancer is characterized by an average mortality rate of 4.28%, whereas a similar figure can be observed for prostate cancer (average mortality equal to 4.03%). These descriptive statistics are the average of the quality indicator among hospitals. In orthopedics, readmission rates are different, depending on the involved joint: hip replacement is associated with twice the readmission rate as that of knee replacement. However, there is more heterogeneity in the outcomes of knee replacement given that the coefficient of variation is equal to 1.67.

The spatial distribution of hospital quality indicators is represented in the right panel of Figure 1. In general, quality is increasingly distributed from Southern Italy to the North.

5.2 | HM in Italy

Table 4 summarizes the main features of HM. In the period of analysis (2010–2016), 9.2% of the hospitalizations are related to inter-regional mobility. The largest share is cardiology patients, with hospitals admitting on average 12.4% of their patients from other regional health care systems. Cardiology is followed by orthopedics (10.1%). In the case of oncology, 6.8% of the total admissions are extra-regional. The phenomenon of mobility is related to approximately 95% of the Italian hospitals. Considering our unit of observation (the triplet region of origin-hospital-year), we report that each hospital attracts on average 2.38 patients annually from a region outside. The largest medical contribution to extra-regional mobility is related to cardiology (1.69 admissions per hospital-region). On average, distance related to overall extra-regional mobility (whole sample) is equal to approximately 435 km. Patients with longer distance movements are those hospitalized for cancer procedures, traveling on average approximately 510 km, followed by cardiology (480 km) and orthopedics (382 km).

TABLE 3 Descriptive statistics of Italian hospitals included in the sample

		Whole sample	Cardiology	Oncology	Orthopedics
Urban	mean	0.489	0.833	0.498	0.479
	sd	0.500	0.373	0.500	0.500
Private	mean	0.320	0.317	0.173	0.311
	sd	0.466	0.466	0.378	0.463
Hospital beds	mean	346.7	663.4	457.9	361.7
	sd	324.1	478.7	335.4	333.6
	median	239	622	392	258
	min	8	31	21	8
	max	2248	2248	2248	2248



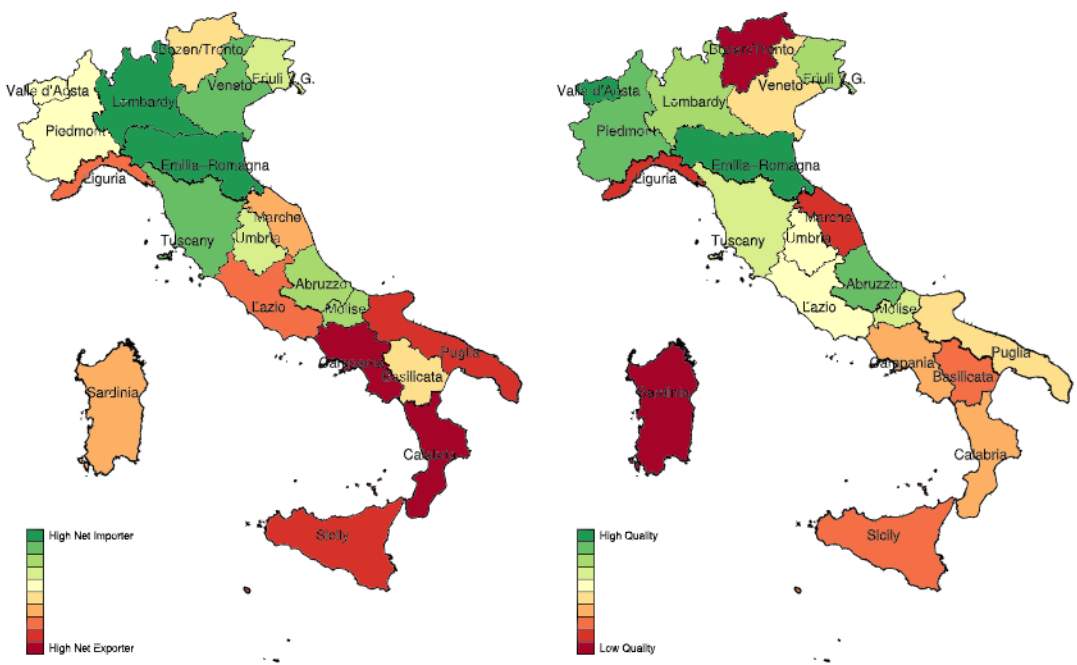


FIGURE 1 Quantile regional distribution of Italian HM (left) and hospital quality (right)

TABLE 4 Descriptive statistics: HM and hospital admissions in Italy

		Whole sample	Cardiology	Oncology	Orthopedics
Share of extra-regional patients	mean	0.0918	0.124	0.0683	0.101
	sd	0.133	0.138	0.105	0.147
	median	0.0381	0.0785	0.0293	0.0419
	min	0	0	0	0
	max	0.752	0.598	0.735	0.809
Share of hospitals with zero extra-regional patients	mean	0.0542	0.0357	0.0878	0.0544
	sd	0.226	0.186	0.283	0.227
Extra-regional flows	mean	2.376	1.695	1.165	1.434
	sd	14.83	7.149	7.750	12.46
	min	0	0	0	0
	max	627	155	276	627
Distance (Extra-regional flows, km)	mean	435.144	480.732	510.570	382.164
	sd	392.457	369.907	419.071	371.725
	median	239.492	317.530	340.312	202.614
	min	24.231	57.667	24.231	24.231
	max	1728.107	1588.617	1728.107	1728.107





A large share of the total patient extra-regional mobility is generated from Southern regions (43%); this is remarkable because 34% of the Italian population lives in such regions (ISTAT, 2020). Interestingly, 56% of the total extra-regional flows are directed to Northern and Central Italian hospitals. The net migration flow per region is

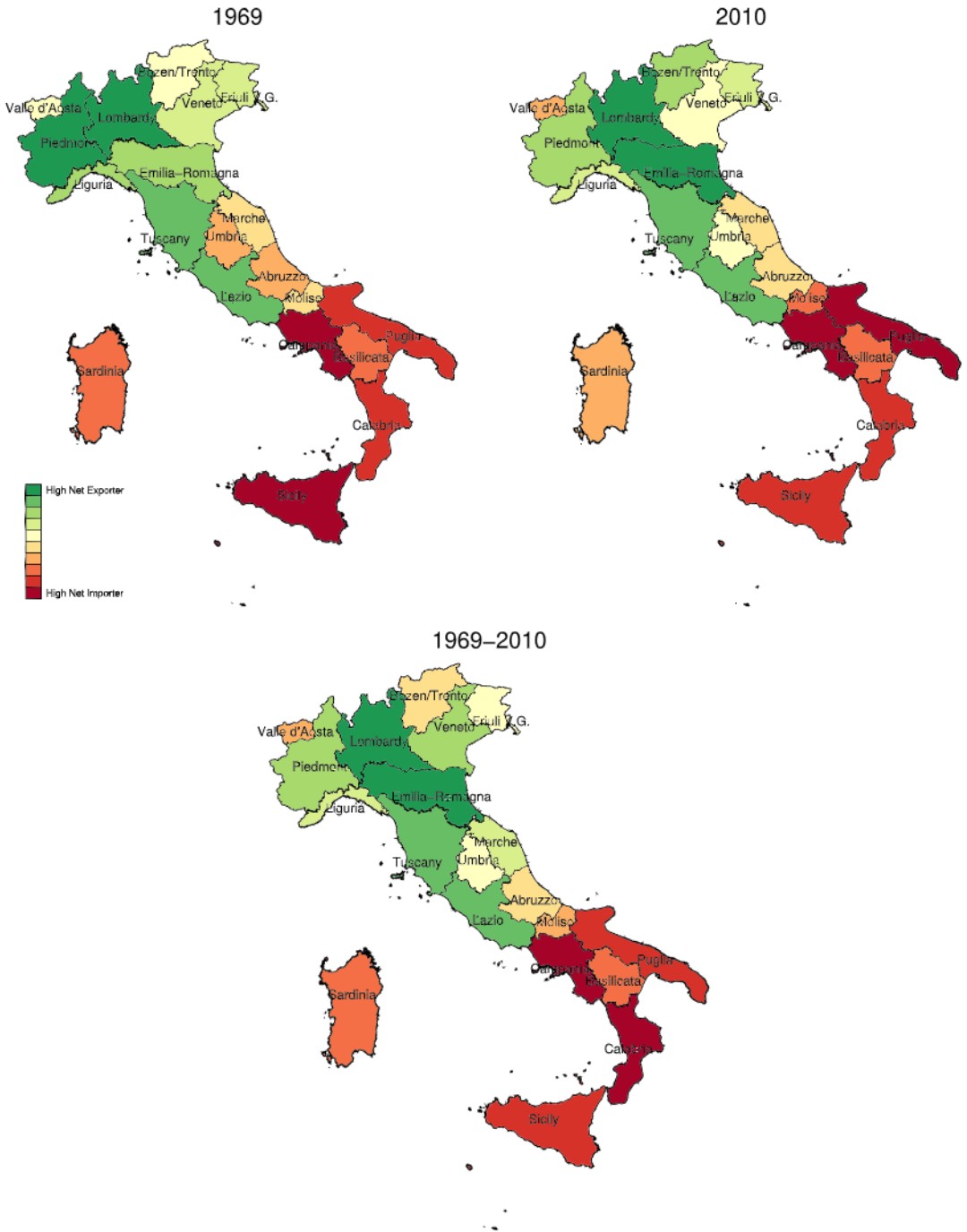


FIGURE 2 Quantile regional distribution of Italian inter-regional migration, 1969–2010: net importer (red) and net exporter (green) regions



represented in the left panel of Figure 1. Regions in green are net patient exporter, meaning that they have more incoming extra-regional patients than outgoing. Regions in red are instead net patient importer. The colors express the quantile distribution. Northern regions (especially Lombardy and Emilia Romagna) are the biggest net patient exporters. On the contrary, Campania and Calabria are the two biggest net patient importers, followed by Puglia and Sicily. Important net patient importers are also Lazio and Liguria.

Figure 2 displays the regional distribution of past migration flows, i.e., the beaten paths. Again each region is classified as net migrant exporter or net patient importer. Net migrant exporter regions are those where the beaten path effect can be stronger, because family and social ties with the region of origin of patients are larger. The left panel shows the Italian inter-regional migration in year 1969, the center panel in year 2010, and the right panel shows the aggregate migration flows over all the observed period. It is evident that Northern regions are net exporter (in green), especially Lombardy and Piedmont in year 1969, and Lombardy and Emilia Romagna in 2010. On the contrary, Campania and Sicily are strong net importer in 1969, Campania and Puglia in 2010, whereas Campania and Calabria are the bigger net importer of migrants during the period 1969–2010. It is rather evident that Italian inter-regional migration and HM are correlated.

6 | RESULTS

In this section, we present the results of the econometric model in Equation (9) that we design to investigate inter-regional patient mobility. Moreover, we present some sensitivity analyses to test if sign and statistical significance of our results regarding the impact of beaten paths on HM depend upon the econometric model specification. Estimates of the HM model in Equation (9) are presented in Table 5. The first column is related to the full sample, whereas the second column presents the results only for cardiology treatments, the third column for oncology treatments, and the fourth column only for orthopedics admissions.

The estimated coefficient of the main variable of interest, i.e., $\ln(\text{BeatenPath})$, is significant, positive, and equal to about 0.32 for the whole sample of observations. Therefore, as expected, beaten paths are a factor explaining inter-regional patient mobility. The estimated overall elasticity of beaten paths is such that an increase of 1% in social and family ties due to past migration in the region of destination gives rise to a +0.32% of inflow patients in the same region. The beaten path effect is therefore very important in explaining the concentration of HM in hospitals located in regions that in the past have been subject to migratory flows originating in the same region of residence as the patients currently moving, as shown in Figures 1–2. Family relationships due to beaten paths make it possible to break down barriers to access to good quality health care for those patients who are willing to travel long distances, and to sustain high mobility costs to be admitted in hospitals with better quality than those in the region of origin.

Regarding the different hospital disciplines, the highest elasticity estimate for the beaten path effect is reported for oncology (0.41). Indeed, oncology admissions may need longer length-of-stay in hospital, and also the transfer of relatives nearby the hospital to provide informal care. Therefore, to reduce mobility costs, migrating patients are looking for help and accommodation from family and social ties in the region of destination. The elasticity of the beaten path effect is slightly lower (0.36) for orthopedics, whereas there is no significant effect of beaten path for cardiology if we look at the full sample of data. A possible explanation for the absence of the beaten path effect in cardiology is that these patients have the highest preferences to leave their region (the coefficient of *Extra* is maximum among the clinical area and also with respect to the full sample), but have also the lowest (in absolute terms) elasticity of distance. Thus, they are more likely to seek admission in neighboring regions without the need of hospitality for their relatives. Indeed, cardiology differs from orthopedics and oncology because it usually involves long-term post-surgery procedures such as physical therapy and chemotherapy.

Interestingly, the beaten path effects are stronger for private hospitals. The estimated coefficient of the interaction variable $\text{Private} \times \ln(\text{BeatenPath})$ is always positive and statistically significant, also for cardiology (about +0.06).





TABLE 5 Determinants of health migration in Italy: PPML estimates

	Full sample	Cardiology	Oncology	Orthopedics
Extra	−10.239*** (0.566)	−5.565** (1.731)	−12.116*** (0.710)	−10.892*** (0.874)
Quality	0.097*** (0.021)	0.128** (0.047)	0.146*** (0.027)	0.063** (0.019)
Extra × Quality	0.079* (0.037)	0.108 (0.063)	0.164*** (0.040)	0.089* (0.036)
Urban	0.374*** (0.030)	0.890*** (0.129)	0.703*** (0.053)	−0.098** (0.038)
Private	1.386*** (0.040)	0.933*** (0.085)	0.923*** (0.064)	1.704*** (0.048)
ln(BeatenPath)	0.318*** (0.032)	0.053 (0.098)	0.408*** (0.040)	0.361*** (0.049)
Private × ln(BeatenPath)	0.059*** (0.003)	0.056*** (0.006)	0.054*** (0.005)	0.060*** (0.004)
ln(GDPDest)	0.491 (0.691)	0.151 (1.315)	0.127 (0.951)	0.771 (0.837)
ln(HospitalBeds)	0.572*** (0.021)	0.131** (0.043)	0.622*** (0.041)	0.169*** (0.024)
ln(HotelBeds)	0.010 (0.056)	0.010 (0.110)	−0.006 (0.077)	0.015 (0.068)
ln(WT)	0.028* (0.012)	−0.012 (0.017)	0.047 (0.028)	0.056*** (0.013)
ln(Dist)	−0.262*** (0.023)	−0.375*** (0.059)	−0.169*** (0.032)	−0.314*** (0.030)
ln(PopDest)	−0.591 (2.528)	−3.243 (3.456)	−0.141 (2.916)	0.393 (3.803)
ln(PopOrig)	1.437 (2.458)	2.172 (3.411)	−0.114 (3.005)	1.909 (3.645)
ln(ShareOver65Dest)	−0.315 (2.144)	2.206 (3.781)	0.900 (2.717)	−1.078 (3.305)
ln(ShareOver65Orig)	1.182 (2.156)	−1.712 (3.821)	−0.332 (2.778)	1.978 (3.309)
Constant	−11.879 (25.502)	20.953 (45.975)	7.568 (35.032)	−34.927 (30.154)
Observations	97,776	14,721	65,919	87,402
Origin region FE	Yes	Yes	Yes	Yes
Dest. region FE	Yes	Yes	Yes	Yes
Spatial filtering	Yes	Yes	Yes	Yes
Pseudo R ²	0.784	0.811	0.781	0.740
JG p	0.887	0.600	0.816	0.618
Quality and WT are lagged by 1 year				

Notes: Robust standard errors in parentheses.
****p* < 0.001, ***p* < 0.01, **p* < 0.05.





In the full sample, and in orthopedics, is similar to the cardiology estimated coefficient, while it is slightly lower (about +0.05) in oncology. The dummy variable *Private* is also always significant and positive. Combined with the results obtained for the interaction variable $Private \times \ln(BeatenPath)$, this implies that private hospitals attract more extra-regional patients than their publicly owned competitors. Therefore, there is enough evidence to identify the presence of a pull effect in Italian HM, because the impact of past migration is stronger in private hospitals. The mechanism of hospital reimbursement in Italy may help to explain this result. Public and private hospitals are prospectively reimbursed by regional governments through budgets assigned on the basis of past costs. However, only public hospitals may receive ex-post extra-funding in cases of budget override (Fabbri & Robone, 2010). There is an exception to this rule: all hospitals receive additional reimbursements, out of the regional budget, in the case of extra-regional patients. Thus, private hospitals have greater incentives to search revenues outside their region of accreditation (Levaggi & Menoncin, 2013), and to exploit family and social ties (even related to their personnel) to achieve this goal.

In all data samples, the coefficient of the dummy variable *Extra* is negative and significant, i.e., regional patients involved in HM are less than those admitted in hospitals of their origin region. In the full sample, the coefficient of hospital quality (*Quality*) is positive and significant. This is also observed when a model for each clinical area is estimated and pathology-specific quality is considered. Therefore, a positive decile change in hospital quality is associated with +9.7% in admission flows in the full sample, +12.8% in cardiology, +14.6% in oncology, and +6.3% in orthopedics. This implies that hospitals with higher clinical quality are stronger patient attractors. Interestingly, the coefficient of the interaction variable $Extra \times Quality$ is always positive and significant. Therefore, for all treatment, patients involved in HM are searching for better quality hospitals, differently from patients remaining within their region of origin. The evidence is that patient inter-regional flows are more sensitive than patient intra-regional flows to hospital quality in all types of treatment. Specifically, the semi-elasticity of HM with respect to quality for patients involved in HM is 7.9% higher than its intra-regional counterpart. The same figure ranges between 8.9% (orthopedics) and 16.4% (oncology) in the single medical branch models. This finding confirms that if the gradient between internal hospital quality and external hospital quality is sufficiently high, patients would react by seeking treatment outside their region of residence.

Patient flows are significantly higher in urban hospitals than in rural hospitals (*Urban*). Specifically, the positive and significant coefficient in the full sample (0.37) is driven by cardiology and cancer patients (respectively with coefficient 0.89 and 0.7). This effect may reflect better connectivity of urban areas and, thus, an easier long-distance move. On the contrary, mobility generated for orthopedics is higher in rural hospitals than in urban hospitals (the estimated coefficient is -0.1). This effect is observed after considering hospital distance.

The impact of both *GDPDest* and *HotelBeds* in the region of destination on hospital flows is not significant, probably because these factors are captured by fixed effects. The variable $\ln(HospitalBeds)$ is positive and significant in all models represented in Table 5. Elasticity for the full sample is equal to about +0.6%, similar to oncology. It is instead much lower in orthopedics (+0.17%) and in cardiology (+0.13%).

The results concerning waiting time ($\ln(WT)$) are mixed. Although the full sample model highlights that a +1% in waiting time is associated with a +0.03% in patient flows, this result is driven by orthopedics patients. Indeed, their elasticity of waiting time is equal to about +0.06% and significant. This unexpected result might imply that patients are willing to wait more to decide where to be hospitalized for orthopedic procedures. In fact, as knee- and hip-replacement procedures are usually non-urgent, patients are likely to choose higher-quality hospitals, and this may imply longer waiting time.

Consistent with other studies (Balía et al., 2018), and as expected, distance ($\ln(Dist)$) has a negative impact on patient mobility regardless of the branch of medicine. Elasticity is equal to -0.26% for the full sample, -0.38% for cardiology, -0.17% for oncology, and -0.31% for orthopedics. As previously mentioned, oncology is the clinical area where distance has the lower impact on patient's hospital mobility. Last, mass variables (i.e., population at the origin $\ln(PopOrig)$ and population at destination $\ln(PopDest)$) have no impacts on patient flows, as well as the share of





elderly both at the origin ($\ln(\text{ShareOver65Orig})$) and at destination ($\ln(\text{ShareOver65Dest})$). These variables exhibit low variation over time and therefore are likely to be captured by origin and destination fixed effects.

As mentioned before, each model is corrected for both residual spatial correlation and endogeneity of quality and waiting time. The first correction is achieved through spatial filtering, and the second one through the inclusion of the lags of *Quality* and waiting times ($\ln(WT)$).

6.1 | Sensitivity analysis

In this section, we investigate whether changes in the definition of some independent variables in the model shown in Equation (9) alter the sign and statistical significance of the previously identified effect of beaten paths on HM. Specifically we consider two changes, one related to the beaten path variable and the other to hospital quality. First, the econometric model shown in Equation (9) is estimated using past migration flows in different decades: 1969–1979, 1980–1989, 1990–1999, and 2000–2010. In this way, we can observe whether the influence of beaten paths on HM is a long-run effect or it is more concentrated in recent periods. We will estimate this specification both for the full sample of our data (results are shown in Table 6) and, separately, for cardiology, oncology, and orthopedics (see Tables A4–A6 in the Appendix). Second, to control for a more pathology-specific causal effect between quality of care and patient flows, we estimate model in Equation (9) using, for each hospital treatment considered here, a single quality indicator provided by AGENAS, i.e., coronary artery bypass graft (CABG) surgery and heart valve surgery mortality for cardiology, brain cancer surgery mortality, colon cancer surgery mortality, lung cancer surgery mortality, prostate cancer surgery mortality, and breast cancer surgery 3-months' proportion of resections for oncology, hip replacement and knee replacement readmission rates for orthopedics. Results are shown in Table 7.

Table 6 shows that the beaten path effect is always positive and statistically significant in all decades of population migration. Therefore, we find evidence of a long-run impact of beaten path on HM. Moreover, the elasticity is greater in more recent decades: during the periods 1969–1979 and 1980–1989 the beaten path elasticity is about +0.11%, whereas it is much higher in the last two time windows: +0.34% in period 1990–1999 and +0.44% in period 2000–2010. The recent greater influence of the beaten path may be due to (1) a greater willingness of the population to leave their region to receive adequate care, (2) widening of the gap in hospital quality between regions, and (3) the greater roots of past emigration in the destination regions. Interestingly, the private hospitals' pull effect on HM combined with beaten paths ($\text{Private} \times \ln(\text{BeatenPath})$) is always positive and significant, and also stable over the different time windows: +0.06%/+0.07%.

Table A4 in Appendix presents the results for cardiology data. Although we find no evidence of a beaten path effect using the integral of past migration flows over the 1969–2010 period, a positive and significant coefficient for $\ln(\text{BeatenPath})$ is identified in the last decade, i.e., 2000–2010, equal to +0.19%. Therefore, recent trends confirm the importance of beaten paths on HM even for cardiology. Tables A5–A6 display the results for the oncology and orthopedics data. In oncology the estimated elasticity of beaten paths is always positive and significant, equal to about +0.24% in the first two time windows (i.e., 1969–1979 and 1989–1989) and increased to +0.42–0.48% in the two most recent time windows. In orthopedics we obtain similar results, both in terms of sign (always positive), significance, and trend (+0.11% in period 1969–1979 and +0.52% in the last decade). These results confirm that beaten paths are a long-run factor regarding HM, and of increasing importance over time. Interestingly, in all three treatment types beaten paths are more important for private hospitals, because the estimated coefficients for the interaction variable $\text{Private} \times \ln(\text{BeatenPath})$ are always positive and significant, in all time windows. Moreover, the magnitude of the coefficient is stable over time (about 0.06) and similar for all three clinical treatments.

Our second check is related to the hospital quality indicator. Rather than using as an independent variable in Equation (9) a single composite quality indicator for each hospital, we consider, for each pathology, a specific quality indicator provided by AGENAS. Table 7 shows the results. Focusing on the beaten path variable, in cardiology we do not find evidence, as when using a single hospital quality indicator, of a beaten path effect on HM. As before, we





TABLE 6 Sensitivity analysis #1: Past migration by decades, full sample

Migration	Full sample			
	1969–1979	1980–1989	1990–1999	2000–2010
Extra	–6.431*** (0.518)	–6.322*** (0.500)	–10.129*** (0.478)	–11.873*** (0.452)
Quality	0.103*** (0.021)	0.103*** (0.021)	0.097*** (0.021)	0.098*** (0.021)
Extra × Quality	0.075* (0.037)	0.075* (0.037)	0.081* (0.037)	0.079* (0.037)
Urban	0.367*** (0.030)	0.367*** (0.030)	0.374*** (0.030)	0.374*** (0.030)
Private	1.442*** (0.040)	1.444*** (0.040)	1.418*** (0.040)	1.405*** (0.040)
ln(BeatenPath)	0.112*** (0.032)	0.106*** (0.031)	0.340*** (0.029)	0.439*** (0.027)
Private × ln(BeatenPath)	0.067*** (0.003)	0.068*** (0.003)	0.064*** (0.003)	0.062*** (0.003)
ln(GDPDest)	0.501 (0.692)	0.501 (0.692)	0.491 (0.691)	0.487 (0.692)
ln(HospitalBeds)	0.577*** (0.021)	0.577*** (0.021)	0.572*** (0.021)	0.572*** (0.021)
ln(HotelBeds)	0.008 (0.057)	0.008 (0.057)	0.010 (0.056)	0.010 (0.056)
ln(WT)	0.031* (0.012)	0.031* (0.012)	0.028* (0.012)	0.028* (0.012)
ln(Dist)	–0.290*** (0.024)	–0.291*** (0.024)	–0.262*** (0.023)	–0.255*** (0.022)
ln(PopDest)	–0.393 (2.545)	–0.401 (2.542)	–0.615 (2.524)	–0.716 (2.513)
ln(PopOrig)	1.189 (2.475)	1.197 (2.472)	1.464 (2.453)	1.569 (2.439)
ln(ShareOver65Dest)	–0.151 (2.114)	–0.146 (2.115)	–0.331 (2.143)	–0.475 (2.157)
ln(ShareOver65Orig)	1.032 (2.119)	1.027 (2.120)	1.197 (2.157)	1.342 (2.175)
Constant	–12.248 (25.611)	–12.302 (25.613)	–11.764 (25.518)	–11.128 (25.547)
Observations	97,776	97,776	97,776	97,776
Origin region FE	Yes	Yes	Yes	Yes
Dest. region FE	Yes	Yes	Yes	Yes
Spatial filtering	Yes	Yes	Yes	Yes
Pseudo R ²	0.783	0.782	0.784	0.786
JG p	0.871	0.835	0.925	0.785
Quality and WT are lagged by 1 year				

Notes: Robust standard errors in parentheses.
***p < 0.001, **p < 0.01, *p < 0.05.





TABLE 7 Sensitivity analysis #2: Unstandardized hospital quality measures

	Cardiology		Oncology	
	CABG Mortality	Heart valve surgery	Brain cancer surgery Mortality	Colon cancer surgery Prop. of resections
Extra	-4.926** (1.592)	-5.927** (1.854)	-12.260*** (1.293)	-12.030*** (0.821)
Quality	-0.033 (0.017)	-0.036** (0.012)	-0.015 (0.010)	-0.011*** (0.002)
Extra × Quality	-0.054* (0.023)	-0.024 (0.019)	-0.031* (0.014)	-0.024*** (0.004)
Urban	0.574*** (0.128)	0.899*** (0.128)	0.966*** (0.110)	0.901*** (0.058)
Private	0.886*** (0.082)	0.929*** (0.084)	0.535*** (0.096)	1.012*** (0.064)
ln(BeatenPath)	0.031 (0.089)	0.077 (0.103)	0.441*** (0.069)	0.405*** (0.044)
Private × ln(BeatenPath)	0.053*** (0.006)	0.054*** (0.006)	0.064*** (0.006)	0.065*** (0.005)
ln(GDPDest)	0.104 (1.355)	0.330 (1.308)	0.153 (1.217)	0.227 (1.011)
ln(HospitalBeds)	0.051 (0.049)	0.134** (0.043)	0.383*** (0.068)	0.558*** (0.049)
ln(HotelBeds)	0.013 (0.116)	0.011 (0.111)	-0.014 (0.099)	0.012 (0.081)
ln(WT)	-0.003 (0.017)	-0.006 (0.018)	-0.018 (0.027)	0.057 (0.031)
ln(Dist)	-0.417*** (0.059)	-0.371*** (0.059)	-0.374*** (0.058)	-0.215*** (0.037)
				0.056 (0.029)
				-0.150*** (0.037)



TABLE 7 (Continued)

	Cardiology		Oncology	
	CABG Mortality	Heart valve surgery	Brain cancer surgery Mortality	Colon cancer surgery
In(PopDest)	-4.977 (3.474)	-2.887 (3.452)	1.299 (3.317)	0.166 (2.875)
In(PopOrig)	3.432 (3.433)	1.619 (3.408)	-1.728 (3.597)	0.033 (3.001)
In(ShareOver65Dest)	1.398 (3.806)	2.229 (3.786)	1.222 (2.863)	0.605 (2.809)
In(ShareOver65Orig)	-1.218 (3.841)	-1.909 (3.831)	-0.492 (2.897)	-0.329 (2.879)
Constant	29.070 (44.726)	22.076 (46.065)	13.385 (44.412)	-0.828 (37.598)
Observations	13,419	14,742	18,900	55,041
Origin region FE	Yes	Yes	Yes	Yes
Dest. region FE	Yes	Yes	Yes	Yes
Spatial filtering	Yes	Yes	Yes	Yes
Pseudo R ²	0.812	0.811	0.839	0.808
JG p	0.752	0.770	0.693	0.959

Quality and WT are lagged by 1 year.
Robust standard errors in parentheses.
***p > 0.001, **p > 0.01, *p > 0.05.



TABLE 7 (Continued)

	Oncology		Orthopedics	
	Lung cancer surgery Mortality	Prostate cancer surgery	Hip replacement Readmission rate	Knee replacement
Extra	-11.338*** (1.339)	-11.982*** (1.440)	-11.242*** (0.939)	-11.625*** (0.935)
Quality	-0.005 (0.005)	-0.020 (0.011)	-0.017** (0.007)	-0.003 (0.006)
Extra × Quality	-0.026 (0.014)	0.010 (0.012)	-0.027* (0.013)	-0.005 (0.010)
Urban	1.110*** (0.119)	1.365*** (0.221)	-0.108** (0.042)	-0.019 (0.041)
Private	1.158*** (0.079)	0.980*** (0.123)	1.729*** (0.048)	1.517*** (0.052)
ln(BeatenPath)	0.380*** (0.072)	0.415*** (0.078)	0.385*** (0.051)	0.399*** (0.051)
Private × ln(BeatenPath)	0.069*** (0.006)	0.081*** (0.005)	0.061*** (0.004)	0.060*** (0.004)
ln(GDPDest)	-0.220 (1.340)	0.357 (1.309)	0.988 (0.864)	0.733 (0.855)
ln(HospitalBeds)	0.175** (0.066)	0.546*** (0.071)	0.143*** (0.024)	0.189*** (0.024)
ln(HotelBeds)	0.008 (0.110)	0.005 (0.103)	0.024 (0.070)	0.010 (0.070)
ln(WT)	0.236*** (0.056)	0.001 (0.030)	0.046*** (0.012)	0.050*** (0.014)
ln(Dist)	-0.326*** (0.057)	-0.441*** (0.055)	-0.359*** (0.029)	-0.347*** (0.030)



TABLE 7 (Continued)

	Oncology		Orthopedics	
	Lung cancer surgery Mortality	Prostate cancer surgery	Hip replacement Readmission rate	Knee replacement
ln(PopDest)	1.233 (3.279)	0.104 (3.336)	1.527 (3.912)	0.212 (3.868)
ln(PopOrig)	-2.464 (3.527)	-2.418 (3.648)	1.307 (3.742)	2.258 (3.704)
ln(ShareOver65Dest)	1.734 (3.142)	1.932 (3.212)	-0.525 (3.444)	-1.074 (3.368)
ln(ShareOver65Orig)	-1.496 (3.261)	-0.932 (3.346)	1.393 (3.448)	2.182 (3.371)
Constant	27.028 (48.234)	38.427 (52.020)	-44.554 (32.016)	-35.983 (31.004)
Observations	19,131	15,939	77,553	69,216
Origin region FE	Yes	Yes	Yes	Yes
Dest. region FE	Yes	Yes	Yes	Yes
Spatial filtering	Yes	Yes	Yes	Yes
Pseudo R ²	0.814	0.839	0.750	0.746
JG p	0.658	0.704	0.840	0.601

Quality and WT are lagged by 1 year.
Robust standard errors in parentheses.
***p > 0.001, **p > 0.01, *p > 0.05.



identify it only for private hospitals, and both for CABG and heart valve surgery mortality indicators. In oncology, beaten path influences HM if we include in the estimation as quality variable, in turn, mortality rates in brain cancer surgery, in colon cancer surgery, in lung cancer surgery, and in prostate cancer surgery. It is also present if we consider breast cancer surgery 3 months' proportion of resections. Again, the $Private \times \ln(BeatenPath)$ interaction variable is always positive and significant. The same results are obtained for orthopedics, if we include hip replacement readmission rates or knee replacement readmission rates.

Therefore, these results confirm that even if we consider different time windows for past migration flows and more pathology-specific hospital quality indicators, there is evidence that beaten paths are an important determinant of HM, and that private hospitals exploit them as a pull factor.

7 | DISCUSSION AND CONCLUSIONS

We investigate HM due to patients' inter-regional mobility by developing an empirical model that focuses on the impact of the migration beaten path (Rodríguez-Pose, 2020) on the concentration of patient flows in some regions with high hospital quality. The econometric model is applied to a data set that considers all patients flows in Italy during the 2010–2016 period using a PPML estimator. To identify the beaten path effect on HM, we deal with three econometric challenges arising in the estimation of the determinants of health care mobility: (1) the possible selection bias that could arise if the estimation sample does not also include intra-regional flows, (2) the endogeneity of quality and waiting time, and (3) the possible network autocorrelation of patient flows.

We show that migration beaten path is a determinant of patient inter-regional mobility flows and helps us understand the concentration of extra-regional flows in some regions. The estimated elasticity of migration beaten path is +0.32%. The sign and significance of beaten paths are confirmed by our sensitivity analysis, where we consider different time windows for the past migration flows and specific quality indicator for cardiology, oncology, and orthopedics. These results highlight the importance of the patient's network of relationships in the destination region when they have to be admitted in a hospital with better health quality, because we also find evidence that patients involved in HM are more sensible to hospital quality than those admitted in local hospitals. Furthermore, we find a robust evidence that the beaten path effect is stronger for private hospitals. We believe that family and social ties between past migrants and people still leaving in the same region of origin are exploited by private hospitals for financial motivations, because in Italy extra-regional patient flows are reimbursed out of regional budgets; that is, they are a pull factor in HM. This is similar to the evidence provided by Berta et al. (2021) when investigating the impact of extra-regional patient flows on the waiting times of local patients: they find longer waiting times for the local patients, in comparison with extra-regional ones, and explain it for financial motivations. We highlight another pull factor present in HM, in this case for private hospitals. These insights yield some interesting policy implications.

First, policy makers have to consider that regional health asymmetries are a long-run phenomenon that generates not only financial regional disparities (high quality regions receive extra funds for attracting extra-regional patients) but also discrimination problems. The latter arise because regional health asymmetries induce HM, which implies high mobility costs that may be sustained only by high-income people. In turn, wider asymmetries and high mobility costs can create strong barriers to access to good health care to patients remaining in their region of origin. As a confirmation of the relevance of mobility costs, migration beaten paths are a factor explaining HM.

Second, as hospital admission is free of charge, and beaten paths decrease mobility costs, local population searching for good hospital quality may find convenient to be admitted in other regions, even at long distance. This means a reduction in the pressure exerted by people living in regions with low hospital quality on regional governments. Therefore, beaten paths may be part of a vicious circle in these regions: low hospital quality may persist in the long run because local population may find good hospital quality elsewhere at low costs. Therefore, it is essential that the national government implements some policies that may improve the hospital quality in the regions with low hospital quality. In the long run a national health care system with asymmetric health care quality in the 21 Italian





regions might generate social problems for the local population. These policies may be based on monitoring regional hospital quality and linking to it a share of the national health care expenditure transferred to the regions. Furthermore, it is important to include the share of health migrants in monitoring and benchmarking of regional health care systems, because they are a signal of the hospital quality level perceived by the local population. Transparency on health emigration flows is therefore essential, because it increases the accountability of regional governments regarding health care provided locally, and might partly restore the incentives to invest in health.

Last, the importance of past migration flows for private hospitals confirms, as shown by Berta et al. (2021), that pull factors matter when extra-regional patient flows for hospital admissions are investigated. This implies that hospitals respond to financial incentives regarding the type of admitted patients, and this may generate discrimination among people asking for acute treatments and asymmetries among hospitals with different ownership types.

This work has limitations that represent starting points for further research. First, we only consider a limited amount of procedures within three medical disciplines (cardiology, oncology, and orthopedics). Thus, expanding the range of procedures would give a more detailed picture of the treatments related to unequal access to quality of care. Second, the phenomenon of beaten paths can be explored in greater depth, for example, by identifying more precisely family and cultural ties and the channels through which informal care takes place. These issues are left for future research.

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APPENDIX

TABLE A1 Hospital quality indicators included in PNE–Italian health public agency AGENAS

Medical procedure	Quality indicator	Clinical area
Acute myocardial infarction	One-month mortality	Cardiology
Heart valve replacement	One-month mortality	Cardiology
Lung cancer surgery	One-month mortality	Oncology
Colon cancer surgery	One-month mortality	Oncology
Prostate cancer surgery	One-month mortality	Oncology
Brain cancer surgery	One-month mortality	Oncology
Breast cancer surgery	Three-months proportion of resections after conservative surgery	Oncology
Hip replacement	One-month readmission rate	Orthopedics
Knee replacement	One-month readmission rate	Orthopedics





TABLE A2 Descriptive statistics of hospital quality indicators computed by AGENAS-PNE

Discipline	Procedure	Indicator	Mean (sd)	Min-max
Cardiology	Acute myocardial infarction	One-month mortality, %	2.43(2.44)	0-28.04
	Heart valve replacement	One-month mortality	3.42(2.90)	0-20.97
Oncology	Lung cancer surgery	One-month mortality, %	1.52(3.73)	0-81.28
	Colon cancer surgery	One-month mortality, %	4.28(3.89)	0-29.23
	Prostate cancer surgery	One-month mortality, %	4.03(3.41)	0-28.91
	Brain cancer surgery	One-month mortality, %	3.07(2.82)	0-21.28
	Breast cancer surgery	Three-months proportion of resections after conservative surgery, %	11.29(9.92)	0-100
Orthopedics	Hip replacement	One-month readmission rate, %	3.93(2.52)	0-19.06
Orthopedics	Knee replacement	One-month readmission rate, %	1.59(2.67)	0-100





TABLE A3 Determinants of origin–destination population migration flows in Italy with different lags for previous out and in migration flows

Dependent variable: Migration flows in year t , M_{ijt}									
Lags in TotMigIn and TotMigOut									
	Lag = 1	Lag = 2	Lag = 3	Lag = 4	Lag = 5	Lag = 6	Lag = 7	Lag = 8	Lag = 9
$\ln(\text{TotMigIn})$	−0.200* (0.098)	−0.154 (0.105)	−0.186 (0.104)	−0.018 (0.091)	−0.046 (0.093)	−0.001 (0.095)	−0.017 (0.095)	−0.139 (0.096)	−0.200* (0.098)
$\ln(\text{TotMigOut})$	0.292** (0.106)	0.399** (0.123)	0.518*** (0.114)	0.492*** (0.099)	0.472*** (0.097)	0.389*** (0.100)	0.421*** (0.098)	0.336** (0.102)	0.292** (0.106)
$\ln(\text{GDPOrig})$	0.009 (0.313)	0.210 (0.309)	0.170 (0.309)	0.152 (0.308)	0.147 (0.306)	0.141 (0.307)	0.087 (0.309)	0.031 (0.312)	0.009 (0.313)
$\ln(\text{GDPDest})$	0.083 (0.316)	−0.126 (0.311)	−0.141 (0.312)	−0.131 (0.312)	−0.100 (0.310)	−0.075 (0.311)	−0.033 (0.313)	0.047 (0.315)	0.083 (0.316)
$\ln(\text{Dist})$	−0.264*** (0.018)	−0.264*** (0.018)	−0.264*** (0.018)	−0.264*** (0.018)	−0.264*** (0.018)	−0.264*** (0.018)	−0.264*** (0.018)	−0.264*** (0.018)	−0.264*** (0.018)
$\ln(\text{PopOrig})$	1.240* (0.506)	1.170* (0.485)	0.858 (0.475)	0.793 (0.477)	0.735 (0.487)	0.887 (0.517)	0.847 (0.507)	1.087* (0.513)	1.240* (0.506)
$\ln(\text{PopDest})$	0.209 (0.495)	−0.186 (0.450)	0.100 (0.443)	−0.325 (0.436)	−0.293 (0.464)	−0.491 (0.500)	−0.376 (0.497)	0.033 (0.496)	0.209 (0.495)
Constant	−16.708* (6.826)	−11.367 (7.167)	−11.403 (6.339)	−5.508 (6.266)	−4.797 (6.581)	−3.849 (7.230)	−5.037 (6.939)	−12.783 (6.853)	−16.708* (6.826)
Observations	7600	7600	7600	7600	7600	7600	7600	7600	7600
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.836	0.836	0.836	0.836	0.836	0.836	0.836	0.836	0.836

Notes: Robust standard errors in parentheses.

***p < 0.001, **p < 0.01, *p < 0.05.



TABLE A4 Sensitivity analysis #3: Past migration by decades, cardiology

	Cardiology			
Migration	1969–1979	1980–1989	1990–1999	2000–2010
Extra	–3.242*** (0.836)	–3.324*** (0.848)	–6.468*** (1.609)	–7.698*** (1.461)
Quality	0.129** (0.048)	0.129** (0.048)	0.127** (0.047)	0.127** (0.047)
Extra × Quality	0.099 (0.063)	0.099 (0.063)	0.114 (0.063)	0.113 (0.063)
Urban	0.891*** (0.129)	0.891*** (0.129)	0.890*** (0.128)	0.890*** (0.128)
Private	0.984*** (0.085)	0.986*** (0.085)	0.958*** (0.084)	0.943*** (0.084)
ln(BeatenPath)	–0.088 (0.051)	–0.083 (0.052)	0.114 (0.099)	0.187* (0.088)
Private × ln(BeatenPath)	0.064*** (0.006)	0.064*** (0.006)	0.059*** (0.006)	0.056*** (0.006)
ln(GDPDest)	0.157 (1.315)	0.157 (1.315)	0.149 (1.315)	0.146 (1.315)
ln(HospitalBeds)	0.130** (0.043)	0.130** (0.043)	0.131** (0.043)	0.131** (0.043)
ln(HotelBeds)	0.010 (0.110)	0.010 (0.110)	0.010 (0.110)	0.010 (0.110)
ln(WT)	–0.012 (0.017)	–0.012 (0.017)	–0.012 (0.017)	–0.013 (0.017)
ln(Dist)	–0.390*** (0.058)	–0.389*** (0.058)	–0.370*** (0.058)	–0.361*** (0.057)
ln(PopDest)	–3.215 (3.456)	–3.216 (3.458)	–3.257 (3.457)	–3.264 (3.444)
ln(PopOrig)	2.136 (3.410)	2.136 (3.412)	2.191 (3.410)	2.204 (3.398)
ln(ShareOver65Dest)	2.278 (3.762)	2.277 (3.762)	2.170 (3.784)	2.101 (3.794)
ln(ShareOver65Orig)	–1.783 (3.794)	–1.782 (3.795)	–1.677 (3.828)	–1.608 (3.843)
Constant	20.129 (45.960)	20.162 (45.959)	21.305 (45.983)	21.705 (46.013)
Observations	14,721	14,721	14,721	14,721
Origin region FE	Yes	Yes	Yes	Yes
Dest. region FE	Yes	Yes	Yes	Yes
Spatial filtering	Yes	Yes	Yes	Yes
Pseudo R ²	0.811	0.811	0.811	0.812
JG p	0.602	0.601	0.607	0.629

Notes: Quality and WT are lagged by 1 year.
Robust standard errors in parentheses.
***p < 0.001, **p < 0.01, *p < 0.05.





TABLE A5 Sensitivity analysis #3: Past migration by decades, oncology

Migration	Oncology			
	1969–1979	1980–1989	1990–1999	2000–2010
Extra	–8.909*** (0.643)	–8.794*** (0.622)	–11.788*** (0.609)	–12.816*** (0.588)
Quality	0.146*** (0.027)	0.146*** (0.027)	0.146*** (0.027)	0.146*** (0.027)
Extra × Quality	0.167*** (0.040)	0.166*** (0.040)	0.163*** (0.040)	0.162*** (0.040)
Urban	0.703*** (0.053)	0.703*** (0.053)	0.703*** (0.053)	0.703*** (0.053)
Private	0.969*** (0.064)	0.970*** (0.064)	0.951*** (0.064)	0.941*** (0.064)
ln(BeatenPath)	0.246*** (0.039)	0.240*** (0.038)	0.424*** (0.037)	0.478*** (0.035)
Private × ln(BeatenPath)	0.061*** (0.005)	0.061*** (0.005)	0.058*** (0.005)	0.056*** (0.005)
ln(GDPDest)	0.128 (0.951)	0.128 (0.951)	0.127 (0.951)	0.127 (0.952)
ln(HospitalBeds)	0.621*** (0.041)	0.621*** (0.041)	0.622*** (0.041)	0.623*** (0.041)
ln(HotelBeds)	–0.006 (0.077)	–0.006 (0.077)	–0.006 (0.077)	–0.006 (0.077)
ln(WT)	0.047 (0.028)	0.047 (0.028)	0.047 (0.028)	0.047 (0.028)
ln(Dist)	–0.179*** (0.033)	–0.180*** (0.033)	–0.169*** (0.032)	–0.164*** (0.032)
ln(PopDest)	–0.019 (2.930)	–0.040 (2.923)	–0.149 (2.915)	–0.177 (2.902)
ln(PopOrig)	–0.256 (3.025)	–0.232 (3.018)	–0.103 (3.002)	–0.072 (2.987)
ln(ShareOver65Dest)	0.896 (2.693)	0.902 (2.695)	0.897 (2.715)	0.888 (2.721)
ln(ShareOver65Orig)	–0.323 (2.746)	–0.329 (2.749)	–0.330 (2.778)	–0.322 (2.786)
Constant	6.804 (34.970)	6.729 (34.980)	7.645 (35.049)	7.935 (35.088)
Observations	65,919	65,919	65,919	65,919
Origin region FE	Yes	Yes	Yes	Yes
Dest. region FE	Yes	Yes	Yes	Yes
Spatial filtering	Yes	Yes	Yes	Yes
Pseudo R ²	0.780	0.780	0.782	0.783
JG p	0.820	0.832	0.825	0.809

Notes: Quality and WT are lagged by 1 year.
Robust standard errors in parentheses.
***p < 0.001, **p < 0.01, *p < 0.05.





TABLE A6 Sensitivity analysis #4: Past migration by decades, orthopedics

Migration	Orthopedics			
	1969–1979	1980–1989	1990–1999	2000–2010
Extra	–6.303*** (0.737)	–6.123*** (0.707)	–10.717*** (0.742)	–13.094*** (0.726)
Quality	0.063** (0.019)	0.063** (0.019)	0.063** (0.019)	0.062** (0.019)
Extra × Quality	0.088* (0.036)	0.088* (0.036)	0.091* (0.036)	0.091* (0.036)
Urban	–0.093* (0.039)	–0.093* (0.039)	–0.098** (0.038)	–0.086* (0.038)
Private	1.750*** (0.048)	1.753*** (0.048)	1.738*** (0.048)	1.724*** (0.048)
ln(BeatenPath)	0.108* (0.045)	0.098* (0.044)	0.382*** (0.045)	0.517*** (0.043)
Private × ln(BeatenPath)	0.069*** (0.004)	0.069*** (0.004)	0.065*** (0.004)	0.063*** (0.004)
ln(GDPDest)	0.781 (0.836)	0.782 (0.836)	0.778 (0.838)	0.797 (0.837)
ln(HospitalBeds)	0.164*** (0.024)	0.164*** (0.024)	0.170*** (0.024)	0.167*** (0.024)
ln(HotelBeds)	0.014 (0.068)	0.014 (0.068)	0.014 (0.068)	0.014 (0.067)
ln(WT)	0.055*** (0.013)	0.055*** (0.013)	0.057*** (0.013)	0.055*** (0.013)
ln(Dist)	–0.329*** (0.031)	–0.330*** (0.031)	–0.315*** (0.030)	–0.304*** (0.030)
ln(PopDest)	0.580 (3.829)	0.576 (3.826)	0.364 (3.794)	0.221 (3.783)
ln(PopOrig)	1.687 (3.676)	1.692 (3.672)	1.918 (3.635)	2.085 (3.619)
ln(ShareOver65Dest)	–0.872 (3.255)	–0.869 (3.254)	–1.094 (3.303)	–1.345 (3.334)
ln(ShareOver65Orig)	1.786 (3.250)	1.783 (3.249)	2.004 (3.309)	2.283 (3.347)
Constant	–36.120 (30.092)	–36.196 (30.098)	–34.514 (30.185)	–34.132 (30.183)
Observations	87,402	87,402	87,402	87,402
Origin region FE	Yes	Yes	Yes	Yes
Dest. region FE	Yes	Yes	Yes	Yes
Spatial filtering	Yes	Yes	Yes	Yes
Pseudo R ²	0.738	0.738	0.741	0.745
JG p	0.620	0.682	0.646	0.701

Notes: Quality and WT are lagged by 1 year.
Robust standard errors in parentheses.
***p < 0.001, **p < 0.01, *p < 0.05.

