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The geography of hospital admission in a National Health Service with patient choice: Evidence from Italy

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PRELIMINARY VERSION

Abstract: Every year 35% of the 10 million hospital admissions in Italy occurs outside the patients' Local Health Authority of residence. In this paper we look for explanation for this phenomenon and estimate gravity equations for "trade" in hospital care using a Poisson pseudo maximum likelihood method. Our results suggest that the gravity model is a good framework for explaining patient mobility in most of the examined diagnostic groups. We find that the ability to restrain the imports of hospital services increases with the size of the pool of enrollees. Moreover, the ability to export hospital services, as proxied by the ratio of export-to-internal demand, is U-shaped. Therefore our evidence suggests that there are scale effects played by the size of the pool of enrollees.

Keywords: patients mobility, hospital care, gravity model, Italian National Health Service

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1 INTRODUCTION

Every year, about 35% of the 10 million hospital admissions in Italy occurs outside the patients' Local Health Authority (LHA) of residence. This figure goes up to almost 42% for cancer treatment and more than 58% for complex surgery. This situation raises policy concerns due to the peculiar institutional setting that drives the allocation of resources in this sector.

In the Italian NHS patients are enrolled into health plans managed by LHAs. Enrolment is based on a patient's place of residence, while funds from general taxation accrue to enrolling LHAs according to a per enrolee capitation payment. LHAs are responsible for the healthcare consumption of their enrollees, using the resources available to them. Patients are entitled to hospital care treatments completely free of charge, with providers being reimbursed by a patient's LHA according to a mix of prospective payment schemes. A distinctive feature of the Italian NHS is that within this institutional framework (similar to many other "decentralized" tax-funded NHS systems, such as Spain, Norway, Denmark, and the UK) patients can freely choose the provider of their hospital treatment .

Equity of access and financial sustainability are the main concerns arising from this situation. Exit rates and average distance travelled to access hospital care are, for instance, much larger for enrollees in southern LHAs. Observed imbalances in patient mobility make the distribution of private mobility costs uneven and promote the accumulation of financial resources towards the already better endowed LHAs. In this paper we aim to evaluate the extent to which the observed geographical imbalances of Italian hospital admissions are due to scale effects, depend on a core/periphery equilibrium, or reflect a deeper, long lasting north/south divide. In particular, we focus on the scale effect played by the size of the pool of enrollees. 25% of Italian LHAs have fewer than 150,000 enrollees, while 20% have more than

400,000 enrollees. Since funds accrue to LHAs on a capitation basis, and smaller LHAs suffer from relatively larger patient outflows while receiving smaller inflows, this policy variable is crucial in determining the financial stability of LHAs.

We work on an origin/destination matrix provided by the Italian Ministry of Health, comprising all inpatient admissions to public hospitals in Italy during the year 2001. We classify hospital admissions into 4 broad diagnostic groups. To control for distance, contiguity, and supply characteristics, we estimate a gravity equation for the full matrix of pair-wise flows. We estimate gravity equations in multiplicative form adopting a Poisson pseudo maximum likelihood approach, as proposed by Santos Silva and Tenreyro (2006). This method is robust to different patterns of heteroskedasticity and provides a natural way to deal with the zero flows. Our results suggest that the gravity model proves to be a good framework for explaining the patient mobility phenomenon for most of the examined diagnostic groups. We find evidence to suggest that the ability to restrain the import of hospital services increases with the size of the pool of enrollees. Moreover the ability to export hospital services, as proxied by the ratio of export-to-internal demand, appears to follow a U-shaped curve.

Our paper contributes to the literature in several ways. We provide an analysis of the scale effect in the import/export of hospital care (played by the size of the pool of enrollees) that is novel in the literature. To our knowledge Wholey et al. (1996) is the only paper providing clear empirical evidence of the presence of scale economies in the size of the pool of enrollees for the case of US HMOs. Moreover our study is the first one in healthcare migration analysis relying on the Poisson pseudo maximum likelihood method, as proposed by Santos Silva and Tenreyro (2006). Finally an analysis of the determinants of patient mobility across LHAs in Italy using a gravity approach has not been performed before.

The paper is organized as follows. The following section provides a concise institutional background on the market for hospital care in Italy. Section 3 presents our base of data and some preliminary evidence. Section 4 details our econometric model and estimation strategy. Section 5 describes the data and the empirical specification of our model. Major results are presented in section 6. Section 7 concludes.

2 INSTITUTIONAL BACKGROUND AND MOTIVATION

The Italian National Health Service was established in 1978 as a universal system providing comprehensive insurance and uniform healthcare for the whole population. It is mainly financed through general taxation with limited recourse to co-payments for drugs, out-patient treatment, some diagnostic and laboratory tests, and medical appliances, depending on a citizen's income, age and health condition. Every year the central government allocates funds to each Regional Health Authority (RHA) according to a "negotiated" capitation payment. These funds are then reallocated according to a mix of political patronage, historical precedent and cost-plus reimbursement among approximately 200 LHA.[1] Within its budget, each LHA is responsible for financing the healthcare consumption of the "enrolled" population, and most of the time is also responsible for healthcare production.

The provision of hospital treatment is completely free of charge for patients. The supply side largely relies on public production supplemented by privately licensed hospitals. Public hospitals are run by LHAs or by autonomous public trusts (Aziende Ospedaliere). Privately licensed hospitals can treat patients within the SSN, i.e. free of charge, being refunded by the LHA which the patient is enrolled to. Patients are free to choose the admitting hospital; it may

[1] A typical LHA assists a population of about 300.000 enrollees.

be public or private, either within or outside the enrolling LHA or region. Provided patients are unaware of treatment costs and are free to choose between publicly financed hospitals, choice is essentially determined by distance from home, hospital specialization, waiting lists, and perceived quality.

Since fiscal year 1995, hospitals are financed according to a mix of pay-per-case and prospective activity budget based on the pricing of each clinical episode, with clinical episodes being classified according to the US Diagnosis Related Groups (DRG). The mix basically works as follows. Hospital admissions taking place within each LHA (either directed to LHAs hospitals, a local Hospital Trust or a private licensed hospital) are regulated according to the prospective block budget attributed to each local provider. Hospital admissions that take place from outside the enrolling LHA are regulated on a pay-per-case basis using centrally set tariffs as a reference.[2]

According to this overall arrangement LHAs that are net "exporters" of hospital treatment receive additional financial resources for the treatment they export. Similarly LHAs that are net "importers" will suffer from unpredictable financial outflows for the treatment they import. This mechanism could create large financial flows across LHAs thus leading to perpetuating imbalances in healthcare financing, with the LHAs that provide hospital care of a lower quality paying the better endowed ones (presumably the richer ones) for the treatment consumed there by their mobile enrollee. In this framework each LHA has a strong incentive to restrain enrollees' outflows to outside LHAs and to attract inflows, in particular those

[2] This is exactly the case for regional cross-border caseloads. In case the flows involve LHAs belonging to the same region it is common practice to settle financial imbalances according to regional fee schedules. Regions set their tariffs by referring to national tariff rates, which represent a ceiling and allow flexibility downward (so far they have been reduced by up to 30% of the national tariff) (France et al., 2005).

originating from a different region. The aim of our empirical analysis is to shed some light on the determinants of the LHAs' dual ability to restrain enrollees' outflows and to attract patient inflows.

Our analysis relies upon the premise that observed patient mobility to some extent reflects patient choice. Actually patient mobility is partly unavoidable. It would be inefficient to provide more specialized or very rare treatments at every hospital. On the contrary, it is efficient, to some extent, to concentrate their production in a few centres. Apart from these treatments, it makes sense to consider the decision to move as a manifestation of dissatisfaction for the local supply of health care, as suggested by Tiebout's "voting with the feet" mechanism.

3 THE GEOGRAPHY OF HOSPITAL ADMISSION IN THE ITALIAN NHS

We analyse patient mobility across Italian LHAs using data on hospital admissions that occurred in all public hospitals during the year 2001. Patient flows are reported in an origin/destination matrix provided by the Italian Ministry of Health. For each DRG the matrix reports the flows of patients occurring between each pair of origin-destination LHAs, with the origin referring to the LHA to which the patients are enrolled in, and the destination referring to the LHA where the patients receive the hospital treatment. In the reference year, the Italian territory is partitioned into 197 LHAs. However, only 190 LHAs are present in our dataset due to the fact that we were forced to aggregate those LHAs operating in a single municipality.[3] Given the huge demographic dimension of these artificial LHAs we opt to exclude them from the analysis. Moreover, we disregard all the flows generated and directed

[3] The municipalities of Turin and Rome comprise 4 and 5 LHAs, respectively.

to the LHAs of Sardinia and Sicily. These two regions are islands and the patient flows to and from them may follow peculiar patterns. We end up with a set of 171 LHAs.

To provide a comprehensive and informative analysis of mobility patterns in hospital admission, while maintaining manageability, we reduce the dimension of the matrix by aggregating the DRGs into 7 broad groups (PRODUCT). In order to account for different patient severity we consider the following groups of clinical procedures and/or conditions: complex surgery (CS), emergencies (EM), cancer (CA), HIV, delivery (DE), basic surgery (BS) and basic medicine (BM). Table A1 in the appendix details the aggregation. The market shares of these categories vary significantly the larger being BM (47.6%) and BS (23.6%), and the smaller ones being complex surgery (1.7%) and HIV (0.5%).

In the following analysis, we disregard the HIV, DE and EM products. There are too few HIV cases to make the analysis reliable for this product. Observed EM mobility is hardly attributable to a deliberate decision by a patient, but rather to the need of a hospital admission when far from home for holiday or work. Finally, concerning DE, we notice that patients naturally tends to gravitate towards the place of residence, with little or almost none mobility, or to the place where their family of origin lives, thus leading to temporary residential relocation.

Table I reports the following set of indicators for patient flows in Italy: exit rate (the share of hospital admissions received by LHA enrollees outside that LHA), inflow rate (the share of hospital admissions in a given LHA that are provided to non-enrollees), accessibility (the average distance travelled by the enrollees in a given LHA to receive hospital treatment outside their LHA[4]), attractiveness (the average distance travelled by non-enrolled patients admitted to hospital in a given LHA[5]).

INSERT TABLE I ABOUT HERE

According to our data exit rates are larger from LHAs located in the south of Italy, while inflow rates do not exhibit any regional variation. Accessibility is remarkably poorer for enrolees from southern LHAs, namely almost 200 km vis-a-vis less than 90 km for those enrolled in the remaining LHAs. Attractiveness is greater for LHAs in the North-West. It is apparent that search areas are larger in the South while, at the same time, catchment areas are smaller there. Overall this evidence suggests that the distribution of flows is uneven across Italy. If mobility is a "defensive strategy" in the face of poor quality, this pattern clearly suggests that hospital care in the south of Italy is less satisfactory to enrollees than the care provided in the rest of the country.

To go beyond descriptive statistics and gain insights into the factors behind the observed mobility patterns we adopt a modelling framework which allows us to control for distance, contiguity, and supply characteristics.

4 ECONOMETRIC MODEL AND ESTIMATION

Our dependent variable of interest is the number of patients admitted to hospital that flow from each LHA of origin to each possible LHAs of destination. Given our interest into the determinants of LHAs dual ability to restrain enrollees' outflows and to attract patient

[4] It measures the radius of the search area for hospital care and therefore proxies the private costs of mobility suffered by enrollees in order to receive hospital treatment at their chosen admitting hospital.
[5] It gives a measure of the radius of the catchment's area for the hospital care supplied by an LHA. The higher this value the higher the ability of the LHAs supply to attract outside patients.

inflows, we focus here only on those patients that seek care outside the LHA they are enrolled in. Therefore our analysis is akin to a standard gravity analysis of trade. The theoretical and empirical literature on the gravity equation for trade is vast and expanding (see McCallum, 1995; Anderson and van Wincoop, 2003; Santos Silva and Tenreyro, 2006 to quote just a small set of papers in this literature).

In its simplest form the gravity equation approach states that trade flows between two regions is proportional to the product of the trading parties GDPs and inversely proportional to their spatial distance. We adopt this framework and assume that, for each product we examine, the observed matrix of pair-wise "trade" flows is determined, in its simplest form, by the following equation:

$$m_{ij} = \alpha_0 push_i^{\alpha_1} \times pull_j^{\alpha_2} \times f(d_{ij}, k_{ij}) \times \eta_{ij} \qquad (1)$$

where m_{ij} is the number of patients enrolled in LHA_i that receive a hospital treatment in LHA_j, $push_i$ and $pull_j$ represent a push and a pull factor in origin LHA_i and in destination LHA_j respectively, f is the spatial deterrence as a function of the distance between LHA_i and LHA_i, d_{ij} , and pair-specific impeding factors other than distance, k_{ij}, and η_{ij} is an error term with $E\left(\eta_{ij} \middle| push_i , pull_j , d_{ij}, k_{ij}\right) = 1$ assumed to be statistically independent from the regressors. Since, as we mentioned earlier, our dataset comprises 171 LHAs, a typical origin\destination matrix contains 29070 pairs (observations). Table II provides some detail on the dependent variable considered in this piece of work.

INSERT TABLE II ABOUT HERE

Application of the gravity modelling to the issue of patient flows and hospital choice dates back to the late sixties (see the early works of Morrill and Earickson, 1968; Studnicki, 1975; Roghman and Zastowney; 1979). More recently, papers by Lowe and Sen (1996), Congdon (2001), Levaggi and Zanola (2004) and Cantarero (2006) adopt this framework to investigate patient mobility. Lowe and Sen (1996) utilize the gravity model to study the flows for acute inpatient hospital care from six-country metropolitan Chicago area to 92 hospitals in that same area in year 1987. The model is used to forecast how potential changes in hospital financing policy can change patient flows. Congdon (2001) models patient flows to emergency units in 127 electoral wards in North East London and Essex and describes how such models may be adapted to allow for unit closures and expansion, or the opening up of other units. The estimation of the gravity model is based on simulation based Bayesian methods. Levaggi and Zanola (2004) study the net flows of people moving from one Italian region to another as determined by regional differences in the quality of healthcare and distance. The dataset they use consists of a sample of observations over the period 1994-1997. A similar analysis is developed by Cantarero (2006) working on patient mobility across Spanish regions during the period 1996-1999. Both Levaggi and Zanola (2004) and Cantarero (2006) rely upon panel data models.

As far as the empirical estimation of the gravity models is concerned, there is a long tradition in the literature of making a log-linearization of them and to estimate the parameters of interest using OLS. This procedure is appealing because it is very simple. However it fails to work when no flow is observed between some pairs of origin and destination, thus making the dependent variable a true zero (Porell and Adams, 1995; Stillwell, 2008). Several methods have been adopted to deal with log-linearization of the zero observations. In a number of studies the pairs with null flows have just been dropped from the dataset. Others have used a Tobit estimator. Rather than throwing away observations with zero flows, some authors have attributed the value of 1 to these observations. For a more complete description of the various procedures see Frankel (1997). These procedures will generally lead to biased estimators for the parameters of the model, the bias being particularly severe when the proportion of zero flows is large.[6] Moreover, as pointed out by Santos Silva and Tenreyro (2006), when the error term in the log gravity equation is heteroskedastic, the OLS regression leads to inconsistent estimates. The expected value of the logarithm of a random variable depends both on its mean and on the higher-order moments of the distribution. Hence, if the variance of the error term in the gravity equation depends on the regressors, the expected value of the logarithm of the error term will also depend on the regressors, violating the condition of consistency of OLS.

To address these two problems we follow the approach proposed by Santos Silva and Tenreyro (2006) and estimate model (1) using a PML estimator (see McCullagh and Nelder, 1989). This approach relies upon the assumption that the conditional variance is proportional to the conditional mean.[7] Under this assumption the parameters of the model can be estimated by solving a set of first-order conditions numerically equal to the Poisson pseudo-maximum-likelihood (PPML) estimator. All that is needed for this estimator to be consistent is the correct specification of the conditional mean, that is, $E\left(m_{ij} \middle| push_i , pull_j , d_{ij} , k_{ij}\right)$ = $\alpha_0 push_i^{\alpha_1} \times pull_j^{\alpha_2} \times f(d_{ij}, k_{ij})$. In case the assumption that the conditional variance is proportional to the conditional mean does not hold (which is often the case), the estimator does not fully account for the heteroskedasticity in the model. For this reason, the inference has to be based on an Eicker-White robust covariance matrix estimator (Eicker, 1963; White, 1980).

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[6] Santos Silva and Tenreyro (2006) provide a clear picture of the magnitude of this bias.

[7] For the sake of completeness, we underline that the Poisson regression has already proposed in the literature as a way to address the problem of zero flows (See for instance, Goodman et al., 1997). However, to our knowledge, Santos Silva and Tenreyro (2006) are the first ones to use this method to address the issue of heterogeneity.

5 DATA AND MODEL SPECIFICATION

Our dependent variable is the number of patients admitted to hospital that flow from each LHA of origin to each possible LHA of destination. We focus here only on those patients that seek care outside the LHA they are enrolled in. Therefore our analysis is akin to a standard gravity model of trade.

Our preferred specification emerged out of an extensive specification analysis we conducted using several other controls not detail here, and considering various forms for the link function.[8] Our search was mainly driven by the correct specification of the conditional mean. This was tested through the RESET test (Ramsey, 1969) and the LINK test (Pregibon, 1980). Although the PPML estimator is consistent even if the variance function is not well specified, we also test for the assumption that the conditional variance is proportional to the conditional mean. If we assume that the conditional variance belongs to the class of variance functions examined by Manning and Mullahy (2001) where $Var(m_{ij}|x) = \lambda_0 E[m_{ij}|x]^{\lambda_1}$, it is possible to estimate λ_1, by running an auxiliary Park-type regression (Park, 1966). Assuming $\overline{m}_{ij}$ denotes the estimated value for $E[m_{ij}|x]$, λ_1 can be obtained by the GLM estimation of the following equation:

$$\left(m_{ij} - \overline{m}_{ij}\right)^2 = \lambda_0 (\overline{m}_{ij})^{\lambda_1} + \xi_i \tag{2}$$

This approach is asymptotically valid and the inference about λ_1 can be made using the Eicker-White robust covariance matrix estimator. Values of λ_1 not statistically different from

[8] A complete report on the specification analysis is available upon request.

1 are consistent with our assumption that the conditional variance is proportional to the conditional mean.

In the following sections we discuss the variables included in our preferred specification. We organize our presentation under the headings of push\pull factors, spatial deterrence, and spatial pattern factors. Tables III and IV provide some descriptive statistics for the included regressors.

INSERT TABLE III and TABLE IV ABOUT HERE

5.1 PUSH AND PULL FACTORS

We are particularly interested in analysing the effects on patient flows of some LHA specific variables. The regressors included in our preferred specification are all proxies capturing the broad concept of quality in the supply of hospital care. Note that all these variables enter the model both as push factors (i.e. referred to the LHAs of origin) and pull factors (i.e. referred to the LHAs of destination).

POPULATION indicates the number of enrollees of the LHA. We will consider this measure in 10,000 units. If we assume that the hospital utilization rate in each given product does not vary with the size of the pool of enrollees then population proxies the internal demand for hospital admissions in each given product arising at a given LHA. There are good reasons to expect that the larger this demand the greater the possibility of reaching scale economies in hospital production and of risk sharing among the enrollees should be, leading to economies of scale in insurance cost. This implication has found empirical support in the analysis of Wholey et al. (1996). Because of such scale effects patients enrolled in bigger LHAs are, other things being equal, more likely to receive high quality, specialized hospital care. Since enrolment is basically defined on the place of residence, Italian LHAs are quite similar to US health maintenance organizations (HMOs) except for the absence of any adverse selection. Therefore our case study is particularly well suited to conducting an empirical test for the presence of scale effect due to the size of the pool of enrolees. We expect that the larger this pool the lower the outflow of patients seeking care outside and the larger the inflow of patients coming from other LHAs will be. According to the specification analysis population enters our gravity models via a power function and an exponential function as follows:

$$E\left(m_{ij} \middle| push_i, pull_j, d_{ij}, k_{ij}\right) =$$

$$\alpha_0 POP_i^{\beta_1} \times \exp(\beta_2 POP_i) \times POP_j^{\beta_3} \times \exp(\beta_4 POP_j) \times f(d_{ij}, k_{ij})$$

This formulation allows for a very convenient, flexible modelling of the elasticity of patient flows to the number of enrollees, which takes the form (with respect to the size of enrollees at the LHA of origin):

$$\varepsilon_{POP_i} = \frac{\partial E\left(m_{ij} \middle| POP_i, POP_j, d_{ij}, k_{ij}\right)}{\partial POP_i} \frac{POP_i}{E\left(m_{ij} \middle| POP_i, POP_j, d_{ij}, k_{ij}\right)} = \beta_1 + \beta_2 \times POP_i$$

The variable INCOME PER CAPITA is measured as the after-tax income per capita available on average to individuals living in a given LHA. It is estimated using data from the Survey on Household Income and Wealth conducted by the Bank of Italy. In the literature on hospital choice income is shown to positively affect mobility, i.e. richer individuals are able to choose destinations further away. However in our aggregate spatial interaction modeling average income per capita is likely to capture broadly defined socio-economic factors operating at each LHA level. We expect to observe, *ceteris paribus*, better quality of care in richer LHAs and therefore an emergent pattern of patient flows moving from poorer to richer LHAs. Finally we include the DOCTORS PER BED ratio defined as the number of doctors per 100 hospital beds. This is a rather commonly used characteristic in the literature on hospital choice, shown to negatively influence the outflows and positively influence the inflows of patients. Both INCOME PER CAPITA and DOCTORS PER BED enter our preferred specification via a power function.

5.2 SPATIAL DETERRENCE

As a result of our specification analysis we reached the following specification for the deterrence function:

$$f(d_{ij}, k_{ij}) = d_{ij}^{\gamma_1 + \gamma_2 BARR_{ij}} \exp(\gamma_3 BARR_{ij}) \exp(\gamma_4 CONTIG_{ij}) \exp(\gamma_5 CONTIG_{ij} * BARR_{ij})$$

The DISTANCE (d_{ij}) between each pair of LHAs has been calculated as the Euclidean norm between the LHAs' centroids.[9] Geo-referenced coordinates of the centroids were constructed from ESRI datasets reporting geographical coordinates (in metres) for each municipality of Italy. The variable was finally expressed in 10 kilometres. Other things being equal, distance should capture the deterrence effect on patient flows due to direct and indirect cost of mobility. Distance enters our preferred specification of the conditional mean via a power function. CONTIGUITY is a dummy variable assuming a value of 1 when the LHAs of origin and destination share a border, and 0 otherwise. This variable is often included in the gravity models as a trade facilitator since contiguity leads trading entities to specialize in a complementary way. This variable assumes a peculiar value in our case study. As a matter of fact it is common practice in the Italian NHS to arrange special agreements between

[9] Other measures of distance could have been adopted in our analysis. We could have considered, for example, the “road distance” between the LHAs` centroids or the “driving time” required to travel from one LHA to another. The computation of these measures of distance, however, is more complex and requires the formulation of more assumptions (for example, travelling routes, average driving speed) than the Euclidean distance between the LHAs` centroids. This also requires adding unavailable data to our study. Therefore, we have chosen to rely on the Euclidean measure as a more objective measure of distance.

contiguous LHAs to handle the problems posed by excess mobility. Finally, the dummy BARRIER, assuming a value of 1 if the “trading” LHAs belong to different regions, and 0 otherwise, is intended as a control for the presence of “institutional barriers” that can affect patient flows.

5.3 CONTROLS FOR SPATIAL PATTERNS

To control for peculiar geographical patterns in hospital admissions in Italy we inserted a set of spatial controls. In our specification analysis we tried several combinations of these controls (and also a full set of regional dummies), ending up with the preferred specification including only REMOTENESS and a proxy for LATITUDE. The variable REMOTENESS is defined as the mean distance (in 10 kilometres) of each LHA from all other LHAs, weighed by the number of enrolees of each LHA. We control for REMOTENESS to allow for the hypothesis that larger distances to all other LHAs might increase, other things being equal, bilateral flows between two LHAs. We expect, coherently with evidence in the empirical literature on trade, this variable to positively affect patient flows (see Deardoff, 1998). This point is clarified by Santos Silva and Tenreyro (2006) when they notice that the most remote countries (LHAs) will tend to trade more between each other because they do not have alternative trading partners (on this point, see also Congdon, 2001). It is well accepted (see Japelli et al., 2007) that the gradient of healthcare quality in Italy declines from north to south. Our proxy for LATITUDE aims at capturing the implications that originate from this stylized fact. This variable is defined as the distance (in 10 kilometres) of each LHA from the LHA that lies furthest north. Therefore this proxy captures how far south in Italy a given LHA lies. Overall we expect it to positively affect the outflow of patients and negatively affect the inflow. Both REMOTENESS and LATITUDE enter our preferred specification via a power function.

6 RESULTS

Table V reports our estimates of the preferred gravity models specification for patients' flows in each considered product: complex surgery, cancer, basic surgery and basic medicine.

INSERT TABLE V ABOUT HERE

All the estimated models pass the LINK test with the notable exception of the one for complex surgery. This one is most likely considered "on the edge of rejection" (the p-value of the test being 0.041). According to the RESET test however the model for complex surgery is clearly to be considered as misspecified. Concerning the particular pattern of heteroskedasticity assumed for our Poisson PML, i.e. conditional variance being proportional to the conditional mean, our Park-type test cannot reject this hypothesis even at very low significance levels. Therefore, by considering the overall results of our specification tests, we believe that our gravity model provides an adequate frame to explain patient mobility in our case for cancer, basic surgery and basic medicine, but not for complex surgery. For this reason, although we present results for this last product in the rest of the paper, we will abstain from commenting on them.

Since we are dealing with a non-linear model, only some of the coefficients presented in Table V are clearly interpretable. Income, docs-to-beds ratio, remoteness and latitude enter the specification via a simple power functions therefore their estimated coefficients are interpretable as (constant) elasticities. It is worth noticing that, when significant, the signs of these elasticities are as expected. In particular we notice that the elasticity of outflows to income is about -3.2/-3.8 while the corresponding inflow elasticity is almost 6 for cancer, 5 for basic surgery and 4.1 for basic medicine. This evidence suggests that a 10% increase in available income reduces patients outflows from an LHA by more than 30% while it quite dramatically increases the inflows (between 40% to 60%). It is therefore quite clearly proved by our analysis that, other things being equal, in Italy patients tend to flow from poorer, less developed LHAs to richer, better endowed ones, especially for the more severe caseload of patients with cancer.

The impacts attributable to population and arguments of the deterrence function can be evaluated provided we estimate appropriate marginal effects and elasticities.

Figures 1 and 2 plot the estimated outflow and inflow elasticities to the size of the pool of enrolees for each LHA in our sample (shaded areas are informative for the estimated 95% confidence interval). To interpret an outflow elasticity let us note that it represents the percentage variation of $\frac{m_{i\bullet}}{POP_i}$ where $m_{i\bullet}$ is the total outflow of patient from LHA i. Assuming that hospital utilization rate in a given product does not vary with the size of the pool this ratio is informative on how dependent an LHA's demand is on the supply from external providers. Similarly, inflow elasticity is the percentage variation of $\frac{m_{\bullet j}}{POP_j}$, where $m_{\bullet j}$ is the total inflow of patient to LHA j, the ratio being the share of external to internal demand for LHA hospital supply.

INSERT FIGURES 1 and 2 ABOUT HERE

According to our estimated models outflow elasticities assume positive, and clearly below one, values for small LHAs. The values decline along the whole range of sizes and turn to zero once a certain size in the pool of enrollees is reached. We evaluate this size to be rather large (approximately 400-600 thousand enrollees depending on the class of treatment). This evidence implies that an LHA's demand for hospital treatment becomes less dependent on the supply from external providers as its size increases. After a given size is reached the total outflow of patients does not increase with total demand. Provided that more than 80% of LHAs in Italy have less than 400 thousands enrollees, we conclude that the ability to restrain "import" of hospital services in Italian LHAs increases with the size of the pool.

Turning to inflow elasticities, it is worth noticing that unit elasticity would imply that the exports-to-internal demand ratio does not change with the size of the pool of enrolees. Values below (above) 1 imply that exports increase at a slower (faster) rate than internal demand. In our case inflow elasticities are always positive and, more remarkably, increase along the whole range of sizes going from values below 1 for the smaller LHAs to values close to or above two for the bigger ones. This implies that the share of export-to-internal demand for LHA hospital care follows a U-shaped curve with a minimum of about 300 thousand enrollees for cancer, and about 500 for basic surgery and basic medicine.

Table VI reports absolute marginal effects and relative marginal effects, estimated at the sample mean, for arguments entering the deterrence function.[10] As expected, CONTIGUITY exerts a positive marginal effect on patient flows which is relatively larger for flows directed to LHAs out of region than for those remaining within the regional border. It is worth noticing that the effect of contiguity is relatively larger the less complex the hospital treatment being considered. This pattern is particularly pronounced in the case of flows directed towards extra regional destinations. With reference to the relative marginal effects, for extra regional flows in basic medicine contiguity results in an increase that is 5.5 times the baseline flow directed to non contiguous LHAs. The corresponding figure is 3.6 for basic surgery and only 1.9 for cancer. This pattern suggests that contiguity strengthens competition for attracting demand

[10] Relative marginal effects are measured as the ratio between the absolute marginal effect and the relevant baseline prediction.

originating outside the region more than that originating within the same region. In a way contiguous LHAs belonging to the same region compete less fiercely to attract patients from each other than those belonging to different regions. Moreover contiguity strengthens competition more in basic medicine.

INSERT TABLE VI ABOUT HERE

Looking at the impact of institutional BARRIER we notice that it exerts an absolute negative marginal effect which is of the same relative magnitude irrespective of contiguity. In a way contiguity is of no help in making a barrier less insurmountable. The deterrence effect of an institutional barrier is clearly larger the more complex the hospital treatment is. Crossing the regional border reduces patient outflows in cancer product by an amount that is .9 times the baseline flow directed to regional destinations. The corresponding relative reductions are smaller for basic surgery and basic medicine.

7 FINAL REMARKS

The geography of hospital admissions in Italy raises policy concerns for issues related to equity of access and financial sustainability. The patients' right to choose their admitting hospital undermines the financial stability of enrolling LHAs. Since the quality of hospital care is not evenly distributed across the country, patients take advantage of their right to be referred to better quality providers, even outside their enrolling LHA. Provided reimbursements follow the patients, funds tend to outflow from LHAs "importing" hospital services to those that "export" them. This situation leads to an uneven distribution of private mobility costs and promotes the accumulation of financial resources towards the already better endowed LHAs. In this paper we try to evaluate to what extent the observed imbalances in the Italian geography of hospital admissions are due to scale effects or reflect the presence of other spatial factors in the distribution of healthcare resources.

We work on an origin/destination matrix comprising of all ordinary admissions to public hospitals in Italy during the year 2001. To control for distance, contiguity, and supply characteristics, we estimated a gravity equation for the full matrix of pair-wise flows as grouped into four broad diagnostic products. We estimate gravity equations adopting a Poisson pseudo maximum likelihood approach, a method that is robust to different patterns of heteroskedasticity and provides a natural way to deal with the zero flows.

Our results suggest that the gravity model is a good framework for explaining the patient mobility phenomenon for most of the examined diagnostic groups. Our evidence suggests that the ability to restrain the import of hospital services from other LHAs increases with the size of the pool of enrolees. Moreover we find that the ability to export hospital services, as proxied by the ratio of export-to-internal demand, is U-shaped. Therefore our evidence suggests that there are scale effects played by the size of the pool of enrolees. Since funds accrue to LHAs on a capitation basis, and smaller LHAs are relatively less likely to contain patient outflows while receiving smaller inflows, the size of the pool is crucial in determining an LHA's financial stability. A natural way to deal with these issues is to adjust resource allocation formulas, namely the capitation rule, to account for the size of the pool.

8 References

Anderson JA, van Wincoop E. 2003. Gravity with gravitas: a solution to the border puzzle. *The American Economic Review* **93** (1).

Cantarero D. 2006. Health care and patients' migration across Spanish regions. *European Journal of Health Economics* **7**: 114–116.

Congdon, P. 2001. The Development of Gravity Models for Hospital Patient Flows under System Change: A Bayesian Modelling Approach. *Health Care Management Science* **4**: 289–304.

Deardorff AV 1998. Determinants of bilateral trade: does gravity work in a neoclassical world?. in Frankel JA (eds.), The Regionalisation of the World Economy, NBER : 7-22.

Eicker F. 1963. Asymptotic normality and consistency of the least squares estimators for families of linear regressions. *The Annals of Mathematical Statistics* **34**: 447-456.

France G, Taroni F, Donatini A. 2005. The Italian health-care system. *Health Economics* **14**: S187–S202.

Frankel J. 1997. *Regional Trading Blocs in the World Economic System*. Institute for International Economics: Washington DC.

Goodman DC, Fisher E, Stukel T, Chang C. 1997. The distance to community medical care and the likelihood of hospitalization: is closer always better?. *American Journal of Public Health* **87**(7): 1144-1150.

Japelli T, Pistaferri L, Weber G. 2007. Health care quality, economic inequality, and precautionary saving. *Health Economics* **16**(4): 327-346.

Levaggi R, Zanola R. 2004. Patient's migration across regions: the case of Italy. *Applied Economics* **36:** 1751-1757.

Lowe JM, Sen A. 1996. Gravity model application in health planning: analysis of an urban hospital market. *Journal of Regional Science* **36**(3): 437-461.

Manning WG, Mullahy J. 2001. Estimating log models: to transform or not to transform?. *Journal of Health Economics* **20**: 461-494.

McCullagh P, Nelder JA. 1989. *Generalized Linear Models,* 2nd ed. Chapman and Hall: London.

McCallum J. 1995. National borders matter: Canada-US regional trade patterns. *American Economic Review* **85**: 615–623.

Morill RL, Earickson R. 1968. Hospital variation and patient travel distances. *Inquiry* **5**: 26-35.

Porell FW, Adams EK. 1995. Hospital choice models: a review and assessment of their utility for policy impact analysis. *Medical Care Research and Review* **52**(2): 158-195.

Pregibon D. 1980. Goodness-of-link tests for generalized linear models. *Applied Statistics* **29**:15–24.

Ramsey JB. 1969. Tests for specification errors in classical linear least squares regression analysis. *Journal of the Royal Statistical Society* B **31**: 350-371.

Roghman KJ, Zastowny TR. 1979. Proximity as a factor in the selection of health care providers: emergency room visits compared to obstetric admissions and abortions. *Social Science and Medicine* **13** D: 61-9.

Santos Silva J, Tenreyro S. 2006. The log of gravity. *The Review of Economics and Statistics* **88**(4): 641-658.

Stillwell JCH. 2008. Inter-regional migration modelling: a review. Chapter 2 in Poot, J, Waldorf, B and van Wissen, L (eds) Migration and Human Capital, New Horizons in Regional Science Series, Edward Elgar, Cheltenham: 29-48.

Studnicki J. 1975. The minimization of travel efforts as a delineating influence for urban hospital service area. *International Journal of Health Service* **5**: 679-93.

White, H. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* **48**: 817-838.

Wholey D, Feldman R, Christianson JB, Engberg J. 1996. Scale and scope economies among health maintenance organizations. *Journal of Health Economics* **15**: 657-684.

TABLES AND GRAPHS TO BE INCLUDED IN THE MAIN TEXT

TABLE I: Performance measures

	EXIT RATE	INFLOW RATE	ACCESSIBILITY	ATTRACTIVENESS	# obs.
OVERALL	27%	21%	105.4	95.8	171
By REGION					
North-West	25%	20%	76.3	107.0	39
North-East	24%	22%	63.4	92.9	45
Centre	24%	21%	90.0	90.4	36
South	36%	22%	196.6	94.5	51

TABLE II: Descriptive statistics: dependent variable

	COMPLEX SURGERY	CANCER	BASIC SURGERY	BASIC MEDICINE
MEAN Patients' flow (#of patients flowing) (all flows)	2.8	4.3	14.3	23.4
SD Patients' flow (all flows)	29.2	47.6	130.2	237.8
% positive flows	0.18	0.20	0.45	0.61
# positive flows	5070	5674	13207	17775
MEAN Patients' flows (positive flows)	15.9	22.2	31.4	38.2
SD Patients' flows (positive flows)	67.8	105.8	191.7	303.2

TABLE III: Descriptive statistics: regressors

Variable	Mean	Std. Dev.	Min	Max
Push/pull factors				
Log population at origin/destination LHA	12.31	0.67	9.57	14.08
Population at origin/destination LHA	27.78	20.86	1.43	130.16
Log income per capita at origin/destination LHA	2.12	0.15	1.71	2.34
Log docs-to-beds ratio in the origin/destination LHA	1.43	0.28	-0.16	2.35
Spatial deterrence				
Log distance	5.72	0.77	2.22	7.01
Contiguity dummy	0.03	0.17	0.00	1.00
Institutional barrier dummy	0.93	0.25	0.00	1.00
Log distance for out of region flows	5.45	1.59	0.00	7.01
Contiguity dummy*Institutional barrier	0.01	0.10	0.00	1.00
Spatial patterns				
Origin/destination LHA's remoteness	5.99	0.18	5.73	6.46
Origin/destination LHA's log distance from the north	5.62	0.91	0.00	6.85

TABLE IV: Descriptive statistics on spatial deterrence factors: positive flows

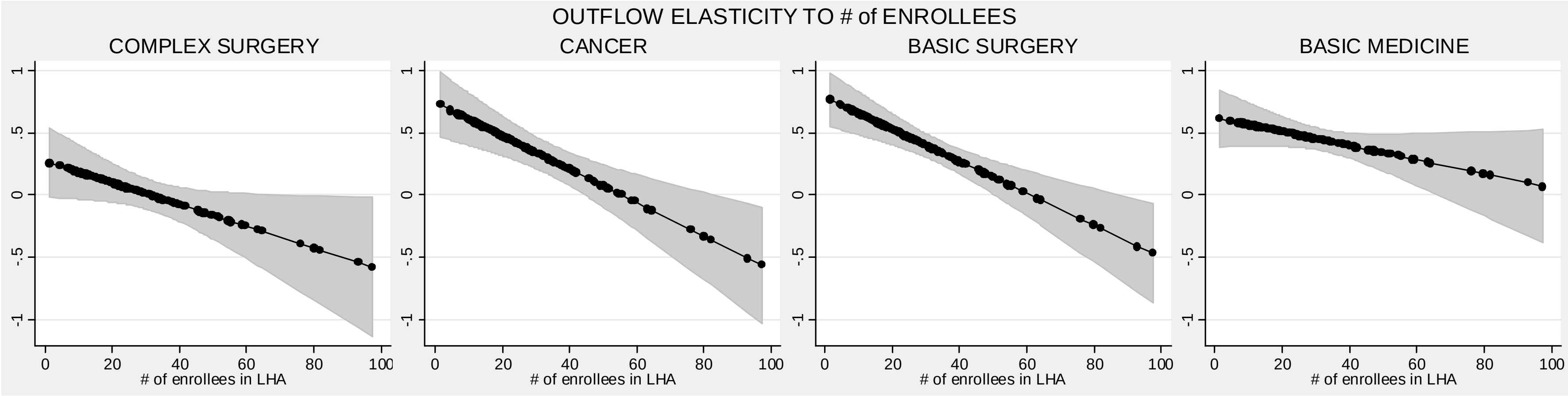
	Mean	Std. Dev.
COMPLEX SURGERY (# obs. 5070)		
Log distance	5.18	1.01
Contiguity dummy	0.14	0.34
Institutional barrier	0.77	0.42
Log distance for out of region flows	4.26	2.45
Contiguity dummy*Institutional barrier	0.04	0.19
CANCER (# obs. 5674)		
Log distance	5.21	1.03
Contiguity dummy	0.14	0.35
Institutional barrier	0.77	0.42
Log distance for out of region flows	4.29	2.47
Contiguity dummy*Institutional barrier	0.04	0.20
BASIC SURGERY (# obs. 13207)		
Log distance	5.47	0.90
Contiguity dummy	0.06	0.25
Institutional barrier	0.86	0.35
Log distance for out of region flows	4.89	2.09
Contiguity dummy*Institutional barrier	0.02	0.14
BASIC MEDICINE (# obs. 17775)		
Log distance	5.59	0.86
Contiguity dummy	0.05	0.21
Institutional barrier	0.89	0.31
Log distance for out of region flows	5.15	1.90
Contiguity dummy*Institutional barrier	0.02	0.12

TABLE V: Model estimates on the reduced set of pairwise flows

VARIABLES	COMPLEX SURGERY	CANCER	BASIC SURGERY	BASIC MEDICINE
Log population at origin LHA	0.267*	0.741***	0.782***	0.621***
	0.071	0.000	0.000	0.000
Population at origin LHA	-0.009**	-0.013***	-0.013***	-0.006
	0.041	0.000	0.000	0.105
Log population at destination LHA	1.013***	0.298**	0.071	0.228*
	0.000	0.046	0.480	0.063
Population at destination LHA	0.008**	0.022***	0.018***	0.014***
	0.019	0.000	0.000	0.000
Log income per capita at origin LHA	-3.409***	-3.757***	-3.248***	-3.453***
	0.000	0.000	0.000	0.000
Log income per capita at destination LHA	9.444***	5.819***	4.854***	4.121***
	0.000	0.000	0.000	0.000
Log docs-to-beds ratio in the origin LHA	-0.204	-0.506***	-0.365***	-0.441***
	0.198	0.000	0.000	0.000
Log docs-to-beds ratio in the destination LHA	0.663***	0.619***	-0.038	0.076
	0.000	0.000	0.731	0.536
Log distance	-0.904***	-0.764***	-0.973***	-1.028***
	0.000	0.000	0.000	0.000
Contiguity dummy	0.895***	0.947***	1.283***	1.315***
	0.000	0.000	0.000	0.000
Institutional barrier	0.670	3.412***	1.988***	-0.126
	0.357	0.000	0.000	0.835
Log distance for out of region flows	-0.504***	-1.047***	-0.704***	-0.218
	0.001	0.000	0.000	0.105
Contiguity dummy*Institutional barrier	0.246	0.130	0.245	0.554***
	0.333	0.568	0.132	0.001
Origin LHA's remoteness	1.253***	1.796***	1.668***	0.571***
	0.000	0.000	0.000	0.010
Destination LHA's remoteness	0.994***	0.085	-0.365	0.719***
	0.003	0.840	0.151	0.003
Origin LHA's log distance from the north	0.447***	0.914***	0.624***	0.352***
	0.001	0.000	0.000	0.000
Destination LHA's log distance from the north	0.356***	-0.232***	-0.210***	0.160*
	0.001	0.004	0.004	0.061
Constant	-41.377***	-26.979***	-15.864***	-13.862***
	0.000	0.000	0.000	0.001
Observations	26625	27357	28955	29041
LINK test p-values	0.041	0.244	0.333	0.852
RESET test p-values	0.000	0.108	0.047	0.697
PARK test p-values	0.291	0.818	0.948	0.908

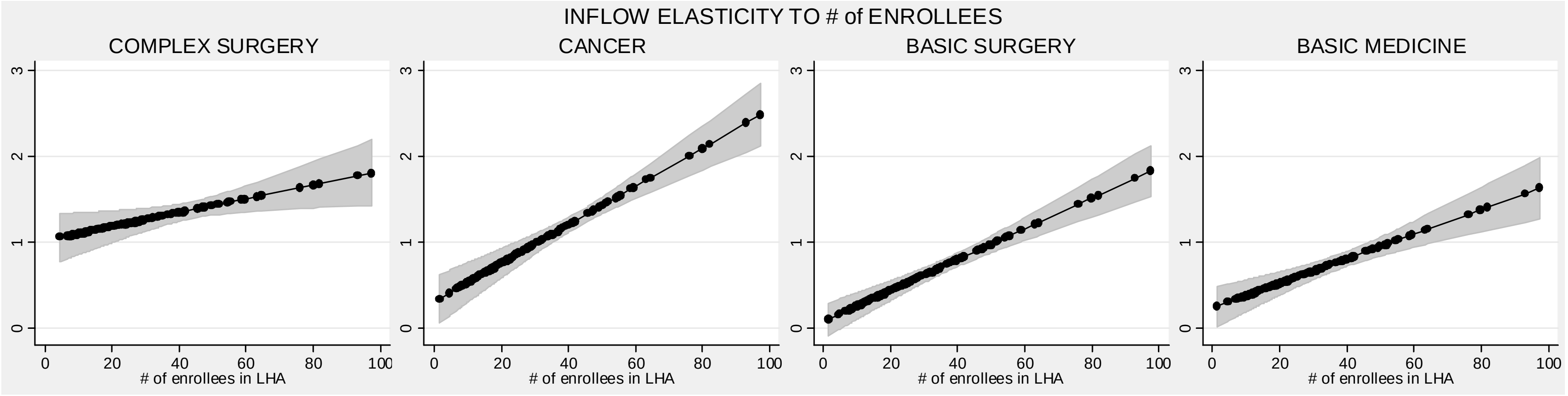
Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. We estimate these models on a slightly reduced set of observations obtained by purging out those destinations (LHAs) that never received any inflow of patients.

Figure 1: Estimated outflow elasticities to the size of the pool of enrolees for each LHA



Note: Shaded area represents the 95% confidence band

Figure 2: Estimated inflow elasticities to the size of the pool of enrolees for each LHA



Note: Shaded area represents the 95% confidence band

Table VI: Absolute marginal effects and relative marginal effects.

	COMPLEX SURGERY	CANCER	BASIC SURGERY	BASIC MEDICINE	COMPLEX SURGERY	CANCER	BASIC SURGERY	BASIC MEDICINE
	Marginal Effect				Relative Marginal Effect			
Contiguity for INTRA Regional flows	3.23	6.92	23.20	31.27	1.45	1.58	2.61	2.73
	(1.25)	(2.77)	(6.22)	(10.28)	(0.39)	(0.39)	(0.41)	(0.49)
Contiguity for EXTRA Regional flows	0.57	0.70	4.36	16.35	2.13	1.93	3.61	5.49
	(0.18)	(0.20)	(0.79)	(2.40)	(0.65)	(0.53)	(0.56)	(0.77)
Barrier for CONTIGUOUS LHAs	-4.84	-10.42	-27.89	-31.73	-0.86	-0.91	-0.83	-0.56
	(1.51)	(3.55)	(7.08)	(11.12)	(0.05)	(0.03)	(0.05)	(0.13)
Barrier for NOT CONTIGUOUS LHAs	-1.98	-4.04	-7.74	-8.56	-0.89	-0.92	-0.87	-0.75
	(0.41)	(1.01)	(1.39)	(2.24)	(0.02)	(0.02)	(0.02)	(0.05)
Distance OVERALL	-0.39	-0.66	-2.09	-4.01	-1.37	-1.74	-1.63	-1.23
	(0.03)	(0.04)	(0.09)	(0.16)	(0.09)	(0.09)	(0.06)	(0.06)
Distance INTRA Regional flows	-2.07	-3.45	-8.99	-12.26	-0.90	-0.76	-0.97	-1.03
	(0.18)	(0.33)	(0.65)	(1.14)	(0.12)	(0.14)	(0.10)	(0.12)
Distance EXTRA Regional flows	-0.36	-0.65	-2.03	-3.83	-1.41	-1.81	-1.68	-1.25
	(0.03)	(0.05)	(0.09)	(0.17)	(0.10)	(0.10)	(0.07)	(0.06)

Note: Robust standard errors in parentheses. All estimates are evaluated at the sample mean. The absolute marginal effects for contiguity and barrier dummies are evaluated by measuring the variation of the prediction when the dummy switches from 0 to 1. Relative marginal effects are measured as the ratio between the absolute marginal effect and the relevant baseline prediction (i.e. dummy set to 0). Standard errors are estimated by the Delta method.

APPENDIX

TABLE A1

PRODUCT	Overall share of hospital treatments	description
CS = Complex Surgery	1.7%	Surgical Neurology Pulmonary Surgery Cardiovascular Surgery Transplants
CA = Cancer	7.8%	Surgical Oncology Medical Oncology Chemotherapy and Radiotherapy
BS = Base Surgery	23.6%	Surgical Ophthalmology Surgical Othorinolaryngology Surgical Gastroenterology Orthopedic Surgery Surgical Endocrinology Urologic Surgery Vascular Surgery General Surgery
BM = Base Medicine	47.6%	Medical Neurology Medical Ophthalmology Medical Otorhinolaryngology Pulmonary Medicine Cardiology Medical Gastroenterology Orthopedic Medicine Medical Endocrinology Urologic Medicine Psychiatry Vascular Medicine General Medicine Rehabilitation
EM = Emergency	4.0%	Surgical traumatology Major traumatology Minor traumatology
HIV	0.5%	HIV
DE = Delivery	14.8%	Gynecology Surgical obstetrics Medical obstetrics Neonatology