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Social interaction in patients' hospital choice: evidence from Italy

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Summary. We study the influence of social interaction on patients' choice of hospital and its relationship with the quality that is delivered by hospitals, using Italian data. We explore the effect on individual choices of a set of variables such as travel distance and individual- and hospital-specific characteristics, as well as a variable capturing the effect of the neighbourhood. The richness of our data allows us to disentangle the influence of sharing information (the network) on patients' choices of hospital from contextual effects. Our empirical investigation suggests that past experience in the utilization of health services by the network plays a significant role in explaining current patients' choices of hospital. Other relevant factors that influence patients' decisions of being admitted in a particular hospital are prior use of health services in that hospital, patient-to-hospital distance and supply factors such as the number of beds and number of doctors. We then investigate the relationship between a set of health outcome indicators and the sensitivity of patients' choices to the network, to test whether sharing information increases the likelihood of selecting a high quality hospital. Our results suggest that social interaction does not have an influence on health outcomes, and in some cases it may even mislead patients, who end up in low quality institutions. One explanation for this result is the absence of a source of information on the quality of hospitals that is accessible to all individuals, such as guidelines or star ratings, which may exacerbate the influence of information that is gathered locally on choices of hospital and may result in a lower degree of competition between hospitals and lower quality.

Keywords: Health care; Quality; Social interaction

1. Introduction

In this paper we empirically study the role that social interaction has on the demand for healthcare in Italy. We investigate whether the choice of hospitals for patients with cardiac illness is influenced by the information that is shared with their peers. Our hypothesis is that individuals, before deciding in which hospital to be treated, may seek advice by speaking with friends, relatives or trusted people experiencing similar health problems in what has been termed by Freidson (1960) a *lay referral network*.

A large empirical literature has supported the important role of social influences in explaining individual choices regarding a variety of economic, social and health behaviours (see Brock

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and Durlauf (2001) and Birke (2009) for a survey). In what follows, we use the terms social interaction, network effects and peer or social influences as synonymous, to indicate what has been referred to by Manski (1993) as an endogenous effect. For example, there is evidence that interaction between economic agents has an effect on unemployment (Conley and Topa, 2002), criminality (Glaeser *et al.*, 1996), the demand for addictive goods (Jones, 1994) or the adoption of technological standards (Skinner and Staiger, 2005). The study of how social interaction affects health services utilization was first investigated by Freidson (1960), who argued that a patient, before seeking professional advice, usually consults an informal network made of, for example, family and friends. Many works, also by the means of interviews and surveys, have attempted to identify such a network effect on the choice of a health specialist, and its influence on individuals' health status (for example, see Schoenberg *et al.* (2003), Chaix *et al.* (2008) and Cornford and Cornford (1999)). For example, Schoenberg *et al.* (2003) and Chaix *et al.* (2008) have provided evidence on the relationship between lay referral patterns and medical care seeking for patients with myocardial infarction and emphasized an increasing effect of the neighbourhood on patients' survival probability. Aizer and Currie (2004) showed that the use of public prenatal and delivery services in California was correlated within groups defined by race, ethnicity and zip code, though such correlation was not found to be linked to information sharing. A recent study by Deri (2005) on Canadian data has detected strong interdependence in the decision of neighbouring people to visit a general practitioner (GP) or a dentist, due, in particular, to social norms and transmission of information.

In the literature that studies the determinants of hospital choices, the role of social interaction has not been explored yet. However, network effects in patients' choices are likely to be strong, especially in healthcare systems where no comparative information on the quality of hospitals is available to all citizens, like in the Italian case. If social influence in choices of hospital is found to exist, one important research question is whether using information from the network increases the likelihood of choosing a high quality hospital. Thus, in this paper we shall also investigate how the sensitivity of patients' choices to local information is associated with hospital quality indicators based on health outcomes. Interacting and sharing information with neighbours does not necessarily help to choose a high quality hospital. For example, the reference group may give importance to attributes, such as appearance, comfort and convenience of hospitals (the so-called amenities; see Goldman and Romley (2010) and Romano and Mutter (2004)), which may not necessarily be related to clinical quality, or more generally neighbours do not hold the basic knowledge to perceive hospital quality correctly.

Studying the effect of interaction between individuals on hospital choice, and its effect on the quality that is delivered by hospitals, has important policy implications. If such an interaction is found to exist and is negatively related to quality then policy makers (e.g. the local authority) should put effort into implementing mechanisms of diffusion of information, for example, by making available to citizens guidelines and comparative information on hospital quality. In the case of a positive relationship between network effects and hospital quality, although on average information sharing leads to better quality, policy makers are called to intervene to reduce geographical inequality in the access to information. As shown (at aggregate level) by a recent strand of literature in public economics (see, for example, Revelli (2006)), interaction may be reduced over time by introducing, for example, publicly released star rating indicators on the performance of hospitals. In particular, Revelli (2006) has provided evidence that interaction between municipalities in the distribution of social care resources reduces over time after the publicly released star rating indicators for the performance of local authorities.

We use data on 144 Italian hospitals from the Lombardy region and on all patients being admitted to these hospitals for a cardiac illness, in the years from 2004 to 2007. Focusing the analysis on this region, rather than the entire nation, allows us to restrict attention to a competitive health system, as established by the 1997 regional health reform (see Section 2 for a description of this reform and how it has introduced competition between hospitals). The Lombardy model, as also emphasized by a recent article in the Wall Street Journal (2010), has received considerable attention for being an examplar in the delivery of high quality healthcare. Another advantage of limiting the study to Lombardy hospitals is that we reduce the heterogeneity that arises from different rules underlying the health systems of other Italian regions.

We consider all patients whose source of admission was elective or emergency room. We note that flows of patients admitted via the emergency room are governed by rules that are different from those driving flows of elective patients. An individual requiring emergency care often cannot choose her hospital, since her admission is mainly determined by external factors such as the availability of beds and the ambulance service. Tay (2003), using data on patients admitted for acute myocardial infarction to US hospitals in 1994, detected that half of heart attack patients arrive at the hospital via ambulance. Even in the cases that these individuals could make a decision, it is very unlikely that they have the opportunity to engage in social interaction before deciding the hospital where to be treated. Therefore, it is reasonable to assume for these patients that they do not use information from the network to make a choice. On the contrary, elective patients have the time to gather information and to consult other people with similar health problems before selecting their hospitals. For these individuals it is plausible that the neighbourhood has some influence on their choices. In this paper we exploit differences between urgent and elective patients in terms of use of network information to identify and measure the effect of social interaction on choices of hospital. Under the assumption that urgent care patients do not exploit the network to make a decision, we use information on these patients to identify contextual (and correlated) factors in choices of hospital (see Manski (1993)), and we interpret the remaining correlation within neighbourhood as the effect of pure social interaction. We observe that other identification strategies may be used. For example, the different information sets of patients who are admitted to a hospital for the first time *versus* those for repeat customers may be used to disentangle the effect of experience from other determinants. In our empirical model we control directly for possible contextual and correlated effects also, by incorporating in the patients' choice equation provincial and local health authority dummy variables, as well as a variable indicating the fraction of people in the neighbourhood sharing the same GP. By including these variables, we aim to capture the correlation that arises from unobserved factors that may affect the behaviour of patients coming from the same province, and/or admitted to hospitals in the same local health authority, as well as the correlation that may arise from GP advice on which hospital to be treated at.

A final point to observe is that, since urgent care patients need immediate care, typically at the closest hospital with an emergency department, their choice set will be very limited and confined to around the place where they live. For this reason, the literature studying admissions of urgent care patients typically considers as the potentially relevant market for each patient the set of hospitals within a short predetermined distance from the patient (Tay, 2003; Romano and Mutter, 2004; Volpp *et al.*, 2003). In contrast, for elective patients the set of choices will be wider and less constrained by geographical factors than in the case of emergency care. For these people, all hospitals compete with each other, and their potentially relevant geographical market is the entire region. Accordingly, in our model of hospital choice, as it includes both types of patient, we shall allow the choice set to vary across patients to account for local and global choice behaviour.

Our estimation and testing strategy allows us to find some interesting results. First, individuals use also neighbours' past experience to make an 'informative' decision on the hospital where to be treated. However, the variables that are linked to social interaction do not swamp the effect of 'traditional' determinants of choice of hospital, such as prior use, geographical distance or hospital characteristics, which still play an important role in explaining individual decisions. Another interesting result is that sharing information does not seem to have a significant influence on the likelihood of choosing a high quality of hospitals and, in some cases, patients who are more dependent on the network seem to end up in low quality hospitals.

The remainder of the paper is organized as follows. Section 2 briefly describes the Lombardy health system and the reform that has introduced competition between hospitals. Section 3 describes the data set. Section 4 discusses the role of social interaction in the choice of the health provider. Accordingly, it introduces a model for patients' choice that includes a measure of social interaction. Section 5 models the relationship of social interaction and a set of quality indicators. Section 6 comments on the empirical findings. Section 7 concludes.

2. Healthcare pro-competition reform in Lombardy

The last decade has witnessed a deep institutional change in the Italian National Health Service, which has gradually transferred the responsibilities for financing and managing healthcare services from the central system to the regions. This has led to a marked heterogeneity in the supply of healthcare services across Italian regions.

The Lombardy region has been the first to implement, through the 1997 regional health reform, an innovative healthcare model that promotes competition between agents and increases patients' choice, with the ultimate aim of improving the quality of healthcare services and to reduce costs. The reform has introduced a net distinction between the role of local health authorities (LHAs) and that of hospitals within the healthcare system. Whereas the LHAs are responsible for programming, financing and controlling the quality and quantity of National Health Service activities in their target area, hospitals provide healthcare services purchased by the LHA. Such a distinction between the purchaser (the LHA) and the provider (the hospital) has led the former to develop tools for monitoring the quality of providers, and the latter to search for quality and technical efficiency. The health reform has also introduced competition between public and private hospitals, by allowing the latter to provide free healthcare. To enter such competition, health providers are required to satisfy minimum technology and organizational standards set by the region. Private hospitals satisfying such standards are indicated as accredited. Although patients are assigned to the LHA on the basis of their place of residence, they have the choice of receiving free healthcare in any (accredited) hospital in the region. In Section 6 we provide some statistics on migration flows of patient between areas.

Since 1995, the Lombardy region has implemented the financing mechanism known as the prospective payment system. This is a financing system where a predetermined fixed reimbursement is paid by the government to the hospital for each patient, on the basis of his or her diagnosis-related group (DRG), which is established by using clinical information reported in the hospital discharge chart (HDC). The reimbursement for a particular DRG does not vary if the length of stay falls within a threshold. The tariff and the threshold rule paid for each DRG is set at a regional level and covers all healthcare services relative to hospital admissions, as well as out-patient activity. The tariff scheme is updated at irregular intervals and may change even more than once within a year. Note that, although other Italian regions are also in the process of adopting the prospective payment system, to date Lombardy is the only region that has *de facto* implemented it.

A great proportion of resources for financing the Lombardy healthcare system is tax based. Whereas out-of-pocket spending is also significant, private health insurance is negligible in

Italy, accounting for less than 1% of total health spending (source: Organisation for Economic Co-operation and Development, health data, 2010). The changes that were introduced by the 1997 reform and discussed above have determined a significant transformation in the supply and demand for healthcare. First, the number of private healthcare facilities has increased, boosting the total number of providers from 181 to 193 in the years from 1995 to 2006. Public hospitals have reduced their number of beds for ordinary admission, while increasing those for day hospital and rehabilitation. Another effect of this reform is that hospital attraction of patients from other Italian regions has significantly increased. In the years from 1995 to 2003, the number of patients from other regions who were admitted to Lombardy hospitals has increased by 34%. For further details on the Lombardy reform we refer to Amigoni *et al.* (1998) and Zangrandi (1998).

3. Sources of data and sample construction

We gathered administrative data on all patients admitted to any hospitals in Lombardy, in the years from 2004 to 2007, whose principal diagnosis is an ischaemic heart disease. (These data were kindly provided by the Region of Lombardy, in conformity with all privacy regulations.) According to the international classification of diseases, 9th revision, clinical modification, which we denote by ICD-9-CM, published by the World Health Organization, these can be subdivided into five categories: acute myocardial infarction, other acute and subacute forms of ischaemic heart disease, old myocardial infarction, *angina pectoris* and other forms of chronic ischaemic heart disease. We removed from the data set any patient whose source of admission was other than the emergency room or elective. We define as *elective* all booked or planned admissions, where patients have been given a date or approximate date at the time that the decision to admit was made. As shown in Table 1, 60–80% of acute myocardial infarction and other acute forms of ischaemic heart disease admissions (i.e. for ICD-9-CM codes 410 and 411) are an emergency. In contrast, only 15–24% of admissions for diseases belonging to the remaining ICD-9-CM categories are an emergency, the rest being ordinary or planned. In this case patients have the time to gather information, perhaps consulting other people, and to plan their choice. We observe that the most common procedures that are performed on elective patients in our data set are angioplasty, coronary bypass and stenting surgery.

Data on patients have been extracted from the HDC that is available for each patient. These include sociodemographic characteristics such as age, gender and place of residence

Table 1. Number of observations and percentage of emergency cases by ICD-9-CM category†

Year	*Total, N*	*Results for the following categories:*									
		410		*411*		*412*		*413*		*414*	
		N	*% emergency*	*N*	*% emergency*	*N*	*% emergency*	*N*	*% emergency*	*N*	*% emergency*
2004	57351	19439	79.97	10603	59.48	1365	15.90	12501	23.21	12501	18.60
2005	58291	21067	80.91	10864	58.71	1095	17.99	11273	23.16	13992	19.63
2006	56730	13992	82.14	10472	61.01	931	17.99	10853	24.54	13484	18.93
2007	58230	21232	83.60	10346	63.05	852	21.24	10688	23.41	15112	18.79

†See Table 2 for definitions of the variables.

(the municipality), clinical information like principal diagnosis, severity of the illness, length of stay, the type of admission (planned or via the emergency room), the ward of admission, type of discharge (e.g. death), and financial information such as the DRG and HDC reimbursement. We also gathered information on postal code of residence of patients, their mortality and the GP with whom they are registered from the General Register Office. The characteristics of the hospital include its capacity expressed in its number of beds, the number of doctors employed, its ownership (e.g. private or public), teaching status, whether it is a specialist hospital and the LHA to which the hospital belongs. We also have a variable indicating whether it has a catheterization laboratory, namely, an examination room with diagnostic imaging equipment that is used to support catheterization procedures. We refer to Table 2 for a description of the variables that are used in our analysis.

We kept records only for public or private hospitals that are accredited by the region, thus providing free healthcare (see Section 2 on this). By excluding non-accredited hospitals, we dropped from our analysis a few observations (less than 1% of our sample). We also cleaned the data by eliminating records with missing entries on either the hospital or the patient identifier. After this selection process, our data set contains around 230 600 patients admitted to 144 hospitals.

4. Social interaction in patients' choice of hospital

In healthcare systems with fixed prices and where patients have free choice of hospitals, the quality that is delivered by hospitals is an important determinant of individuals' choices. However,

Table 2. Definition of variables

Variable	*Description*
Patient characteristics	
Distance_{ih}	Distance of patient i to hospital h − distance of i to her nearest hospital
Prior use_{ih}	1 if patient i has already been admitted to hospital h in the previous 12 months
Old_i	1 if patient i is over 75 years of age
Males_i	1 if patient i is male
ICD-9-CM=410_i	1 if patient i suffers from acute myocardial infarction
ICD-9-CM=411_i	1 if patient i suffers from other acute and subacute forms of ischaemic heart disease
ICD-9-CM=412_i	1 if patient i suffers from old myocardial infarction
ICD-9-CM=413_i	1 if patient i suffers from *angina pectoris*
ICD-9-CM=414_i	1 if patient i suffers from other forms of chronic ischaemic heart disease
Elective_i	1 if patient i's admission is booked or planned
GP_i	100 × number of patients in the postal code area sharing the GP with i/number of patients in the postal code area
Price_i	Total expenditure for patient i
Hospital characteristics	
n. beds_h	Total number of beds (ordinary plus day hospital) in hospital h
$\text{n. doctors per n. beds}_h$	Number of doctors in hospital h/number of beds in hospital h
$\text{Read. within 30 days}_h$	100 × number of readmissions in hospital h within 30 days/number of admissions in hospital h
$\text{Death within 30 days}_h$	100 × number of deaths within 30 days/number of admissions
Teaching_h	1 if hospital h is teaching (i.e. it provides clinical education and training to doctors or nurses etc.)
Specialist_h	1 if hospital h is specialist (i.e. it specializes in a particular area of treatment)
Private_h	1 if hospital h is private
Technology_h	1 if hospital h has a catheterization laboratory
Large_h	1 if hospital h has more than 299 beds

differences of quality between hospitals may be difficult for people to observe. These constraints have raised concerns among policy makers on whether hospital markets are competitive and have encouraged initiatives to diffuse information about 'true' hospital quality. Institutions such as the National Committee for Quality Assurance in the USA and the Care Quality Commission in the UK diffuse reports on comparative information, or star rating indicators, about the quality of hospitals in terms of rates of post-operative mortality, hospital-acquired infections and readmission rates. We observe that the influence of quality reports on choice of hospital is still controversial. Some studies have determined a low influence of these reports on the selection of the health provider (see, for example, Schneider and Epstein (1996) and Cutler *et al.* (2004)). Schneider and Epstein (1996), by interviewing a sample of patients from Pennsylvania, found that only 14 of 474 patients questioned consulted available public information on the hospital for their selection of a clinic. For New York State, Jha and Epstein (2006) reported no significant changes in the market share of cardiac patients due to the introduction of the cardiac surgery ratings. Some researchers pointed at badly prepared and incomprehensible information on quality of hospital as one reason why patients do not always react to information about quality (Wubker *et al.*, 2008). In contrast, other studies have found a positive relationship between the published quality of a hospital and its market share, showing that the demand reacts especially when the published actual quality deviates significantly from expected quality (see, for example, Pope (2009) and Romano and Zhou (2004)).

Another way of diffusing information on hospital quality is by training local GPs. The UK healthcare system for example has explored the possibility of implementing educational meetings for GPs to standardize GP referral behaviour, and ultimately to reduce unplanned admissions.

Since true hospital quality is difficult to observe, and choosing a low quality hospital could be costly, individuals try to obtain as much information as possible when making a choice. Therefore, it may be sensible to use information about the decisions of others with the same pathology, who have had a comparable decision to make. Friends, relatives or trusted people who have experienced a similar health problem may act as filters for the quality of hospitals, thus shaping preferences of individuals. Individuals may also seek reassurance about whether their thinking is reasonable, by looking at whether people with similar features have come to the same conclusion. These processes may be more relevant in healthcare systems where no measures are publicly available on the performance of hospitals, like in the Italian case. We observe that, in systems that provide star rating indicators, information that is gathered locally can reinforce or be in contrast with that provided at the central level by the star ratings.

It is plausible that an individual who is admitted at a particular point in time may not observe choices of people who were admitted in the same period but can easily gather information from the choices of patients who were admitted in the past. Therefore, in this paper we assume as neighbours for a patient admitted at time t all individuals sharing the same pathology, admitted to (and discharged from) any hospital in the region in the 12 months before time t, alive after the hospitalization and living in the same postal code area.

As suggested by Manski (1993) and Brock and Durlauf (2001), correlation between the behaviour of a patient and that of her neighbourhood could reflect not only social influences but also the effect of other factors. In particular, such interdependence may arise because of contextual effects, if individual action varies with observed attributes that define her group membership, or correlated effects, if individuals in the same group tend to behave similarly because they have similar characteristics or they face similar opportunities and constraints. For example, the decision to refer patients for hospital admission by the local GP may induce contextual effects in choices of hospital. An example of correlated effects is the behaviour of hospitals towards certain categories of patients. Indeed, some hospitals may encourage or discourage groups of individuals from presenting on the basis of whether it is profitable or not to treat them (the so-called 'cream skimming' effect; see Berta *et al.* (2010) on this).

Our strategy to disentangle social interaction and contextual or correlated effects is based on estimating the correlation between the behaviour of a patient and that of her neighbourhood for patients on both emergency and non-emergency care. Under the plausible assumption that patients in emergency care cannot engage in communication with other people when choosing their hospital, the additive neighbourhood effect of elective patients is likely to reflect pure social interaction.

In the following section we introduce an econometric model for individuals' choices of hospital, and we define a measure of social interaction.

4.1. Modelling patients' choice of hospital

Consider an individual i with cardiac illness from a population of N agents choosing from a set of H_i hospitals, i.e. from $\{1, 2, \ldots, H_i\}$, at time t. We assume that each individual is drawn randomly from a set of neighbourhoods and that, within each neighbourhood, all individuals interact with each other. Thus, membership of various neighbourhoods is not endogenously determined. Suppose that the observable choice of individual i of being admitted to hospital h at time t, $y_{ih,t}$, is related to the expected utility of i choosing h, $y^*_{ih,t}$, according to $y_{ih,t} = \mathbf{1}[y^*_{ih,t} > 0]$, where $\mathbf{1}[\cdot]$ is an indicator function.

The literature on social interaction decomposes $y^*_{ih,t}$ into three components: the private utility, the social utility and a random-utility term (Brock and Durlauf, 2003). In this paper we hypothesize that private utility of the ith patient from choosing hospital h at time t depends on her characteristics, $\mathbf{x}_{it}$, the characteristics of hospital h, $\mathbf{z}_{ht}$, and the distance of i from h relative to the distance from her nearest hospital, $d_{ih,t}$. We further assume that social utility depends on $\bar{y}_{ih,t-1}$, the percentage of people with identical category of disease and living in the same postal code area who made the same choice in the 12 months before the admission of the ith patient and who are alive after hospitalization. We refer to Brock and Durlauf (2001) for a discussion of the dependence of social utility on past society behaviour. Although the variable $\bar{y}_{ih,t-1}$ captures the number of patients with the same diagnosis who choose the same hospital in the previous year, the treatments and procedures used to cure these patients might have been different.

Accordingly, we model patient i's expected utility at time t from choosing h out of a total of H_i hospitals, $y^*_{ih,t}$, as

$$y^*_{ih,t} = \alpha + \theta_h \bar{y}_{ih,t-1} + \delta_h (\bar{y}_{ih,t-1} \, \text{elective}_{it}) + \boldsymbol{\beta}'_h \mathbf{x}_{it} + \boldsymbol{\gamma}' \mathbf{z}_{ht} + \eta d_{ih,t} + \varepsilon_{ih,t}, \tag{1}$$

where α, θ_h, δ_h, $\boldsymbol{\beta}_h$, γ and η are parameters to be estimated. Under the further hypothesis that each individual makes the choice that maximizes her total utility, and the double-exponential assumption for the random-utility term, the multinomial logit structure can be derived for the conditional probability that i chooses h (see Brock and Durlauf (2003)).

In the above model, elective_{it} is an indicator variable taking value 1 if individual i's source of admission is elective and 0 otherwise. The vector of individual-specific characteristics, $\mathbf{x}_{it}$, contains demographic, health and geographic attributes, such as gender, age, whether patient i's source of admission is elective, the disease category (ICD-9-CM) and a dummy variable indicating the province where the patient lives. Note that around 86% of patients in our data set share the GP with at least another patient in the data set (see Table 6 in Section 6.1). Hence, we have decided to include the variable GP_i, given by the percentage of the patients living in the same neighbourhood (the postal code) and sharing the same GP. Around 22.40% of observations in

Table 3. Descriptive statistics of patients

Statistic	*Results for the following years:*			
	2004	*2005*	*2006*	*2007*
% males	68.98	69.07	69.86	69.42
Age (average years)	67.83	68.28	68.43	68.43
% 65–74 years	29.51	29.44	29.28	29.15
% $\geqslant$ 75 years	28.62	30.20	31.12	31.93
Length of stay (average number of days)	9.14	9.01	8.78	8.56
Expenditure per patient (average) (€)†	5117.4	5208.5	5288.5	5400.4
30-day readmission (%)	9.54	9.00	8.71	8.13
30-day mortality (%)	4.72	5.08	5.01	5.05

†The aggregate has been deflated by using the consumer price index (2005 ≡ 100).

our data set refer to individuals who have already experienced a hospital admission in the last 12 months, and roughly half of these individuals choose the same hospital. Accordingly, in our regression we have added the dummy prior use$_{ih}$, taking value 1 if patient i has already been admitted to hospital h in the past 12 months and 0 otherwise. We also incorporate in the model interactions of $\bar{y}_{ih,t-1}$ with the patient-to-hospital distance and with a dummy variable indicating whether the patient is aged 75 years or over, to see whether the network is more influential in certain categories of population. The vector of hospital-specific characteristics, $\mathbf{z}_{ht}$, contains the size, the LHA of the hospital, the number of doctors per number of beds, ownership and teaching status, dummy variables indicating whether the hospital is specialist and whether it has a catheterization laboratory (Jensen *et al.*, 2009). See Table 2 for the definitions of the variables. We also add in the model the interaction of $\bar{y}_{ih,t-1}$ with a dummy variable indicating whether the hospital is large, to check whether network effects are weaker or stronger for larger hospitals. In a separate regression we also try to incorporate in model (1) indicators capturing true hospital clinical quality. We do this because we cannot exclude the possibility that patients have other channels of information (e.g. the cardiologist's advice) on the clinical quality of a particular hospital (Luft *et al.*, 1990). We focus on two health quality indicators: the outcome variables readmission and mortality within 30 days from discharge, which are commonly used indicators in the literature (see Table 3 for some descriptive statistics). We express our quality indicators as percentages over total admissions. We refer to Romano and Mutter (2004) for a review of quality indicators that have been adopted in the literature.

Finally, in our model we have incorporated dummy variables for the LHA to capture unobserved heterogeneity in health policies at LHA level, and province dummy variables to account for contextual effects, including recommendations by the local GP. The influence on patients' choice of the local GPs is (in part) detected by the dummy variable GP$_i$ and may also be captured by the hospital-specific characteristics (see Luft *et al.* (1990) on this).

As explained at the beginning of this section, the coefficient δ_h that is attached to the variable $\bar{y}_{ih,t-1}$ elective$_{it}$ measures the correlation between individual behaviour and the behaviour of her neighbours as an effect of pure social interaction. We allow this parameter to vary across hospitals. We remark that estimation of one coefficient for each hospital is possible only if there is some geographical variability in patient flows within hospitals that enables identification of parameters. This is not a problem for our analysis, as shown in our exploratory data analysis. It is also worth nothing that, since the above model contains neighbours' lagged decisions, it does not entail any restriction on the size of the interaction effects, δ_h and θ_h. The interpretation of δ_h plays a central role in our study. $\hat{\delta}_h$, which is obtained from estimating equation (1), measures the average effect of neighbourhood choices on the probability that a patient chooses the hth hospital. A positive and significant $\hat{\delta}_h$ means that a subset of the population, sharing information on the quality of the hth hospital, increases the conditional probability of choosing it for each member of this subset. A negative and significant $\hat{\delta}_h$ implies that, *ceteris paribus*, a patient on average will make a choice that is different from that of her neighbours, in relation to the hth hospital. Namely, individuals choosing the hth hospital are surrounded by people who, on average, have not been admitted to that hospital in the past. The key mechanism underlying a significant $\hat{\delta}_h$, either positive or negative, is the existence of clusters of information on the quality of the hth hospital. Such information shapes the preferences of individuals, ultimately influencing their decisions. An insignificant $\hat{\delta}_h$ means that patients do not use information from the network to choose that hospital, and hence their choice is driven only by personal and hospital level characteristics.

Before concluding, we remark that in equation (1) we allow the choice set to vary across patients. As pointed out in Section 1, the potentially relevant geographical market differs between patients who are admitted via the emergency room and all other patients. Indeed, we believe that hospitals compete for urgent care patients in a localized market, as opposed to a global market where all hospitals compete with each other for non-urgent-care patients. Therefore, for patients in emergency care we restrict the choice set to the hospitals within a distance of 15 km from where they live, whereas for patients who are not under emergency we extend the choice set to include all hospitals in the region. Some robustness checks show that using two different choice sets rather than the same unconstrained set for both types of patient does not significantly affect the results.

Whether there is a relationship between δ_h and quality has important policy implications. In the next section we shall introduce a measure of quality and discuss its link with social interaction.

5. Social interaction and the quality of healthcare

We estimate the relationship between social interaction and the quality of hospitals at individual level by using a regression framework. As quality indicators, we consider the outcome variables readmission and mortality within 30 days of discharge, which are commonly used indicators in the literature. We refer to Romano and Mutter (2004) for a review of quality indicators that have been adopted in the literature.

If the correlation between $\hat{\delta}_h$ (in absolute value) and quality is either insignificant or negative and significant then, on average, sharing information within the neighbourhood does not help to select a hospital with better quality. Since quality is inversely related to our quality indicators, this implies that the correlation between $|\hat{\delta}_h|$ and our quality indicator—readmission within 30 days—is insignificant, or positive and significant. In this case, social interaction does not help in choosing a high quality hospital. One possible reason behind such a mismatch is, for instance, that the group identifies hospital quality not only with clinical quality but also with amenities such as convenience, good food, attentive staff and pleasant surroundings. Conversely, a positive and significant correlation between $|\hat{\delta}_h|$ and the level of quality of hospital (namely, whether the correlation between $|\hat{\delta}_h|$ and $q_{ih,t}$ is negative and significant) indicates that social interaction is related to higher quality. In this case, the reference group can identify and suggest high quality hospitals. From a policy perspective, in both cases (negative and positive relationships between social interactions and quality) more information is needed, perhaps accompanied by an effective advertisement (e.g. through the media). However, we believe that the existence of a negative relationship between the network effect and quality of hospital would call policy makers to create specific interventions to contrast such local interaction, by convincing citizens that the network may often be wrong. One example of interventions is an advertisement (e.g. through television) that explains to the citizen what are the appropriate sources of information and warning them against misinformation coming from non-expert advice.

We consider the following regression model for the latent continuous variable $r^*_{ih,t}$ underlying our quality indicators:

$$r^*_{ih,t} = \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\gamma}'\mathbf{z}_{h,t-1} + \lambda\hat{\delta}_h + \varphi\,\mathrm{pr}_{it} + \varepsilon_{ih,t}, \qquad (2)$$

where $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, λ and φ are parameters to be estimated, $\mathbf{x}_{it}$ indicates the individual-specific characteristics—age, gender, disease category and a dummy variable indicating whether the patient's source of admission was elective—$\mathbf{z}_{ht}$ is the vector of hospital attributes, namely the number of beds, number of doctors per number of beds, LHA dummy variables, ownership and teaching status, and whether the hospital is specialist. The variables 'n. of beds' and 'n. doctors per n. beds' have been lagged at time $t-1$ to avoid potential endogeneity problems. Other hospital-specific characteristics, such as whether the hospital is private, specialist or teaching oriented, can be considered as fixed attributes, established well before the time period that is considered in this analysis. The variable pr_{it} is the regulated (hence exogenous) price attached to the HDC of the ith individual. This variable is included in the regression to control for the effect of different reimbursements that are disease specific, and for variations in the DRG reimbursements that occur within a year. The coefficient λ that is attached to $\hat{\delta}_h$ indicates the sensitivity of indicators of quality to changes in social interaction. Again, we assume a logistic specification for the conditional probability.

Before concluding this section, we remark that, although estimated at individual level, equation (2) carries information on the influence of social interaction on quality of hospital. Indeed, the coefficient that is attached to $\hat{\delta}_h$ explains differences in health outcomes across groups of patients due to variations in social interaction, where the group is made of patients belonging to the same hospital h. Using data at individual level rather than aggregated at hospital level has the advantage of enabling us to control for patients' characteristics.

6. Results

6.1. *Exploratory data analysis*

Table 3 shows some descriptive statistics that can be recovered from patients' HDCs. As expected in the case of heart diseases, the number of males in the data set is high, accounting for around 75% of the sample. The average age of patients is 68 years, and roughly 30% of the sample is more than 75 years old. The length of stay of patients reduces over time, passing from 9.14 to 8.56 days on average. The bottom panel of Table 3 summarizes the variables that were used to capture hospital clinical quality in equation (2), namely readmission and mortality within 30 days from the date of discharge, expressed as percentages over total admissions. The readmission variable has been constructed by including all patients who have been readmitted at least once in the period considered, also via the emergency room. Readmission within a fixed length of time as a quality indicator has been employed in various studies on hospital quality, such as Kessler and McClellan (2000) and Ho and Hamilton (2000). The relatively high likelihood of 30-day readmission (around 9% of the sample; see Table 3) suggests that this is an appropriate measure of quality of hospital. As for 30-day mortality, the other quality indicator that is used in our analysis, Table 3 shows that this outcome concerns *circa* 5% of our

Table 4. Lombardy hospital characteristics

Characteristic	*Results for the following years:*			
	2004	*2005*	*2006*	*2007*
Number of hospitals	128	132	129	127
Catheterization laboratory	51	60	63	69
Teaching (number)	10	10	10	10
Specialist (number)	10	10	8	6
Public (number)	85	86	83	80
Patients (average number)	448.7	441.5	439.7	458.5
Medium† (%)	49.22	47.73	48.06	51.97
Large‡ (%)	29.69	30.30	30.23	31.50
Beds (average number)	259.8	262.53	267.4	275.7
Ordinary	233.0	235.3	239.3	245.5
Day hospital	26.83	27.22	28.06	30.23
Doctors per number of beds	0.53	0.54	0.55	0.55

†Medium hospitals are those with a number of beds between 100 and 299.
‡Large hospitals are those with more than 299 beds.

sample. Such a small figure can be explained by the lower risk of dying of elective patients in our sample.

Table 4 summarizes the characteristics of hospitals in the data sets. We observe an increasing pattern in the average number of total beds, passing from around 260 to 276, indicating that hospitals tend to expand in size over time. Such a trend is largely explained by the rise in the number of ordinary beds. The number of doctors per number of beds ranges between 0.53 and 0.55.

Table 5 reports some descriptive statistics on migration flows of patients, as well as join count measures of spatial correlation. The upper panel shows that the average patient-to-hospital distance is around 55 km. However, when restricting the sample only to those living in Lombardy (around 91% of the sample), the average patient-to-hospital distance drops to 12 km; 8 and 16 km respectively for emergency and elective patients. The middle panel shows that the majority of emergency patients (around 83%) choose a hospital within 15 km from their residence, whereas only 55% of elective patients make such a choice. If we extend to 50 km from the place of residence, we note that around 20% of elective patients move out of their area of residence, choosing a hospital that is at least 50 km away from their residence. These statistics seem to support our selection for different choice sets of emergency and elective patients in the estimation of equation (1). The lower panel of Table 5 reports the average number of people living in the same neighbourhood and choosing the same hospital. It is interesting to note that a large fraction of people living in the same postal code area and with similar disease (i.e. the same category of disease) make similar choices, and that these figures tend to remain constant over time. The lower panel of Table 5 also shows join count statistics of spatial correlation. We adopt the statistic

$$n_{H,t} = \frac{1}{2} \sum_{h=1}^{H} \left(\sum_{i=1}^{N} \sum_{j=1,\, i \neq j}^{N} s_{ij} c_{ih,t} c_{jh,t} \right),$$

where $c_{ih,t} = 1$ if at time t individual i chooses hospital h, and $c_{ih,t} = 0$ otherwise, and $s_{ij} = 1$ when i and i belong to the same postal code, and $s_j = 0$ otherwise. Under the null hypothesis of independence in choices of hospital of neighbouring individuals, this statistic has approximately mean 0. We refer to Epperson (2003) for a detailed discussion on the theoretical moments and

Table 5. Migration flows of patients and their concentration across the territory

	Results for the following years:			
	2004	*2005*	*2006*	*2007*
Average patient-to-hospital distance (km)	56.99	54.83	54.12	53.70
Average patient-to-hospital distance (Lombardy only, km)	12.36	12.25	12.35	12.59
Emergency patients	8.45	8.81	9.02	9.28
Elective patients	16.46	16.10	16.33	16.55
Median patient-to-hospital distance (km)	6.86	6.79	6.85	7.16
Migration characteristics for emergency patients				
% admitted within 15 km of residence	83.70	82.32	81.96	81.35
% admitted within 25 km of residence	92.62	91.75	91.36	91.06
% admitted within 50 km of residence	96.92	96.76	96.34	96.28
Migration characteristics for elective patients				
% admitted within 15 km of residence	54.84	55.60	55.57	54.97
% admitted within 25 km of residence	68.93	69.67	68.99	67.99
% admitted within 50 km of residence	81.38	81.58	80.88	80.63
Number of patients in the neighbourhood with same choice	50.23	46.06	44.22	41.54
% patients in the neighbourhood with same choice	38.40	37.59	37.96	37.04
$n_{H,t}$	2.16‡	2.03‡	2.18‡	2.13‡

†For these statistics we focus only on patients living in the Lombardy region.
‡Significant at the 5% level.

the distribution of this statistic. If the null hypothesis of absence of spatial correlation is rejected and the statistic is significantly larger than its expected value, it indicates positive spatial auto-correlation, meaning that patients with similar choices of hospital are more spatially clustered than could be caused by chance. The estimated $n_{H,t}$-statistic is positive and significant in all years, although it shows a slight decrease over time.

Table 6 shows the distribution of GPs across patients in the data set. Around 86% of patients share a GP with one or more patients in the sample, and on average nine patients in the data

Table 6. Distribution of GPs across patients

Variable	*Results for the following years:*			
	2004	*2005*	*2006*	*2007*
Number of GPs†	7037	6998	6962	6908
Number of patients sharing GP‡	41784	43224	42678	44672
% patients sharing GP	85.59	86.07	85.98	86.61
Average number of patients with same GP	9.83	9.96	9.87	10.20

†This variable is the number of GPs who treat patients in the data set.
‡This variable measures the number of patients in the data set who share the GP with at least another patient in the data set.

set are registered with the same GP. Sharing a GP clearly may induce correlation in patients' behaviour that needs to be taken into account when modelling patients' choice of hospital.

6.2. Social interaction in patients' choice of hospital

We estimated model (1) by maximum likelihood over the sample period 2005–2007, and for each year separately. In the estimation of this model we focused only on patients living in the Lombardy region, to avoid potential heterogeneity in patients flows from other provinces of Italy. When excluding patients living in provinces outside the Lombardy region, we dropped around 8% of the sample (see Table 5). We also dropped hospitals with fewer than 50 observations (i.e. patients) within a year, since estimation of one set of regression coefficients for each hospital requires enough observations for each hospital.

Tables 7 and 8 report the output for the estimation of equation (1) for the sample period 2005–2007, as well as for each year separately, imposing that regression coefficients are homogeneous

Table 7. Determinants of patients' choice of hospital†

Variable	*Results for the following periods:*							
	2005–2007		*2005*		*2006*		*2007*	
	Coefficient	*Standard error*	*Coefficient*	*Standard error*	*Coefficient*	*Standard error*	*Coefficient*	*Standard error*
Elective$_i$	−2.841‡	0.018	−2.851‡	0.031	−2.825‡	0.033	−2.878‡	0.031
$\bar{y}_{ih,t-1}$	0.061‡	0.001	0.056‡	0.001	0.074‡	0.001	0.055‡	0.001
$\bar{y}_{ih,t-1}$*Elective$_i$	0.029‡	0.001	0.027‡	0.001	0.034‡	0.001	0.028‡	0.001
Prior use$_{ih}$	6.244‡	0.055	6.296‡	0.092	6.014‡	0.100	6.307‡	0.093
Age$_i$	−0.001	0.000	−0.001	0.001	−0.001	0.001	−0.001	0.001
Male$_i$	−0.030‡	0.010	−0.025	0.018	−0.033	0.020	−0.033	0.018
Distance$_{ih}$	−0.261‡	0.003	−0.264‡	0.004	−0.255‡	0.005	−0.267‡	0.005
ICD-9-CM=411$_i$	0.100‡	0.015	0.104‡	0.025	0.087‡	0.027	0.109‡	0.025
ICD-9-CM=412$_i$	0.102‡	0.041	0.202‡	0.070	−0.194‡	0.076	0.200‡	0.070
ICD-9-CM=413$_i$	0.165‡	0.016	0.162‡	0.027	0.143‡	0.029	0.187‡	0.027
ICD-9-CM=414$_i$	0.169‡	0.016	0.170‡	0.027	0.143‡	0.029	0.191‡	0.027
GP$_i$	0.007‡	0.000	0.006‡	0.000	0.008‡	0.000	0.006‡	0.000
$\bar{y}_{ih,t-1}$*age$_i$	0.001‡	0.000	0.002‡	0.001	0.001	0.001	0.002‡	0.001
$\bar{y}_{ih,t-1}$*distance$_{ih}$/100	0.024‡	0.003	0.002	0.005	0.065	0.005	0.003	0.005
$\bar{y}_{ih,t-1}$*Large hospitals$_h$§	0.001	0.000	0.003‡	0.001	−0.007‡	0.001	0.003‡	0.001
Catheterization lab.$_h$	−0.260‡	0.019	−0.257‡	0.034	−0.261‡	0.033	−0.277‡	0.034
n. beds$_h$/100	0.091‡	0.002	0.093‡	0.003	0.090‡	0.003	0.092‡	0.003
n. doctors per n. beds$_h$	0.774‡	0.033	0.829‡	0.061	0.608‡	0.057	0.848‡	0.061
Specialist$_h$	1.389‡	0.028	1.656‡	0.051	1.031‡	0.049	1.667	0.051
Teaching$_h$	−0.033‡	0.014	−0.062‡	0.024	−0.009	0.025	−0.070‡	0.024
Private$_h$	−0.043‡	0.010	−0.051‡	0.017	−0.044‡	0.019	−0.047‡	0.017
Number of observations	109146		36709		36011		36426	
Log-likelihood	−240963.1		−84617.6		−82679.1		−84619.9	

†LHA and province dummy variables have been included. Robust standard errors against unknown heteroscedasticity have been used. See Table 2 for a definition of the variables.
‡Significant at the 5% level.
§Hospitals with more than 299 beds.

Table 8. Determinants of patients' choice of hospital, including hospital quality (years 2005–2007)†

Variable	*(I)*		*(II)*	
	Coefficient	*Standard error*	*Coefficient*	*Standard error*
Elective_i	−2.813‡	0.018	−2.806‡	0.018
$\bar{y}_{ih,t-1}$	0.062‡	0.001	0.062‡	0.001
$\bar{y}_{ih,t-1}{*}\text{Elective}_i$	0.028‡	0.001	0.028‡	0.001
Prior use_{ih}	6.229‡	0.055	6.193‡	0.055
Age_i	−0.001	0.000	−0.001	0.000
Male_i	−0.031‡	0.011	−0.030‡	0.010
Distance_{ih}	−0.262‡	0.003	−0.262‡	0.003
ICD-9-CM=411_i	0.099‡	0.015	0.094‡	0.015
ICD-9-CM=412_i	0.089‡	0.041	0.090‡	0.041
ICD-9-CM=413_i	0.146‡	0.016	0.152‡	0.016
ICD-9-CM=414_i	0.154‡	0.016	0.154‡	0.016
GP_i	0.007‡	0.000	0.007‡	0.000
$\bar{y}_{ih,t-1}{*}\text{age}_i$	0.001‡	0.000	0.001‡	0.000
$\bar{y}_{ih,t-1}{*}\text{distance}_{ih}$ /100	0.020‡	0.003	0.020‡	0.003
$\bar{y}_{ih,t-1}{*}$Large hospitals_h§	−0.044	0.050	0.000	0.000
Quality_h(readmission within 30 days)	−0.035‡	0.001	—	—
Quality_h(death within 30 days)	—	—	−0.087‡	0.002
Catheterization lab._h	−0.286‡	0.019	−0.272‡	0.019
n. beds_h/100	0.095‡	0.002	0.080‡	0.002
n. doctors per n. beds_h	0.753‡	0.034	0.471‡	0.033
Specialist_h	1.241‡	0.028	1.069‡	0.029
Teaching_h	−0.102‡	0.014	0.013	0.013
Private_h	−0.050‡	0.010	−0.051‡	0.010
Number of observations	109146		109146	
Log-likelihood	−240261.1		−240281.1	

†LHA and province dummy variables have been included. Robust standard errors against unknown heteroscedasticity have been used. See Table 2 for a definition of the variables.
‡Significant at the 5% level.
§Hospitals with more than 299 beds.

across hospitals. In this case, we estimate a single coefficient for each regressor, measuring its average influence on patients' choices. In Table 8 we report results for estimation of equation (1), where we include measures of hospital clinical quality, to check whether this has an influence on the choice of hospital.

Table 7 shows that the coefficient that is attached to $\bar{y}_{ih,t-1}$ is positive and significant. This coefficient measures the correlation between the behaviour of a patient and that of her neighbourhood, due to contextual or correlated factors. Our results show that an increase of 1 point in the percentage of neighbours that make the same choice generates an increase between 5.7% and 7.7% in the odds of taking the same decision, in the years 2005–2007. Such a correlation in choice of hospital may arise if, for example, hospitals encourage (or discourage) certain categories of patients from being admitted, because their disease (i.e. their DRG) or the treatment that they need is lucrative (or not) (Berta *et al.*, 2010). The coefficient of the variable $\bar{y}_{ih,t-1}$ elective_{it} shows that, in the years 2005–2007, an increase of 1 percentage point in $\bar{y}_{ih,t-1}$ for elective patients generates a rise varying between 2.7% and 3.5%, in the odds of choosing the same hospital h. This coefficient captures the effect on choice of hospital of the correlation within groups that is attributable to information sharing, since it relates only to elective patients. Our results indicate that, after controlling for contextual and correlated effects, individuals try to access information on the quality of hospitals by observing the choices of their neighbours with similar pathology who have been admitted in the past.

The regressor prior use$_{ih}$ has a strong positive effect on the dependent variable, implying that past experience is a key factor in determining current patients' decisions. The age of patients does not seem to play a role in the choice of the hospital, and gender turns significant only when pooling the data over the sample period. As expected, the patient-to-hospital distance (relative to the distance from the nearest hospital) has a negative significant influence on choices, implying that closer hospitals are more likely to be chosen over similar alternatives at longer distances (Sivey, 2011). The coefficient that is attached to GP$_i$ is positive and significant, although the influence of this variable is mild. This result shows that sharing a GP plays a role in determining patients' behaviour, though this is less important than that played by the network. This variable may also capture part of the correlation in choices of hospital due to contextual effects. The interaction effect between $\bar{y}_{ih,t-1}$ and age is positive and significant in two years out of three, suggesting that network effects are more important in the choice of older people. This result may be explained by the fact that older people tend to rely more on the lay referral network that is represented, for example, by relatives or trusted people, who may decide on their behalf. We emphasize that in general the sign that we should expect for this variable is not clear, since it is also true that older people are usually more isolated, and thus may rely less on the network.

The interaction term between $\bar{y}_{ih,t-1}$ and patient-to-hospital distance is positive, although significant only when pooling the data, suggesting that sharing information is more relevant when the choice concerns hospitals that are distant from the place of residence. This result may be implied by a greater need to consult neighbours before bearing the cost of moving to a hospital that is distant from the place of residence. Among the hospital-specific characteristics, as expected, the coefficients of the variables n. beds, n. doctors per n. beds and whether the hospital is specialist are positive and significant in all periods considered. A higher supply of beds and doctors may be perceived as a signal of better health assistance, and hospitals specializing in a particular area of treatment may attract cardiac patients more than general hospitals. Finally, a negative coefficient for the variable ownership status shows that private hospitals are less likely to be chosen when compared with public alternatives. It is interesting to observe that, although both private and public hospitals in our data sets provide free healthcare, patients on average prefer the public option. The interaction term between $\bar{y}_{ih,t-1}$ and the dummy variable indicating whether the hospital is large (i.e. with at least 300 patients) does not impact on choices of hospital when pooling the data, whereas in the year-by-year estimation its effect is not clear. On the basis of these results, we cannot draw any conclusions on whether network effects for large hospitals are more important than those of small and medium-size hospitals.

As shown in Table 8, similar results have been obtained when including in the regression two alternative indicators of hospital clinical quality. We observe that the effect of these variables on individual decisions is negative and significant, with a magnitude (in absolute value) that is similar to that of the network. When including these regressors in the equation for hospital choices, the log-likelihood increases significantly, rising from −240 963 (see the last row of the first column in Table 7) to above −240 260 (see the last row in Table 8). This suggests that patients, despite the absence of official statistics, manage to gather information on clinical quality. For example, a cardiologist's experience with previous similar cases in a given hospital could advise patients on its quality. This result, namely that quality affects choices even before explicit data are available, confirms the findings in Luft *et al.* (1990).

In conclusion, from our estimation results it emerges that the variables that are linked to social interaction do not swamp the effect of traditional determinants of choice of hospital, such as geographical distance or hospital characteristics. However, the network plays a significant role in shaping preferences of individuals, which continues to be in action even after introducing in the model measures of clinical quality.

Table 9 reports results for the estimation of model (2) for the years 2005–2007 and for each year separately. Unlike the regression that is reported in Table 7, $\hat{\delta}_h$ has been obtained by estimating

Table 9. Effect of social influences on quality indicators

Variable	*Results for the following periods:*							
	2005–2007		*2005*		*2006*		*2007*	
	Coefficient	*Standard error*	*Coefficient*	*Standard error*	*Coefficient*	*Standard error*	*Coefficient*	*Standard error*
Quality indicator: readmission within 30 days								
Elective_i	−0.049†	0.026	0.008	0.043	−0.048	0.046	−0.106†	0.048
$\hat{\delta}_h$	1.104†	0.419	1.402†	0.70	1.482	3.453	1.504†	0.322
Age_i	0.005†	0.001	0.005†	0.001	0.006†	0.001	0.003†	0.001
Male_i	0.189†	0.023	0.227†	0.038	0.209†	0.039	0.132†	0.040
ICD-9-CM=411_i	−0.248†	0.026	−0.219†	0.045	−0.269	0.047	−0.266†	0.047
ICD-9-CM=412_i	−1.115†	0.102	−1.037†	0.165	−1.243†	0.193	−1.058†	0.183
ICD-9-CM=413_i	−0.589†	0.033	−0.530†	0.054	−0.578†	0.057	−0.686†	0.061
ICD-9-CM=414_i	−1.036†	0.036	−1.112†	0.062	−1.014†	0.064	−0.964†	0.064
$\text{Price}_i/1000$	−0.093†	0.003	−0.087†	0.006	−0.094†	0.005	−0.098†	0.006
n. $\text{beds}_h/100$	0.040†	0.004	0.032†	0.006	0.034†	0.007	0.057†	0.007
n. doctors per n. beds_h	0.430†	0.092	0.716†	0.160	−0.072	0.184	0.811†	0.163
Teaching_h	−0.339†	0.031	−0.371†	0.054	−0.321†	0.055	−0.316†	0.057
Private_h	−0.402†	0.032	−0.312†	0.053	−0.319†	0.057	−0.433†	0.052
Specialist_h	−0.016	0.074	−0.690†	0.120	−0.489†	0.150	−0.637†	0.172
Log-likelihood	−38720.9		−13219.4		−12774.7		−12265.8	
Quality indicator: death within 30 days								
Elective_i	−0.731†	0.048	−0.676†	0.079	−0.751†	0.086	−0.809†	0.088
$\hat{\delta}_h$	0.003	0.010	0.019	0.034	0.032	0.044	0.005	0.032
Age_i	0.088†	0.002	0.088†	0.003	0.082†	0.003	0.093†	0.003
Male_i	0.049†	0.029	0.042†	0.050	0.082	0.051	−0.001	0.050
ICD-9-CM=411_i	−1.530†	0.049	−1.474†	0.083	−1.658†	0.090	−1.472†	0.085
ICD-9-CM=412_i	−1.423†	0.197	−1.940†	0.413	−0.973†	0.289	−1.431†	0.361
ICD-9-CM=413_i	−2.386†	0.097	−2.516†	0.174	−2.269†	0.158	−2.431†	0.180
ICD-9-CM=414_i	−1.192†	0.053	−1.264†	0.089	−1.263†	0.097	−1.037†	0.091
$\text{Price}_i/1000$	0.040†	0.002	0.042†	0.005	0.043	0.005	0.036	0.005
n. $\text{beds}_h/100$	−0.022†	0.006	−0.027†	0.009	−0.010	0.010	−0.019	0.010
n. doctors per n. beds_h	−0.263†	0.114	−0.296†	0.188	−0.533†	0.219	0.075	0.202
Teaching_h	0.068	0.044	0.113	0.077	−0.007	0.078	0.090	0.079
Private_h	−0.131†	0.045	−0.068	0.077	−0.200†	0.080	−0.125†	0.073
Specialist_h	−0.710†	0.114	−0.780†	0.188	−0.775†	0.214	−0.566†	0.211
Log-likelihood	−20851.1		−6864.98		−6922.5		−6855.7	
Number of observations	109146		36709		36011		36426	

†Significant at the 5% level.

model (1) where parameters are allowed to vary across hospitals. In this case, we obtained that most estimated coefficients $\hat{\delta}_j$, for $j=1,\ldots,H$, are positive over time, with mean 0.030 and standard deviation 0.046. Only a few hospitals show negative coefficients, but none of them are significant.

We first observe that, when using 30-day readmission as the indicator of quality, the coefficient that is attached to the variable $\hat{\delta}_h$ is positive and significant when pooling the data, and in the years 2005 and 2007. This result suggests that, *ceteris paribus*, a higher sensitivity of a patient's decision to local information decreases the probability of choosing a high quality hospital. One explanation for this result is that network effects, implied by asymmetric information, are a signal of low competition in the market, which in turn decreases quality (Kessler and McClellan, 2000). A further reason is that the reference group may give importance to hospital attributes, such as convenience or single-room accommodation, which are not related to clinical quality, as measured by our health outcomes indicators. In a recent study, Goldman and Romley (2010) found evidence that patients' choices react much more to increases in hospital amenities rather than improvements in various measures of clinical quality, although we note that there is no proven link between hospital amenities and hospital clinical quality. An alternative reason for finding a negative relationship between the neighbourhood effect and the quality of hospitals is that sicker patients, who are more likely to be readmitted, may spend more time, relying on their network, to find out the best hospital. If this is so, higher readmission rates associated with hospitals having larger network effects would not necessarily mean that trusting the network leads to low quality hospitals.

When adopting 30-day mortality as the indicator of quality, the coefficient that is attached to $\hat{\delta}_h$ is positive although statistically insignificant. Accordingly, results show that using network information does not lead, on average, to selecting a higher (or lower) quality hospital than if this was chosen without using network information. We note, however, that the relatively low risk of dying of patients in our data set may negatively affect the precision of our estimates. One general result looking at Tables 8 and 9 is that, although individual choices are influenced by clinical quality, the information that is passed through the network on average does not help in choosing the 'best' hospital where to be treated.

As for the remaining regressors, the (exogenous) price variable does not have a neat effect on indicators of quality. The positive coefficient that is attached to this variable when adopting 30-day mortality as indicator may be because it partially captures the severity of the disease which implies more expensive treatments and procedures. The coefficient attached to n. beds (lagged at time $t-1$) has a positive and significant effect on the 30-day readmission variable in all years. This may be explained by the fact that the severity of illness in larger hospitals is higher, thus inducing higher readmission rates. However, the coefficient that is attached to this variable has a negative sign when the dependent variable is 30-day mortality. The n. doctors per n. beds variable (lagged at time $t-1$) shows a positive and significant effect on 30-day readmission, at the beginning and at the end of the sample period, whereas 30-day readmission is on average smaller for teaching, private and specialist hospitals.

7. Concluding remarks

In this paper we have explored the effect of social interaction on individuals' choice of hospital for patients with cardiac illness. To our knowledge, this is the first attempt at identifying, testing and modelling social interaction in patients' decisions on the hospital where to be treated. Our findings support the existence of positive and statistically significant correlation between the choice of hospital of an individual and that of her neighbours, also after having controlled for

GP effects. The strategy that we have proposed allows us to conclude that part of this correlation is due to social interaction between patients. Therefore, individuals rely also on information that is gathered from neighbours when choosing their health provider. Following the work by Luft *et al.* (1990), in a separate regression we also included some measures of hospital clinical quality. Our results show that these variables influence choices of hospital, thus indicating that patients can gather some knowledge on the quality of hospitals, perhaps exploiting specialists' experience of a given hospital. It is interesting to observe that the network effect is still present after introducing clinical quality. The estimation of our model of hospital choice indicates that other important factors explaining individual decisions are the prior utilization of health services in the hospital, distance of travel, and supply factors such as the number of beds and number of doctors.

We then assess whether sharing information within the neighbourhood increases the likelihood of selecting a high quality hospital. We look at the relationship between two alternative health outcome indicators and the sensitivity of patients' choices to the network. When adopting 30-day mortality as a proxy of quality of hospital, the use of neighbourhood information does not seem to have a significant influence on the likelihood of choosing a high quality of hospitals in all years. However, it is interesting to observe that, when we adopt 30-day readmission as the indicator of quality, our results show that, the higher the strength of interaction between individuals for a particular hospital, the lower its quality is likely to be.

One important implication for these results is that policy makers should put effort into implementing central and local mechanisms of diffusion of information such as guidelines or star rating indicators, that reduce geographical inequalities in the access to information.

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