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The association between asymmetric information, hospital competition and quality of healthcare: evidence from Italy

Paolo Berta,

University of Milan Bicocca, Italy, and Brunel University London, UK

Gianmaria Martini,

University of Bergamo, Italy

Francesco Moscone

Brunel University London, UK

and Giorgio Vittadini

University of Milan Bicocca, Italy

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Summary. We study the effect of competition on adverse hospital health outcomes in a context in which information about hospital quality is not publicly available. We use data on patients who were admitted to hospitals in the Lombardy region of Italy. Although risk-adjusted hospital rankings are estimated yearly in this region, such rankings are provided to hospital managers only and are not available to general practitioners or citizens. Hence, patients may choose the hospital where to be admitted on the basis of different criteria such as their geographical closeness to the hospital, local network information and referrals by general practitioners. We first estimate a model of patient hospital choices and include among the determinants a variable capturing social interaction, which represents a proxy for the quality of hospitals perceived by patients. Using patient-predicted choice probabilities, we then construct a set of competition indices and measure their effect on a composite index of mortality and readmission rates that represents, in our settings, hospital quality in terms of adverse health outcomes. Our results show that no association exists between such adverse events and hospital competition. Our finding may be the result of asymmetric information, as well as the difficulty of building good quality health indicators.

Keywords: Asymmetric information; Hospital competition; Multilevel model; Network effect; Patients' choice; Quality

1. Introduction

A great debate exists, both at the national and at the international level, on the role of competition in different sectors of the economy, including the healthcare sector. In recent years, many governments have introduced competition between healthcare providers to meet the growing demand for healthcare in a climate of fiscal austerity. For example, the last Labour administration in the UK introduced competition in the form of increased patient freedom to choose a

Address for correspondence: Francesco Moscone, Room ESGW 210, Brunel University London, Uxbridge, UB8 3PH, UK.
E-mail: Francesco.Moscone@brunel.ac.uk

healthcare provider with the intent of reaching higher quality without increasing expenditures. Similarly, at the beginning of the 1990s, some regional governments in Italy (e.g. Lombardy) implemented healthcare reforms to give patients increased freedom of choice to stimulate competition between hospitals. These interventions originate from a well-known theoretical result in economics: when prices are fixed and firms compete, a higher degree of competition is likely to produce better quality. Economists have gathered empirical evidence on the effects of competition in the healthcare sector, finding mixed results on the size and direction of these effects (Gaynor, 2006). Some empirical studies have corroborated the hypothesis that more competition between hospitals leads to better health outcomes (e.g. Gaynor *et al.* (2012)) whereas other studies reject this hypothesis, arguing that more competition may harm people's health (e.g. Propper *et al.* (2004)).

This paper sheds light on why empirical literature often rejects the theoretical result that more competition leads to better health outcomes in a fixed price setting. For this, we use data from 194020 patients admitted to one of the 126 hospitals in the Lombardy region of Italy in 2012. We first estimate a model of patient hospital choice. In the Lombardy region, although risk-adjusted hospital rankings based on different quality and efficiency indicators are estimated yearly, such rankings are provided to hospital managers only and are not available to general practitioners (GPs) and citizens.

Hence, to adjust for asymmetric information on the quality of hospitals, having taken distance into account, we include a GP effect, and a local network proxy. We then construct a set of competition indices and measure their effect on hospital performance in terms of quality. As quality indicators, we consider outcome variables such as readmission and mortality rates within 30 days from discharge (Romano and Mutter, 2004), as well as a composite index of mortality and readmission rates (Neuman *et al.*, 2014).

Our results show that, after controlling for patient characteristics, the choice of a specific hospital seems to depend on the number of people who live in the same area who have previously chosen the hospital. Further, *ceteris paribus*, we provide evidence that there is no statistically significant relationship between hospitals facing more competition and their adverse event health outcomes. Hence, our results indicate that, in the absence of publicly available information on hospital rankings, there is no association between adverse health outcomes and hospital competition. One interpretation for this result is that asymmetric information may act as a barrier for competition to work effectively. A further explanation is the lack of health outcome indicators that are sufficiently able to capture quality.

We explore these issues by implementing an empirical strategy based on two stages. In the first stage we estimate a mixed logit model to investigate the determinants of patient hospital choice. We then use the predicted probabilities of the mixed logit model to compute a set of Herfindahl–Hirschman indices (HHIs) of competition, following the approach by Kessler and McClellan (2000) to avoid distortion in defining the hospital's catchment area. In the second stage we estimate a multilevel model to study the effect of hospital competition on adverse health outcomes.

We carry out our analysis at the ward level, using patients who were admitted to three different wards—cardiac surgery, cardiology and general medicine. We expect that patients choose hospitals according to the treatment that they need; hence, they look specifically at the ward rather than the hospital as a whole. As noted by Carey and Burgess (1999), page 519,

> 'the hospital level of analysis is too general to be capable of revealing variation in quality as measured by rate-based adverse events'.

This suggests that hospital level health outcome measures may be too broad to capture the effectiveness that is achieved by different departments operating within the same hospital. Another alternative would be to measure hospital quality at the surgical or medical team level. In fact, patients could choose their provider depending on the national and international reputation of a particular surgeon or medical team. Although we have no data on surgeon quality, hospital quality at the ward level may be a good proxy.

We have selected different wards to test the sensitivity of our results when changing wards, i.e. when moving from a more specialized, high technology ward such as cardiac surgery to a wider department with a more extensive range of treatments and pathologies such as general medicine. We would expect patients who need more complicated and risky interventions, such as heart surgery, to be more conscientious about gathering information on the quality of the ward when compared with patients who face less complex or life threatening interventions.

Another feature of this paper is that, contrary to previous work, we consider only non-urgent, or elective, patients in our analysis. The reason for excluding urgent patients is that these patients need immediate care typically at the closest hospital and in an emergency department. As such, patients' choice sets would be very limited and confined to places that are close to where they live (Tay, 2003) whereas elective patients are less constrained by geographical factors.

The remainder of the paper is organized as follows. Section 2 reviews the literature on the influence of competition on health outcomes and discusses the indicator to consider in the relationship between hospital quality and competition. Section 3 briefly introduces the Lombardy healthcare system. Section 4 describes the data. Section 5 introduces the econometric strategy and Section 6 presents some descriptive statistics. Section 7 discusses estimation results. Finally, Section 8 concludes with some suggestions for future research. In Table 1, we report the details of the variables that are included in the empirical analysis.

2. The influence of competition on health outcomes

Four key factors exist that may shape how competition between hospitals impacts quality:

(a) institutional settings of the hospital market supply side (Kessler and McClellan, 2000; Tay, 2003; Propper *et al.*, 2004, 2008; Gaynor, 2006; Moscone *et al.*, 2012, Gaynor *et al.*, 2012),
(b) the degree of patient freedom of choice (Luft *et al.*, 1990; Tay, 2003; Howard, 2005, Cooper *et al.*, 2011; Beckert *et al.*, 2012; Varkevisser *et al.*, 2012; Moscone *et al.*, 2012),
(c) hospital competitive strategy (Kessler and McClellan, 2000; Tay, 2003; Cooper *et al.*, 2011) and
(d) the degree of information regarding hospital quality (Dranove *et al.*, 2003; Dranove and Sfekas, 2008).

The first factor is related to how competition is implemented in healthcare systems in which prices are fixed. In some countries, such as the UK, the criteria are dependent on hospital market performances whereas other countries boost hospital competition by providing patient information on where to obtain the best treatment. Italy encourages competition by expanding patient choice sets and offering private hospitals per-treatment public reimbursement funding. The degree of hospital competition also depends on patients' freedom of choice of where to be treated. Some markets have complete freedom (e.g. in the USA)—i.e. patients can choose any hospital in the relevant market—whereas others have limited freedom (e.g. Italy) either because patients are free to choose but do not know the hospital quality or because they must select between a limited number of hospitals. The third factor (hospital competitive strategy) describes how hospitals compete with other hospitals. In some markets, hospitals can choose both price and quality (e.g. in the USA), whereas, in others (e.g. in the UK and Italy), prices

Table 1. List of variable definitions

Variable	*Definition*
Individual-specific variables	
Choice_{ij}	1 if patient i is admitted to hospital j
Distance_{ij}	Time distance from residence of patient i and hospital j (in minutes)
$\text{Network}_{i,wj}$	% of residents living in the same municipality as patient i admitted in ward w of hospital j in the 12 months previous to the analysis
Age_i	Patient i age in years
Male_i	1 if patient i is male
Gp_i	100 × the number of patients in the zip code sharing their GP with i/the number of patients in the zip code
Ward- and hospital-specific variables	
Death_{wj}	Hospital j 30-day mortality rate in ward w
Readmission_{wj}	Hospital j 30-day after discharge readmission rate in ward w
Adverseout_{wj}	Hospital j composite index of adverse health outcomes (i.e. 30-day mortality or readmission) in ward w
Male_{wj}	% of males in ward w of hospital j
Age65_{wj}	% of patients over 65 years old in ward w of hospital j
ICU_{wj}	% of transits in intensive care unit for patients in ward w of hospital j
DRGWEI_{wj}	Average DRG weight in ward w of hospital j
Private_j	1 if hospital j's ownership is for profit
NFP_j	1 if hospital j's ownership is not for profit
Mono_j	1 if hospital j is mono specialized
Teaching_j	1 if hospital j is a teaching hospital
Technology_j	1 if the hospital has a high technology assessment (i.e. an intensive care unit department) and 0 otherwise
Heart_{wj}	1 if ward w in hospital j is cardiac surgery
Cardio_{wj}	1 if ward w in hospital j is cardiology
Medicine_{wj}	1 if ward w in hospital j is general medicine
Beds_{wj}	Number of beds in ward w of hospital j
Ranking_{wj}	Percentile rank of ward w in hospital j in the league table of the Lombardy quality evaluation programme

are regulated by a central or local government and they can compete only through quality that is usually measured in terms of a set of health outcomes. Finally, the degree of competition depends on the level of hospital information that is available to patients when they choose where to be admitted. In some markets, like in the USA and the UK, patients are fully informed since hospital rankings are publicly advertised through league tables. See, for instance, the Web sites `www.medicare.gov/hospitalcompare/search.html` (for the USA) and `www.chooseandbook.nhs.uk` (for the UK). In other countries (Italy), patients are free to choose but, as they are not privy to hospital rankings, this choice is mainly based on informal information such as word of mouth, reputation and the media.

Our analysis considers a setting in which hospital competition is quality based and depends on the number of hospitals that a patient can reach in a reasonable time as well as fixed prices and asymmetric information regarding the quality of providers. In this context, it is important to understand the possible effects of hospital competition under different degrees of information regarding quality that is available to patients. We are working under the assumption that patients are rational agents who will maximize their utility if properly informed regarding quality and that they will choose the hospital that provides the best combination between quality and geographical distance (or travel time) from their residence. It is reasonable also to assume that, for more complicated treatment, patients will be willing to travel for a high quality hospital and, even for non-complicated treatment, patients also will select a high quality hospital that is relatively close to their residence and not simply the closest hospital. Under these circumstances, although top quality hospitals will attract more patients, the intensity of such an effect will depend on the hospital market structure. For example, if the hospital is a local monopolist, the effect is negligible since only those who are willing to travel long distances provide the incremental number of attracted patients. If, on the contrary, the hospital is operating in a market structure with other hospitals acting as nearby competitors, we can imagine two effects. The first is a short-run effect, whereby the top quality hospital attracts more patients (as limited by bed capacity), gains market share and is subject to less competition because it enjoys a quality difference compared with its competitors. This implies that its competition index—e.g. the HHI—will increase, signalling a decrease in the degree of competition. The second is a long-term effect whereby competitors will react to the quality gap and (at least those remaining in the market) will also raise their levels of quality. This implies that, in the long run, market shares may even be unchanged compared with those existing before the quality gap.

The situation changes completely in the case of asymmetric information. Under this scenario, patients tend to choose the nearest hospital or base their decision on informal information. The latter may be based on GP referrals and neighbour assessments. For example, patients may use information about the decisions of people living in the same area and have or had the same pathology as those who must make comparable decisions. Friends, relatives or trusted people who have experienced similar health problems may also act as filters for the quality of hospitals, thus shaping individual preferences. However, as also emphasized by Moscone *et al.* (2012), interacting and sharing information with neighbours does not necessarily help in selecting a high quality hospital. For example, the reference group may give importance to certain attributes such as appearance, comfort and convenience of hospitals (the so-called amenities; see Goldman and Romley (2010)), which may not necessarily be related to clinical quality. Patients may be influenced in their decisions by GPs, who may have better information and act as agents in a principal (patient)–agent framework (Scott, 2000). GPs may base their referrals on previous experiences of patients but nevertheless are not completely informed about true hospital quality in regard to every possible treatment. Under this scenario, high quality hospitals may fail to attract more patients. Even if institutions have implemented measures to increase competition between hospitals, such measures may not obtain the returns from investing in quality (e.g. hiring the best physicians, buying the most expensive equipment and adopting costly control procedures in internal operations). Patients have a difficult time recognizing better quality hospitals and, hence, hospitals may not have an incentive to increase quality. To sum up, in a situation in which asymmetric information exists and prices are fixed, increasing competition may not produce an effect on health outcomes.

The literature on hospital competition has focused mainly on the US and UK markets. Although patients are free to choose in both markets, hospitals in the USA may set both prices (outside Medicare and Medicaid programmes providing health coverage for people over 65 years old, or with a severe disability or with very low income) and quality. In contrast, in the UK, hospitals can only move quality since prices are regulated. Most studies have investigated the effect of hospital competition on health outcomes as measured by the HHI (Gaynor and Haas-Wilson, 1999; Dranove and White, 1994; Kessler and McClellan, 2000; Tay, 2003; Propper *et al.*, 2004, 2008; Gaynor, 2006; Cooper *et al.*, 2011; Moscone *et al.*, 2012; Gaynor *et al.*, 2012). Recent work, following the approach by Kessler and McClellan (2000), has used predicted flows based on (exogenous) patient characteristics and patient-to-hospital distance when computing the HHI, rather than actual patient flows. This allows us to avoid endogeneity problems when studying the effect of the HHI on healthcare quality as well as distortions in defining the geographical area representing the potential hospital market (Kessler and McClellan, 2000). The geographical area, if defined by using observed choices, may be influenced by hospital quality, which leads to larger areas for high quality hospitals, and remains unobserved by the researchers. The approach by Kessler and McClellan (2000) proposes to use only exogenous patient characteristics factors affecting patient's choice that are not linked to the selection process.

Several studies have investigated the effects of hospital competition on hospital quality in the US market. Kessler and McClellan (2000) have individual data on non-rural elderly Medicare patients hospitalized for heart attack treatment in 1985, 1988, 1991 and 1994. They provided ordinary least squares estimates of the effect of hospital competition and showed that competition leads to better health outcomes, lowering 30-day mortality hospital rates, reducing treatment costs. Tay (2003) used data from 1994 for patients with acute myocardial infarction (AMI). She estimated a mixed logit model and showed the importance of quality in patient choice and provided evidence that they are willing to travel more if the quality of treatment is higher. Ho and Hamilton (2000) investigated the effects of hospital mergers on mortality rates, using a data set from patients who were admitted to hospitals in California for AMI treatments between 1991 and 1996. They estimated Cox regressions and found no effect of increased market power (through a merger) on mortality rates as well as a moderate effect on readmission and early discharges rates.

Various studies have analysed the influence of competition on healthcare quality in the UK. Propper *et al.* (2004, 2008) studied hospital mortality rates for AMI and found a negative effect of competition. They used aggregated hospital level measures and tried to avoid endogeneity problems in the HHI by estimating potential demand rather than observed choice. Cooper *et al.* (2011) implemented a difference-in-differences econometric model to study the effect of recent UK pro-competition reforms on mortality rates and found that they fell after the reforms in more competitive hospital markets. In a more recent study, Gaynor *et al.* (2012) adopted patient level data for a coronary artery bypass graft procedure and investigated the effect of patients' freedom of choice on mortality rates. They found that giving patients the possibility of selecting their hospitals when they know the quality of the hospitals significantly reduces mortality rates. Gaynor *et al.* (2012) tackled the issue of freedom of choice and information on hospital quality and the results are very close in spirit to our contribution.

Little empirical work exists on the effect of competition on the healthcare sector in Italy. Moscone *et al.* (2012) studied the effect of patient hospital choice of an imperfect measure of hospital quality (the effect of word-of-mouth social interaction given by the percentage of patients living in the same area who have previously made the same treatment choice). They studied the choices of patients suffering from heart disease who were receiving treatment in one Italian region (Lombardy). Using administrative data that include the whole population, they showed that the informal neighbourhood effect has no effects on health outcomes and even may lead patients to make suboptimal selections.

Last, only a few references have explored the possible effects of asymmetric information in healthcare despite the relevant insights that are achieved by some very famous early contributions (e.g. Akerlof (1970) and Spence (1973)) and the massive number of subsequent references (an excellent review is in Mas-Colell *et al.* (1995)). Dranove *et al.* (2003) analysed the effect of disclosing hospital report cards in the USA and showed that it may induce selection of patients—i.e. hospitals may not admit patients with bad health statuses because they do not want to worsen their rankings. Dranove and Sfekas (2008) showed that spreading information on hospital quality does not necessarily improve the performances of top ranking hospitals, probably because the rankings confirm patients' informal perceptions on the different quality levels. Although Varkevisser *et al.* (2012) provided evidence that patients tend to choose better quality hospitals in the Netherlands, their study did not show whether this choice produces a market premium for top quality hospitals. It is important to observe that we expect the problem of patient selection to have a mild effect in Lombardy. In fact, as explained in Section 3, hospital managers are unaware of their institutions' exact rankings unless the institution has a risk-adjusted health outcome that is significantly above, equal to or below the regional average.

Another key factor in the relationship between hospital quality and competition is the choice of variables representing health outcomes. Several works in the literature use the mortality rate as the quality indicator (see, among others, Kessler and McClellan (2000), Tay (2003), Propper *et al.* (2004, 2008), Beckert *et al.* (2012) and Cooper *et al.* (2011)). Although most of these references focused on treatments for AMI, some researchers (see among others Goldstein and Spiegelhalter (1996), Iezzoni *et al.* (1996) and Lilford *et al.* (2004)) have criticized the use of mortality in treatments different from AMI as many diseases (e.g. chronic illness) have very low mortality risks associated. In the USA, there is growing evidence (Neuman *et al.*, 2014) that mortality rates alone cannot capture hospital differences in treatment provided to patients.

Other references (e.g. Kessler and McClellan (2000) and Kessler and Geppert (2005)) have considered another health outcome indicator: readmission rates. Repeated admissions are included in this analysis either as a single indicator in the relationship between hospital quality and competition or separated by mortality rate (evaluating the previous relationship by using two dimensions of quality). Readmission rates may be a good proxy of hospital quality for many diseases (e.g. surgical operations) since repeated admissions for the same patient may be a signal of poor prior treatment. However, in some cases, poor treatment quality may lead to death without readmission: an event that is considered an adverse health outcome and contributes to the level of hospital quality. As a result, as suggested by Neuman *et al.* (2014), a composite index of mortality and readmission rates may be a better indicator of quality of treatment in a specific hospital. The composite index is a proxy for the frequency of adverse health outcomes that are incurred by patients who are admitted in a specific ward of a given hospital. This indicator increases the frequency of adverse outcomes (which may also be very low if we focus only on mortality rates in some wards) and may cover different episodes of bad treatment. Hence, differently from previous contributions on the relationship between hospital quality and competition, we use a composite index of mortality and readmission rates as a quality indicator in our empirical application.

3. The Lombardy healthcare system

In Italy, universal coverage for healthcare services is provided by the Italian National Healthcare System and funded through general taxation. Financial resources are transferred to the various regions that are in charge of managing their individual systems. In 1992, a major reform of the National Healthcare System transformed the local health authorities into companies known as an Azienda Sanitaria Locale (ASL) and introduced a separation between the healthcare service buyers (the ASL) and the providers (i.e. the hospitals).

Among the Italian regions, Lombardy, with population 10 millon, is a very interesting environment in which to study the effects of asymmetric information on hospital competition. In 1997, the regional government implemented pro-competition healthcare reform with the aim of improving the quality of services in a financially sustainable environment. Such reform has given patients the freedom to choose between all the hospitals in the region. It has also introduced competition between public and private hospitals by allowing the latter to be accredited as suppliers of healthcare, thus providing free healthcare and public reimbursement entitlement.

Since 1995, the Lombardy region has used a financing mechanism known as the prospective payment system. This is a financing system in which the region pays a predetermined fixed reimbursement to the hospital for each patient on the basis of his or her diagnosis-related group (DRG) that is established by using clinical information that is reported in the hospital discharge chart. The *ex post* reimbursement for a specific DRG does not vary if the length of stay falls within a given threshold. The DRG tariffs are set at the regional level and cover all healthcare services relative to hospital admissions as well as outpatient activity (see Berta *et al.* (2010, 2013) and Vittadini *et al.* (2012) for further details). Hence, in our analysis, price is not a strategic variable when dealing with hospital competition. As previously mentioned, we assume that competition is based on quality and is affected by the present number of hospitals in the market.

Since 2002, the regional Lombardy government also implemented a *quality evaluation programme* within which a set of indicators is computed every year to evaluate the performance of healthcare providers in terms of quality of care. In line with the international literature on the relative effectiveness of hospitals (see, for example, the Agency for Healthcare Research and Quality (2012)), these measures include the following five outcomes:

(a) mortality within 30 days from discharge (including intrahospital mortality);
(b) discharges against medical advice;
(c) additional surgery room readmission;
(d) readmission for the same condition in the major diagnostic categories within 12 months from the date of discharge;
(e) transfer to a different hospital.

We have decided to focus on mortality and readmission (by using a composite index) as patient transfer and voluntary discharge may depend on factors that are unrelated to treatment and additional surgery may be relevant for specific treatments only. Lastly, we do not have information on intrahospital infections and complications.

Using data from hospital discharge charts, the region estimates a set of risk-adjusted multilevel logistic models to evaluate the relative effectiveness of each hospital ward. This class of models exploits the hierarchical structure of the data, accounting for heterogeneity between and within hospitals (see Hox (1995), Goldstein (1995), Rice and Leyland (1996) and Goldstein and Spiegelhalter (1996)). Every year, the region publishes the results on a Web portal in which only hospitals that are included in the regional healthcare system can log in, access their performance results (at ward level) and compare the results with the average performance. For each ward the region provides a hospital classification into three groups depending on whether the quality is significantly (at 5% confidence level) above the regional average (group 1), not different (group 2) or significantly below the regional average (group 3). By allowing hospitals to look at their own performance relative to others, the aim is to promote an improvement in health quality.

4. Data

We gathered administrative data from 2012 on all patients who were admitted to the cardiac surgery, cardiology and general medicine wards in any public or private hospital in the Lombardy region that was financed by regional public funds. The Lombardy region provided data for research purposes.

Data on each patient were extracted from the hospital discharge chart and include sociodemographic characteristics such as age, gender and place of residence (the municipality), clinical information such as principal diagnosis and codiagnosis, main and secondary procedures, comorbidity, length of stay, type of admission (planned or via the emergency room) the ward of admission and type of discharge (e.g. death), financial information such as the DRG and hospital discharge chart reimbursement. Such data were matched with information on hospitals (ownership and teaching status, technology, etc.), and on the travel distance in minutes from the patient's residence (the municipality) to the hospital. Information on travel distance, expressed in units of time, was computed by using *GoogleMaps*. The algorithm computes the fastest route from an individual's residence to the hospital by car. The distance is set to 0 if an individual's street address and the hospital location are identical.

We also gathered information on the GPs with whom patients are registered from the General Register Office, which was provided by the Lombardy region and represents the 7605 GPs operating in the region.

We removed from the data set any patient whose source of admission was other than elective. We define as elective all booked or planned admissions in which patients have been given a date or approximate date at the time that the decision to admit was made. After this cleaning procedure, we are left with a total of 194 020 patients of whom 9121 were admitted to cardiac surgery, 71 499 to cardiology and 113 400 to general medicine. These patients were admitted to the cardiac surgery ward of 20 hospitals, the cardiology ward of 76 hospitals and to the general medicine ward of 124 hospitals in the Lombardy region.

Table 1 reports a list of variables and their definitions. We observe that, in the computation of readmission rates, patients not surviving past the 30-day window were excluded from the denominator.

5. The econometric strategy

To study the effect of competition between hospitals on health outcomes we adopt a two-stage approach. In the first stage we study patient hospital choices as a function of a set of patient characteristics, the hospital travel distance and the network effect. In the second stage, we compute a set of HHIs (one for each ward and for each hospital) by using the predicted choice probabilities estimated in the first stage and then analyse their effect on hospital quality. As previously mentioned, we focus on a composite index of mortality and readmission rates, namely ward level rates of mortality and readmission within 30 days from discharge.

In the first stage, we investigate patient choices by using a discrete choice model. Patients maximize their utility functions given their characteristics and hospital travel distance. Given that information on the quality of hospitals is not publicly available, we assume that information regarding the quality of past treatment received at a specific hospital is transmitted through social interaction among the population living in the same neighbourhood. As patients within a neighbourhood interact, the choice of one patient is influenced by the choice of neighbouring patients (Brock and Dourlaf, 2001). Suppose that, for ward w, the observable choice of individual i of being admitted to hospital j, $y_{i,wj}$, is related to the expected utility of i choosing j, $y^*_{i,wj}$, according to $y_{i,wj} = 1$ if $y^*_{i,wj} > 0$. Our choice model is

$$y^*_{i,wj} = \rho_w d_{i,wj} + \delta_{wj}\,\mathrm{Network}_{i,wj} + \gamma_{wj}\,\mathrm{GP}_i + \boldsymbol{\pi}'_{wj}\mathbf{x}_i + \varepsilon_{i,wj}, \tag{1}$$

where d_{ij} is the distance between patient i and hospital j, GP_i is the percentage of patients living in the zip code as patient i and sharing their GP with patient i and $\mathbf{x}_i$ are a set of exogenous, patient level characteristics. As for the distance variable, we have taken the travel distance expressed in minutes. The variable $\mathrm{Network}_{i,wj}$ is a continuous variable given by the share of people living in the same municipality as patient i and admitted to ward w of the same hospital j, in the

12 months before patient i's admission. In the Lombardy region, like in the rest of Italy, most of the population is concentrated in small-to-medium sized municipalities that are characterized by a strong historical and cultural identity as well as autonomy guaranteed by the Italian legislative structure. Family members usually live within the same municipality and meeting with friends and relatives is encouraged through local associations, cultural events, activities of the local parishes and so forth. Within the same municipality, historical, political, social and religious forces may encourage interaction between people, which is the main reason for using it as a reference area for building the network variable.

A positive and significant coefficient attached to the network effect and relative to hospital j means that a subset of the population, sharing informal information on the quality of the jth hospital, increases the conditional probability of choosing it for each member of this subset. A negative and significant coefficient implies that, *ceteris paribus*, a patient will make a choice that is different from that of her neighbours. The key mechanism underlying a significant coefficient attached to the jth hospital, either positive or negative, is the existence of clusters of informal information on the quality of the jth hospital. Such information, which we call a *network effect*, shapes the preferences of individuals and ultimately influences their decisions. A statistically insignificant coefficient means that patients do not use information from the network to choose that hospital and hence their choice is driven only by personal characteristics.

In equation (1) vector $\mathbf{x}$ of patient characteristics includes as regressors a dummy equal to 1 if patient i is over 65 years old, Age_i, and a dummy equal to 1 if patient i is male, Male_i. We also include a variable measuring the fraction of patients in the postal code area of patient i sharing a GP with patient i, GP_i. By including this variable, we aim to capture the potential correlation that arises from GP advice on the hospital at which to be treated. We estimate equation (1) for each ward separately by maximum likelihood using a mixed logit approach (Tay, 2003; Varkevisser *et al.*, 2012). To estimate our model, we have applied the `asclogit` procedure in the statistical software Stata 13 (StataCorp, 2013).

We then calculate the HHI of competition by computing the theoretical patient flows by using the predicted choice probabilities that are obtained from the first stage. This is done to avoid potential endogeneity in patient flows and in defining hospital catchment areas as underlined by Kessler and McClellan (2000). In fact, real patient flows can be influenced by variables such as the teaching status or the size of a hospital, which are connected with health outcomes and hospital quality. The endogeneity problem may also arise because hospitals with higher quality could obtain higher market shares and thus the index of competition may be affected by the dependent variable. Such endogeneity may bias results when regressing the HHI on health outcomes. Moreover, defining hospital geographic markets as a function of actual choices may lead to areas that are increasing in the unobservable quality. This has an influence on the HHIs and may give rise to competition effect estimates on hospital outcomes that are due both to the true effect and to the unobservable quality. As indicated by Kessler and McClellan (2000), building theoretical patients based on exogenous factors may overcome these problems. Hence, in our empirical application we compute the HHI indices for each ward or hospital with a three-stage approach: first, we estimate patient level hospital choice as a function of exogenous determinants of the admission decision (e.g. age and distance). This produces predicted probabilities of admission for each patient in each ward or hospital of the relevant geographical area. Summing these predicted probabilities at the ward or hospital level gives the predicted flow of patients who are admitted to each ward or hospital in the sample on the basis of exogenous characteristics of patients and hospitals. Second, we compute the HHI by using the exogenously determined patient flows that are assigned to each ward or hospital. Third, in the quality–competition relationship, we insert this HHI as a regressor.

Previous literature defines potential markets of hospital-specific HHIs as the area surrounding each hospital by using an array of arbitrary lengths—e.g. 30 km (Bloom *et al.*, 2010; Siciliani and Martin, 2007). To avoid the possible biases in computing the HHI by using these *ad hoc* methods, we follow Kessler and McClellan (2000) and use the predicted flows that are estimated with model (1) to compute HHI indices by exogenously assigning each patient to a given geographic area identified by the local healthcare zone, called the ASL (local health authority). In Lombardy, there are 15 ASLs and each patient is exogenously assigned to one. Let $\hat{\pi}_{i,wj}$ be the predicted probability that patient i chooses hospital j (in ward w), obtained from equation (1). The share of patients living in ASL area q who are predicted to choose hospital j over the predicted flow of patients living in ASL q to all the hospitals is

$$\alpha_{q,wj} = \sum_{\forall\, i \text{ living in } q} \hat{\pi}_{i,wj} \Bigg/ \sum_{j=1}^{J} \sum_{\forall\, i \text{ living in } q} \hat{\pi}_{i,wj}, \tag{2}$$

where J is the number of hospitals operating within a given ward (e.g. cardiology) in Lombardy. Expression (2) is computed for each hospital in Lombardy and for each ward that are considered in the analysis. Hence, we can compute the ASL q competition index HHI_{wq}, given by

$$\mathrm{HHI}_{wq} = \sum_{j=1}^{J} \alpha^2_{q,wj}. \tag{3}$$

The next step consists of defining the weight for hospital j of ASL area q relative to all ASL areas in Lombardy:

$$\hat{\beta}_{q,wj} = \sum_{\forall\, i \text{ living in } q} \hat{\pi}_{i,wj} \Bigg/ \sum_{i=1}^{Nwj} \hat{\pi}_{i,wj}, \tag{4}$$

where N_{wj} is the total number of patients admitted in ward w of hospital j in Lombardy. The last step is computing the HHI for ward w in hospital j, given by

$$\mathrm{HHI}_{wj} = 10000 \sum_{q=1}^{Q} \hat{\beta}_{q,wj}\, \mathrm{HHI}_{wq}. \tag{5}$$

Hence, each ward–hospital has an HHI competition index that is a weighted average (using each hospital patient share in ASL q) of the exogenously defined ASL q competition index. HHI_{wj} varies between $10\,000 \times 1/J$ (competition) and $10\,000$ (monopoly), with larger values indicating a decrease in the degree of competition.

The second stage of our econometric approach is designed to verify the influence of competition on hospital adverse health outcomes. Let y_{wj} be the adverse health outcome (either mortality or readmission) for ward w of hospital j. In our second stage we consider the following multilevel model for y_{wj}:

$$y_{wj} = \alpha + \sum_k \beta_k x_{k,wj} + \sum_m \gamma_m z_{m,j} + \theta\, \mathrm{HHI}_{wj} + u_j + \varepsilon_{wj}, \tag{6}$$

where $x_{k,wj}$ is a set of ward and hospital-specific characteristics z_{mj} is a set of hospital-specific attributes and u_j is a hospital-specific random effect. We consider, as adverse health outcomes y_{wj}, the (ward-specific) 30-day mortality rate Death_{wj} and the readmission rate $\mathrm{Readmission}_{wj}$ in hospital j. We consider also an adverse outcome index given by the combination of readmission and mortality. As regressors, in addition to the HHI, our key variable, we control also for some other variables. We include the percentage of patients who are older than 65 years to account for patient health status given that age is highly correlated with chronic conditions. We have also included the ward or hospital average DRG weight DRG_{wj}, identification of treatment complexity and the percentage of patients receiving treatment in the intensive care unit, ICU_{wj}. Further, we have included dummies indicating whether the hospital specializes in a particular area of treatment, Mono_j, is a university, $\mathrm{Teaching}_j$, a not-for-profit, NFP_i, or a private hospital, $\mathrm{Private}_j$, and whether the hospital uses advanced technology for patient treatment, Tech_j. Since we do not have information on specific technological equipment, we adopt the presence in hospital *i* of an intensive care unit as proxy for hospital classification. Although this feature fits well in the case of general medicine and cardiology, for heart surgery we identify a set of treatments that require high technology equipment such as

(a) repair of atrial and ventricular septa with prostheses,
(b) total repair of certain congenital cardiac anomalies and
(c) heart replacement procedures.

We include ward dummies Heart_{wj} and Cardio_{wj} and an interaction term identifying the effect of the HHI for not-for-profit and private hospitals only. This is to include the interward variability in the relation adverse outcomes–competition. Lastly, we take into account also that some choices are repeated in our patient level data. In other words, a patient making a second hospital choice for the same treatment is more informed than when the patient made the first decision. Hence, we include in the analysis the percentage of repeated choices (made by the same patient) that are different from the first choice at the hospital level. This variable identifies a share of patients who were admitted for the first time in hospital *i* who did not repeat the same choice later—i.e. a possible signal of poor treatment in hospital *i*. This may explain the level of adverse health outcomes in hospital *i*. The average percentage of these choices is 4% in cardiac surgery, 8.4% in cardiology and 8.1% in general medicine. However, as this percentage was not statistically significant, we dropped it from our empirical results.

We estimate multilevel model (6) (Goldstein and Spiegelhalter, 1996; Leyland and Goldstein, 2001) by applying the `Mixed` procedure in Stata. Multilevel models are very suitable for our application given the hierarchical structure of data in which patients are nested within wards and hospitals. Various alternative techniques have been proposed in the literature to estimate multilevel equation (6). One important approach is the use of Bayesian methods for hierarchical models that estimate posterior distributions for provider-specific parameters that influence patient outcomes (see, among others, McClellan and Staiger (1999)). The comparison of multilevel and Bayesian models when data have a hierarchical structure has not been widely studied. Browne and Draper (2006) performed several comparisons and found a better performance by using a Bayesian estimator only in a three-level, random-effects logistic regression. Our analysis concerns a large sample and, as also observed in the conclusion of Browne *et al.* (2006), the log-likelihood approach should not give rise to concerns of lower performance than the Bayesian approaches.

The main focus in this second stage is on the magnitude and significance of the parameter attached to the HHI. A positive and significant coefficient indicates that more competition increases the level of quality that is offered by hospitals, whereas a coefficient that is statistically insignificant would point to no effect of competition.

In this last stage, as a final check, we also test whether there is a relationship between the regional risk-adjusted, hospital quality ranking and patient-predicted choices. Specifically, we estimate the following multilevel model by using data at the patient level:

$$\hat{\pi}_{i,wj} = \alpha + \beta\,\mathrm{Ranking}_{wj} + \gamma\,\mathrm{Beds}_{wj} + \mathrm{Heart}_{wj} + \mathrm{Cardio}_{wj} + u_j + \varepsilon_{i,wj}, \tag{7}$$

where $\hat{\pi}_{i,wj}$ is patient *i*'s maximum probability among all her predicted probabilities (obtained from equation (1)) of selecting each hospital in the region with ward *w*, and $\mathrm{Ranking}_{wj}$ is the hospital level ranking calculated by the Lombardy region within the *quality evaluation programme*. Beds_{wj} is the number of beds for each ward and Heart_j and Cardio_j are ward fixed effects to control for hospital-specific characteristics. An insignificant coefficient for the ranking variable indicates that actual levels of quality do not drive patients' choice of hospital. We observe that, as emphasized by Austin *et al*. (2015), hospital quality as measured by ranking may offer a poor representation of the true level of hospital quality.

6. Descriptive statistics

Table 2 summarizes the set of patient-specific characteristics that are included in our analysis. Table 3 displays some descriptive statistics for the hospital-specific variables.

The statistics show that cardiac pathology affects more males than females and that patients in cardiology and general medicine are older than patients in cardiac surgery. Looking at the distance variables, we note that patients who are admitted to cardiac surgery are more willing to travel longer distances and that their network size is smaller compared with cardiology and general medicine patients.

Focusing on the ward and hospital level variables, we note that general medicine has high mortality rates. As expected, patients who are admitted to cardiac surgery are (relatively) young and are undergoing highly specialized expensive treatment and interventions. Conversely, patients who are admitted to cardiology and general medicine are older, often affected by a number of comorbidities, and admitted for a variety of treatments and interventions.

Table 3 shows also that the three wards have different compositions in terms of ownership and teaching status. Private and teaching hospitals often have cardiac surgery wards, whereas public, non-teaching hospitals often have cardiology and general medicine wards. Also, as expected, cardiac surgery wards have high technology equipment.

Table 4 offers a set of descriptive statistics on patient-to-hospital distance, measured in minutes of time, for the three wards. It is interesting to observe that the average distance to the cardiology ward is much shorter than for the cardiac surgery ward: about 19 min for the former *versus* 29 min for the latter. This may be explained by the fact that patients who are admitted for cardiac surgery may face more complex interventions and thus are more willing to travel further to receive high quality treatment. Table 4 shows that, overall, patients tend to choose nearby hospitals, showing little propensity to travel for hospital treatments in a context of asymmetric information regarding hospital quality in Lombardy.

Table 2. Descriptive statistics on individual-specific variables

Variable	*Results for cardiac surgery*		*Results for cardiology*		*Results for general medicine*	
	Average	*Standard deviation*	*Average*	*Standard deviation*	*Average*	*Standard deviation*
Distance_{ij}	29.18	20.72	19.10	15.72	15.87	13.02
$\text{Network}_{i,wj}$	38.01	29.77	66.10	33.59	77.86	29.15
Age_i	64.78	17.11	69.34	13.82	72.91	15.68
Male_i (%)	65.52	47.50	64.78	47.77	49.56	50.00
GP_i	14.11	17.85	14.23	18.02	18.27	20.54

Table 3. Descriptive statistics on ward- and hospital-specific variables

Variable	*Results for cardiac surgery*		*Results for cardiology*		*Results for general medicine*	
	Average	*Standard deviation*	*Average*	*Standard deviation*	*Average*	*Standard deviation*
Death_{wj} (%)	1.03	1.07	2.23	1.83	12.82	5.28
Readmission_{wj} (%)	4.43	1.30	5.13	1.8	4.94	2.45
$\text{Death+Readmission}_{wj}$ (%)	5.31	1.62	7.25	2.54	17.12	5.60
Male_{wj} (%)	66.71	4.74	63.08	6.76	48.32	6.45
Age65_{wj} (%)	64.51	7.68	70.76	8.13	77.05	8.39
ICU_{wj} (%)	76.38	42.47	20.77	40.57	1.55	12.36
DRGWEI_{wj}	5.10	2.86	1.67	1.07	1.07	0.71
NFP_{j} (%)	10.00	30.77	10.52	30.89	12.10	32.61
Private_{j} (%)	40.00	50.26	26.31	44.37	13.59	34.26
Technology_{j} (%)	95.00	22.00	92.10	27.14	74.57	43.55
Teaching_{j} (%)	40.00	50.26	15.71	36.72	17.81	38.26
Mono_{j} (%)	5.0	22.36	1.31	11.47	0.91	9.48
Beds_{wj}	21.12	14.83	22.50	16.44	43.87	31.39
Ranking_{wj} (rank)	49.45	29.46	53.13	28.21	49.18	27.54
Number of hospitals	20		76		124	

Table 4. Descriptive statistics on patient-to-hospital time distance by ward

Ward	*Minimum (min)*	*25th percentile (min)*	*Average (min)*	*Median (min)*	*75th percentile (min)*	*Maximum (min)*
Cardiac surgery	0	16	29.18	24	38	152
Cardiology	0	10	19.10	16	24	188
General medicine	0	7	15.87	13	20	197

7. Estimation results

Table 5 summarizes results for the estimation of patient hospital choice. It reports a set of statistics on regression coefficients estimated by maximum likelihood. Although for brevity we do not show all hospital-specific coefficients, we provide information on their distribution.

As expected, patient-to-hospital travel distance has a negative significant influence on choices, implying that patients are more likely to choose closer hospitals relative to similar alternatives at longer distances (Sivey, 2012). The coefficient that is attached to GP_i is positive, though with mild effect and weak evidence.

Looking at the results for the network variable, it is interesting to observe that the estimated coefficients are large and the average t-ratio is statistically significant in all models, thus indicating neighbourhood effects. For cardiac surgery, the average coefficient is higher than for other wards, indicating that patients, *ceteris paribus*, are strongly influenced by the choice of their neighbours. However, we remark that we do not have enough information to understand the mechanism underlying this network effect. We observe that patients who are admitted to this ward often need complicated and risky interventions and may spend more time and effort on gathering information on the quality of the ward when compared with other patients.

Table 5. Determinants of patient hospital choices

Independent variable	*Results for dependent variable choice and the following wards:*					
	Cardiac surgery		*Cardiology*		*General medicine*	
	Coefficient	*Standard error*	*Coefficient*	*Standard error*	*Coefficient*	*Standard error*
Distance$_{ij}$	−0.100†	0.001	−0.160†	0.001	−0.171†	0.001
Hospital's random coefficients (base = code 030106)						
Network$_{i,wj}$						
Mean	5.732		4.024		1.036	
Standard deviation	3.701		11.556		3.786	
Minimum	−2.407		−6.579		−6.053	
Maximum	11.854		58.730		16.460	
Mean standard error		0.516		0.522		0.259
Mean absolute values of t-ratios		12.095		10.961		7.457
Age$_i$						
Mean	0.001		0.024		0.021	
Standard deviation	0.028		0.032		0.025	
Minimum	−0.050		−0.040		−0.042	
Maximum	0.080		0.124		0.092	
Mean standard error		0.007		0.007		0.005
Mean absolute values of t-ratios		2.742		3.881		4.820
Male$_i$						
Mean	−0.094		−0.064		0.012	
Standard deviation	0.489		0.385		0.296	
Minimum	−0.600		−1.122		−1.067	
Maximum	1.577		1.936		0.814	
Mean standard error		0.199		0.188		0.152
Mean absolute values of t-ratios		1.674		1.261		1.621
GP$_i$						
Mean	0.003		−0.001		−0.002	
Standard deviation	0.013		0.019		0.013	
Minimum	−0.030		−0.054		−0.063	
Maximum	0.022		0.039		0.023	
Mean standard error		0.006		0.006		0.005
Mean absolute values of t-ratios		1.805		2.300		2.187
Constant						
Mean	1,730		−5.931		−3.316	
Standard deviation	2.717		11.888		4.061	
Minimum	−8.441		−67.110		−19.830	
Maximum	4.937		5.455		4.586	
Mean standard error		0.516		0.720		0.336
Mean absolute values of t-ratios		4.728		7.840		6.648
Observations	172280		4601876		12700700	
Bayesian information criterion	29003.2		228815.3		370129.8	

†1% statistical significance.

We have performed some robustness checks. First, we tried to estimate the choice model by changing the definition of the network variable (see the definition in Table 1). In particular, we have estimated equation (1) by measuring the network variable lagged 6 and 24 months before admission as an alternative to the 12-month measure. Results are robust against different lags of the network variable. As an additional check, we also compared these results with those

Table 6. Descriptive statistics on computed HHIs in the three wards

Ward	*Mean (standard deviation)*	*Minimum*	*25th percentile*	*Median*	*75th percentile*	*Maximum*
Cardiac surgery	2323.27 (1140.86)	1438.92 Ca' Granda Niguarda	1641.56	2007.57	2532.19	6480.12 C. Poma Mantua
Cardiology	1319.98 (630.86)	564.94 Fatebenefratelli Milan	875.74	1201.26	1538.25	3739.27 Valcamonica Esine
General medicine	1041.85 (601.20)	550.50 San Pellegrino Terme	642.11	949.65	1115.02	5238.45 Valcamonica Esine

obtained by multinomial and conditional logit model approaches. The results are very similar and therefore not reported.

We note that the coefficients that are attached to the network variable might not only reflect social influences but also the effect of other factors. In particular, such interdependence may arise because of contextual effects, i.e. if individual action varies with observed attributes that defines her group membership—or correlated effects—and if individuals in the same group tend to behave similarly because they have similar characteristics or similar opportunities and constraints (Manski, 1993; Brock and Durlauf, 2001). In addition, our data do not allow us to know whether patients, when choosing a hospital, use sources of information other than the local network such as advice from a specialist or forum groups on the Web. Such external sources may have an influence on the network effect and reduce its size.

Table 6 shows the distribution of the HHIs calculated for the three wards and computed by using theoretical patient flows. The average, median, 25th and 75th percentiles of the HHI are consistently higher for heart surgery, indicating a lower degree of competition compared with cardiology and general medicine. It is interesting that we obtain the largest HHIs for hospitals that are quasi-local monopolists—in rural areas or very small cities—whereas the lowest HHI values are attached to hospitals in the densely populated areas of Milan and Bergamo.

Table 7 shows the estimation results for equation (6), highlighting the influence of competition on hospital quality measured by adverse health outcomes after controlling for various sets of regressors. In all specifications, the estimated coefficient attached to the HHI is statistically insignificant. The interaction term between the HHI and ownership status is also insignificant, indicating that there are no significant differences regarding the effect of competition on adverse outcomes for public, private and not-for-profit hospitals. Given the relatively small sample size when estimating equation (6), we ran a sensitivity analysis to check the robustness of our results. After checking for the variance–covariance matrix of residuals and obtaining the standard errors by bootstrapping methods, we achieved robust estimates. We computed the standard error power for the HHI coefficient by following the approach that was proposed by Snijders (2005). The power is 0.7, which is considered satisfactory (Cohen, 1988).

As for the remaining regressors, the dummy variable for heart surgery has a negative and (weakly) significant coefficient attached in model 1, suggesting that the likelihood of adverse outcomes for patients in this ward is relatively lower than for patients in general medicine. The estimated coefficient attached to $\mathrm{Age65}_{wj}$ is positive and statistically significant in all models, indicating that hospitals with a higher share of patients who are older than 65 years tend to have more adverse health outcomes. High technology hospitals have more adverse outcomes than non-high-technology hospitals. This result may be explained by the fact that high technology

Table 7. Effect of competition on hospital health outcomes†

Independent variable	*Results for dependent variable hospital composite index of adverse health outcomes and the following models:*		
	Model 1	*Model 2*	*Model 3*
	Coefficient (standard error)	*Coefficient (standard error)*	*Coefficient (standard error)*
HHI_{wj}	0.031 (0.051)	0.013 (0.039)	0.018 (0.056)
$Age65_{wj}$	0.193 (0.047)‡	0.212 (0.048)‡	0.215 (0.055)‡
$Gender_{wj}$	−0.111 (0.090)	−0.046 (0.104)	−0.046 (0.105)
Drg_{wj}	0.006 (0.018)	0.006 (0.014)	0.008 (0.014)
ICU_{wj}	−0.009 (0.026)	−0.037 (0.029)	−0.037 (0.031)
$Tech_j$		0.022 (0.008)‡	0.022 (0.010)§
$Mono_j$		−0.005 (0.020)	−0.005 (0.022)
$Teaching_j$		−0.004 (0.008)	−0.002 (0.008)
NFP_j		−0.026 (0.013)§	−0.014 (0.038)
$Private_j$		−0.013 (0.007)§§	−0.017 (0.017)
$Hearth_{wj}$	−0.137 (0.072)§§	−0.105 (0.064)	−0.109 (0.062)§§
$Cardio_{wj}$	−0.106 (0.014)‡	−0.095 (0.016)‡	−0.096 (0.020)‡
$HHI_j{*}NFP_j$			−0.110 (0.274)
$HHI_j{*}Private_j$			0.034 (0.134)
Constant	0.069 (0.050)	0.016 (0.043)	0.013 (0.056)
Number of observations	220	220	220
Log-likelihood	382.51	391.82	392.19
ICC	0.065	0.066	0.075

†Results show estimates of multilevel model (6) by pseudolikelihood techniques by maximum likelihood. Standard errors are obtained by block bootstrapping at the ward level.
‡1% significance.
§5% significance.
§§10% significance.

hospitals generally also have an intensive care unit. There is weak statistically significant evidence in model 2 that private hospitals have lower adverse outcome rates than public hospitals.

The absence of evidence of a relationship between quality and competition may be explained by the presence of asymmetric information about the ‘true’ quality of hospitals, which was also suggested by Moscone *et al.* (2012). In fact, the presence of asymmetric information may act as a barrier for competition to work effectively, since it may reduce the possible returns from investing in hospital quality. A complementary explanation, of lack of such evidence, is the difficulty of using health outcomes that are sufficiently sensitive to detect differences in ward level quality as discussed at the end of Section 2.

Table 8 reports results for the estimation of the effect of hospital quality ranking on patient-predicted choice probabilities obtained from the three wards in stage 1. It is interesting that the effect of hospital rankings on predicted probabilities is always statistically insignificant. This result reinforces the role that is played by the presence of asymmetric information on elective patients.

8. Concluding remarks

In this paper we investigated how competition affects the health of patients in quasi-healthcare in the Lombardy regional market. We found that more competition does not seem to have a

Table 8. Impact of hospital quality ranking on patient-predicted choice probabilities†

Independent variable	*Results for dependent variable patient-predicted probability of choice*	
	Coefficient	*Standard error*
Ranking_j	−0.000001	0.00003
Beds_j	0.001‡	0.00002
Heart_j	0.140‡	0.0025
Cardio_j	0.076‡	0.0014
Constant	0.430‡	0.021
Number of observations	171616	
ICC	0.67	

†Results show estimates of multilevel model (6) by pseudolikelihood techniques by maximum likelihood.
‡1% significance.

significant influence on the quality of hospitals. One explanation for this result is a lack of publicly available information on the quality of hospitals. The presence of such asymmetric information may exacerbate the influence of information that is gathered locally. It may also result in a reduced freedom of choice for patients, a lower degree of competition between hospitals and a lack of market premium for top quality hospitals. Our results point to the network effect as a barrier for competition to work effectively and indicate that patient choice is likely to be not affected by the true quality of hospitals. Our analysis may shed light on why empirical literature often rejects the theoretical result that more competition should lead to better health when prices are fixed.

Our contribution has two important policy implications. First, the results show that it is necessary and urgent to disclose information regarding hospital quality ranking computed within the regional quality evaluation programme, to GPs, patients and the wider public. As shown by Austin *et al.* (2015), a set of indicators delivered to the public must remain fixed for a sufficiently long period of time to avoid misunderstandings and confusion. As such, the presence of asymmetric information will be reduced and patients will tend to choose high quality hospitals and to enjoy the benefits of having invested in better healthcare. Although publicly available hospital rankings may certainly support patient choice and encourage providers to improve their quality, this may not be enough to encourage low quality hospitals to improve their quality of care. Hence, our second policy implication is that the regional government should make a special intervention on behalf of these hospitals. For instance, such an intervention may give hospitals with only one or two wards, which is significantly below the regional average (i.e. indicated as belonging to group 3 within the quality evaluation programme), a time period—say, 1–2 years—within which they must make improvements. If a ward is still ranked in the bottom quality group after this period of time, it would be closed or receive a monetary penalty. These interventions in the regional hospital structure are essential to form a competitive hospital market.

Our results are open to further new research developments. In this paper, following Moscone *et al.* (2012), we have used hospital network effects as a proxy for patient sensitivity to local information or social interaction. However, we observe that social interaction may be the result of other forces such as contextual or correlated effects (Manski, 1993; Brock and Durlauf, 2001). Future work will consider strategies for disentangling social interaction from the effect of other factors. A limitation of our work is that the study focuses on only a single cross-section. Future work will explore whether our results are consistent when using panel data. Another interesting extension is the analysis of healthcare quality at the surgical or team level or using the average surgical quality within the ward weighted by the number of surgeries. In fact, patients could choose their provider depending on the national and international reputation of a particular surgeon or medical team and average surgical quality is a more accurate measure of quality.

Finally, we remark that the indicators that are usually used in the literature are not sufficiently sensitive to detect variations in ward level quality. Although in our paper we have mitigated this issue by using a composite index of adverse health outcomes, future work should include other indicators for hospital quality—e.g. clinical indicators describing the quality of the treatment that is used in various pathological conditions (Iezzoni *et al.*, 1996; Damberg *et al.*, 1998), process measures such as the frequency of using best practices in the treatment of a pathology (Joint Commission on Accreditation of Healthcare Organization, 1994), sentinel events representing unexpected occurrences (e.g. death or severe physical or psychological injury) (Joint Commission on Accreditation of Healthcare Organization, 1994) and quality-of-life outcomes indicating the general health condition of the patient (Damberg *et al.*, 1998).

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