

Does Hospital ownership influence quality of care?

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Abstract

The aim of this paper is to investigate the impact of hospital ownership on quality of care. We show that public hospitals have a high mortality rate, although quality improves in correlation with increases in hospital size. This interaction is reversed for private hospitals, with smaller facilities offering a higher quality of service.

Keywords: Hospital Ownership, Quality of Health Care, Risk Adjustment, Multilevel Model, Standardization, Effectiveness.

1 Introduction

The primary purpose of this paper is to investigate if hospital ownership affects quality of care. We start from some studies which address the influence of competition on quality of care, ([7]Propper, Burgess, Green, 2004; [6]Propper, Burgess, Gossage 2008; [3]Kessler, McClellan 2000). We use the findings of these works to identify evidence linking ownership with quality of care.

In recent years observers have become increasingly attentive to the level of costs related to health care services, including hospital services. At the same time both consumers and policy makers prioritize the quality of service in these facilities, and a holistic approach is required to identify areas for improvement in this regard. Quality in healthcare services means the ability to satisfy specific needs, and is the result of scientific, technical and technological, organizational, procedural and relational elements, in which the human variable plays primary role, interacting closely with the production process ([8] Vittadini, 2006).

Presently many industrialized countries have healthcare systems which designate resources to hospitals according to a predetermined tariff for each pathology. For example the Region of Lombardy in Northern Italy creates an annual tariff for Diagnostic Related Groups (DRG). Therefore the structure of the public health system depends on national and regional political decisions but then becomes autonomous from an operational point of view. Accordingly hospitals may be compared to firms, which allow us to use functional model in an entrepreneurial way with, for example, competition between various healthcare structures. Hospitals seek to identify an organizational model that allows the reduction of costs by optimizing the use of available resources, while simultaneously increasing patient satisfaction by utilizing optimal clinical conditions.

Healthcare is currently trending in this direction and in many countries is organized according to a mixed welfare system characterized by private profit-orientated agencies, private non-profit companies and public hospitals. Consumers are free to choose among these. The consumer freedom is restricted by rules, but also by particular conditions (for example the fact that “experiences good” cannot manifest until

the actual moment of supply). The purpose is to create decisional models like that one used in financial planning, that typically use a great number of variables, with the aim of estimating the entity and the kind of risks involved in determined initiatives, and studying more efficient allocation.

We have a wide range of data obtained from an administrative source at the Region of Lombardy, one of the most populated and richest regions in Italy, which allow us to render this process feasible. The determinant of quality that we have focused on is hospitals ownership. Hospitals form a mixed market, where both public and private hospitals try to respond to the demand for health care. Our goal is to determine whether a specific type of ownership provides a higher quality.

The paper is structured on the following basis: in Section 2 we discuss the methods of evaluation of quality in the healthcare system while in Section 3 we outline a case of study, and in Section 4 present concluding considerations.

2 Measurement of Healthcare Services Quality

When analyzing Healthcare Institutions it is necessary to purify the data from the effects of case mix variables, to facilitate comparisons on a like for like basis between different healthcare institutions. Specifically this requires the adjustment of data according to patient-specific and hospital-specific variables. We consider different Risk Adjustment Methodologies. These techniques allow us to measure quality in terms of relative effectiveness, without bias due to the case mix influence.

2.1 Direct and indirect standardization

Direct standardization ([9] Zaslavsky, 2001) is computed as follows: given y_{kj} health outcome observed in the k -eth status of the population patient and $\pi_{kj} = w_{kj} / \sum w_{kj}$ ($k = 1, \dots, q$), proportion of the k -eth case mix characteristic in the j -eth health structure, the weights of the outcome. The observed adjusted outcome is the weighted sum: $y_j = \sum_k \pi_{kj} y_{kj}$. This type of standardization has limitations: it is not possible to compute a standardized score for a stratum with no cases or with missing cases, and moreover it is not adapted to adjusting simultaneously for several variables or for continuous variables. Another approach is the indirect standardization. Given the weighted sum: $\hat{y}_j = \sum_k \hat{\pi}_{kj} y_{kj}$, where the weights $\hat{\pi}_{kj}$ are obtained from a standard theoretical population, in order to evaluate the relative effectiveness of the j -eth health structure, we compare the observed adjusted outcomes with the expected adjusted outcomes: $u_j^* = \hat{y}_j / y_j$. This standardization is not suitable when there are several case mix indicators or when the indicators are not discrete.

2.2 Linear and logistic models

Below we describe the linear and logistic models used as a method of risk-adjustment. We can define: $y_{ij} = \beta x_{ij} + e_{ij}$, where y_{ij} is the j -eth quantitative outcome for i -eth patient, x_{ij} the corresponding patient characteristics, e_{ij} the error term, and β is a vector of coefficients. The first term of the equation captures the effects of individual characteristics x on outcomes for the patients of the same unit. In other cases a covariance analysis is proposed: $y_{ij} = \beta x_{ij} + u_j + e_{ij}$, where u_j captures the hospitals heterogeneity in reaching a given quality in healthcare services of the j -eth agent. In the simplest formulation with dichotomic outcomes (the most commonly used is the hospitals mortality risk), the logistic function models calculate the logit of the

outcome p_{ij} as a linear function of the case mix variables x_k ($k = 1, \dots, p$):

$$\ln \left(\frac{p_{ij}}{1 - p_{ij}} \right) = \alpha + \beta_1 x_{1ij} + \beta_2 x_{2ij} + \dots + \beta_k x_{kij} = RS_{ij}$$

with RS_{ij} risk score associated to i - *eth* patient of j - *eth* structure. It can be illustrated in terms of probability:

$$p_{ij} = \frac{e^{\alpha + \beta_1 x_{1ij} + \beta_2 x_{2ij} + \dots + \beta_k x_{kij}}}{1 + e^{\alpha + \beta_1 x_{1ij} + \beta_2 x_{2ij} + \dots + \beta_k x_{kij}}} = \frac{e^{RS_{ij}}}{1 + e^{RS_{ij}}}$$

Where p_{ij} is the observed probability (equal to 0 or 1) regarding the positive or negative occurrence of the dichotomic outcome. By estimating the vector of parameter β and substituting $\hat{\beta}$ we obtain the expected probability $\hat{p}_{ij} = \frac{e^{\hat{\beta}_{ij}}}{1 + e^{\hat{\beta}_{ij}}}$. Comparing $\hat{p}_{ij}$ with p_{ij} we arrive at an estimation of the effectiveness of the j - *eth* health structure for the j - *eth* patient. Therefore the expected value of $\hat{p}_{ij}$ is obtained as: $E(\hat{p}_{ij}) = \sum_{i=1}^{n_j} \hat{p}_{ij}$ and the correspondent value of the observed probabilities $\sum_{i=1}^{n_j} p_{ij}$ the ratio $\hat{u}_j = \frac{\sum_{i=1}^{n_j} \hat{p}_{ij}}{\sum_{i=1}^{n_j} p_{ij}}$, estimates the effectiveness of the j - *eth* health structure.

In some cases logistic or linear models are not adequate for the calculation of the the relative effectiveness of health structures for the following reasons: first of all a sample of agents is chosen in the agents population; and more importantly secondly, the data often shows highly structured hierarchies because patients or episodes of care are nested within health structures and the higher levels of health institutions. In addition measures of quality are likely to differ for subgroups of patients within a single broad category, where the variety in numbers of secondary diagnoses, patients of different ages and sexes, and previous medical histories are all likely to influence outcomes. The characteristics of both patients and health structures need to be taken into account ([5] Normand et al., 1995). The solution to all of these drawbacks is the use of hierarchical models, and in particular we advocate the multilevel model, following the finding of several authors.

2.3 The Multilevel Model

We now consider the most important element of risk adjustment. It is not a technique, but a model that takes into account the hierarchical structure of the data. This is a global method of adjustment of the data, and has a strong assumption of linearity, but it is more complete. Multilevel models are a particular specification of hierarchical models, that offer solutions for studying relationship between outcomes (like mortality, health, quality of life ...) and contextual variables in complex hierarchical structures, considering both individual and aggregate levels of analysis ([2] Goldstein, 1995). The Multilevel model specified for the j - *eth* outcome is:

$$Y_{ij} = \beta_{0j} + \beta_j X_{ij} + \epsilon_{ij}$$

where Y_{ij} measures the outcome relative to the i - *eth* subject inside the j - *eth* hospital. Here β_{0j} is the random coefficient interpretable as the hospitals-specific heterogeneity with regard to outcome Y_{ij} adjusted for patient characteristics made up of fixed coefficients of patient covariates, a measure of relative effectiveness; X_{ij} is the vector of explicative variables whereas ϵ_{ij} are the independent residual, with zero mean, at subject level. Casual parameters are usually obtained by means of bayesian inference ([4] Leyland, Boddy, 1998) and they can have prior distribution, above all, in the case of patients. Subsequently, there must be particular focus on

estimation parameter procedures as well as the statistical properties of the estimators with respect to single model parameters and different parameter typologies (fixed effects and variance components at different levels of hierarchical structure) as a whole.

Given the hypothesis that the parameters β_{0j} and β_{1j} are random variables, with constant variance and known distribution, it is also possible to insert into the model variables of superior level, so the multilevel model becomes:

$$Y_{ij} = [\gamma_{00} + \gamma_{10}X_{ij} + \gamma_{01}Z_j + \gamma_{11}Z_jX_{ij}] + [u_{1j}X_{ij} + u_{0j} + \epsilon_{ij}]$$

with $\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + u_{0j}$ and $\beta_{1j} = \gamma_{10} + \gamma_{11}Z_j + u_{1j}$, where the Z_j represent the explanatory variables at hospitals level. The distribution of the dependent variable influences the choice of linear model -if we have a dichotomous outcome- the linear model will have the characteristics of a logistic regression model. The u_{0j} is a random variable that identifies the relative effectiveness of the j -eth hospital structure net of risk factors. We assume that the residual of the model ϵ_{ij} are uncorrelated with null expected value: $E(\epsilon_{ij}) = 0$; $Var(\epsilon_{ij}) = \sigma^2$. We assume that the casual parameter u_{0j} has $\Phi(u_{0j})$ distribution with constant variance : $Var(u_{0j}) = \sigma_u^2$. This model is particularly suited to evaluate the relative effectiveness because allows for the specification of variability *within* and *between* groups.

2.3.1 Restrictions

The basic version of the Multilevel Model is subject to some restrictions which limit its utility in practice. Some of the restrictions include: it considers only one outcome at a time, like the response variable; it does not consider hospital-specific characteristics as possible covariates; it makes the assumption of binomial distribution of the outcome and of multinomial distribution of random disturbance and the random parameter of effectiveness; there is no correlation between the expected values of the patients characteristic and the effectiveness of casual parameters, and finally it is a static model with fix effects (multilevel with mix effects).

2.3.2 Generalizations

We can make some generalizations to assure the utility of the model in real cases. Outcomes can be interpreted as latent constructs underlying a set of observable indicators, they can be defined -in statistical terms- as latent variables. In order to obtain solutions we avoid traditional structural equation models, which lead to indeterminacy of latent scores. Instead Partial least Squares and Regression Component Decomposition methods, which approximate latent variables by means of linear combinations of their indicators, can be utilized.

When the indicators are qualitative or mixed, we can act in order to obtain quantified observable indicators and their quantitative linear transformations simultaneously, or as an alternative multidimensional scaling methods can be utilized. The Rasch model is suitable for the estimation of latent outcomes as it allows the estimation of objective measurement of performance with the most agreeable properties.

Relative effectiveness needs to be adjusted for hospital characteristics. We can introduce further equations describing hospital characteristics, which a second level equation that expresses the random parameters $u_{jv}, (j = 1, \dots, p; v = 1, \dots, q)$ as a function of hospital characteristics. We can employ families of distribution other than normal or binomial, in order not to be too restrictive.

Mixed effects models assume that random agents effects are independent and not correlated with the expected values of patient's characteristics. In complex models

this assumption might not be realistic. Individual heterogeneity can be modeled poorly by the available subject-level covariates, and this can dramatically affect the estimation of random effects. In the linear case, possible remedies are based on the use of fixed-effects modeling in place of random effects, correcting the incidental parameter problem caused by using one parameter for each subject. In non-linear cases, fixed-effects estimation is too complicated; we cannot rely on exact conditioning to eliminate the subject-specific parameter, and therefore this is only possible in a generalized linear model with canonical link functions.

3 Empirical results

3.1 The data

The dataset regards the entire population of 135 hospitals within the Italian region of Lombardy. These hospitals have public, private profit and private not-for-profit ownership structures. We observed these hospitals over a period of four years, from 2005 to 2008. The model is population based, at both Hospital and patient level. We have applied a few exclusion criteria to avoid bias. These do not influence the correctness of the results. For instance we have considered all the ordinary discharges, excluding the day-hospitals and rehabilitations. In addition, to avoid bias connected with the peculiarity of the case study, we have also excluded children under 2 years old.

In order to compute the quality of health care received by a single patient, we started from the Hospital Discharge Chart (HDC) where all of the information regarding patients' characteristics and the treatments received during the admission period are recorded. We have tested the model on a sample of about 240000 patients per year, that is about the 20% of the entire population. The case selection of the sample is based on sex and age distribution, using the SAS procedure "proc survey select", that provides methods for both equal probability sampling and sampling with probability proportional to size. In the case of the latter, the selection probability of a unit is proportional to its size measure. Considering the large size of the sample we are satisfied there are no problems with bias, or its significance. Finally we have applied the model to the whole population.

To start the process we have to select the outcome to implement the multilevel model. There are several possibilities available to compute a proxy for the quality of care in hospital services. These are: in-hospital mortality, voluntary discharges, transfers between hospitals, repeated admissions for the same MDC (Major Diagnostic Categories), return to the operating room, mortality within 30 days from discharge and total mortality. The latter is given by the sum of in-hospital mortality and mortality within 30 days from discharge. This is a measure of quality in healthcare services received from hospitals that we adopted in our investigation, and that we chose as the proxy for quality, in line with the desired outcome of our study. It is a dichotomous variable that assumes only two values: 0 in case of no event, 1 in case of death event. The dichotomy nature of the variable creates a necessity for a logistic multilevel model.

Figure 1 displays the raw total mortality rate, and provide an idea of the distribution within the population.

The data has a hierarchical structure as patients are classified within different structures, and patients from the same hospital could have similarities in terms of particular characteristics compared to patients from different hospitals. Therefore it seems reasonable to take into account a set of characteristics, covariates of the model,

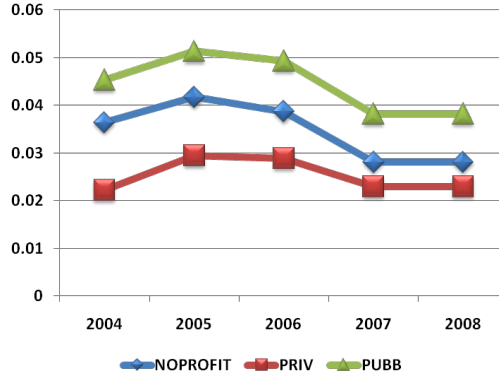


Figure 1: Total mortality rate

at both levels of the analysis.

The first level is the patients level, for which we gather socio-demographic variables, like age, gender, length of stay in hospital, length of stay before the operation and USA weight (this is the name of the index of seriousness of single case compared to the DRG). Then we obtain some variables referred to the diagnosis of disease, from the HDC. The last variable that we measure at patient level is the commorbidity, that indicates the number of pathologies for each single record.

The second level is the Hospital level, for which we obtain the following characteristics: number of operating rooms, number of operational units, mean number of hours for which operational rooms are in use, number of hours of activity of operational rooms, dimension of hospitals (small, medium, big) and whether they are private or public. Other variables are: percentage of beds used, a variable referred to the case mix and another variable that describe the accident and emergency.

3.2 The impact of ownership on quality in healthcare

We classify the variable of interest ownership as a dichotomous variable, without considering the diversification between private profit and private not for profit, and we apply some standard techniques to search possible hospitals characteristics that have the biggest influence on the estimation of dependent variable total mortality. In practice the variable that we analyze is an “odds”, the ratio between probability of success and the probability of failure, and we make a logarithmic transformation of this ratio in order to obtain a range of variation inside the whole space of real numbers. It is informative to analyze the log of the ratio between two odds.

We investigate if structures with particular characteristics have, on average, values of $\log(\text{or})$ significantly different from values of others structures with others characteristics. We conduct different analysis for different years, to underline the existence of changes over periods. It is necessary to check if the $\log(\text{or})$ is approximately distributed like a normal, which allow us to do a mean test. It is possible to use a *t-test for two independent sample* when the variable of comparison is dichotomous, but when there are categorical variables with more than two categories we have to use the *Analysis of Variance test*(ANOVA).

For the first year analyzed the most meaningful variable is “MONO” (mono-specialist Hospitals or generalist hospitals). This result is from the means test, which is then confirmed by introducing the linear regression model, with some covariates

that give the multivariate approach. Moreover the non parametric tests give the same results confirming the correctness of the results.

The analysis for the second year is similar: 2006, they catch our attention in year 2007, where an important factor is the interaction term between dimension of structure “ dim_3cat ”, 0 for hospitals of small dimension, 1 for medium and 2 for big, and the nature “ $PUBB$ ” public characterized with a 1, or private characterized with a 0. First of all the public hospitals show a major total mortality rate, whereas the effect of the dimension varies depending on whether a hospital is public or private. We implement a REG procedure that shows how all the characteristics are meaningful. Looking at the following table we observe that for a unitary increase of “ dim_3cat ” (that is going from a small structure to a medium, or from a medium to a big) the $log(or)$ of private hospitals increase on average of 0.09. For public hospitals the effect of dimension is the opposite, for a unitary increase of “ dim_3cat ”, the $log(or)$ decrease of -0.05 , that is the sum of the two coefficient of dimension and interaction. This means that private hospitals have better performances with small dimensions of the structure, while public hospitals reach better performances if the structures is big.

<i>Analysis of Variance</i>					
Source	DF	SSQ	MSQ	F Value	Pr > F
Model	3	0.22966	0.07655	4.58	0.0044
Error	129	2.1568	0.01672		
Corrected Total	132	2.35647			

<i>Parameter estimates</i>					
Variable	DF	Estimate	s.e.	t Value	Pr > t
Interc.	1	-0.0988	0.04132	-2.39	0.0182
dim_3cat	1	0.09488	0.03308	2.87	0.0048
PUBB	1	0.15909	0.05104	3.12	0.0023
interazio2	1	-0.14373	0.03922	-3.67	0.0004

It is possible to introduce several correction factors in the linear regression model, e.g. the different levels of emergency. In this case the direction and meaning of coefficient remain the same with small changes in intensity.

<i>Analysis of Variance</i>					
Source	DF	SSQ	MSQ	F Value	Pr > F
Model	8	0.30555	0.03819	2.28	0.0263
Error	124	2.08091	0.01678		
Corrected Total	132	2.38647			

<i>Parameter estimates</i>					
Variable	DF	Estimate	s.e.	t Value	Pr > t
Interc.	1	-0.09023	0.04806	-2.15	0.0339
dim_3cat	1	0.14556	0.05863	2.48	0.0144
PUBB	1	0.08177	0.03709	2.2	0.0293
interazio2	1	-0.13769	0.04341	-3.17	0.0019
UNI	1	-0.02609	0.04645	-0.56	0.5753
MONO	1	-0.0847	0.05224	-1.62	0.1075
dumdea	1	0.0308	0.0387	0.8	0.4276
dumeas	1	0.03508	0.05252	0.67	0.5055
dumps	1	0.01405	0.03487	0.4	0.6877

In year 2008 the meaningful variable is only *PUBB*, and it is the covariate most able to explain the variability of $\log(or)$.

4 Conclusions

This paper has investigated the impact of ownership on the quality of health care provided by different types of hospitals. We show that public hospitals have a negative influence on mortality rate, although when considering the interaction with hospital size we noticed that large public hospitals have higher quality of services. This represent our first investigation, and we believe that a deeper analysis of the interaction between patient characteristics and the hospital where it is admitted is required. Indeed, it may be the case that public hospitals have a higher mortality rate because they admit patients with bad health status. This issue is left for future research.

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