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Hospital Production In A National Health Service: The Physician's Dilemma*

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Abstract

There is a paucity of literature concerning the relation between the resource utilization decisions of the salaried hospital based physician and patient outcomes in a national health service. The purpose of our study is to model and test hospital production where the major decision makers are physicians. We view the output of the hospital as a distribution function over final health states of the patient. Our model contains a utility function for physicians whose arguments include the expected final health status of the patient and a pressure function which reflects the resource allocation and hospital financing policy of the Portuguese Health Ministry. Two sets of first order conditions derived from the theoretical model are estimated within a simultaneous equations framework using data consisting of inpatient discharges for the most frequent non-obstetric DRG during the 1992-1999 time period. We find evidence that budget setting methods and the possession of a third party payer outside of the NHS are important predictors for use of the resource in question. Moreover, we find that use of the resource is important in predicting the final health status of the patient.

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1 Introduction

Avedis Donabedian, according to the World Health Organization, is the most influential thinker on the quality of health care. His lecture on the evaluation of physician competence provides us with an intuition as to the decision-making process of the hospital based physician (Donabedian, 2000). He states that the primary responsibility of the physician is for the individual patient. However, the physician is responsible not only for one individual but a caseload so that limits must be placed on the time, attention and resources attributed to any given patient. This implies that the physician becomes a important figure in resource allocation and the optimal resource allocation is important for quality of care. He also distinguishes between the role of the physician in private practice and in an organization. He claims that in private practice the physician resolves contradictions between the optimal solution for an individual and caseload by limiting the number of cases. However, in an organized setting such as the hospital, the physician may not have this capability. Here the physician may be asked to consider the cost of clinical decisions, not for the individual patient, but for the collectivity, introducing a third element into the physician-patient relationship. We can conclude from Professor Donabedian's writing that the physician may be faced with a dilemma of acting in the interests of the patient and society, when the optimal solutions differ. Moreover, this dilemma may be exacerbated when the health care system is characterized by a national health service.

There is a paucity of literature concerning the relationship between the diagnosis and treatment decision-making of the hospital based physician and inpatient outcomes in health care systems characterized by a National Health Service (NHS). Acute care hospitals in many European health care systems are owned by either a central or regional government authority and are constrained by annual budgets set by the government authority. Generally, all personnel including physicians are contracted on a salary basis. Unlike physician behavioral models which typify private health care markets, the hospital based physician in this type of system can not alter his income via his diagnosis and treatment decisions. We propose that the typical NHS hospital based physician faces a dilemma between acting as a perfect agent for the patient and his or her role as an agent for the hospital administration whose objective is to restrain hospital spending within targets set by the Health Administration Authority (e.g. Ministry of Health).

The purpose of our study is to model and test hospital production in a national health service where the major resource decision makers are physicians. We depart from most existing literature in two ways. First, we propose a different theoretical model of hospital output. We view the output of the hospital as a distribution function over final possible health states of the patient. Second, we characterize the dilemma faced by the hospital based physician by specifying his utility as a function of the expected final health status of the patient and financial pressure resulting from resource allocation and financing policy of the Health Administration Authority. Finally we estimate a simultaneous equations model using all inpatient non-transfer discharges in the most frequent non-obstetric diagnosis related group for all Portuguese public hospitals during the January 1992-July 1999 time period. This illustrates the use of a structural approach to physician decision-making in the hospital.

We provide a framework for the theoretical model in section two and a description of the data, empirical specification and estimation technique in section three. The empirical results and conclusions are elaborated in sections four and five respectively.

2 Previous Physician Behavioral Models

The theoretical literature regarding physician behavior in hospitals traditionally models physician utility as a function of income and leisure as well as ethical and prestige constraints (e.g. Pauly, 1980; Dionne and Contandriopoulos, 1985; Folmer *et.al.*,1997). However, the applicability of these models is restricted to health care systems where physicians are paid in some manner other than a fixed salary and can therefore augment their hospital related incomes by altering resource utilization. Physicians employed in public hospitals in a national health service that are paid by salary for a certain number of hours per time period should have other arguments in their utility function. They may seek to maximize the utility of an expected ex post patient group as described by Clark and Olsen (1994), or their goal may be to maximize the expected health outcome of a particular patient, taking into account the opportunity cost per unit of financial resources as shown in Whynes (1996).These two studies show that even when own income considerations do not condition the decision making of the physician, he or she will be aware of some sort of constraint on resource usage. Clark and Olsen argue that in the case where physician's resource decisions can endogenously affect the health service budget, physicians will maximize the utility of society, which may be different from the desires of the individual patient, in order to avoid punishment from private contributors. Whynes argues that ethical physicians in a national health service will not behave myopically but recognize that their decisions regarding a particular patient may affect the availability of resources for other patients and will thus take into account the opportunity cost of their resource decisions.

While Whynes' model of physician behavior does describe the physician as assigning subjective possibilities to a range of possible post-treatment outcomes, he does so in a general way and does not specify the outcomes. Hospital outcomes research has received a great deal of attention in the health services literature, particularly regarding the effects of prospective payment systems on adverse outcomes (Cutler, 1995). Cutler's model assumes that an individual is admitted to a hospital with a latent measure of illness which is a function of individual frailty characteristics and hospital treatment. The probability of an adverse outcome defined as death in the hospital, death after discharge or re-admission, is increasing in the level of sickness. Cutler goes on to model in-hospital mortality as a logit model and the probabilities of the other two adverse outcomes as a proportional hazard model. However, the linkage between the physician's decision regarding resource utilization and patients outcomes is not clear. Our model attempts to clarify this relation in the context of a national health service by taking into account the impact of the physician's decisions regarding resource usage on the patient's outcome.

The model must maintain a manageable and simple formulation, in order to be viably estimated using the available data. The building blocks are, first, a production function, describing the relation between the inputs, hospital resources, and the output, patients' health status. Second, a characterization of the physician's decision concerning resource utilization must be provided. We now describe each block in detail.

2.1 Our Notion of Hospital Production

Our model of hospital production begins by defining output as a distribution of probabilities of the patient being discharged with a particular outcome. It differs somewhat from Cutler's model in that we consider that individuals are endowed with an initial health stock which can be increased through investment in health (medical care, life-style changes, etc.) and is subject to stochastic discrete depreciation shocks characterized by any illness or injury that causes a large reduction in the stock of health (e.g. Picone et al., 1998; Grossman, 1972). Whenever the health stock is below some threshold, the individual seeks hospital treatment.[1]

At the moment of entry to the hospital, the individual can be described by an initial health status, H^0, and by a set of personal characteristics. These personal characteristics influence effectiveness of any future treatment. Health status as well as personal characteristics may have unobservable as well as observable elements. The goal of hospital treatment is to change the distribution so that, in our model, the production of the hospital is a change in the distribution function over possible final health states or outcomes, given the initial health status of the patient, H^0, and other patient

[1] Patients in Portugal are obliged to seek treatment in the hospital whose catchement area includes their residence so that selectivity issues which characterize U.S. and U.K. studies (Hamilton and Hamilton, 1997) are not relevant for this study.

characteristics which may affect the self-healing capabilities and resources used in the diagnosis and treatment of the patient.

This approach implies that a discharge with full recovery and death can be seen as the same output of the hospital. The two very different outcomes are just distinct realizations of the same distribution function. Both outcomes can be associated with the very same use of resources. The problem to the outside observer is that he can not observe the true distribution function for each patient. Typically, only a finite (and small) partition of the outcomes space will be observed. For example, in the application (described in detail below) what we observe are two possible health outcomes for each patient: discharged alive or in-hospital death. In our framework, these two outcomes represent discrete values of a continuous random variable, the final health status of the patient. Thus, the modelling of hospital output must incorporate this observational constraint. More specifically, if the health status of a hospitalized individual falls below a certain threshold, H^d, the outcome is in-hospital death. For values above H^d the patient is discharged alive. Obviously such simple coding of final health status implies a loss of information.[2] We also cannot include death after discharge as an outcome due to a lack of computerized obituary information as well as privacy laws in Portugal.

We now define the production function of the hospital as:

$$\Pr(H_k^1) = p(H_k^0, \mathbf{x}_k, \mathbf{y}_k, \eta) \tag{1}$$

where $\mathbf{x}_k$ is a vector of resources used in the diagnosis and treatment of patient k, containing $i = 1, \ldots, I$, possible resources, $\mathbf{y}_k$ is a vector of patient characteristics which may affect healing capabilities, indexed by $j = 1, \ldots, J$ and η is a hospital quality indicator. Our notion of quality is a simple one: for the same initial health status, patient characteristics and resource utilization, a higher quality hospital has a better probability distribution over final health states. Hence, a distribution of final health states, $\hat{H}$

[2] We exclude outcomes which result in transfers due to a lack of information regarding the receiving hospital and reason for transfer. This information has begun to be recorded in Portuguese hospitals as of January 2000.

is *better* than another distribution $\tilde{H}$ if $\hat{H}$ exhibits first-order stochastic dominance over $\tilde{H}$.

2.2 The Role of Physicians

The major decision makers in our model are physicians. They affect the final health status distribution of the patient through their decisions regarding resource utilization. We assume that it is the physician who decides whether a patient will receive a particular resource based on his or her expectations regarding the efficacy of the resource and taking into account the financial pressure exerted by the hospital administration. The physician chooses x_{ik} to maximize his/her own utility, x_{ik} being the i-th element of $\mathbf{x}_k$. Utility of physicians is derived from two arguments. One is the expected final health status of the patient ,$E\left(H_k^1\right)$,which enters positively into the utility function. The second is the pressure exerted by the hospital administration to constrain resource utilization within an annual budget set by the Health Administration Authority. The form in which pressure enters the utility function will depend on the manner in which budgets are set.

In the case of our application, hospital budgets in Portugal are set in a unique manner. Since 1997, DRG case-mix has been a gradually increasing component of budgets.[3] Also, for financing purposes, hospitals are allocated into five different groups where the DRG base price is adjusted depending on the group the hospital belongs to. These differences range from group 1 whose hospitals receive 30% more than the base price to group 5 whose hospitals receive 20% less than the base price. As a further complication, inpatient admissions which are covered by non-NHS third party payers are obliged to pay all public hospitals based on the DRG base price.[4] This formulation actually implies that hospital budgets are partially flexible to the extent that a hospital receives a significant number of patients with alternate third party payers.

[3] In 1999, 30% of hospital budgets were based on inpatient case-mix.

[4] Payment may be less than or greater than the base price if the patient's length of stay is less than the inferior outlier limit or greater than the superior outlier limit defined for that DRG.

Another important potential factor in the pressure function may be the availability of the resource in the hospital. Many hospitals in Portugal do not have important technologies physically on site. When a hospital does not have the technology whose services are ordered by the physician, the exam or treatment must be done in other public hospitals or private clinics and paid for out of the hospital's budget.

Formally, the physician's utility function can be depicted as:

$$U = U(E(H_k^1), \varphi_k), \frac{\partial U}{\partial E(H)} > 0, \frac{\partial U}{\partial \varphi} < 0, \frac{\partial^2 U}{\partial E(H)^2} < 0, \frac{\partial^2 U}{\partial \varphi^2} > 0 \tag{2}$$

where φ is the *pressure* function.

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The dilemma or "choice problem" faced by the physician regarding patient k is thus:

$$\max_{x_{ik}} U(E(H_k^1 \mid H_k^0, \mathbf{x}_k, \mathbf{y}_k, \eta), \varphi) \tag{3}$$

For the case of continuous variables, the first-order conditions for solving this problem are:[5]

$$\frac{\partial U}{\partial E(H)} \frac{\partial E(H)}{\partial x_i} + \frac{\partial U}{\partial \varphi} \frac{\partial \varphi}{\partial x_i} = 0 \tag{4}$$

Since many types of treatment or diagnostic resources are only used once if at all , the first-order conditions accommodate a discrete change setting:

$$x_i^* = \begin{cases} 1 & if \quad U(E(H^1 \mid x_i = 1), \varphi(x_i = 1)) \geq \\ & \qquad (E(H^1 \mid x_i = 0), \varphi(x_i = 0)); \\ 0 & if \quad otherwise \end{cases}$$

The first-order conditions will be the basis of our analysis, as they describe optimal behavior of physicians. The next section describes the empirical implications of this simple model of physician behavior.

[5]Second-order conditions are satisfied, given the regularity assumptions made.

3 Econometric Specification and Estimation

To illustrate the potential application of our model of hospital output and physician decisions, we will estimate resource usage coupled with health outcome with data from all Portuguese public hospitals for a particular Diagnosis Related Groups (DRG). The specific DRG is *Cerebrovascular Disorders except transient ischemic attack* and is the most frequent non-obstetric DRG. The resource we focus on is the *Computerized Tomography scan* (CAT). This procedure is essentially a diagnostic tool. As such, the use of the CAT may improve the diagnostic capacity of the physician and thereby shift the health outcome distribution towards higher health status levels.

The data were made available by the Portuguese Ministry of Health and include 140 829 discharges whose outcomes did not end in transfer for 79 hospitals in this DRG. The mortality rate for this DRG is quite high (22%) and varies between hospitals from 10.01% to 47.61%. The use of the CAT is widespread (it is performed on approximately 60% of patients in this DRG), which seems to make this DRG a good candidate for testing the model. Despite its widespread use, there is a great variability in the use of the CAT between hospitals, ranging from 0.8 percent in the hospital with the lowest utilization to 92.45 percent in the hospital with the most frequent use of this technology.Patients in this DRG are essentially elderly (average age of 71 years) and with no predominance of either gender (see Tables 3 and 4 for descriptive statistics).

The econometric specification contains, according to the model presented, an equation for the generation of health outcomes and an equation describing usage of resources. We first specify the production process of final health status. We assume that the efficacy of a diagnostic or treatment resource may interact with patient and hospital characteristics due to differences in patient healing capacity and hospital quality, so that the underlying response model is specified as non-linear:

$$H_k = (1+\sum_i \theta_i x_{ik}) \left(\sum_j \alpha_j y_{jk} + \sum_h b_h \eta_{hk} \right) + \varepsilon_k \qquad (5)$$

where $k = 1, .., n$ indexes the observations from the sample, $\boldsymbol{\alpha}$ are the parameters on the individual characteristics which impact on the healing capabilities of the patient,$\mathbf{b}$ are the parameters on hospital characteristics and $\boldsymbol{\theta}$ are the parameters on resources. Finally, ε_k is a random term, assumed to follow a normal distribution.

To proxy for initial conditions, we include dummy variables for age and gender, severity (using primary and secondary diagnoses) as well as the manner in which the patient was admitted to the hospital (planned, transfer from another acute care hospital or emergency room). In order to test this model we consider only one resource, the use of the CAT(x_1). The specific functional form allows for the prediction of a final health status when the resource is not used and the use of the resource is expected to increase the final health outcome (thus, $\theta_i > 0$).

The health index H is not observed. As mentioned above, only two crude indicators are available: death or discharged alive. This situation indicates the applicability of a probit model, as death results if $H < H^d = 0$ (normalization at no generality cost), and discharge alive if $H > H^d$. Therefore, each observation can fall into one of these two categories. For each observation in the sample we can define a variable $d_k = 1$ if the patient is discharged alive and zero otherwise.

The log likelihood for the probit is thus:

$$L = \sum_{k=1}^{n} d_k \ln \Phi(H_k) + (1 - d_k) \ln [1 - \Phi(H_k)]$$

where Φ is the cumulative standard normal distribution.

The second element of the empirical model is an equation for resource use. The response function is determined by

$$U(E(H \mid x_1 = 1), \varphi(x_1 = 1)) \geq U(E(H \mid x_1 = 0), \varphi(x_1 = 0)) \qquad (6)$$

which also lends itself naturally to a probit model.

To proceed to estimation, we need to specify a functional form for the utility function of doctors. We assume an additive separable function on the expected health status of patients and financial pressure. The form of the physician's utility function should reflect that his change in utility from ordering the CAT will depend on the physician's belief regarding the efficacy of the CAT for that particular patient. We assume that utility changes resulting from increases in patient health status due to the use of the resource is greater for patients with lower levels of initial health status than for those in the upper tails of the distribution function so that the logarithmic function is an adequate specification for this component of the physician's utility function.

$$U(E(H), \varphi) = \gamma_1 \ln(E(H)) - \gamma_2(\varphi) \tag{7}$$

The utility change due to a CAT in the first component is therefore:

$$\gamma_1 \ln(E(H \mid x_1 = 1)) - \gamma_1 \ln(E(H \mid x_1 = 0)) = \gamma_1 \ln(1 + \theta_1) = \lambda_1 \tag{8}$$

The pressure function $\varphi(\cdot)$ is specified to be negative and increasing in diminishing levels of hospital funding, reduced availability of a CT scanner in the hospital and the lack of a third party payer for the patient. We also include dummy variables for the year of admission in the pressure function to reflect changes in technology adoption and budget setting methodologies over time.

Thus, the difference in the pressure functions from ordering the scan is simply:

$$\gamma_2(\varphi(x_1 = 1)) - \gamma_2(\varphi(x_1 = 0)) = \omega_0 + \sum_l \omega_l z_l$$

¿From these assumptions, the equation defining the physician's decision to order a scan is associated with a latent variable m^* given by:

$$m^* = \lambda_1 - \omega_0 - \sum_l \omega_l z_l + v = b_0 - \sum_l \omega_l z_l + v \tag{9}$$

is therefore making use of (6) where b_0 collects all the constant terms (λ_1 and ω_0), the z_l are the variables representing financial pressure and ν is a random term (which follows a normal distribution) .

The corresponding log likelihood is given by:

$$L = \sum_{k=1}^{n} m_k \ln \Phi(b_0 + \sum_l \omega_l z_l) + \sum_{k=1}^{n} (1 - m_k) \ln[1 - \Phi(b_0 + \sum_l \omega_l z_l)] \quad (10)$$

where m_k is the indicator function for observation k, which has value 1 if $x_i = 1$. Technically, the model is estimated using the method of maximum likelihood. The joint log likelihood is just the sum of individual log likelihoods, as the error terms were assumed to be independent (the assumption was not made on the reduced form equations but on the structural equations).[6]

The definitions of the variables used in the estimation of the model are presented in Tables 1 and 2.

4 Results for the Health Status and Resource Utilization Equations

The probit equation for health status whose results are shown in Tables 5 and 6 includes variables for age (the youngest category being omitted), gender, admission status, primary and secondary diagnosis codes, time, and the resource of interest (CAT). We include 78 hospital dummy variables in order to control for hospital fixed effects and measure differences in hospital quality. The omitted hospital is that with the greatest number of admissions in DRG 14 in Portugal. The signs on the age variables show that individuals between 66 and 80 (OLD) and those older than 80 (VERYOLD) are predicted to have a lower final health status, ceteris paribus, than younger patients as could be expected. The difference between patients under the age of 18 (MIDAGE) and between 18 and 65 is not statistically significant. We find that masculine patients (MALE) have a lower expected final health

[6]The structural parameters ω_0 and γ_1 cannot be estimated directly from the model as specified.

status than their female counterparts, a result consistent with prior studies (Yuan *et al.*,1998) Admission status is very important as well in predicting final health status. Those patients who were transferred in from another acute care hospital (TRANSIN) and those who were admitted through the emergency room (URGADM) have a lower predicted final health status than those patients whose admission was planned.[7]

Since DRG 14 includes a number of pathologies, descriptive statistics show that these patients are diagnosed with one of eleven diagnosis codes. The most frequent diagnosis code (Cerebral artery occlusion, unspecified, ICD-9-CM 434.9) is the omitted primary diagnosis in our estimation. Secondary diagnoses may also be important in determining the final health status of the patient. Therefore we include secondary diagnoses which have previously been determined to influence the final health status of patients admitted with stroke. (Yuan *et al.*,1998).

Our results indicate the importance of controlling for both primary and secondary diagnosis codes. A primary diagnosis of Subarachnoid hemorrhage (PD430), Intracerebral hemorrhage (PD431), Subdural hemorrhage (PD4321), Unspecified intracranial hemorrhage (PD4329) and Acute, but ill-defined cerebrovascular disease (PD436) has a negative impact on predicted final health status of the patient relative to the most frequent diagnosis while a primary diagnosis of Cerebral aneurysm, nonruptured (PD4373) or Aphasia (7843) has a positive impact. Though there is a potential infinite number of secondary diagnosis codes that these patients may have on admission or acquire during their hosptal stay, eleven are found to be important in negatively affecting the patient's predicted health status. These are: Pneumonia, organism unspecified (SD486), Congestive heart failure (SD4280), Left heart failure (SD4821), Heart failure, unspecified (SD4289), Pneumococcal pneumonia (SD481), Bacterial pneumonia unspecified (SD4829), Bronchopneumonia, organism unspecified (SD485), Acute renal failure, unspecified (SD5849), Chronic renal failure, unspecified (SD585), Renal failure, unspec-

[7] Third party payer status as a potential measure of socio-economic status was tested but not found to be significant in predicting final health status

ified (SD586) and Alcoholic cirrhosis of liver (SD5712).[8]

The most important result from this equation is the large and significant positive coefficient on CAT which indicates that performance of a scan has a strong positive impact on the predicted health status of patients classified in DRG 14. This result confirms the efficacy of this technology in the diagnosis of patients with cerebrovascular disorders. However, there are clearly other factors affecting the final health status of patients which cannot be identified from the available information but can be proxied by hospital fixed effects. Given that the omitted hospital is that with the highest caseload, it is interesting to note that a majority (51) of hospitals have a significantly higher expected final health status for these patients than the omitted hospital, with only six having significantly lower coefficients at the 99% and 95% confidence levels This result is contrary to the positive volume effects normally encountered in surgical pathologies.(Hamilton and Hamilton, 1997) We conclude that 21 hospitals (26.9%) have a similar quality as the coefficients on these hospital dummies were not statistically significant.[9]

Perhaps the most disturbing results from the health status equation is that which can be gleaned from the coefficients on the year dummy variables. Given the magnitude of the coefficients as well as the z scores, our results appear to indicate that expected health status for patients in DRG 14 was higher between during the years 1992-1995 than in latter years. The coefficient on 1996 is positive and significant at the 90% confidence level and the coefficients on 1997 and 1998 are positive but not statistically significant. Moreover, the coefficients as well as the z scores increase between 1992 and 1994 and then begin to decline.

This result may be due to an important problem with our study, the inability to control for re-incidence. Our data do not include patient identifiers due to privacy concerns by the Portuguese Ministry of Health. Previous

[8]Other secondary diagnosis codes such as 250-Diabetes mellitus, 429.0-Myocarditis, unspecified, 412-.Old myocardial infarction, and 427.31-Atrial fibrillation were not found to be statistically significant.

[9]One of these hospitals has a negative coffecient and one has a positive coefficient statistically significant at the 90% confidence level.

studies have shown that the cumulative risk for recurrence of stroke over 5 years is high, ranging from 33% to 50% of people who have previously had a stroke. (Bonita, 1992). Since our data cover a 7 1/2 year time period, it is likely that there are a significant number of admissions due to a second or higher incidence of stroke for the same previously admitted patient. Since recurrent strokes have a higher case fatality (Bonita, 1992), this phenomena could account for the decline in expected health status despite an increase in the use of the CAT.

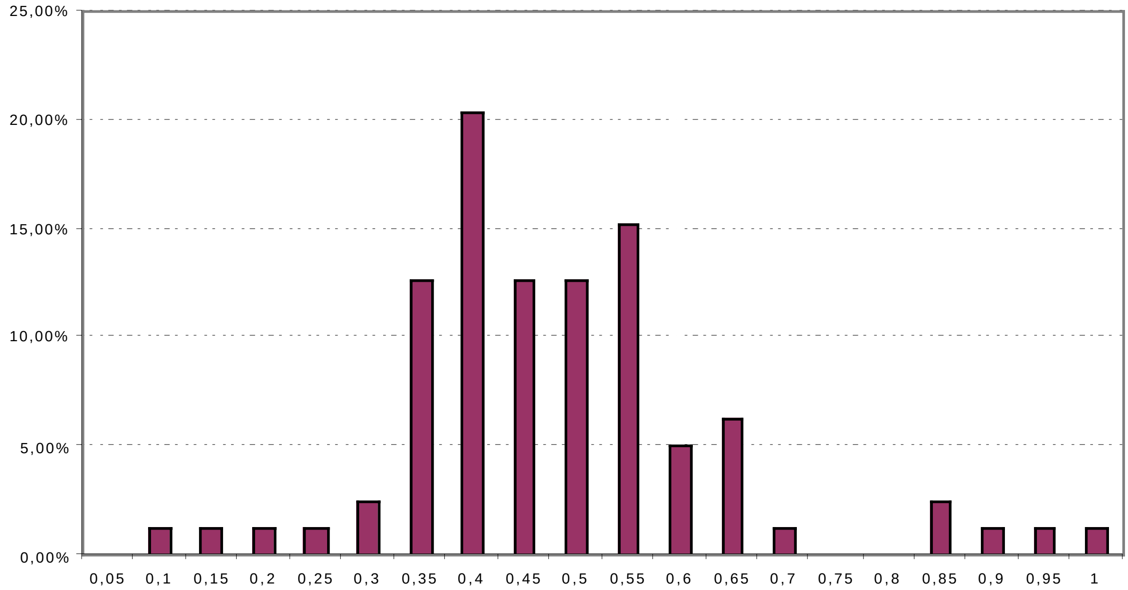
The estimated hospital fixed effects can be taken as a quality/efficiency effect. Everything else constant, a higher value of the fixed effect means a higher expected health status for the patient, which is equivalent to a higher survival probability. The hospitals in Portugal differ considerably in size and specialties. In order to test for overall group differences due to the special characteristics of lower level (smaller) hospitals, the model was re-estimated with their exclusion (resulting in 17 790 observations being removed from the sample). The results for this more restricted sample demonstrate similar qualitative and quantitative implications.[10]

To provide a more intuitive interpretation of hospital fixed effects, we compute a efficiency score in the following way. Assume that we want to measure the expected health status of patients under a common usage of resources and in a given year, allowing for differences in hospital characteristics. Holding constant the physician's decision to order the CAT, this implies that we observe the latent health index averaged over all patients in the sample. The reason to maintain constant the resource usage decision is to avoid confusing hospital-specific effects with physician decision variabes. After computing the average health index for each hospital (including the fixed effect), we normalize the highest value of the expected health index to 1. Hence, the resulting values can be seen as efficiency scores which by construction fall in the range [0,1].

Figure 1 reports the histogram of the efficiency scores. From it, we see that there are five hospitals that stand out as clearly more efficient than the

[10]Estimates and details are available from the authors upon request.

Figure 1: Histogram of Hospital Efficiency Scores



others (average efficiency score of 0.9). The majority of hospitals cluster around an efficiency score of 0.47, with a mean value of 0.46 for the total sample.Further research should be devoted to understanding the sources of these differences.[11]

Given the importance of the CAT scan in determining the predicted final health status of the patient, we now turn to the variables that potentially affect the physician's decision to order the scan. Here we use year dummies to reflect changes in technology adoption and budget setting methods with 1999 being the omitted year. We also include dummy variables for the budget groups with the highest budget group (group 1) being the omitted category. We control for availability of the resource on site by including variables reflecting the presence of the CT Scanner with multiple number of scanners being the omitted category. We control for the influence of the

[11] Regression of fixed effects on hospital characteristics such as hospital type, size, teaching status and region reveals that hospitals of medium size and those in the northern region of Portugal appear to be the most efficient. However, the equation has a low overall significance so that these are probably not the most adequate measures of efficiency differences. Details are avaible upon request from the authors.

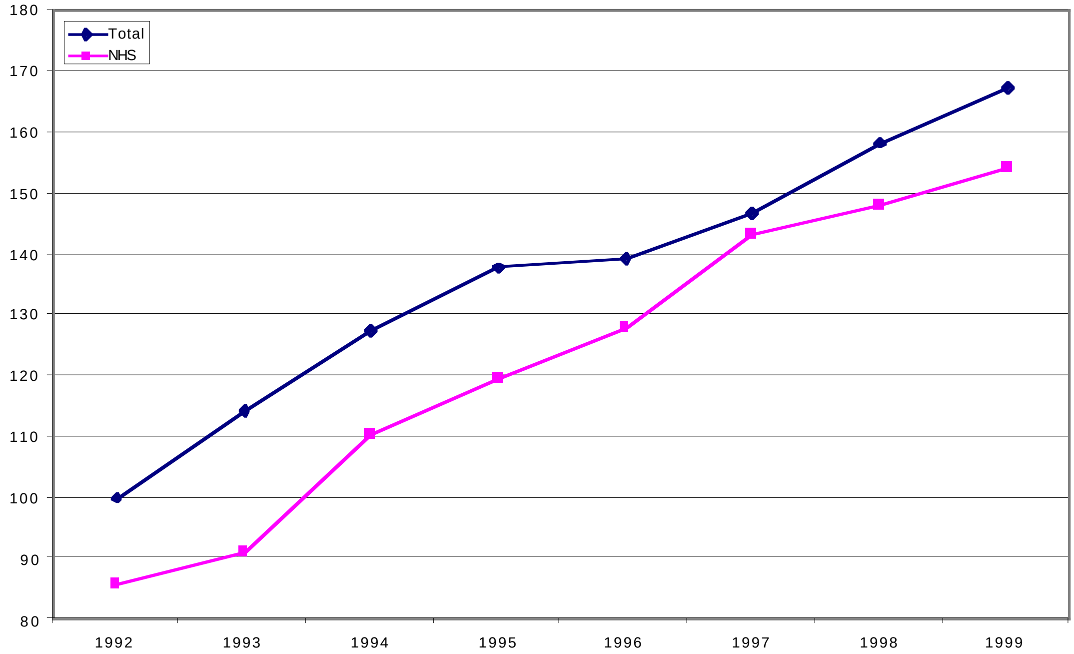
patient's payer status using possession of an alternative third party payer as the omitted category. We also include interaction terms between year and payer status in order to assess changes of the impact of payer status over time. Finally, we include regional dummy variables in order to control for potential variations in medical practice style. The results are presented in Table 7.

We can verify that the probability of doing a scan has increased with time whether due to technology adoption or modifications in budget methodologies, apparently resulting in a monotonic decrease in pressure over time. Even so, we find that the differences in budgets reflected by membership in a particular payment group is very important with the lower budget categories generally impacting negatively on the probability of the physician ordering a scan, ceteris paribus.

A curious result is the larger negative coefficients on two of the more generous groups (GRP2 and GRP3) relative to that whose budget is based on 100% of the DRG payment (GRP4). Since the rationale for partitioning of hospitals into these budget categories is not always clear (e.g. Group 3 consists of only one hospital), the coefficients may reflect a lack of consistency in attributing some hospitals to the most adequate category. The patient's payer status is also very important with national health service only (NHS) patients seeing their likelihood of receiving a scan decline relative to other patients who have an alternative third party payer, a result which has quite serious implications for those individuals lacking an alternative third party payer. We can infer from the coefficients on the interaction terms that this phenomena was exacerbated in 1993. For the years 1992, 1994-1996 and 1998, the coefficients on the interaction terms are not significantly different from zero and the coefficient is positive and significantly different from zero (95% level) for 1997, a curious result.

Still, we cannot infer unequivocally that doctors in the NHS react to the third party coverage of patients. According to our structural model, the influence of third party coverage on decisions is exerted in an indirect way, through the pressure function of hospital administrators. Even taking into

Figure 2: Third Party Payer Effect On Probability of CAT Usage Over Time



consideration the (lack of) statistical significance of estimated coefficients, it is instructive to further explore the economic significance of the phenomenon these coefficients may be capturing. This interpretation is motivated by the fact that pressure from hospital managers comes from total activity of the hospital and not on the basis of each particular patient, our unit of observation. Hospitals with a higher proportion of third party covered patients will have lower pressure overall so that physicians will conduct more CAT scans on all patients. Viewing the estimates in this manner, we observe that usage of the CAT scan in NHS patients has increased more rapidly as a percentage of total patients over time as shown in Figure 2.

The underlying trend seems to be that hospitals with a higher proportion of NHS only patients had a relatively steeper decrease in pressure (increase in the probability of ordering the CAT) over time. Of course, one must keep in mind that differences between the two are only statistically significant in 1993 and 1997, the year in which the NHS hospital budgets were first calculated partially based on case-mix (10%).Still, this raises an interesting question to be answered with data from other DRGs. Namely, the impact of (topping-up) insurance coverage in a NHS type health system. Moreover, we cannot take a normative view on this effect. It may be judged as positive or negative, depending on whether one believes that usage of the CAT has been below or above the social optimum level. Nonetheless, our findings suggest that future work should explore this effect.

Resource availability on site is extremely important. It is not surprising that the lack of a CT scanner (NOCAT) has a significantly negative influence on the probability of the patient having a scan. From an economic standpoint, the cost of doing a scan is much higher for hospitals who do not have a scanner because they must pay the full cost of the scan out of their budget (versus variable costs for those with a machine) as well as transportation costs. It is also possible that lack of a scanner may increase the utilization of other resources if patients stay longer in the hospital waiting for a scan , further increasing total patient costs .The number of scanners also appears to be important in determining utilization of the scan, with possession of only one scanner (ONECAT) negatively impacting the probability of doing a scan relative to the possession of a multiple number of scanners.

Regional variations in medical practice do appear to exist with all four other regions having statistically significant negative coefficients relative to the omitted Lisbon and Vale de Tejo region. The negative coefficients are largest for the Alentejo region (ALENTEJO), also the poorest in Portugal. One must question why patients entering Lisbon hospitals have a higher probability of receiving a scan. Since Lisbon is the capital of Portugal as well as the center for all government policy, including health, physicians may have better access to medical information and/or other resources, variables which cannot be measured in our model.

5 Conclusions

The aim of our paper is to test a model of physician behavior in a hospital setting within a national health service. Not only do we consider the factors affecting the physician's decision regarding resource utilization but also its impact on the final health status of the patient. We find evidence that for at least one major diagnosis related group and one important resource, budget setting methods and the possession of a non- National Health Service third party payer by the patient is important in the decision to the use the resource in question, the Computerized Tomography Scan. The availability and quantity of CT Scanners in the hospital is also a very important predictor in the patient receiving a Scan. Though the likelihood of a patient receiving a scan has increased with time, there are regional differences in the probability of receiving a scan with patients in regions outside of the capital city having a lower probability. Since we also find evidence that the use of the Scan has an important positive impact on the patient's final health status, the decision to not use a Scan on patients classified in DRG 14 is a serious decision. These results may have important policy implications for the Portuguese Ministry of Health as well as other countries whose systems are characterized by a national health service or by a similar professional structure. Further research needs to be conducted on other diagnoses and resources in order to verify if these results are particular to this DRG and resource.

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APPENDIX

Table 1: Variable Descriptions

NAME	DEFINITION
LIVE	=1 if the patient is discharged alive
MIDAGE	=1 if 18 <= age <=65
OLD	=1 if 66<=age<= 80
VERYOLD	=1 if age> 80
TRANSIN	=1 if the patient is admitted by transfer
URGADM	=1 if the admission is through the emergency room
NHS	=1 if the patient has only national health service coverage
1992	=1 if the patient was admitted in 1992
1993	=1 if the patient was admitted in 1993
1994	=1 if the patient was admitted in 1994
1995	=1 if the patient was admitted in 1995
1996	=1 if the patient was admitted in 1996
1997	=1 if the patient was admitted in 1997
1998	=1 if the patient was admitted in 1998
1999	=1 if the patient was admitted in 1999
CAT	=1 if the patient received a CT scan
NOCAT	=1 if the hospital does not have a CT Scanner
ONECAT	=1 if the hospital has one CT Scanner
GRP2	=1 if the budget based on 120% of DRG rate
GRP3	=1 if the budget based on 105% of DRG rate
GRP4	=1 if the budget based on 100% of DRG rate
GRP5	=1 if the budget based on 80% of DRG rate
NORTH	=1 if hospital located in the northern region
CENTRAL	=1 if hospital located in the central region
ALENTEJO	=1 if hospital located in the Alentejo region
ALGARVE	=1 if hospital located in the Algarve region

Notes: (a) Group classification GRP2-GRP5 is an administrative classification, defined by the Portuguese Ministry of Health; (b) regions are Administrative Health Regions.

Table 2: Variable Descriptions Continued

NAME	DEFINITION
PD430	primary diagnosis Subarachnoid hemorrhage (ICD-9-CM 430)
PD431	primary diagnosis Intracerebral hemorrhage (431)
PD4320	primary diagosis Nontraumatic extradural hemorrhage (432.0)
PD4321	primary diagnosis Subdural hemorrhage (432.1)
PD4329	primary diagnosis Unspecified intracranial hemorrhage (432.9)
PD4340	primary diagnosis Cerebral thrombosis (434.0)
PD4341	primary diagnosis Cerebral embolism (434.1)
PD436	primary diagnosis Acute, but ill-defined crebrovascular disease (436)
PD4373	primary diagnosis Cerebral aneurysm, nonruptured (437.3)
PD7843	primary diagnosis Aphasia (784.3)
SD486	secondary diagnosis of Pneumonia organism NOS (486)
SD4280	secondary diagnosis of Congestive heart failure (428.0)
SD4281	secondary diagnosis of Left heart failure (428.1)
SD4289	secondary diagnosis of Heart failure NOS (428.9)
SD481	secondary diagnosis of Pneumococcal pneumonia (481)
SD4829	secondary diagnosis of Bacterial Pneumonia NOS (482.9)
SD485	secondary diagnosis of Bronchopneumonia, NOS (485)
SD5849	secondary diagnosis of Acute renal failure NOS (584.9)
SD585	secondary diagnosis of Chronic renal failure NOS (585)
SD586	secondary diagnosis of Renal failure NOS (586)
SD5712	secondary diagnosis of Alcoholic cirrhosis of liver (571.2)

Table 3: Descriptive Statistics

VARIABLE	MEAN	STD DEV
ALIVE	.7773541	.416024
MIDAGE	.2684603	.44316
OLD	.5017148	.4999988
VERYOLD	.228078	.4195947
MALE	.5039516	.4999862
TRANSIN	.102486	.3032874
URGADM	.8761619	.329398
SNS	.8523173	.3547864
1992	.1111419	.3143089
1993	.127069	.3330514
1994	.1297531	.3360328
1995	.1341627	.3408283
1996	.1474625	.3545677
1997	.1467098	.3538177
1998	.1520425	.3590634
NOCAT	.3966726	.4892087
ONECAT	.4347187	.4957218
CAT	.5891258	.4919942
GRP2	.321972	.467234
GRP3	.0053469	.0729271
GRP4	.5431694	.4981347
GRP5	.1263234	.3322147
NORTH	.3185778	.4659265
CENTRAL	.2634756	.4405197
ALANTEJO	.0507353	.2194574
ALGARVE	.0357739	.1857266

Table 4: Descriptive Statistics Continued

VARIABLE	MEAN	STD DEV
PD430	.0163461	.1268029
PD431	.1464755	.3535835
PD4320	.0008308	.0288116
PD4321	.0097281	.0981506
PD4329	.0186538	.1352996
PD4340	.204624	.4034281
PD4341	.0145354	.1196837
PD4349	.3075503	.4614809
PD436	.2764345	.4472359
PD4373	.0039765	.0629339
PD7843	.000845	.0290566
SD486	.0290139	.1678461
SD4280	.0187177	.1355268
SD4281	.0035007	.0590633
SD4289	.0038841	.062202
SD481	.0026628	.0515338
SD4829	.009224	.0955978
SD485	.0097707	.0983632
SD5849	.0042321	.0649169
SD585	.0131649	.113981
SD586	.0042179	.0648083
SD5712	.0028119	.0529531

Table 5: Probit for the Health Status Equation

VARIABLE	COEFFICIENT	z	$p > \|z\|$
CONSTANT	1.259641	15.410	0.000
MIDAGE	-.0040099	-0.054	0.957
OLD	-.1959544	-2.630	0.009
VERYOLD	-.408544	-5.466	0.000
MALE	-.0144551	-2.500	0.012
TRANSIN	-.5003517	-16.912	0.000
URGADM	-.4116199	-14.859	0.000
PD430	-.3748965	-17.248	0.000
PD431	-.4139447	-41.910	0.000
PD4320	.0749847	0.636	0.525
PD4321	-.3865966	-14.628	0.000
PD4329	-.188884	-7.425	0.000
PD4340	-.0117405	-1.134	0.257
PD4341	-.0367491	-1.440	0.150
PD436	-.2445699	-23.272	0.000
PD4373	.2784135	3.678	0.000
PD7843	.7109804	3.743	0.000
SD486	-.4309944	-27.765	0.000
SD481	-.5482991	-11.207	0.000
SD4280	-.1876719	-9.560	0.000
SD4281	-.2607063	-5.766	0.000
SD4289	-.1411173	-3.212	0.001
SD4829	-.3715191	-13.552	0.000
SD485	-.4455322	-16.865	0.000
SD5849	-.5834706	-15.213	0.000
SD585	-.2365623	-10.264	0.000
SD586	-.3285104	-8.204	0.000
SD5712	-.2033436	-4.220	0.000

Table 6: Probit for the Health Status Equation Continued

VARIABLE	COEFFICIENT	z	$p > \|z\|$
1992	.0324109	2.089	0.037
1993	.0332731	2.219	0.026
1994	.0594012	4.047	0.000
1995	.0374745	2.605	0.009
1996	.0241094	1.715	0.086
1997	.0179912	1.295	0.195
1998	.0133962	0.974	0.330
CAT	.6354571	28.223	0.000

Note: 57 of 78 hospital coefficients are significantly different at the 95% or 99% confidence level.

Table 7: Probit for the CAT Scan Utitlization Equation

VARIABLE	Coefficient	z	$p > \|z\|$
CONSTANT	3.113652	36.218	0.000
NHS	-.2448051	-4.498	0.000
NOCAT	-1.251719	-74.765	0.000
ONECAT	-.688168	-50.023	0.000
GRP2	-1.116164	-16.156	0.000
GRP3	-1.51132	-17.957	0.000
GRP4	-.9638382	-14.131	0.000
GRP5	-1.572044	-22.805	0.000
1992	-1.25392	-21.285	0.000
1993	-.9856612	-17.460	0.000
1994	-.7421068	-12.979	0.000
1995	-.5481388	-9.483	0.000
1996	-.5237258	-9.230	0.000
1997	-.3830189	-6.687	0.000
1998	-.1699833	-2.899	0.004
NHS92	-.0160209	-0.255	0.799
NHS93	-.1829312	-3.029	0.002
NHS94	-.0767691	-1.259	0.208
NHS95	-.0959297	-1.559	0.119
NHS96	.0346843	0.573	0.566
NHS97	.1773061	2.903	0.004
NHS98	.0562109	0.902	0.367
NORTH	-.1350657	-14.146	0.000
CENTRAL	-.2727925	-27.235	0.000
ALENTEJO	-.6495152	-35.092	0.000
ALGARVE	-.220718	-10.574	0.000

Number of obs = 140829

Log likelihood = -146583.45

Wald chi2(112) = 5984.15

Prob > chi2 = 0.0000