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Demand Uncertainty and Hospital Costs: An Application to Portuguese NHS Hospitals

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DEMAND UNCERTAINTY AND HOSPITAL COSTS: AN APPLICATION TO PORTUGUESE NHS HOSPITALS

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Abstract

In this paper, we evaluate the effect of demand uncertainty on hospital costs. Since hospital managers want to minimize the probability of not having enough capacity to satisfy demand, hospitals have to build excess capacity since demand is uncertain, and incur on the associated costs.

Using panel data that comprises information for 43 Portuguese NHS hospitals for the period 2007 to 2009, we estimate a translog cost function that relates total variable costs to the usual variables (outputs, the price of inputs, some of the hospitals' organizational characteristics) and an additional term measuring the excess capacity related to the uncertainty of demand. Demand uncertainty is measured as the difference between actual and projected demand for emergency services.

Our results indicate that the cost function term associated with the uncertainty of demand is significant, which means that cost functions that do not include this type of term may be misspecified. For most of our sample, hospitals that face higher demand uncertainty have higher excess capacity and higher costs. Furthermore, we identify economies of scale in hospital costs, at least for smaller hospitals, suggesting that a policy of merging smaller hospitals would make a significant contribution to the reduction of hospital costs.

Keywords: hospitals, demand uncertainty, cost function

JEL Classification: D24; I11

1. INTRODUCTION

The role of hospitals has been changing significantly, and hospital reform has become a key issue in health policy discussions. Changes in demographic patterns, epidemiological and technological pressures, and political constraints (not least the financing constraints that public health systems in many OECD countries face), have forced changes in the pattern of clinical care, and are strong drivers for change in the organization of hospitals. One of the major lines of the reform is a demand for greater operating efficiency that may deliver better health outcomes with lower costs (Durán *et al.*, 2011).

Epidemiological and technological changes have allowed hospital managers to increase efficiency by reducing the number of acute beds, for instance, a trend that most European countries have been following for years (OECD, 2012). The reduction of excess capacity may increase efficiency, since unused resources increase costs without contributing to improve the health of patients.

However, in healthcare excess capacity may be a rational response of hospital managers to demand uncertainty, and reducing this “excess” capacity may endanger the ability of hospitals to provide timely services to patients. As such, it is important to assess if, and how much, “excess capacity” is a response to demand uncertainty, and to estimate the impact on hospital costs of this uncertainty. Health policy decisions regarding hospital capacity must take into consideration these two effects, but very little empirical work has been done recently on this issue.

This paper estimates the impact of demand uncertainty on the costs of Portuguese National Health Service (NHS) hospitals. Using a cost function that includes a cost factor associated with the excess capacity determined by the uncertainty of demand, we are able to identify the impact of demand uncertainty on hospitals costs. We are also able to propose policy options that may contribute to the reduction of hospital costs by reducing demand uncertainty and the costs associated with it.

The rest of this paper is organized as follows. In section 2 we provide a brief review of the relevant literature. Section 3 describes the methodology used in this paper. Our results are in section 4. Section 5 concludes.

2. LITERATURE REVIEW

When fixed factors are important, production capacity does not adjust to demand fluctuations in the short and medium term, implying that if demand exceeds the production capacity, some demand will not be satisfied. In sectors where the costs of having unsatisfied demand are high, such as the hospital sector, it is important that companies have a sufficient capacity to keep the excess demand probability below the (small) desired level (Gaynor and Anderson, 1995).

The variability of demand for hospital care may be decomposed in two parts (Boutsioli, 2010): the predictable variations of demand, such as seasonal effects, like weekends and holidays, and the unpredictable variations, or demand uncertainty.

Empty beds, empty operating rooms and unused equipment may result from inefficient management, but it may also be an efficient way of meeting the uncertainty of demand (Duncan, 1990), since the lack of available capacity would be prejudicial to the patients who really needed health care (Pauly and Wilson, 1986). Hospital managers will choose a given level of capital and labor to face all demand with a certain (high) probability of attendance, and thus the actual production will be, most of the time, less than the maximum production that would be possible for the set of used inputs.

There are many studies that analyze the cost structure of hospitals in a context of certain demand, for example Breyer (1987), Vitaliano (1987), Cowing et al. (1983), Vita (1990), and Ellis (1991), but the analysis of the effects of the uncertainty of demand on hospital costs has deserved less attention. Joskow (1980) was the first to analyze the uncertainty in the hospital demand services, using a queuing model, having concluded that if a hospital wanted to keep the turn away probability below a given value, the uncertainty of demand would influence in the decision of providing a greater capacity. Thorpe (1988) showed that in urban areas, where markets are competitive, hospital managers enhance available services, increasing the hospital capacity, as a way of reducing the turn away probability of their patients to other providers.

Friedman and Pauly (1981, 1983) used a model with a latent variable, wherein the uncertainty factor was introduced on the cost function by the ratio between the forecasted and expected output, to conclude that hospital costs were highly sensitive to variations in this ratio, and that eliminating or restricting the number of empty beds did not have a greater impact on costs.

Similar results were obtained by Pauly and Wilson (1986), who conclude that the elimination of beds would not produce significant savings, especially in small and medium-sized hospitals.

Gaynor and Anderson (1995) showed that demand uncertainty affects hospital costs, with hospitals with a higher variation in their forecasted demand having higher costs. Similar results were obtained by Carey (1998), Hughes and McGuire (2003), Baker et al. (2004), Smet (2007), Lovell et al. (2009), and Boutsioli (2011).

Many different econometric specifications have been used in studies of the hospital cost structure. The ad hoc functions with Cobb Douglas specifications, used by many authors to explain variations in production costs per unit (for example, Thorpe, 1988 and Pauly and Wilson, 1986), are simple functional forms that allow the introduction of a large number of explanatory variables, but impose constant returns to scale, where the average and marginal costs of each product are constant and independent of the quantity of the other outputs (Butler, 1995). This fact is a major limitation of these functional forms, since it is usually assumed in the literature that there are economies of scale and scope in the hospital sector.

Several alternative functional forms derived from the theory of the firm, assuming the objective of hospitals is cost minimization, have been used, such as the quadratic cost function, the translog cost function, or the generalized translog cost function (Smet, 2002). The translog specification has been particularly popular, since it allows for the imposition of restrictions on the parameter values, being therefore possible to analyze and test hypotheses that could not be tested on traditional specifications, such the joint production and the possibility of economies of scale. Cowing and Holtmann (1983), Conrad and Strauss (1983) and Carreira (1999) provide examples of the application of the translog cost function to hospitals.

3. METHODOLOGY

In this paper, we evaluate the effect of demand uncertainty on hospital costs, using panel data that comprises information for 43 Portuguese NHS hospitals for the period 2007 to 2009. The activity of Portuguese NHS hospitals may be decomposed in two parts: programmed production, that is scheduled well in advance, and as such has no uncertainty, and non-programmed production, that responds to immediate needs that appear through emergency services, which may vary substantially. Since demand uncertainty in Portuguese NHS hospitals is directly related to emergency services, this paper includes data for all Portuguese NHS hospitals with emergency care service (see Table A1 in Annex for a list of the hospitals considered).[1]

The cost, input and output data were obtained from the Database of Analytical Elements of the Central Administration of Health System (ACSS)[2] and the statistical reports of the NHS resources and production from the Directorate-General of Health (DGS).[3] The monthly data on the number of emergency episodes for each hospital were provided by ACSS.[4]

Demand uncertainty was estimated using an autoregressive process (AR1), where demand expectations are related to prior demand realizations, following Hughes and McGuire (2003). Demand uncertainty was estimated for each hospital individually, since the information on monthly emergency episodes is not publicly available. Thus, the information set used by managers to form expectations about demand is restricted to the information for their hospital.

The expected demand for hospital i is estimated using equation (1):

$$D_{it} = \alpha_i M_t + \rho_i (D_{it-1} - \alpha_i M_{t-1}) + \varepsilon_t \qquad (1)$$

where D_{it} is the number of emergency episodes in period t for hospital i, M_t is a variable representing the month, which intends to capture time trends, ρ is the autocorrelation between periods and α_j is a coefficient to estimate.

The variable that measures demand uncertainty (RES) corresponds to the difference, in absolute terms, between actual demand and the predicted value obtained from the model in equation (1), for each hospital each year.

[1] Some of the hospitals in the sample are integrated in Local Health Units (ULS), which are organizational structures that place under the same management primary care health centres and hospitals. Since the publicly available data refer to the ULS as a whole, and this study is applied exclusively to hospitals, data for hospitals included in ULS were estimated. The estimation is based on the weight of human resources used in the hospital in total ULS human resources, which is a good proxy given the importance of personnel cost on the operating costs of health care institutions.

[2] "Base de Dados de Elementos Analíticos", a database with analytical accounting data for Portuguese NHS hospitals provided by the ACSS (Administração Central do Sistema de Saúde), available at http://www.acss.min-saude.pt/bdea/ (ACSS, 2012).

[3] "Recursos e Produção do SNS", published by Direção-Geral de Saúde, available at http://www.dgs.pt/ (DGS, 2007, 2008, 2009).

[4] A list of the variables used in the analysis and some descriptive statistics are presented in the Annex, Table A2 and Table A3, respectively.

For the cost function, we compared a traditional Cobb Douglas specification (equation 2) and a flexible translog specification (equation 3):

$$ln(\overline{TVC}) \; = \alpha_0 + \sum_{i=1}^{4} \alpha_i \, ln(Y_i) + \beta_1 \, ln(W) + \rho_1 ln \, (X1) + \gamma_1 DMC + \gamma_2 DUP + \gamma_3 Dteaching + \varepsilon \qquad (2)$$

$$ln(\overline{TVC}) = \alpha_0 + \sum_{i=1}^{4} \alpha_i \, ln(Y_i) + \frac{1}{2}\sum_{i=1}^{4}\sum_{j=1}^{4} \alpha_{ij} \; ln(Y_i) \; ln(Y_j) + \beta_1 l\,n(W) + \frac{1}{2}\beta_{11} ln \, (W)^2 + \sum_{i=1}^{4} \delta_{i1} ln \, (Y_i) l\,n(W) + \rho_1 \ln \, (X_1) + \rho_{11} \ln \, (X_1)^2 + \gamma_1 DMC + \gamma_2 DUP + \gamma_3 Dteaching + \varepsilon \qquad (3)$$

The dependent variable (TVC) is "annual total variable cost", measured in thousand of 2006 Euros.[5] It includes costs of goods consumed, costs related to external services and supplies, and personnel costs. Y_i represents a vector of annual outputs, including the number of ambulatory surgeries (AMB),[6] the average length of stay for in-patient admissions (ALOS),[7] the number of outpatient visits (OPAT), and the number of emergency episodes (EATT). All these variables (with the exception of ALOS) were normalized by the number of in-patient admissions, meaning that outputs and costs used in the model are costs and outputs per in-patient admission.

The price of inputs is measured by the annual average wage (W), the ratio of total personnel costs to the number of permanent staff in each hospital. DMC, DUP, and Dteaching are dummy variables that assume the value 1 when the hospital has a medical-surgical emergency service, when the hospital has polyvalent emergency service,[8] and when the hospital is associated with a medical school, respectively.[9]

The variable X1 measures the part of empty hospital capacity that depends of the unexpected

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[5] The nominal current costs were transformed into real values for 2006 using the GDP deflator provided by National Statistics Institute (INE) and Bank of Portugal (BP).

[6] Since there are some null observations for the variable "AMB", and given the inability of the translog function to handle null values for output categories, we followed Cowing and Holtmann (1983) and Carreira (1999) and replaced the zero values with 0.1, a constant close to zero.

[7] The variable "average length of stay" is the ratio of the total number of inpatient days and the total number of discharged patients. It is an output variable, since a hospital may produce more health care, increasing the number of admissions or raising the average length of stay (Vita, 1990).

[8] Emergency services in Portuguese NHS hospitals may be of three types: basic, medical-surgical and polyvalent. The polyvalent emergency services are the most differentiated, and receive the more complex patients, which is likely to increase hospital costs.

[9] The dummy variables capture the differences in the complexity of cases treated in each hospital. Teaching hospitals with a polyvalent emergency service treat more complex cases, and thus are likely to have higher costs per patient, than other hospitals with other types of emergency departments and no teaching.

changes in demand. It was estimated using equation (4):

$$1/\text{ocup} = \beta_1 + \beta_2\overline{RES} + \beta_3\overline{RES}^2 + \beta_4\overline{RES}^3 + \varepsilon \qquad (4)$$

where *1/ocup* is the inverse of the occupancy rate, and $\overline{RES}$ is the measure of demand uncertainty normalized by in-patient admissions. Since demand uncertainty is expected to influence costs by creating excess capacity, one should not include both *RES* and *ocup* in the cost function. Therefore, to prevent a multiple effect of the uncertainty on the hospital costs, we chose to include the empty hospital capacity as a function of stochastic demand through variable X1, corresponding to the excess capacity estimated using equation 4.

4. RESULTS

Expected demand was estimated using equation (1) for each hospital, using OLS with standard deviations corrected by White covariance method. The individual results are presented in the Annex, Table A4. Based on these results, the variables *RES* (the measure of demand uncertainty) and $\overline{RES}$ (*RES* normalized by in-patient admissions) were obtained, and used in the estimation of equation 4 whose results are presented in Table 1.

TABLE 1
Estimation of empty hospital capacity as a function of demand uncertainty

Dependent variable: 1/ocup			
Coefficient	Variables	Coefficient	*t* statistic
β_1	C	1.3476	13.0456**
β_2	$\overline{\text{RES}}$	-0.4536	-0.7921
β_3	$\overline{\text{RES}}^2$	0.7051	0.9703
β_4	$\overline{\text{RES}}^3$	-0.2173	-0.9677
R^2	0.1113		
F	5.2177**		
N	129		

** Significant at 1% level.

The results in Table 1 show the estimated model is significant at the 1% level. Given that the sample mean of the variable $\overline{\text{RES}}$ is 0.5278, we can conclude that the empty hospital capacity increases when $\overline{\text{RES}}$ increases (from mean values). This is consistent with previous literature that identified increases in hospital capacity in response to increases in uncertainty.

TABLE 2

Cost function estimation

Dependent variable: ln($\overline{TVC}$)			
Coefficient	Variables	Coefficient	*t* – Statistic
α0	C	-21.0409	-17.1534**
α1	ln(ALOS)	-7.385774	-3.44006**
α2	ln($\overline{OPAT}$)	7.916324	3.13456**
α3	ln($\overline{AMB}$)	-0.644963	-0.907026
α4	ln($\overline{EATT}$)	1.776098	1.200056
β1	ln(W)	9.749097	2.95445**
$(\alpha 11)^2$	0.5*ln(ALOS)^2	1.284844	2.096096*
$(\alpha 22)^2$	0.5*ln($\overline{OPAT}$))^2	-0.301942	-1.073367
$(\alpha 33)^2$	0.5*ln($\overline{AMB}$)^2	0.004148	1.029090
$(\alpha 44)^2$	0.5*ln($\overline{EATT}$)^2	0.070899	0.962150
$(\beta 11)^2$	0.5*ln(W)^2	-1.297662	-0.774065
α12	0.5*ln(ALOS)*ln($\overline{OPAT}$)	0.797271	1.338672
α13	0.5*ln(ALOS)*ln($\overline{AMB}$)	-0.624353	-2.34373*
α14	0.5*ln(ALOS)*ln($\overline{EATT}$)	0.024423	0.142337
δ11	ln(ALOS)*ln(W)	1.116583	2.335885*
α23	0.5*ln($\overline{OPAT}$)*ln($\overline{AMB}$)	0.088102	1.002669
α24	0.5*ln($\overline{OPAT}$)*ln($\overline{EATT}$)	0.315693	2.19752*
δ21	ln($\overline{OPAT}$)*ln(W)	-2.272479	-2.79112**
α34	0.5*ln($\overline{AMB}$)*ln($\overline{EATT}$)	-0.171896	-8.57175**
δ31	ln($\overline{AMB}$)*ln(W)	0.400399	2.250841*
δ41	ln($\overline{EATT}$)*ln(W)	-0.683231	-1.501849
ρ1	ln(X1)	0.751741	3.68922**
$(\rho 11)^2$	ln(X1)^2	-1.263843	-4.91578**
γ1	DUP	0.357786	6.08534**
γ2	DMC	0.168683	2.88192**
γ3	DTEACHING	0.016847	1.77199
R^2	0.818583		
F	18.22908**		
N	127		

** Significant at 1% level. * Significant at 5% level.

Several specifications and estimation methods were used to estimate the cost function, and the appropriate tests allowed us to conclude that the most adequate specification was the translog cost model, estimated with random effects.[10] The results for this model are presented in Table

[10] The fixed effects method may not be used in this case because the model includes dummy variables. However, estimations of the model without dummy variables were performed and the tests allowed us to conclude that the most appropriate estimation method is the random effects method, even if dummy variables were not used. The

2.[11]

The estimated coefficients on the dummy variables are consistent with the expected impact on costs of the variables they represent. Hospitals costs increase with the differentiation of emergency services,[12] since hospitals with more differentiated emergency services should have the more complicated patients (whose treatments involve higher costs), and hospital costs are also higher (although not significantly) in teaching hospitals, that have to allocate additional resources for training.

The effect of the remaining variables on hospital costs may not be inferred directly, but the elasticity of costs to each of the explanatory variables presented in Table 3 allows for an evaluation of that effect.

TABLE 3
Elasticity of costs to each variable

Variables	Elasticity of cost
ALOS	0.4244
$\overline{\text{OPAT}}$	0.5971
$\overline{\text{AMB}}$	0.0040
$\overline{\text{EATT}}$	0.1616
W	0.1791
X1	0.0909

All output variables have a positive effect on costs, as expected, but only the average length of stay and the number of outpatient visits per inpatient admission are significant[13]. The (linear) effect of average wages on costs is also significant.

tests allowed us to conclude that the dummy variables are jointly significant. The results of these tests are presented in the Annex, Table A5. We also compared the results of the translog cost model with the results of the Cobb Douglas model, and tested for the significance of the terms that distinguish both specifications (the cross and squared terms). The results show (see Annex Table A6) that there is statistical evidence to reject the null hypothesis, meaning therefore that a translog model is the adequate specification for the cost function.

[11] The standard deviations are corrected by White covariance method.

[12] Remember that polyvalent emergency services (DUP) are the most differentiated, and that medical-surgical emergency services (DMC) are more differentiated than basic emergency services (the default option on the dummy variables).

[13] For ALOS, both first and second-order terms are significant, implying a "U" shaped relationship with hospital costs. The variable $\overline{OPAT}$ has a linear relationship with hospital costs, since only the first-order term is significant. Neither the first nor the second-order terms are statistically significant for the variables $\overline{AMB}$ and $\overline{EATT}$. Also, when analysing the joint significance of both first and second-order terms for the variables $\overline{AMB}$ and $\overline{EATT}$, we conclude that these are not significant.

Both the first and second-order terms of the variable X1 (the measure of excess capacity determined by demand uncertainty) are significant, suggesting an inverted "U" shaped relationship between hospital costs and X1. For values of X1 below 1.346, the first derivative is positive, implying that increases in excess capacity increase inpatient costs for hospitals where excess capacity is not extremely large, but that as the excess capacity increases the impact on costs decreases.[14] Also, the results in Table 4 show that the impact of X1 on costs varies with hospital size. For small hospitals, an increase in X1 leads to a reduction in costs, but for medium and large hospitals costs increase with X1.[15]

TABLE 4
Elasticity of costs to X1

Hospital size	Elasticity of cost
Small hospital	-0.0845
Medium hospitals	0.1299
Large hospitals	0.1341

The relationship between demand uncertainty and hospital size, measured by number of beds (BEDS), estimated using equation 5,[16] indicates a "U" shaped relationship between the variable $\overline{RES}$ and the variable BEDS, in which the minimum point is reached when the number of beds is 927.

$$\overline{RES} = \beta_1 + \beta_2 BEDS + \beta_3 BEDS^2 + \varepsilon \qquad (5)$$

This result implies that for most of the hospitals in the sample[17] an increase in size reduces demand uncertainty, meaning that a policy of hospital mergers would reduce demand uncertainty. Table 5 shows the estimated effect of three hypothetical mergers on hospitals costs.

The results indicate that for small and medium hospitals (mergers 1 and 2), there is a reduction in X1 resulting from the merger, i.e., the creation of a larger hospital would reduce

[14] When excess capacity is large (X1 above 1.346, corresponding to occupancy rates below 74.3%), the first derivative is negative, implying that costs do not increase with excess capacity. In our sample 86.1% of the values of X1 are below 1.346, which means that for most of the hospitals in the sample increases in excess capacity due to increased demand uncertainty increase inpatient costs.

[15] Small hospitals were defined as those having less than 200 beds. Large hospitals were defined as those having more than 600 beds.

[16] See the Annex, Table A7.

[17] Only 4 of the 43 hospitals in our sample have more than 927 beds.

demand uncertainty and the excess capacity associated with it. However, in the case of merger 1 the reduction of X1 causes an increase in costs, but in merger 2 the reduction of X1 decreases hospital costs. For large hospitals, excess capacity due to demand uncertainty increases with the merger and so do costs. The results in Table 5 also show that small hospitals exhibit economies of scale, but the merger of medium and large hospitals is associated with diseconomies of scale.

TABLE 5

Merger	Hospitals involved		Δ X1	Effect of uncertainty on hospital costs	Total effect on costs of the merger
	Identification number	Size			
1	15+17	Small	-4.30%	0.22%	-2.32%
2	41+42	Medium	-1.73%	-0.15%	0.97%
3	10+11	Large	0.39%	0.05%	1.10%

The estimated translog cost function allows for tests about the structures of production. The test for the hypothesis of input/output separability indicates that there is statistical evidence of interaction between outputs and prices of inputs. Also, the test for the hypothesis of joint production indicates that hospital outputs are not produced separately, since hospital costs do not correspond to the sum of the cost of producing each output independently[18].

5. CONCLUSIONS

In this paper we estimate the impact of demand uncertainty on the costs of Portuguese NHS hospitals, using a translog cost function that includes a cost factor associated with the uncertainty of demand. We find that the coefficient of the excess capacity associated with demand uncertainty is significant, which means that cost functions that do not include this type of term may be misspecified.

Our results indicate that hospitals that face higher demand uncertainty have higher excess

[18] See the Annex, Table A8.

capacity and significant higher costs (except when excess capacity is high). Since hospital managers want to minimize the probability of not having enough capacity to satisfy demand, hospitals have to build excess capacity when demand is uncertain, and incur on the associated costs.

We identify a negative relationship between demand uncertainty and hospital size (except for large hospitals), indicating that merging hospitals would contribute to reduce demand uncertainty. Given the positive relationship between higher demand uncertainty and higher costs in most of our sample, this implies that demand uncertainty may contribute to the existence of economies of scale. Overall, we identified economies of scale for small hospitals, but medium and large hospitals exhibit diseconomies of scale.

Since the hospitals in our sample are state-owned enterprises, the government may choose the size of these hospitals, for instance, by reducing capacity or merging different hospitals. Our results suggest that a policy of hospital restructuring, changing hospital size and/or merging smaller hospitals could make a significant contribution to the reduction of demand uncertainty and of hospital costs.

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Annex

TABLE A1
Hospitals in the sample

Hospital*	Number of the hospital in the sample	Type of emergency service**
ULS Alto Minho	1	SUMC
H. Santa Maria Maior, Barcelos	2	SUB
CH Trás-os-Montes e Alto Douro	3	SUP
CH do Nordeste	4	SUMC
CH Povoa de Varzim/Vila do Conde	5	SUMC
CH Médio Ave	6	SUMC
CH Alto Ave	7	SUMC
CH Tâmega e Sousa	8	SUMC
ULS Matosinhos	9	SUMC
CH São João	10	SUP
CH Porto (inclui H Joaquim Urbano)	11	SUP
CH Vila Nova de Gaia/Espinho	12	SUP
CH entre Douro e Vouga	13	SUMC
H. Infante D. Pedro, Aveiro	14	SUMC
H. Águeda	15	SUB
H. S. Teotónio	16	SUP
H. Cândido Figueiredo	17	SUB
ULS Guarda	18	SUMC
CH Cova da Beira	19	SUMC
CH Coimbra	20	SUP
H. Univ. Coimbra	21	SUP
H. Figueira da Foz	22	SUMC
H. Pombal	23	SUB
H. Sto André, Leiria	24	SUMC
ULS Castelo Branco	25	SUMC
CH Médio Tejo	26	SUMC
CH Oeste Norte	27	SUMC
H. Santarém	28	SUMC
CH Torres Vedras	29	SUMC
CH Lisboa Norte	30	SUP
H. Curry Cabral	31	SUMC
Mat. Alfredo da Costa	32	SUMC
CH Lisboa Ocidental	33	SUP
CH Lisboa Central	34	SUP
CH Barreiro/Montijo	35	SUMC
H. Garcia de Orta, Almada	36	SUP
CH Setúbal	37	SUMC
H. Espírito Santo, Évora	38	SUP
H. Litoral Alentejano	39	SUMC
ULS Norte Alentejano	40	SUMC
ULS Baixo Alentejo	41	SUMC
CH Barlavento Algarvio	42	SUMC
H. Faro	43	SUP

* Hospital Center (CH), Hospital (H.), Maternity Hospital (Mat.) and Local Health Unit (ULS).
** The emergency services are divided into three groups, the polyvalent (SUP), the medical-surgical (SUMC) and the basic emergency (SUB).

TABLE A2
List of variables used in the analysis

Name	Variables definition
D_t	Number of emergency episodes (monthly)
M_t	Variable respecting the month t
TVC	Annual operating costs (excluding depreciation and provisions), in thousand of Euros
ADM_T	Number of admissions (annual)
AMB	Number of ambulatory surgeries (annual)
BEDS	Number of beds
RES	Variable that measures the unexpected variations in demand (annual).
ALOS	Average length of stay (annual)
X1	Unused hospital capacity (as function of the uncertainty)
$D_{teaching}$	Dummy variable, that assumes the value 1 if is a teaching hospital, and 0 otherwise.
D_{MC}	Dummy variable with the value 1, in case of medical-surgical emergency and 0 otherwise
D_{UP}	Dummy variable that takes the value 1, in case of polyvalent emergency and 0 otherwise
OPAT	Number of outpatient visits (annual)
EATT	Number of emergency attendance (annual)
W	Annual average wage (thousand of Euros)
OCUP	Occupancy rate

TABLE A3
Descriptive statistics

Variables	Mean	S.D.	Max.	Min.	*N*
D_t	11114.49	5499.71	34443.00	1875.00	2580*
TVC	100233.88	87082.28	375097.38	6422.78	127
ADM_T	18400.74	12344.27	75923.00	1005.00	129
AMB	4273.385	3686.996	20177	0.00	129
ALOS	7.35	1.16	10.50	4.00	129
OCUP	0.78	0.10	1.17	0.38	129
BEDS	465.42	321.96	1496.00	56.00	129
EATT	134240.55	63521.71	335076.00	14945.00	129
W	29.27	2.33	34.87	21.98	127
OPAT	202217.59	169822.10	767879.00	12508.00	129
DMC					81**
DUP					36**
Dteaching					15**

* Monthly observations obtained between 2007 and 2011.
** Number of observations wherein the dummy takes the value 1.

TABLE A4
Emergency demand estimation for each hospital

Hospital	α	ρ
1	0.015936**	0.598703**
2	0.009277**	0.465361**
3	0.022384**	0.441421**
4	0.009878**	0.392055**
5	0.00985**	0.629468**
6	0.014111**	0.412022**
7	0.017811**	0.043836
8	0.021655**	0.217138*
9	0.010759**	0.874406**
10	0.036204**	0.073266
11	0.017043**	0.316429
12	0.020625**	0.310642**
13	0.023581**	0.584338**
14	0.016021**	0.32516**
15	0.005248**	0.300493*
16	0.017011**	0.150714
17	0.003757**	0.084602
18	0.011388**	0.006348
19	0.010324**	0.725601**
20	0.016043**	-0.297646
21	0.018428**	0.136638
22	0.008826**	-0.185917
23	0.004634**	0.47194**
24	0.017243**	0.217168*
25	0.008563**	0.190737
26	0.021993**	0.445367**
27	0.018899**	0.098459
28	0.014255**	0.407311*
29	0.01019**	0.303076*
30	0.034926**	0.867982**
31	0.010195**	0.886851**
32	0.003702**	0.427912**
33	0.020898**	0.275998*
34	0.028829**	0.055365
35	0.020459**	0.46975**
36	0.018086**	0.253923*
37	0.015356**	0.236253
38	0.008699**	0.138456
39	0.006256**	0.248907
40	0.009717**	0.152776
41	0.007356**	0.379379**
42	0.014768**	0.341721
43	0.016217**	0.287958*

** Significant at 1% level.
* Significant at 5% level.

TABLE A5

Tests for different estimation methods

Test	Null hypothesis	Value
Lagrange Multiplier test	Estimation by pooled OLS	72.8446**
Hausman test	Estimation by random effects	27.470155
F-statistic for significance of dummy variables	Dummy variables are not relevant to the model	3.195747*

** Significant at 1% level.
* Significant at 5% level.

TABLE A6

Test of the specification of the cost function

Redundant Variables Test
Equation: UNTITLED
Specification: LOG(TVCNORM) C LOG(ALOS) LOG(OPATNORM) LOG(AMBNORM) LOG(EATTNORM) LOG(W) 0.5*LOG(ALOS)^2 0.5 *LOG(OPATNORM)^2 0.5*LOG(AMBNORM)^2 0.5*LOG(EATTNORM)^2 0.5*LOG(W)^2 0.5*LOG(ALOS)*LOG(OPATNORM) 0.5*LOG(ALOS) *LOG(AMBNORM) 0.5*LOG(ALOS)*LOG(EATTNORM) LOG(ALOS) *LOG(W) 0.5*LOG(OPATNORM)*LOG(AMBNORM) 0.5 *LOG(OPATNORM)*LOG(EATTNORM) LOG(OPATNORM)*LOG(W) 0.5 *LOG(AMBNORM)*LOG(EATTNORM) LOG(AMBNORM)*LOG(W) LOG(EATTNORM)*LOG(W) LOG(X1) LOG(X1)^2 DUP DMC DTEACHING
Redundant Variables: 0.5*LOG(ALOS)^2 0.5*LOG(OPATNORM)^2 0.5 *LOG(AMBNORM)^2 0.5*LOG(EATTNORM)^2 0.5*LOG(W)^2 0.5 *LOG(ALOS)*LOG(OPATNORM) 0.5*LOG(ALOS)*LOG(AMBNORM) 0.5 *LOG(ALOS)*LOG(EATTNORM) LOG(ALOS)*LOG(W) 0.5 *LOG(OPATNORM)*LOG(AMBNORM) 0.5*LOG(OPATNORM) *LOG(EATTNORM) LOG(OPATNORM)*LOG(W) 0.5*LOG(AMBNORM) *LOG(EATTNORM) LOG(AMBNORM)*LOG(W) LOG(EATTNORM) *LOG(W) LOG(X1)^2

	Value	df	Probability
F-statistic	2.171962	(16, 101)	0.0104

TABLE A7

Dependent variable: $\overline{\mathbf{RES}}$			
Coefficient	Variables	Coefficient	*t* statistic
β_1	C	1.2023	10.0095**
β_2	$BEDS$	-0.0023	-6.7816**
β_3	$BEDS^2$	1.24E-06	6.2475**
R^2	0.445		
F	50.451**		
N	129		

** Significant at 1% level.

TABLE A8

a) Test of joint production

Redundant Variables Test

Equation: UNTITLED

Specification: LOG(TVCNORM) C LOG(ALOS) LOG(OPATNORM) LOG(AMBNORM) LOG(EATTNORM) LOG(W) 0.5*LOG(ALOS)^2 0.5*LOG(OPATNORM)^2 0.5*LOG(AMBNORM)^2 0.5*LOG(EATTNORM)^2 0.5*LOG(W)^2 0.5*LOG(ALOS)*LOG(OPATNORM) 0.5*LOG(ALOS) *LOG(AMBNORM) 0.5*LOG(ALOS)*LOG(EATTNORM) LOG(ALOS) *LOG(W) 0.5*LOG(OPATNORM)*LOG(AMBNORM) 0.5*LOG(OPATNORM)*LOG(EATTNORM) LOG(OPATNORM)*LOG(W) 0.5*LOG(AMBNORM)*LOG(EATTNORM) LOG(AMBNORM)*LOG(W) LOG(EATTNORM)*LOG(W) LOG(X1) LOG(X1)^2 DUP DMC DTEACHING

Redundant Variables: 0.5*LOG(ALOS)*LOG(OPATNORM) 0.5*LOG(ALOS) *LOG(AMBNORM) 0.5*LOG(ALOS)*LOG(EATTNORM) 0.5*LOG(OPATNORM)*LOG(AMBNORM) 0.5*LOG(OPATNORM) *LOG(EATTNORM) 0.5*LOG(AMBNORM)*LOG(EATTNORM)

	Value	df	Probability
F-statistic	2.322427	(6, 101)	0.0384

b) Test of input/output separability

Redundant Variables Test

Equation: UNTITLED

Specification: LOG(TVCNORM) C LOG(ALOS) LOG(OPATNORM) LOG(AMBNORM) LOG(EATTNORM) LOG(W) 0.5*LOG(ALOS)^2 0.5*LOG(OPATNORM)^2 0.5*LOG(AMBNORM)^2 0.5*LOG(EATTNORM)^2 0.5*LOG(W)^2 0.5*LOG(ALOS)*LOG(OPATNORM) 0.5*LOG(ALOS) *LOG(AMBNORM) 0.5*LOG(ALOS)*LOG(EATTNORM) LOG(ALOS) *LOG(W) 0.5*LOG(OPATNORM)*LOG(AMBNORM) 0.5*LOG(OPATNORM)*LOG(EATTNORM) LOG(OPATNORM)*LOG(W) 0.5*LOG(AMBNORM)*LOG(EATTNORM) LOG(AMBNORM)*LOG(W) LOG(EATTNORM)*LOG(W) LOG(X1) LOG(X1)^2 DUP DMC DTEACHING

Redundant Variables: LOG(ALOS)*LOG(W) LOG(OPATNORM)*LOG(W) LOG(AMBNORM)*LOG(W) LOG(EATTNORM)*LOG(W)

	Value	df	Probability
F-statistic	2.627367	(4, 101)	0.0388

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