Economies of scale and scope in the provision of diagnostic techniques and therapeutic services in Portuguese hospitals*

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Abstract

This paper analyses the provision of auxiliary clinical services that are typically carried out within the hospital. We estimate a flexible cost function for the three most important (cost-wise) diagnostic techniques and therapeutic services in Portuguese hospitals: Clinical Pathology, Medical Imaging and Physical Medicine and Rehabilitation. Our objective in carrying out this estimation is the evaluation of economies of scale and scope in the provision of these services. For all services, we find evidence of ray economies of scale and some evidence of economies of scope. These results have important policy implications and can be related to the ongoing discussion of where and how should hospitals provide these services.

JEL Classification: D24, I12, I18

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1 Introduction

Hospital efficiency[1] and cost structure[2] has received over the years' widespread attention in the literature. The analysis of hospitals' cost structure had an initial objective of (i) assessing economies of scale and (ii) understanding the increasing trend in hospital costs (Cowing and Holtmann (1983)). Grannemann et al. (1986) have added one further reason for the importance of hospitals' cost structure: changes in hospitals' reimbursement policies, particularly the introduction of prospective payments. Knowledge of the cost structure is necessary in order to understand the incentives underlying hospitals' output decisions under various reimbursement policies and, for policymakers, this information is crucial in order to define price levels and other details of the payment mechanism (such as whether payment for services should be bundled or paid for on a service by service basis, or whether different types of hospital should receive different prices). In addition to this, from a competition policy perspective, especially when assessing mergers between hospitals, a good understanding of the hospitals' cost structure is necessary in order to evaluate potential merger-related cost efficiencies (Vita (1990), Preyra and Pink (2006)).

The analysis of hospital efficiency has also been studied for a variety of reasons. Zuckerman et al. (1994) note that under a prospective payment mechanism, some hospitals, theoretically those which are more efficient, have positive profit margins, while others, those which are less efficient, do not. In order to evaluate whether this relationship holds, a comparative assessment of hospital efficiency is necessary. In addition, the higher costs and worse outcomes of US hospitals (vis a vis other OECD countries) raise important questions regarding their efficiency. In particular, it becomes important to understand whether managed care, which has had a role in cost containment, had any impact on hospital efficiency (Rosko (2001)). More recently, Herr (2008) has analysed whether hospital ownership, patient structure or other factors, which cannot be considered inputs or outputs of the production process, has an impact on hospital efficiency.

And yet little is known about cost structures of services within the hospital. In particular, some activities such as non-clinical services (e.g. car parking, computing, laundry, engineering, catering) or clinical services (e.g. clinical pathology, medical imaging, pharmacy) are often considered inputs of production (Cowing and Holtmann (1983), Vita (1990)), but little attention is paid to their own production process. Given that such activities usually have a significant weight in total costs, it is surprising that more research on the topic has not been carried out.

Moreover, there is often pressure or need to outsource the provision of such activities, or at the very least to benchmark their provision against private sector practices (Young (2005)). This is particularly important in the light of Coase's (1937) contribution to a proper understanding of the

[1] See, among others, Zuckerman, Hadley and Iezzoni (1994), Rosko and Chilingerian (1999), Rosko (2001), Staat (2006) or Herr (2008).

[2] See, for example, Cowing and Holtmann (1983), Grannemann et al. (1986), Vitaliano (1987), Vita (1990), Fournier and Mitchell (1992), Aletras (1999), Li and Rosenman (2001) or Preyra and Pink (2006).

firm: in the provision of a particular service by a firm, it is important to compare the possibility of in-house production with the use of the market as a resource allocation mechanism (outsourcing) – often defined as a make-or-buy decision. A body of literature has emerged looking in detail at this dilemma, focusing on the role of transaction costs, asset specificity and incomplete contracts as crucial elements to guide a firm's make-or-buy decision (Williamson (1975, 1979, 1985), Grossman and Hart (1986)). More recently, Grossman and Helpman (2002) have explicitly modelled these trade-offs in a framework designed to analyse market structures, where integration and outsourcing emerge as "equilibrium phenomena". In doing so, Grossman and Helpman (2002) have moved away from the typical bilateral relationship established between a single producer and supplier and considered in more detail the interdependence between the choices of the various firms in an industry. For example, outsourcing may be appealing for a firm if many firms provide an input it needs and this depends on whether other firms have chosen to be vertically integrated or to also outsource and buy inputs from others.

This paper is a contribution to a more detailed analysis of the trade-offs involved in the make-or-buy decisions of some clinical services by hospitals. In particular, our objective is to shed some light on an important reason for outsourcing: the existence of economies of scale. As Williamson (1979) notes, by choosing to buy rather than make, and assuming transaction costs are negligible, an external supplier may be in a better position to take advantage of scale economies through aggregation of various firms' demands. Or, viewed from a different perspective, if transaction costs are significant or if outsourcing to private sector contractors is a politically delicate decision, in-house production may bring about benefits to hospitals which enjoy economies of scale and it may be sensible, in so far as possible, for such hospitals to aggregate the production which would normally be carried out by other hospitals. Moreover, economies of scope may exist in the joint provision of several services. For those cases, joint service production would bring about further benefits, whilst for services which do not benefit from economies of scope, there is an economically sound argument for them to be produced independently from others, possibly even outsourced.

In order to address these issues, we analyse the provision of auxiliary clinical services that are typically carried out within the hospital by estimating a flexible cost function for the three most important (cost-wise) diagnostic techniques and therapeutic services in Portuguese hospitals: Clinical Pathology, Medical Imaging and Physical Medicine and Rehabilitation.

Our objective in carrying out this estimation is the evaluation of economies of scale and scope in the provision of these services. We use publicly available data from Portuguese hospitals' analytical cost accounting for the years 2002-2006. In addition, we have also collected information regarding each individual hospital, such as the casemix index - a proxy for the complexity of clinical cases treated - or the number of staff members. The estimation was carried out for a generalized translog cost function, assuming that hospitals operated in the short-run, i.e. assuming that the quantity used of some factors of production could not be easily changed. As is standard in the literature, we have estimated the cost function jointly with the cost share equations in order to improve the quality of the estimation.

For Clinical Pathology and Medical Imaging, and when evaluating the cost function at the sample mean, we find evidence of ray economies of scale, i.e. as we increase the quantity produced of each individual output, costs increase less than proportionally. For Physical Medicine and Rehabilitation, although a slightly different method was used to assess returns to scale, we also find that economies of scale appear to exist. We also find that there is evidence of economies of scope for some of the services provided within each category, but not for all of them. This suggests that some services could be provided independently within each hospital without affecting overall costs. For instance, in Clinical Pathology, we found no evidence of economies of scope between clinical chemistry - by far the most important (cost-wise) service within that category - and all other outputs. Thus, outsourcing the provision of those services would have no cost implications in the production of other outputs. By contrast, and in Imagiology, computed tomography exhibits economies with all other outputs except one (ultrasonography), which suggests that if computed tomography were to be outsourced, it would raise the costs of producing all other outputs (except ultrasonography). In the case of Clinical Pathology, we find that hospitals are under-dimensioned, i.e. they have too little medical equipment (which we proxy by using the number of beds) for the outputs they produce. The reverse is true for Medical Imaging: hospitals appear to be over-dimensioned, i.e. they have too much hospital equipment for the outputs they produce.

These results have important policy implications and can be related to the ongoing discussion of where and how should hospitals provide these services. For instance, they allow us to assess the optimal hospital dimension for the provision of such auxiliary clinical services, as well as to understand whether the joint production of some services is more efficient than stand-alone production. In addition, and at the very least, the results contribute to a more informed view of the possible cost savings arising from aggregating production in fewer hospitals. Moreover, and in the context of the Portuguese National Health Service, the existence of economies of scale may provide a rationale for outsourcing particular services, even if they are to be provided by public or private contractors within the hospital premises. Such a contractor could aggregate larger output levels and take advantage of such economies of scale. This possibility is enshrined in article 10 of Law 27/2002, although, to the best of our knowledge, no Portuguese hospital has ever outsourced the provision of clinical services in such a way. Finally, our results raise important questions associated with the estimated lower costs of service provision by smaller (district and level 1) hospitals, even after adjusting for casemix. This may well be evidence that, as Coase (1937) suggested, central hospitals have surpassed their optimal size and are thus facing "diminishing returns to management"[3]. If that is the case, our results suggest that cost reductions could be achieved if central hospitals reorganized their provision of such services through the creation of smaller independent

[3] Coase (1937), pp. 394-95.

service providing centres within the hospital, which could thus not be subject to such diminishing returns to management.

The paper is organized in the following way: Section 2 presents the cost function to be estimated, whilst Section 3 describes the data used. Section 4 presents the results and Section 5 concludes. An appendix contains a sensitivity analysis of our results.

2 The econometric setup

The main economic concept at the heart of our analysis is the cost function. A firm's long-run cost function depends on the quantitites produced of the various outputs (y_i), as well as on the input prices (w_i). Assuming there are n outputs and m inputs, a firm's long-run cost function is given by:

$$C = C\left(y_1, ..., y_n, w_1, ..., w_m\right) \tag{1}$$

The short-run is defined as a period of time which is too short for the firm to be able to change the quantity it uses of all its inputs. Typically, in the short-run there is at least one factor of production whose quantity the firm cannot easily change. If we define the quantity of this factor to be k, then a firm's short-run cost function will be given by:

$$C^S = C^S\left(y_1, ..., y_n, w_1, ..., w_m, k\right) \tag{2}$$

Because fixed factors of production necessarily lead to the existence of fixed costs, the short-run cost function can also be written as:

$$C^S = VC\left(\mathbf{y}, \mathbf{w}_v\right) + F \tag{3}$$

where VC represents variable costs (i.e. costs associated with the inputs which the firm can vary in the short-run), $\mathbf{w}_v$ is the vector of all input prices except input k, $\mathbf{y} = (y_1, ..., y_n)$ is the output vector and $F = w_k k$ is the fixed cost of production.

We make the assumption that hospitals operate in the short-run. This implies that we believe hospitals cannot easily change the quantity they use of *all* the factors of production, in response to a change in input prices or output levels. We use the generalized translog cost function to represent the variable cost function. This is a generalization of the translog cost function and it is appropriate when a significant number of observations has zero output levels: a Box-Cox transformation of the output levels is used instead of the usual (under the translog cost function) log-transformation. Therefore, output levels y_i are transformed into $Y_i = \frac{y_i^\lambda - 1}{\lambda}$. [4] Similarly to other

[4] We assume $\lambda = 0.1$. The appendix contains a sensitivity analysis for different values of λ. Our results appear to be robust for different values of λ.

flexible functional forms for the cost function, such as the quadratic cost function or the translog cost function, the generalized translog represents a second-order Taylor approximation to the true (but unknown) functional form of a differentiable cost function. The equation representing the generalized translog cost function is:

$$\begin{aligned}\ln VC &= \alpha_0 + \sum_{i=1}^{n}\beta_i Y_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\beta_{ij}Y_iY_j + \\ &+ \sum_{i=1}^{m}\gamma_i \ln(w_i) + \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}\gamma_{ij}\ln(w_i)\ln(w_j) + \sum_{r=1}^{n}\sum_{i=1}^{m}\delta_{ri}.Y_r \ln(w_i) + \\ &+ \beta_K.\ln(k) + \frac{1}{2}\beta_{KK}.(\ln(k))^2 + \sum_{i=1}^{m}\sigma_{Ki}.\ln(k).\ln(w_i) + \sum_{i=1}^{n}\theta_{Ki}.\ln(k).Y_i + \varepsilon \qquad (4)\end{aligned}$$

where w_i represents the price of input i, n is the total number of outputs and m is the total number of inputs. We assume a symmetry constraint, $\beta_{ij} = \beta_{ji}$ and $\gamma_{ij} = \gamma_{ji}$, as well as linear homogeneity in input prices (i.e. doubling the price of all inputs leads to a doubling of costs):

$$\begin{aligned}\sum_{i=1}^{m}\gamma_i &= 1 \\ \sum_{i=1}^{m}\delta_{ri} &= 0,\ r = 1, ..., n \\ \sum_{j=1}^{m}\gamma_{ij} &= 0,\ i = 1, ..., m \\ \sum_{i=1}^{m}\sigma_{Ki} &= 0 \qquad (5)\end{aligned}$$

Shephard's Lemma allows us to obtain the cost share equations through logarithmic differentiation of the cost functions:

$$S_i = \frac{\partial \ln VC}{\partial \ln w_i} = \gamma_i + \sum_{j=1}^{m}\gamma_{ij}\ln(w_j) + \sum_{r=1}^{n}\delta_{ri}.Y_r + \sigma_{Ki}.\ln(k),\ i = 1, ..., m \qquad (6)$$

where $S_i = \frac{w_i.x_i}{\sum_{i=1}^{m} w_i.x_i}$ is the cost share of input i (x_i represents the quantity used of input i).

The Box-Cox transformation is applied to the output data (y_i), but prior to that we mean-scale all our variables (described in detail in the next section). As we will see, we identify two inputs for production: staff and other inputs. We then estimate the generalized translog cost function given by equations (4) and (6) in the following way:

- Model 1: equations (4) and (6) were estimated with the homogeneity restrictions of equation (5) using Zellner's Seemingly Unrelated Regression (SUR) technique. Because the cost shares add up to unity, only one of them is independent. Therefore, the second cost share equation (associated with non-staff costs) was omitted from the regression.

- Model 2: similar to model 1, but only one input price was used - staff unit costs. In this scenario, the unit price of other variable inputs is implicitly used as the numeraire and therefore linear homogeneity is assumed to hold. Therefore, equations (4) and (6) were estimated using Zellner's Seemingly Unrelated Regression (SUR) technique. Because the cost shares add up to unity, only one of them is independent. Therefore, the second cost share equation (associated with non-staff costs) was omitted from the regression.

Both models were estimated using two variants:

- a first variant made use of pooled data, i.e. assuming that all observations were independent from one another, and imposed no restrictions on the model;
- a second variant made use of pooled data, i.e. assuming that all observations were independent from one another, but imposed restrictions on the model, namely (i) homotheticity of the production function and (ii) no dummy variable effects (e.g. hospital type, year or region).

The underlying rationale for the second variant is the possible existence of multicollinearity, i.e. correlations between the explanatory variables. For instance, the dummy variables described above may well be correlated, because, say, central hospitals, which typically present larger casemix indicators, are located in Portugal's two largest cities: Lisbon and Porto. For the same reason, we make the assumption that the production function is homothetic. As Smet (2002) notes, this implies that the mix of inputs which minimizes costs is not affected by the volume or even the mix of outputs. Therefore, changes in input prices will affect costs by a scale factor. In practice, homotheticity implies that $\delta_{ri} = 0, \forall r, i$, in equation (4), i.e. input prices are not interacted with output levels. Hopefully, the imposition of this restriction alleviates possible multicollinearity problems. We report the result of a test of homotheticity for all regressions in Section 4.1.

3 Data

Portuguese hospitals in the National Health Service report their cost breakdown yearly to a central body (IGIF/ACSS). This cost breakdown allows for the identification of costs associated with the main hospital outputs (medical and surgical discharges, outpatient care, emergency room care, etc), as well as with auxiliary services, such as diagnostic techniques and therapeutic services[5]. These costs are further broken down by specialty and cost type (staff, materials and supplies, etc). The main database we have used consists of all the statistical information pertaining diagnostic

[5]The quantities produced by each hospital of the various outputs and/or diagnostic techniques and therapeutic services are also provided.

techniques and therapeutic services in Portuguese hospitals between 2002 and 2006 (IGIF/ACSS (2004a, 2004c, 2006a, 2006c, 2007b)).

In addition, we have collected data related to the total number of staff in each hospital, the number of beds, the casemix index[6], total staff costs and total hospital costs for each year. For the years 2002-2004, all the information was collected from the yearly National Health Service report published by IGIF/ACSS (IGIF/ACSS (2004b, 2005, 2006b)). For the years 2005 and 2006, all the information except the number of staff was collected from the yearly National Health Service report (IGIF/ACSS (2007a, 2008)) and from the yearly report on "EPE" hospitals (public but autonomous hospitals of the National Health Service) (IGIF/ACSS (2007c)). Staff numbers for 2005 and 2006 were collected from a yearly statistical yearbook produced by DGS (2006, 2007).

Among the various diagnostic techniques and therapeutic services carried out at Portuguese hospitals, clinical pathology, medical imaging and physical medicine and rehabilitation have a significant weight in overall costs[7]. Within each of these specialties, some procedures stand out in terms of their share of total costs. For instance, as we can see from Table 1, Clinical Chemistry is the procedure responsible for 57% of the total costs of Clinical Pathology. Similarly, Radiology accounts for some 74% of total Medical Imaging costs and Physical therapy accounts for 60% of total Physical Medicine and Rehabilitation costs.

Due to the large variety of data sources used, some variables had a significant number of missing observations. Therefore, we have eliminated observations which reported missing or zero quantities of the above specialties of diagnostic techniques and therapeutic services when total costs were available[8], observations with a missing casemix index and observations with missing total staff numbers. We have also not considered psychiatric hospitals and oncology hospitals. This has reduced the total number of observations available for Clinical Pathology to 320 (from 357), to 335 (from 365) for Medical Imaging and to 288 (from 333) for Physical Medicine and Rehabilitation. In addition, the data on Clinical Pathology showed the presence of significant outliers at the top of the distribution. Therefore, the top 1% of the distribution (3 observations) was dropped, leaving us with 317 observations.

In the short-run, we expect equipment to constitute a fixed factor of production, which hospitals could not easily (or rapidly) vary. However, we had no data available on hospital equipment. Therefore, we have used the number of beds as a proxy for the equipment available in each hospital (k). It appears reasonable that avaliable equipment for auxiliary medical services such as diagnostic techniques and therapeutic services is purchased as a function of the hospital dimension. The number of beds also captures the potential demand for the services, which are mostly provided to

[6]The casemix index for the years 2005 and 2006 for "EPE" hospitals was not publicly available. In those cases, and because the casemix index does not change significantly over time, we have assumed that those hospitals' casemix index was equal to that of the most recently available year.

[7]In 2004, they accounted for 56% of the total costs of diagnostic techniques and therapeutic services.

[8]In other words, we have not considered observations for which there was clearly misreported output production.

Specialty	Procedure	Variable	Cost (€m)	Percentage of total specialty cost	Number of observations	(Weighted) Unit cost (€)
Clinical Pathology	Clinical chemistry	y_1	569.3	57%	340	2.62
Clinical Pathology	Clinical hematology	y_2	130.5	13%	198	3.16
Clinical Pathology	Immunology	y_3	103.6	10%	164	7.35
Clinical Pathology	Clinical microbiology	y_4	82.6	8%	165	10.36
Clinical Pathology	Endocrinology	y_5	29.7	3%	52	9.89
Clinical Pathology	Virology	y_6	17.4	2%	37	9.54
Clinical Pathology	Clinical hematology/Hematoncology	y_7	59.8	6%	26	6.28
Medical Imaging	Radiology	y_1	475.6	74%	356	17.58
Medical Imaging	Angiography	y_2	54.9	9%	49	134.92
Medical Imaging	Mamography	y_3	6.4	1%	80	39.96
Medical Imaging	Computed tomography	y_4	60.2	9%	109	19.10
Medical Imaging	Ultrasonography	y_5	25.8	4%	187	12.11
Medical Imaging	Magnetic resonance imaging	y_6	16.0	3%	35	33.87
Physical Medicine & Rehabilitation	Electrotherapy	y_1	47.7	24%	85	4.53
Physical Medicine & Rehabilitation	Physical therapy	y_2	121.6	60%	263	5.17
Physical Medicine & Rehabilitation	Hydro-kinesiotherapy	y_3	4.1	2%	32	4.74
Physical Medicine & Rehabilitation	Occupational therapy	y_4	16.4	8%	65	8.76
Physical Medicine & Rehabilitation	Speech and language therapy	y_5	12.2	6%	57	22.45

Note: This table excludes all missing observations

Table 1: Descriptive cost statistics for Clinical Pathology, Medical Imaging and Physical Medicine and Rehabilitation in Portuguese hospitals: 2002-2006

admitted patients.

In addition to the variables described earlier, we have expanded the model with additional dummy variables which could explain differences in costs:

- dummy variables representing the hospital type - hospitals are divided in three hierarchichal categories: central, district and level 1 hospitals; therefore, a dummy variable was created taking on the value of 1 for the latter two categories (central hospitals were omitted): "D - district hospital" and "D - Level 1 hospital";
- dummy variables for each year (except 2002, which was omitted): "D - 2003"; "D - 2004"; "D - 2005"; "D - 2006";
- dummy variables representing the region where the hospital is located - there are 5 regions in Portugal and a dummy variable was created for four of those regions (the Alentejo region was omitted): "D - Region Algarve"; "D - Region Centro"; "D - Region L. V. Tejo" (which includes Portugal's capital and largest city - Lisbon); "D - Region Norte" (which includes Portugal's second largest city - Porto);

For each specialty (Clinical Pathology, Medical Imaging and Physical Medicine and Rehabilitation), total costs were broken down into staff costs, pharmaceutical products, clinical consumables,

	Clinical Pathology		Medical Imaging		Physical Medicine & Rehabilitation	
Variable	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
VC (€)	2,332,378	3,019,846	1,290,709	1,598,582	491,196	437,423
y_1	654,030	814,234	74,768	83,707	33,954	110,782
y_2	120,629	357,442	1,202	12,304	75,060	74,283
y_3	42,222	232,640	398	1,241	2,245	12,397
y_4	24,252	53,499	9,231	47,832	3,831	16,920
y_5	7,934	58,952	6,110	11,083	1,636	13,161
y_6	5,133	60,917	1,358	12,746	n/a	n/a
y_7	23,762	171,947	n/a	n/a	n/a	n/a
w_1 (€)	26,681	4,516	26,478	4,552	26,549	4,675
w_2 (€)	1.88	1.16	5.54	6.35	1.71	5.27
k	293.8	270.3	285.4	268.2	307.1	275.0
Casemix	1.04	0.33	1.05	0.34	1.05	0.32

Table 2: Descriptive statistics of the main variables used in the regressions

depreciation, other expenses and indirect costs. For each observation, variable costs were obtained by subtracting indirect costs and depreciation from total costs.

We have assumed that diagnostic techniques and therapeutic services relied on the use of two variable inputs: staff and other inputs. Staff units costs (w_1) were calculated by dividing total hospital staff costs with the total number of staff. Non-staff inputs are a composite of pharmaceutical products, clinical consumables and other expenses, for which a unit price is difficult to find. We follow Garcia and Thomas (2001) and assume that the price of these non-staff inputs is represented by a unit cost (w_2), which was calculated by dividing the total cost of non-staff related variable costs by the total quantity produced in each specialty. Therefore, the unit cost of other inputs is an imperfect measure for the price of other inputs, as it is expressed as a cost per unit of output.

Table 2 contains the descriptive statistics of the main variables used in our regressions.

4 Results

The results of the estimation of equation (4) are presented in Tables 3, 4 and 5, corresponding, respectively, to clinical pathology, medical imaging and physical medicine and rehabilitation. We only present the results for the cost function - the cost share equation improves the quality of the results, but its coefficients are (as we can see by looking at equations (4) and (6)) the same as in the cost function.

4.1 Economies of scale

Ray economies of scale, in a multiproduct cost function setting, refer to the proportional increase in total costs which result from a proportional increase in all the outputs. Alternatively, viewed from the production function perspective, ray economies of scale refer to the proportional increase in outputs which result from proportional increases in the quantity used of all inputs. Inevitably,

Clinical Pathology		(1) Pooled data	(1) Pooled data - no dummies - homothetic	(2) Pooled data	(2) Pooled data - no dummies - homothetic
		Both input prices		Only one input price	
Parameter	Variable	Coef.	Coef.	Coef.	Coef.
β_1	Y_1	0.767 ***	0.831 ***	1.001 ***	1.146 ***
β_2	Y_2	-0.060	0.044	-0.151	-0.046
β_3	Y_3	0.059 *	0.058	0.026	0.023
β_4	Y_4	0.123	0.111	0.262	0.263
β_5	Y_5	0.021	0.041	0.054	0.086
β_6	Y_6	-0.040 **	-0.032	-0.043	-0.025
β_7	Y_7	-0.003	0.001	-0.043	-0.044
γ_1	$\ln(w_1)$	0.418 ***	0.423 ***	0.416 ***	0.447 ***
γ_2	$\ln(w_2)$	0.582 ***	0.577 ***		
$1/2\ \beta_{11}$	$Y_1.Y_1$	0.053 ***	0.062 ***	0.021 ***	0.034 ***
β_{12}	$Y_1.Y_2$	-0.016 ***	-0.013 ***	-0.012 **	-0.005
β_{13}	$Y_1.Y_3$	-0.007	-0.012 **	0.011	0.002
β_{14}	$Y_1.Y_4$	-0.018 ***	-0.021 ***	-0.009	-0.012
β_{15}	$Y_1.Y_5$	0.011	0.011	0.026	0.030
β_{16}	$Y_1.Y_6$	0.002	0.005	0.017	0.021
β_{17}	$Y_1.Y_7$	0.032 ***	0.037 ***	0.038 **	0.045 **
$1/2\ \beta_{22}$	$Y_2.Y_2$	0.012 ***	0.012 ***	0.004	0.004
β_{23}	$Y_2.Y_3$	-0.007	-0.007	-0.027 ***	-0.026 ***
β_{24}	$Y_2.Y_4$	0.006	0.010 *	0.013	0.020 *
β_{25}	$Y_2.Y_5$	-0.003	-0.002	0.009	0.009
β_{26}	$Y_2.Y_6$	-0.011	-0.007	-0.019	-0.016
β_{27}	$Y_2.Y_7$	-0.003	-0.003	0.007	0.007
$1/2\ \beta_{33}$	$Y_3.Y_3$	0.005 **	0.005 **	0.002	0.002
β_{34}	$Y_3.Y_4$	0.001	0.001	-0.003	-0.002
β_{35}	$Y_3.Y_5$	0.001	0.002	0.002	0.003
β_{36}	$Y_3.Y_6$	0.002 **	0.002 *	0.003	0.004
β_{37}	$Y_3.Y_7$	-0.003	-0.005 **	-0.005	-0.008 **
$1/2\ \beta_{44}$	$Y_4.Y_4$	0.003	0.004 *	0.007	0.008 *
β_{45}	$Y_4.Y_5$	-0.002	-0.002	-0.012	-0.013
β_{46}	$Y_4.Y_6$	0.002	0.004	0.000	0.001
β_{47}	$Y_4.Y_7$	0.007	0.004	0.032 **	0.030 *
$1/2\ \beta_{55}$	$Y_5.Y_5$	0.005 **	0.006 **	0.009 *	0.011 **
β_{56}	$Y_5.Y_6$	-0.001	-0.001	0.000	0.000
β_{57}	$Y_5.Y_7$	-0.002	0.000	-0.003	-0.001
$1/2\ \beta_{66}$	$Y_6.Y_6$	-0.001	0.000	-0.001	0.002
β_{67}	$Y_6.Y_7$	-0.003 **	-0.003 **	-0.005 **	-0.006 **
$1/2\ \beta_{77}$	$Y_7.Y_7$	0.003	0.002	0.001	-0.001
$1/2\ .\gamma_{11}$	$\ln(w_1).\ln(w_1)$	0.017 ***	0.029 ***	0.004	0.002
γ_{12}	$\ln(w_1).\ln(w_2)$	-0.035 ***	-0.058 ***		
$1/2\ \gamma_{22}$	$\ln(w_2).\ln(w_2)$	0.017 ***	0.029 ***		

Clinical Pathology		(1) Pooled data	(1) Pooled data - no dummies - homothetic	(2) Pooled data	(2) Pooled data - no dummies - homothetic
		Both input prices		Only one input price	
Parameter	Variable	Coef.	Coef.	Coef.	Coef.
δ_{11}	$Y_1.\ln(w_1)$	0.005		0.011 ***	
δ_{21}	$Y_2.\ln(w_1)$	0.005 **		0.005 ***	
δ_{31}	$Y_3.\ln(w_1)$	-0.003		-0.004 **	
δ_{41}	$Y_4.\ln(w_1)$	0.000		-0.001	
δ_{51}	$Y_5.\ln(w_1)$	-0.002		-0.002	
δ_{61}	$Y_6.\ln(w_1)$	0.002		0.001	
δ_{71}	$Y_7.\ln(w_1)$	-0.001		-0.003	
δ_{12}	$Y_1.\ln(w_2)$	-0.005			
δ_{22}	$Y_2.\ln(w_2)$	-0.005 **			
δ_{32}	$Y_3.\ln(w_2)$	0.003			
δ_{42}	$Y_4.\ln(w_2)$	0.000			
δ_{52}	$Y_5.\ln(w_2)$	0.002			
δ_{62}	$Y_6.\ln(w_2)$	-0.002			
δ_{72}	$Y_7.\ln(w_2)$	0.001			
β_K	$\ln(k)$	0.040	-0.163	-0.511	-0.834
$1/2\ \beta_{KK}$	$(\ln k)^2$	0.175 ***	0.173 ***	0.285 ***	0.272 ***
σ_{K1}	$\ln(k).\ln(w_1)$	-0.054 ***	-0.050 ***	-0.056 ***	-0.044 ***
σ_{K2}	$\ln(k).\ln(w_2)$	0.054 ***	0.050 ***		
θ_{K1}	$\ln(k).Y_1$	-0.187 ***	-0.206 ***	-0.209 ***	-0.235 ***
θ_{K2}	$\ln(k).Y_2$	0.012 *	0.013	0.018	0.014
θ_{K3}	$\ln(k).Y_3$	0.003	0.001	0.022	0.021
θ_{K4}	$\ln(k).Y_4$	-0.001	0.000	-0.029 **	-0.027 *
θ_{K5}	$\ln(k).Y_5$	-0.017	-0.025 **	-0.051 **	-0.066 ***
θ_{K6}	$\ln(k).Y_6$	0.022	0.013	0.017	0.009
θ_{K7}	$\ln(k).Y_7$	-0.033 ***	-0.034 **	-0.085 ***	-0.090 ***
	D - District hosp.	-0.092 ***		-0.247 ***	
	D - Level 1 hosp.	-0.102 ***		-0.304 ***	
	D - Year 2003	-0.073 ***		-0.071	
	D - Year 2004	-0.062 **		-0.021	
	D - Year 2005	-0.051 *		-0.031	
	D - Year 2006	-0.047 *		-0.005	
	D - Region Algarve	0.123 **		0.216 **	
	D - Region Centro	-0.130 ***		-0.248 ***	
	D - Region L. V. Tejo	0.089 **		0.086	
	D - Region Norte	-0.120 ***		-0.225 ***	
	Casemix	-0.069 **	0.057	-0.081	0.149 **
α_0	Constant	14.601 ***	14.388 ***	14.552 ***	14.108 ***

Number of observations	317	317	317	317
R^2 (cost function)	0.9834	0.9736	0.9314	0.915
R^2 (cost share equation)	0.2112	0.1963	0.1905	0.141

(***) Significant at the 1% level; (**) Significant at the 5% level; (*) Significant at the 10% level

Table 3: Results: Clinical Pathology

Medical Imaging		(1) Pooled data	(1) Pooled data - no dummies - homothetic	(2) Pooled data	(2) Pooled data - no dummies - homothetic
		Both input prices		Only one input price	
Parameter	Variable	Coef.	Coef.	Coef.	Coef.
β_1	Y_1	0.458 ***	0.678 ***	0.611 ***	0.824 ***
β_2	Y_2	0.025	0.058	0.128 **	0.182 ***
β_3	Y_3	0.069 *	0.086 **	0.116 **	0.139 **
β_4	Y_4	-0.066	-0.171 **	-0.371 ***	-0.543 ***
β_5	Y_5	0.027	0.038	-0.052	-0.070
β_6	Y_6	0.063 *	0.037	0.088	0.088
γ_1	$\ln(w_1)$	0.601 ***	0.604 ***	0.608 ***	0.647 ***
γ_2	$\ln(w_2)$	0.399 ***	0.396 ***		
$1/2\ \beta_{11}$	$Y_1.Y_1$	0.040 ***	0.038 ***	0.015 **	0.010 *
β_{12}	$Y_1.Y_2$	0.025	0.021	0.040	0.030
β_{13}	$Y_1.Y_3$	-0.007	-0.001	0.008	0.019
β_{14}	$Y_1.Y_4$	-0.001	0.005	-0.003	-0.006
β_{15}	$Y_1.Y_5$	-0.006	-0.015 ***	-0.007	-0.015 **
β_{16}	$Y_1.Y_6$	-0.011	0.010	0.008	0.039
$1/2\ \beta_{22}$	$Y_2.Y_2$	0.001	0.004	0.008	0.014 **
β_{23}	$Y_2.Y_3$	-0.003	-0.003	-0.001	0.000
β_{24}	$Y_2.Y_4$	-0.004	-0.002	-0.006	-0.005
β_{25}	$Y_2.Y_5$	-0.022 **	-0.033 ***	-0.046 ***	-0.061 ***
β_{26}	$Y_2.Y_6$	0.000	-0.001	-0.002	-0.004
$1/2\ \beta_{33}$	$Y_3.Y_3$	0.004	0.007	0.006	0.009
β_{34}	$Y_3.Y_4$	0.002 *	0.000	0.004 **	0.001
β_{35}	$Y_3.Y_5$	-0.007	-0.009	-0.010	-0.015
β_{36}	$Y_3.Y_6$	0.004 *	0.004	0.004	0.003
$1/2\ \beta_{44}$	$Y_4.Y_4$	0.001	0.000	-0.008	-0.006
β_{45}	$Y_4.Y_5$	0.002 *	0.002	0.004 ***	0.004 **
β_{46}	$Y_4.Y_6$	-0.007	-0.016 *	-0.028 **	-0.045 ***
$1/2\ \beta_{55}$	$Y_5.Y_5$	0.013 ***	0.017 ***	0.010 ***	0.015 ***
β_{56}	$Y_5.Y_6$	0.017 *	0.028 **	0.039 **	0.053 ***
$1/2\ \beta_{66}$	$Y_6.Y_6$	0.006 *	0.005	0.009	0.010
$1/2\ .\gamma_{11}$	$\ln(w_1).\ln(w_1)$	0.066 ***	0.063 ***	0.004	0.016
γ_{12}	$\ln(w_1).\ln(w_2)$	-0.133 ***	-0.126 ***		
$1/2\ \gamma_{22}$	$\ln(w_2).\ln(w_2)$	0.066 ***	0.063 ***		
δ_{11}	$Y_1.\ln(w_1)$	-0.032 ***		-0.012 **	
δ_{21}	$Y_2.\ln(w_1)$	-0.001		-0.003	
δ_{31}	$Y_3.\ln(w_1)$	0.003 *		0.001	
δ_{41}	$Y_4.\ln(w_1)$	-0.002		-0.006 **	
δ_{51}	$Y_5.\ln(w_1)$	-0.001		0.003	
δ_{61}	$Y_6.\ln(w_1)$	0.002		0.001	

Medical Imaging		(1) Pooled data	(1) Pooled data - no dummies - homothetic	(2) Pooled data	(2) Pooled data - no dummies - homothetic
		Both input prices		Only one input price	
Parameter	Variable	Coef.	Coef.	Coef.	Coef.
δ_{12}	$Y_1.\ln(w_2)$	0.032 ***			
δ_{22}	$Y_2.\ln(w_2)$	0.001			
δ_{32}	$Y_3.\ln(w_2)$	-0.003 *			
δ_{42}	$Y_4.\ln(w_2)$	0.002			
δ_{52}	$Y_5.\ln(w_2)$	0.001			
δ_{62}	$Y_6.\ln(w_2)$	-0.002			
β_K	$\ln(k)$	0.228 ***	0.202 **	0.326 **	0.337 **
$1/2\ \beta_{KK}$	$(\ln k)^2$	0.167 ***	0.224 ***	0.216 ***	0.305 ***
σ_{K1}	$\ln(k).\ln(w_1)$	0.008	-0.021 ***	-0.034 ***	-0.064 ***
σ_{K2}	$\ln(k).\ln(w_2)$	-0.008	0.021 ***		
θ_{K1}	$\ln(k).Y_1$	-0.139 ***	-0.180 ***	-0.143 ***	-0.182 ***
θ_{K2}	$\ln(k).Y_2$	0.017	0.025	0.012	0.020
θ_{K3}	$\ln(k).Y_3$	-0.005	0.005	-0.025 *	-0.007
θ_{K4}	$\ln(k).Y_4$	-0.007	-0.016 *	-0.001	-0.008
θ_{K5}	$\ln(k).Y_5$	-0.007	-0.003	-0.016 *	-0.011
θ_{K6}	$\ln(k).Y_6$	-0.035	-0.048 *	-0.047	-0.065
	D - District hosp.	-0.189 ***		-0.217 ***	
	D - Level 1 hosp.	-0.001		0.160 *	
	D - Year 2003	-0.024		-0.007	
	D - Year 2004	0.014		0.057	
	D - Year 2005	0.020		0.072	
	D - Year 2006	0.033		0.131 **	
	D - Region Algarve	0.027		0.018	
	D - Region Centro	-0.115 **		-0.187 **	
	D - Region L. V. Tejo	0.055		0.067	
	D - Region Norte	-0.198 ***		-0.292 ***	
	Casemix	-0.227 ***	-0.062	-0.140	0.053
α_0	Constant	14.564 ***	14.132 ***	14.814 ***	14.358 ***

Number of observations	335	335	335	335
R^2 (cost function)	0.960	0.940	0.913	0.893
R^2 (cost share equation)	0.499	0.438	0.180	0.148

(***) Significant at the 1% level; (**) Significant at the 5% level; (*) Significant at the 10% level

Table 4: Results: Medical Imaging

Physical Medicine and Rehabilitation		(1) Pooled data	(1) Pooled data - no dummies - homothetic	(2) Pooled data	(2) Pooled data - no dummies - homothetic
		Both input prices		Only one input price	
Parameter	Variable	Coef.	Coef.	Coef.	Coef.
β_1	Y_1	0.049	0.062	-0.074	-0.065
β_2	Y_2	-0.143	-0.110	-0.305	-0.253
β_3	Y_3	-0.010	-0.022	-0.028	-0.037
β_4	Y_4	0.039	0.054	0.020	0.067
β_5	Y_5	0.069	0.096 *	0.069	0.099
γ_1	$\ln(w_1)$	0.680 ***	0.673 ***	0.766 ***	0.782 ***
γ_2	$\ln(w_2)$	0.320 ***	0.327 ***		
$1/2\ \beta_{11}$	$Y_1.Y_1$	0.003	0.005	-0.009	-0.008
β_{12}	$Y_1.Y_2$	-0.034 ***	-0.036 ***	-0.033 ***	-0.032 ***
β_{13}	$Y_1.Y_3$	0.000	-0.001	0.000	-0.001
β_{14}	$Y_1.Y_4$	0.004	0.005	0.000	0.001
β_{15}	$Y_1.Y_5$	-0.003	-0.003	0.001	0.000
$1/2\ \beta_{22}$	$Y_2.Y_2$	0.037 ***	0.036 ***	0.022 **	0.022 **
β_{23}	$Y_2.Y_3$	-0.016 **	-0.018 ***	-0.012	-0.012
β_{24}	$Y_2.Y_4$	-0.018	-0.011	-0.027	-0.020
β_{25}	$Y_2.Y_5$	-0.021 ***	-0.021 ***	-0.016 **	-0.015 **
$1/2\ \beta_{33}$	$Y_3.Y_3$	-0.001	0.000	-0.002	-0.001
β_{34}	$Y_3.Y_4$	-0.005	-0.006 *	-0.001	-0.002
β_{35}	$Y_3.Y_5$	-0.002	-0.001	-0.007	-0.005
$1/2\ \beta_{44}$	$Y_4.Y_4$	0.003	0.005	0.003	0.007
β_{45}	$Y_4.Y_5$	0.000	0.000	-0.001	-0.002
$1/2\ \beta_{55}$	$Y_5.Y_5$	0.011 **	0.012 **	0.014 **	0.015 **
$1/2\ .\gamma_{11}$	$\ln(w_1).\ln(w_1)$	0.048 ***	0.050 ***	-0.045	-0.061 **
γ_{12}	$\ln(w_1).\ln(w_2)$	-0.095 ***	-0.100 ***		
$1/2\ \gamma_{22}$	$\ln(w_2).\ln(w_2)$	0.048 ***	0.050 ***		
δ_{11}	$Y_1.\ln(w_1)$	-0.004		-0.006 *	
δ_{21}	$Y_2.\ln(w_1)$	-0.011 ***		-0.015 ***	
δ_{31}	$Y_3.\ln(w_1)$	0.002		0.000	
δ_{41}	$Y_4.\ln(w_1)$	0.007 **		0.012 ***	
δ_{51}	$Y_5.\ln(w_1)$	-0.002		-0.004	

Physical Medicine and Rehabilitation		(1) Pooled data	(1) Pooled data - no dummies - homothetic	(2) Pooled data	(2) Pooled data - no dummies - homothetic
		Both input prices		Only one input price	
Parameter	Variable	Coef.	Coef.	Coef.	Coef.
δ_{12}	$Y_1.\ln(w_2)$	0.004			
δ_{22}	$Y_2.\ln(w_2)$	0.011 ***			
δ_{32}	$Y_3.\ln(w_2)$	-0.002			
δ_{42}	$Y_4.\ln(w_2)$	-0.007 **			
δ_{52}	$Y_5.\ln(w_2)$	0.002			
β_K	$\ln(k)$	0.544 ***	0.388 **	0.847 ***	0.537 **
$1/2\ \beta_{KK}$	$(\ln k)^2$	0.071 ***	0.021	0.078 **	0.021
σ_{K1}	$\ln(k).\ln(w_1)$	-0.012	-0.004	-0.008	0.010
σ_{K2}	$\ln(k).\ln(w_2)$	0.012	0.004		
θ_{K1}	$\ln(k).Y_1$	0.005	-0.001	0.015	0.005
θ_{K2}	$\ln(k).Y_2$	-0.017	-0.012	0.001	0.001
θ_{K3}	$\ln(k).Y_3$	0.022	0.015	0.020	0.008
θ_{K4}	$\ln(k).Y_4$	-0.013	-0.007	-0.028 *	-0.021
θ_{K5}	$\ln(k).Y_5$	0.014	0.006	0.031	0.020
	D - District hosp.	0.075		0.095	
	D - Level 1 hosp.	-0.025		0.052	
	D - Year 2003	-0.050		-0.014	
	D - Year 2004	0.016		0.059	
	D - Year 2005	0.007		0.040	
	D - Year 2006	0.017		0.085	
	D - Region Algarve	0.098		0.087	
	D - Region Centro	-0.300 ***		-0.433 ***	
	D - Region L. V. Tejo	0.030		0.020	
	D - Region Norte	-0.227 ***		-0.292 **	
	Casemix	0.388 ***	0.500 ***	0.495 ***	0.645 ***
α_0	Constant	12.835 ***	12.684 ***	12.440 ***	12.248 ***

Number of observations	288	288	288	288
R^2 (cost function)	0.903	0.881	0.812	0.787
R^2 (cost share equation)	0.626	0.609	0.082	0.005

(***) Significant at the 1% level; (**) Significant at the 5% level; (*) Significant at the 10% level

Table 5: Results: Physical Medicine and Rehabilitation

any concept of economies of scale implicitly refers to the long run. Vita (1990) points out that when a variable cost function is estimated, ray economies of scale (RTS) can be calculated in the following way (see also Braeutigam and Daughety (1983)):

$$RTS = \frac{1 - \frac{\partial \ln VC}{\partial \ln(k^*)}}{\sum_{i=1}^{n} \eta_i} \tag{7}$$

where η_i is the cost elasticity of output i :

$$\eta_i = \frac{\partial C}{\partial y_i^*} \frac{y_i^*}{C} \tag{8}$$

η_i represents the percentual change in costs when output i varies by 1%. In our case, and similarly to Vita (1990), the cost elasticity of input i is given by:

$$\eta_i = \left(\beta_i + \sum_{j=1}^{n} \beta_{ij} Y_j + \sum_{j=1}^{m} \delta_{ij} \ln(w_j) + \theta_{Ki} \ln(k) \right) y_i^{\lambda} \tag{9}$$

where y_i is the untransformed output and λ represents the Box-Cox parameter used in the transformation. At the sample mean, because we have mean scaled our data prior to the Box-Cox transformation, the cost elasticity of output i is simply given by $\eta_i = \beta_i$, where β_i is the output parameter from the estimated cost function (equation (4)). An estimate of RTS in equation (7) larger than one indicates the existence of economies of scale. In particular, an increase of all the outputs in an average hospital by 1% would increase variable costs by $1/RTS$ percent.

In equation (7), k^* should ideally represent the optimal level for the fixed factor. However, the calculation of this optimal level for the fixed factor would require the use of input price data which we do not possess. Therefore, we follow the approach suggested by Caves et al. (1981) and also used by Vita (1990), and use the actual level of the fixed factor (instead of the optimal level) when computing equation (7). As Vita (1990, p. 15) notes, this method "...evaluates scale economies along a ray from the origin that passes through the actual point of operation observed in the sample". Since we are estimating a variable cost function, we are implicitly assuming that firms are not operating on their efficient expansion path, i.e. they are not using the optimal level of the fixed factor. Therefore, it is likely that the two methods for computing equation (7) would yield different results (see Vita (1990) for a more detailed discussion).

As we can see from the estimates of RTS (equation (7)) at the sample mean presented in Table 6, the results for models 1 and 2 under no restrictions (first and third columns) are rather plausible for Clinical Pathology and Medical Imaging. For instance, for Clinical Pathology, the estimate of RTS for models 1 and 2 is 1.11 and 1.37 respectively. Both results suggest the existence of ray economies of scale. Similarly, for Medical Imaging, the estimate of RTS for models 1 and 2 is 1.34 and 1.30 respectively. Again, both suggest the existence of ray economies of scale.

Ray economies of scale	(1) SUR - Pooled data	(1) SUR - Pooled data - no dummies homothetic	(2) SUR - Pooled data	(2) SUR - Pooled data - no dummies - homothetic
	RTS			
Clinical Pathology	1.11	1.10	1.37	1.31
Medical Imaging	1.34	1.10	1.30	1.07

Table 6: Ray economies of scale

Ray economies of scale: Clinical Pathology	(1) SUR Pooled data	(1) SUR - Pooled data - no dummies homothetic	(2) SUR Pooled data	(2) SUR - Pooled data - no dummies homothetic
	RTS			
All Y_i 20% above sample mean	1.05	1.05	1.30	1.24
All Y_i 10% above sample mean	1.08	1.07	1.33	1.27
At sample mean (all variables)	1.11	1.10	1.37	1.31
All Y_i 10% below sample mean	1.14	1.14	1.41	1.35
All Y_i 20% below sample mean	1.17	1.18	1.45	1.40

Table 7: Ray economies of scale above and below sample mean - Clinical Pathology

Imposing the two restrictions referred to earlier - (i) homotheticity of the production function and (ii) no dummy variable effects - (second and fourth columns) changes the estimate of RTS in model 1 marginally for Clinical Pathology (from 1.11 to 1.10)[9], but more significantly for model 2 (from 1.37 to 1.31) and for both models in Medical Imaging (from 1.34 to 1.10 in model 1 and from 1.30 to 1.07 in model 2). This is undoubtedly related to the plausibility of imposing the homotheticity assumption in the first place. A Wald test of the restrictions associated with homotheticity of the production function shows that it cannot be rejected (at a 1% significance level) only for model 1 in Clinical Pathology; for both models in Medical Imaging and for model 2 in Clinical Pathology, homotheticity is rejected. As such, the results of the restricted models should be interpreted with great caution.

For Clinical Pathology and Medical Imaging, we have also calculated the returns to scale indicator for different levels of output (assuming all other variables are at the sample mean, including the number of beds). Tables 7 and 8 present those estimates. Rather importantly, we can see that ray economies of scale are less pronounced as we increase the level of output above the sample mean. This is to be expected, as an increase of all output levels would partly exhaust the existing economies of scale. The reverse is true when we decrease the output levels below the sample mean.

For Physical Medicine and Rehabilitation, the estimates of RTS at the sample mean are implausible and exhibit a wide variability across models. Our conjecture is that the sample mean for all outputs may not be the most appropriate scale to evaluate ray economies of scale in Physical Medicine and Rehabiliation. Looking at Table 9, we can see that in Clinical Pathology and Med-

[9] The homotheticity restriction cannot be rejected at a 1% significance level for model 1, but it is rejected for model 2.

Ray economies of scale: Medical Imaging	(1) SUR - Pooled data	(1) SUR - Pooled data - no dummies homothetic	(2) SUR - Pooled data	(2) SUR - Pooled data - no dummies homothetic
	RTS			
All Y_i 20% above sample mean	1.27	1.04	1.24	1.03
All Y_i 10% above sample mean	1.30	1.07	1.27	1.05
At sample mean (all variables)	1.34	1.10	1.30	1.07
All Y_i 10% below sample mean	1.38	1.13	1.33	1.10
All Y_i 20% below sample mean	1.43	1.17	1.36	1.13

Table 8: Ray economies of scale above and below sample mean - Medical Imaging

Specialty	Procedure	Variable	Number of 0-observations	Number of positive observations	Total number of observations	Total number of observations within 0.5 and 1.5 of sample mean	Percentage of observations within 0.5 and 1.5 of sample mean
Clinical Pathology	Clinical chemistry	y_1	7	310	317	127	40%
Clinical Pathology	Clinical hematology	y_2	141	176	317	54	17%
Clinical Pathology	Immunology	y_3	170	147	317	37	12%
Clinical Pathology	Clinical microbiology	y_4	169	148	317	53	17%
Clinical Pathology	Endocrinology	y_5	280	37	317	4	1%
Clinical Pathology	Virology	y_6	287	30	317	6	2%
Clinical Pathology	Clinical hematology/Hematoncology	y_7	300	17	317	2	1%
Medical Imaging	Radiology	y_1	5	330	335	137	41%
Medical Imaging	Angiography	y_2	288	47	335	11	3%
Medical Imaging	Mamography	y_3	260	75	335	9	3%
Medical Imaging	Computed tomography	y_4	231	104	335	55	16%
Medical Imaging	Ultrasonography	y_5	154	181	335	65	19%
Medical Imaging	Magnetic resonance imaging	y_6	304	31	335	4	1%
Physical Medicine & Rehabilitation	Electrotherapy	y_1	212	76	288	12	4%
Physical Medicine & Rehabilitation	Physical therapy	y_2	44	244	288	120	42%
Physical Medicine & Rehabilitation	Hydro-kinesiotherapy	y_3	259	29	288	6	2%
Physical Medicine & Rehabilitation	Occupational therapy	y_4	240	48	288	12	4%
Physical Medicine & Rehabilitation	Speech and language therapy	y_5	237	51	288	18	6%

Table 9: Sample summary

ical Imaging, a significant percentage of observations (more than 10%) contains output production within 0.5 and 1.5 of the sample mean, and this is true for *several* outputs. By contrast, in Physical Medicine and Rehabilitation, output production within 0.5 and 1.5 of the sample mean is only considerable for physical therapy; for all other outputs, there is a large number of 0-observations and few (less than 6%) are within that interval.

Therefore, we have used the estimates presented in Tables 3, 4 and 5 to calculate an RTS estimate for each observation. In other words, we have estimated RTS from equation (7) using the actual level of the explanatory variables associated with each observation (which may be clearly different from the sample mean). Naturally, such estimates must be interpreted with caution because, as Vita (1990) notes, estimated flexible cost functions perform poorly when evaluated away from the approximation point. Nevertheless, and in order to correct this problem, we present in Table 10 the *median* of all individually calculated RTS estimates[10]. In addition, we have also

[10] Our results indicate that the mean of the individually estimated RTS estimates is heavily influenced by very high and very low RTS estimates, which are clearly related to their distance from the approximation point. Therefore, we have chosen to present the median of such estimates, which is not influenced by their magnitude.

Ray economies of scale (individual observations)		(1) SUR - Pooled data	(1) SUR - Pooled data - no dummies homothetic	(2) SUR - Pooled data	(2) SUR - Pooled data - no dummies - homothetic
		RTS			
Clinical Pathology	Median - per observation	1.24	1.19	1.70	1.38
	Median - per hospital	1.20	1.17	1.63	1.33
Medical Imaging	Median - per observation	1.13	1.07	1.05	1.18
	Median - per hospital	1.12	1.02	0.95	1.19
Physical Medicine and Rehabilitation	Median - per observation	1.22	1.14	1.28	1.27
	Median - per hospital	1.23	1.16	1.23	1.29

Table 10: Ray economies of scale - individual observations

calculated the mean RTS estimate for each hospital (each hospital may have a different number of observations in the panel) and then calculated the *median* of such hospitals' RTS estimates.

Firstly, notice that the estimates for Clinical Pathology and Medical Imaging are not too different from those presented in Table 6: for Clinical Pathology, these estimates are slightly larger, whereas for Medical Imaging they are slightly lower. Nevertheless, with one single exception (median per hospital of Medical Imaging) they all suggest the existence of economies of scale in these two specialties.

As for Physical Medicine and Rehabilitation, the RTS estimates also suggest the existence of economies of scale. More importantly, such estimates do not vary significantly across models or depending on the calculation method (median per observation or median per hospital) and range from 1.14 to 1.29.

In conclusion, there are some benefits from aggregating production across hospitals (which leads to an increase in the output produced), but nothing particularly surprising or strong. In the case of Physical Medicine and Rehabilitation, doubling the size (i.e. doubling the amount produced of all outputs) reduces average costs by 6-11%(roughly speaking). A similar conclusion holds for Clinical Pathology and Medical Imaging, as the estimates of RTS (see Table 6) are not too different from Physical Medicine and Rehabilitation.

4.2 Optimal number of beds

Following Preyra and Pink (2006), we can try and infer the optimal relationship between the number of beds (which we have used as a proxy for hospital equipment) and output. First, we differentiate the short run cost function with respect to $\ln(k)$ and equate to zero:

$$\frac{\partial \ln VC}{\partial \ln(k)} = \beta_K + \beta_{KK} \ln(k) + \sum_{i=1}^{m} \sigma_{Ki}. \ln(w_i) + \sum_{i=1}^{n} \theta_{Ki}.Y_i = 0 \tag{10}$$

which is equivalent to:

$$\ln(k) = \frac{-\beta_K - \sum_{i=1}^{m} \sigma_{Ki}. \ln(w_i) - \sum_{i=1}^{n} \theta_{Ki}.Y_i}{\beta_{KK}} \tag{11}$$

	(1) SUR - Pooled data	(1) SUR - Pooled data - no dummies homothetic	(2) SUR - Pooled data	(2) SUR - Pooled data - no dummies - homothetic	Average number of beds
	Optimal Number of beds				
Clinical Pathology	262	470	719	1362	294
Medical Imaging	144	182	134	164	285

Table 11: Optimal number of beds

From this equation, we can analyse the optimal relationship between hospital equipment (proxied by the number of beds) and output levels (as well as input prices). In particular, at the sample mean for the above variables, we can calculate the optimal number of beds and compare it with the actual average number of beds in hospitals[11]. Table 11 shows the results.

Note that the results for Clinical Pathology are not clear cut. In particular, the estimates of equation (10) at the sample mean for the right hand side variables indicates too low a number of beds for all models except one (model 1 with no restrictions). Broadly, this appears to indicate that hospitals are under-dimensioned compared to their optimal level. As for Medical Imaging, the results are clearer: in all models, the optimal number of beds is lower than the actual number of beds, which indicates that hospitals are over-dimensioned.

These results should be interpreted with great caution, because the number of beds may not be a good proxy for hospital equipment. More worringly, we have no way of checking how good a proxy the number of beds really is. In addition, such caution in the interpretation of the results should be extended to the case where one views the number of beds as a proxy to the demand of services internal to the hospital. The optimal number of beds in the hospital is determined by expected activity. It is obvious that Clinical Pathology, Medical Imaging and Physical Medicine and Rehabilitation are not the main drivers to bed needs in the hospital. Still, the exercise we propose provides useful information. Suppose the optimal bed size for Clinical Pathology is one tenth of actual bed size of the hospital. Then, efficiency of Clinical Pathology services would advise to have several departments within the hospital. On the reverse, if the optimal bed size indicated by this exercise is three times the real hospital bed size, their efficiency would be achieved by having the department of one hospital serving several hospitals in the same geographic region (a feature that may not be feasible for some hospitals).

4.3 Elasticities

From equation (6), we can calculate the own and cross-price elasticities of factor demands, where ε_{ii} represents the own-price elasticity of input i and ε_{ij} represents the cross-price elasticity of input i with respect to the price of input j :

[11] We have not calculated the optimal number of beds for Physical Medicine and Rehabilitation because of the poor results obtained when evaluating the estimated cost function at the sample mean - see Section 4.1.

	Input	(1) SUR - Pooled data	(1) SUR - Pooled data - no dummies - homothetic	(2) SUR - Pooled data	(2) SUR - Pooled data - no dummies - homothetic
		Own price elasticities			
Clinical Pathology	Wages	-0.46	-0.41	-0.52	-0.53
	Other	-0.40	-0.36	-0.45	-0.46
Medical Imaging	Wages	-0.13	-0.14	-0.32	-0.28
	Other	-0.27	-0.29	-0.65	-0.58
Physical Medicine and Rehabilitation	Wages	-0.10	-0.09	-0.34	-0.38
	Other	-0.35	-0.32	-1.20	-1.34

Table 12: Own price elasticities of inputs

	(1) SUR - Pooled data	(1) SUR - Pooled data - no dummies - homothetic	(2) SUR - Pooled data	(2) SUR - Pooled data - no dummies - homothetic
	Cross price elasticities (labour-other)			
Clinical Pathology	0.46	0.41	0.52	0.53
Medical Imaging	0.13	0.14	0.32	0.28
Physical Medicine and Rehabilitation	0.10	0.09	0.34	0.38

Table 13: Cross price elasticities of inputs

$$\varepsilon_{ii} = \frac{\partial x_i}{\partial w_i}\frac{w_i}{x_i} = \frac{\gamma_{ii} + S_i^2 - S_i}{S_i} \tag{12}$$

$$\varepsilon_{ij} = \frac{\partial x_i}{\partial w_j}\frac{w_j}{x_i} = \frac{\gamma_{ij} + S_i S_j}{S_i} \tag{13}$$

where S_i and S_j represent the cost shares of inputs i and j respectively and γ_{ii} and γ_{ij} are the estimated coefficients from equation (4). Tables 12 and 13 present the elasticities evaluated at the sample mean. As we can see, all the own-price elasticities are negative for all specialties and they are also below 1, which suggests that factor demands are inelastic. The own-price elasticity of labour is much larger in Clinical Pathology than in Medical Imaging and in Physical Medicine and Rehabilitation. This immediately suggests that there may be a higher degree of substitutability between inputs in Clinical Pathology than in the other two specialties. Finally, the own-price elasticity of labour is lowest in Physical Medicine and Rehabilitation, which makes sense as it is a labour-intensive specialty and it may not be easy to substitute labour with other inputs. The cross-price elasticities are all positive, which indicates that the inputs are substitutes.

A more direct way of gauging the substitution possibilities between inputs is to calculate the Allen cross-elasticities of substitution, which are given by σ_{ij} :

$$\sigma_{ij} = \frac{\varepsilon_{ij}}{S_j} \tag{14}$$

Table 14 shows that the estimated elasticities of substitution (evaluated at the sample mean) do not vary much across models for Clinical Pathology. By contrast, there is a much more pronounced

	(1) SUR Pooled data	(1) SUR - Pooled data - no dummies - homothetic	(2) SUR Pooled data	(2) SUR - Pooled data - no dummies - homothetic
	Allen cross elasticities of substitution (labour-other)			
Clinical Pathology	0.86	0.77	0.97	0.98
Medical Imaging	0.40	0.43	0.97	0.86
Physical Medicine and Rehabilitation	0.44	0.42	1.53	1.71

Table 14: Elasticities of substitution

variation across the estimates for the other two specialties, particularly for Physical Medicine and Rehabilitation[12].

In summary, the own- and cross-price elasticities take on plausible values across models for the various services and the elasticity of substitution shows that, although possible to an extent, there are limits to the possibilities that an hospital has in substituting its labour input by other inputs (e.g. equipment). Again, this is what we would expect.

4.4 Economies of scope

Economies of scope are said to exist if the joint costs of producing the various outputs are lower than the cost of producing those outputs separately. For instance, in a three-output case, overall economies of scope (ES) are given by:

$$ES = \frac{C\left(y_1, 0, 0\right) + C\left(0, y_2, 0\right) + C\left(0, 0, y_3\right) - C\left(y_1, y_2, y_3\right)}{C\left(y_1, y_2, y_3\right)} \tag{15}$$

As Vita (1990) points out, one could evaluate this expression using the estimated costs function. However, flexible cost functions such as the one in equation (4) do not typically provide plausible cost estimates when evaluated at zero output levels. Therefore, Vita (1990) tests for the existence of weak cost complementarities (WCC) at the point of approximation of the cost function. The advantage of this method, as Vita (1990) notes, is that weak cost complementarities are a sufficient condition for economies of scope to exist. Following Vita (1990), weak cost complementarities exist if the following expression is negative:

$$\begin{aligned} C_{ij} &= \frac{\partial^2 C}{\partial y_i \partial y_j} = C_{vij} + C_{vjK} \cdot \frac{\partial k^*}{\partial y_j} \\ &= \frac{\partial^2 VC}{\partial y_i \partial y_j} + \frac{\partial^2 VC}{\partial y_j \partial k} \frac{\partial k^*}{\partial y_j} \end{aligned} \tag{16}$$

where the latter decomposition is due to Cowing and Holtmann (1983). If $\frac{\partial k^*}{\partial y_j} > 0$, then k is a normal input and a sufficient condition for C_{ij} to be negative is that $C_{vij} = \frac{\partial^2 VC}{\partial y_i \partial y_j} < 0$ and

[12] This result is not totally surprising because of the poor results obtained when evaluating the estimated cost function at the sample mean - see Section 4.1.

Weak Cost Complementarities	(1) SUR - Pooled data	(1) SUR - Pooled data - no dummies - homothetic	(2) SUR - Pooled data	(2) SUR - Pooled data - no dummies homothetic	(1) SUR - Pooled data	(1) SUR - Pooled data - no dummies - homothetic	(2) SUR - Pooled data	(2) SUR - Pooled data - no dummies - homothetic	$C_{vij} < 0$ and $[C_{vjK} < 0$ or C_{vjK} $insig \cdot]$	$C_{vij} < 0$ and $C_{vjK} < 0$
Outputs:		C_{vij}				C_{vjK}			# occasions	# occasions
1 and 2	-0.063	0.024	-0.163	-0.058	0.012	0.013	0.018	0.014	2	0
1 and 3	0.038	0.036	0.038	0.028	0.003	0.001	0.022	0.021	0	0
1 and 4	0.077	0.071	0.253	0.289	-0.001	0.000	-0.029	-0.027	0	0
1 and 5	0.027	0.045	0.080	0.128	-0.017	-0.025	-0.051	-0.066	0	0
1 and 6	-0.029	-0.022	-0.026	-0.008	0.022	0.013	0.017	0.009	4	0
1 and 7	0.030	0.038	-0.006	-0.006	-0.033	-0.034	-0.085	-0.090	2	2
2 and 3	-0.010	-0.004	-0.031	-0.027	0.003	0.001	0.022	0.021	4	0
2 and 4	-0.002	0.015	-0.027	0.008	-0.001	0.000	-0.029	-0.027	2	2
2 and 5	-0.004	0.000	0.001	0.005	-0.017	-0.025	-0.051	-0.066	2	2
2 and 6	-0.009	-0.008	-0.013	-0.014	0.022	0.013	0.017	0.009	4	0
2 and 7	-0.003	-0.003	0.014	0.009	-0.033	-0.034	-0.085	-0.090	2	2
3 and 4	0.008	0.008	0.004	0.004	-0.001	0.000	-0.029	-0.027	0	0
3 and 5	0.002	0.004	0.003	0.005	-0.017	-0.025	-0.051	-0.066	0	0
3 and 6	0.000	0.001	0.002	0.003	0.022	0.013	0.017	0.009	1	0
3 and 7	-0.003	-0.005	-0.006	-0.009	-0.033	-0.034	-0.085	-0.090	4	4
4 and 5	0.001	0.002	0.002	0.009	-0.017	-0.025	-0.051	-0.066	0	0
4 and 6	-0.003	0.000	-0.011	-0.006	0.022	0.013	0.017	0.009	3	0
4 and 7	0.007	0.004	0.021	0.018	-0.033	-0.034	-0.085	-0.090	0	0
5 and 6	-0.002	-0.003	-0.002	-0.002	0.022	0.013	0.017	0.009	4	0
5 and 7	-0.002	0.000	-0.005	-0.004	-0.033	-0.034	-0.085	-0.090	4	4
6 and 7	-0.003	-0.003	-0.003	-0.005	-0.033	-0.034	-0.085	-0.090	4	4

Table 15: Weak Cost Complementarities - Clinical Pathology

$C_{vjK} = \frac{\partial^2 VC}{\partial y_j \partial k} < 0$. Again following Vita (1990), for the former to be verified, it must be true that $\beta_i\beta_j + \beta_{ij} < 0$ (parameters in equation (4)); for the latter to be true, $\theta_{Kj} < 0$ must be verified.

Tables 15, 16 and 17 present the estimates of C_{vij} and C_{vjK} for all possible output combinations and for Clinical Pathology, Medical Imaging and Physical Medicine and Rehabilitation respectively. The column further to the right in each of those Tables assesses the number of occasions (or models) for which the more stringent criteria that both C_{vij} and C_{vjK} are negative is verified; by contrast, the penultimate column assesses the number of occasions (or models) in which $C_{vij} < 0$ and C_{vjK} is negative or insignificant, which constitutes a more relaxed criteria to evaluate weak cost complementarities.

Starting with Clinical Pathology (Table 15), and if we lend more credibility to the results obtained under no restrictions (models 1 and 2) and require that the more stringent criteria is met in both models, the following combinations of outputs appear to exhibit weak cost complementarities: outputs 2 and 4 (clinical hemathology and clinical microbiology), outputs 3 and 7 (immunology and clinical hematology/hematoncology), outputs 5 and 7 (endocrinology and clinical hematology/hematoncology) and outputs 6 and 7 (virology and clinical hematology/hematoncology). Note that output 1, clinical chemistry, does not appear to exhibit any cost complementarities with the other outputs. This suggests that this output could be produced independently within each hospital, without affecting the overall cost of Clinical Pathology.

Following the same approach for Medical Imaging (Table 16), the following output combinations appear to exhibit weak cost complementarities: outputs 1 and 4 (radiology and computed tomography), outputs 2 and 4 (angiography and computed tomography), outputs 2 and 5 (angiography and ultrasonography), outputs 3 and 4 (mamography and computed tomography), outputs 3 and

Weak Cost Complementarities	(1) SUR - Pooled data	(1) SUR - Fixed effects	(2) SUR - Pooled data	(2) SUR - Fixed effects	(1) SUR - Pooled data	(1) SUR - Fixed effects	(2) SUR - Pooled data	(2) SUR - Fixed effects	$C_{vij}<0$ and $\left[C_{vjK}<0 \; or \; C_{vjK} \; insig\cdot\right]$	$C_{vij}<0$ and $C_{vjK}<0$
	C_{vij}				C_{vjK}					
Outputs:									# occasions	# occasions
1 and 2	0.037	0.060	0.118	0.180	0.017	0.025	0.012	0.020	0	0
1 and 3	0.024	0.057	0.079	0.133	-0.005	0.005	-0.025	-0.007	0	0
1 and 4	-0.031	-0.111	-0.229	-0.453	-0.007	-0.016	-0.001	-0.008	4	4
1 and 5	0.006	0.011	-0.038	-0.072	-0.007	-0.003	-0.016	-0.011	2	2
1 and 6	0.018	0.035	0.062	0.111	-0.035	-0.048	-0.047	-0.065	0	0
2 and 3	-0.001	0.002	0.014	0.025	-0.005	0.005	-0.025	-0.007	1	1
2 and 4	-0.005	-0.012	-0.054	-0.103	-0.007	-0.016	-0.001	-0.008	4	4
2 and 5	-0.021	-0.031	-0.052	-0.074	-0.007	-0.003	-0.016	-0.011	4	4
2 and 6	0.002	0.001	0.009	0.012	-0.035	-0.048	-0.047	-0.065	0	0
3 and 4	-0.002	-0.014	-0.039	-0.074	-0.007	-0.016	-0.001	-0.008	4	4
3 and 5	-0.005	-0.005	-0.016	-0.024	-0.007	-0.003	-0.016	-0.011	4	4
3 and 6	0.009	0.007	0.014	0.015	-0.035	-0.048	-0.047	-0.065	0	0
4 and 5	0.000	-0.005	0.023	0.042	-0.007	-0.003	-0.016	-0.011	1	1
4 and 6	-0.011	-0.022	-0.061	-0.093	-0.035	-0.048	-0.047	-0.065	4	4
5 and 6	0.019	0.030	0.038	0.051	-0.035	-0.048	-0.047	-0.065	0	0

Table 16: Weak Cost Complementarities - Medical Imaging

Weak Cost Complementarities	(1) SUR - Pooled data	(1) SUR - Fixed effects	(2) SUR - Pooled data	(2) SUR - Fixed effects	(1) SUR - Pooled data	(1) SUR - Fixed effects	(2) SUR - Pooled data	(2) SUR - Fixed effects	$C_{vij}<0$ and $\left[C_{vjK}<0 \; or \; C_{vjK} \; insig\cdot\right]$	$C_{vij}<0$ and $C_{vjK}<0$
	C_{vij}				C_{vjK}					
Outputs:									# occasions	# occasions
1 and 2	-0.041	-0.043	-0.010	-0.016	-0.017	-0.012	0.001	0.001	4	2
1 and 3	-0.001	-0.003	0.002	0.001	0.022	0.015	0.020	0.008	2	0
1 and 4	0.006	0.008	-0.002	-0.003	-0.013	-0.007	-0.028	-0.021	2	2
1 and 5	0.000	0.003	-0.004	-0.006	0.014	0.006	0.031	0.020	2	0
2 and 3	-0.014	-0.016	-0.003	-0.003	0.022	0.015	0.020	0.008	4	0
2 and 4	-0.023	-0.017	-0.033	-0.037	-0.013	-0.007	-0.028	-0.021	4	4
2 and 5	-0.030	-0.032	-0.037	-0.040	0.014	0.006	0.031	0.020	4	0
3 and 4	-0.005	-0.007	-0.002	-0.005	-0.013	-0.007	-0.028	-0.021	4	4
3 and 5	-0.002	-0.003	-0.009	-0.008	0.014	0.006	0.031	0.020	4	0
4 and 5	0.003	0.005	0.000	0.005	0.014	0.006	0.031	0.020	0	0

Table 17: Weak Cost Complementarities - Physical Medicine and Rehabilitation

5 (mamography and ultrasonography), and outputs 4 and 6 (computed tomography and magnetic resonance imaging). From the output description presented in Table 1, it is worth pointing out here that output 4 - Computed tomography - appears to exhibit weak cost complementarities with all other outputs except output 5 - Ultrasonography. This cost complementarity could be due to the fact that either some of the equipment or some of the staff working in the production of that output is also used (generating cost efficiencies) in the production of all other outputs except output 5 (ultrasonography).

For Physical Medicine and Rehabilitation (Table 17), and using the same criteria outlined above, there appear to exist weak cost complementarities between outputs 2 and 4 (physical therapy and occupational therapy) and outputs 3 and 4 (hydro-kinesiotherapy and occupation therapy). Outputs 1 and 5, electrotherapy and speech and language therapy respectively, do not exhibit any cost complementarities. This suggests, as observed above, that these outputs could be produced independently within the hospital without affecting the overall costs of Physical Medicine and Rehabilitation.

The findings reported above have implications for outsourcing decisions. Outsourcing speech and language therapy, for example, has less implications for costs of other activities than outsourcing occupational therapy. Due to cost complementarities, outsourcing occupational therapy alone would increase average costs in physical therapy and hydro-kinesiotherapy. Outsourcing speech and language therapy keeps other costs unchanged. The same line of reasoning can be applied to the other services.

4.5 Other observations

The results for Clinical Pathology (Table 3) and Medical Imaging (Table 4) suggests that smaller hospitals (district and level 1 hospitals) have lower costs, even after adjusting for output production, input prices and other factors, such as the casemix. Therefore, ceteris paribus, and for a given scale of production, producing in those hospitals is less expensive than producing in larger (central) hospitals. This raises important questions which go beyond the identification of economies of scale. Coase (1937), when discussing the limits of firm size[13], observes that as firms get larger, the costs of organizing additional transactions within the firm may increase and that managers may fail to make the best use of the production factors (inefficiency). Both factors may explain why a single firm does not carry out all production and why outsourcing becomes a reasonable decision once a certain scale of production is reached.

In this context, and at the very least, our results indicate that the way in which production is organized in smaller hospitals yields lower costs for a given scale of production. Alternatively, our results suggest that central hospitals may have surpassed their optimal size and are thus facing "diminishing returns to management" (Coase (1937)). If outsourcing were to be decided, these hospitals would be the more likely candidates to benefit from using the market as a resource allocation mechanism. Or, alternatively, it would make sense to create smaller but independent prodution centres within larger hospitals, which could thus better replicate the (lower cost) organization of production of smaller hospitals.

5 Conclusion

This paper has addressed a yet under-researched topic: the provision of services within hospitals, particularly auxiliary clinical services. Because such services have a significant weight in total hospital costs, a proper analysis of their cost structure is warranted. In particular, it is important to analyse the arguments which should underly the make-or-buy decisions that hospitals must make regarding the provision of these services. Clearly, the possible existence of economies of scale and scope is essential in order to understand whether hospitals are better off through in-house production or through outsourcing.

We estimate a flexible cost function (generalized translog cost function) for the three most important (cost-wise) diagnostic techniques and therapeutic services in Portuguese hospitals (Clinical

[13] Coase (1937), pp. 394-395.

Pathology, Medical Imaging and Physical Medicine and Rehabilitation) and find there to be ray economies of scale in all of them, i.e. as we increase the quantity produced of each individual output, costs increase less than proportionally. We also find that there is some evidence of economies of scope for some of the services provided within each category, but not for all of them. This suggests that some services could be provided independently (or outsourced) within each hospital without affecting overall costs. For Clinical Pathology, we find that hospitals are under-dimensioned, i.e. they have too little medical equipment for the output they produce, whilst the reverse is true for Medical Imaging: hospitals appear to be over-dimensioned.

These results should be viewed as a contribution to the ongoing discussion of where and how should hospitals provide these services. Not only do they allow us to assess the optimal hospital dimension for the provision of such auxiliary clinical services, but they also, and at the very least, allow us to gauge the possible cost savings which could arise from aggregating production in fewer hospitals. Moreover, the Portuguese Health Service allows hospitals to outsource particular services (within the hospitals' premises) to public or private contractors. If economies of scale exist, such a contractor could aggregate larger output levels and take advantage of them. However, and to the best of our knowledge, no Portuguese hospital has ever made use of this possibility.

Naturally, further research is needed. Whilst we have benefited from a particularly rich dataset in terms of number of variables, it is also true that we have used a relatively low number of observations because there are not too many hospitals in Portugal (less than 100) and because we have only used data for 2002-2006 (5 years). The estimation of flexible cost functions imposes great demands on the data because of the large number of explanatory variables used. Moreover, our analysis has not considered a separate strand of the literature which has emerged in the last few years: potential inefficiencies in hospital production. And it has also not considered the changes which have occurred in the way hospitals are reimbursed in Portugal. These, and other considerations, are likely to be the next steps in our research.

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Clinical Pathology	(1) SUR - Pooled data	(1) SUR - Pooled data - no dummies - homothetic	(2) SUR - Pooled data	(2) SUR - Pooled data - no dummies - homothetic
λ	RTS			
0.1	1.11	1.10	1.37	1.31
0.07	1.06	1.08	1.35	1.31
0.05	1.02	1.05	1.32	1.30
0.03	0.96	1.02	1.29	1.29
0.01	0.92	0.99	1.23	1.26

Table 18: Sensitivity Analysis - Returns to scale - Clinical Pathology

Medical Imaging	(1) SUR - Pooled data	(1) SUR - Pooled data - no dummies - homothetic	(2) SUR - Pooled data	(2) SUR - Pooled data - no dummies - homothetic
λ	RTS			
0.1	1.34	1.10	1.30	1.07
0.07	1.40	1.15	1.39	1.15
0.05	1.45	1.20	1.47	1.20
0.03	1.52	1.26	1.55	1.26
0.01	1.60	1.34	1.66	1.35

Table 19: Sensitivity Analysis - Returns to scale - Medical Imaging

A Appendix - Sensitivity analysis

Because of the large number of 0-output observations, we have chosen to use the Box-Cox metric instead of the log metric in equation (4). However, the output variable transformation depends crucially on λ, the Box-Cox parameter. We have used $\lambda = 0.1$ in our analysis and in this appendix we analyse the sensitivity of our results with respect to this parameter.

Tables 18, 19 and 20 reproduce the estimation of RTS, the returns to scale estimate outlined in equation (7), evaluated at the sample mean, with different values of λ for Clinical Pathology, Medical Imaging and Physical Medicine and Rehabilitation respectively.

As we can see, the estimates of RTS for Clinical Pathology and Medical Imaging are rather robust for models 1 and 2, with or without restrictions. With few exceptions (low values of λ for Clinical Pathology in model 1), all results confirm the existence of scale economies in these two specialties. The results for Physical Medicine and Rehabilitation confirm our earlier concerns: the estimates for RTS are very sensitive both to the estimation model as well as the Box-Cox parameter λ used. In almost all cases, the estimates vary widely. As explained earlier, this is probably due to the fact that we are evaluating the cost function away from the approximation point.

We follow a similar approach to estimate own-price elasticities for the labour input for different values of λ. Tables 21, 22 and 23 show that these estimates do not vary much with λ, which reassures us that the Box-Cox parameter used in the estimation is unlikely to have affected our results.

Physical Medicine and Rehabilitation	(1) SUR - Pooled data	(1) SUR - Pooled data - no dummies - homothetic	(2) SUR - Pooled data	(2) SUR - Pooled data - no dummies - homothetic
λ	RTS			
0.1	97.20	7.71	-0.48	-2.45
0.07	4.29	2.96	-0.48	-3.10
0.05	3.33	2.51	-0.48	-3.21
0.03	3.25	2.44	-0.46	-3.00
0.01	3.73	2.59	-0.43	-2.63

Table 20: Sensitivity Analysis - Returns to scale - Physical Medicine and Rehabilitation

Clinical Pathology	(1) SUR - Pooled data	(1) SUR - Pooled data - no dummies - homothetic	(2) SUR - Pooled data	(2) SUR - Pooled data - no dummies - homothetic
λ	Own-price elasticity - Wages			
0.1	-0.46	-0.41	-0.52	-0.53
0.07	-0.45	-0.41	-0.52	-0.53
0.05	-0.45	-0.40	-0.52	-0.53
0.03	-0.44	-0.40	-0.52	-0.53
0.01	-0.43	-0.39	-0.52	-0.53

Table 21: Sensitivity analysis - Own-price elasticity (wages) - Clinical Pathology

Medical Imaging	(1) SUR - Pooled data	(1) SUR - Pooled data - no dummies - homothetic	(2) SUR - Pooled data	(2) SUR - Pooled data - no dummies - homothetic
λ	Own-price elasticity - Wages			
0.1	-0.13	-0.14	-0.32	-0.28
0.07	-0.14	-0.14	-0.31	-0.28
0.05	-0.14	-0.14	-0.31	-0.28
0.03	-0.15	-0.14	-0.31	-0.28
0.01	-0.15	-0.15	-0.30	-0.28

Table 22: Sensitivity analysis - Own-price elasticity (wages) - Medical Imaging

Physical Medicine and Rehabilitation	(1) SUR - Pooled data	(1) SUR - Pooled data - no dummies - homothetic	(2) SUR - Pooled data	(2) SUR - Pooled data - no dummies - homothetic
λ	Own-price elasticity - Wages			
0.1	-0.10	-0.09	-0.34	-0.38
0.07	-0.10	-0.09	-0.33	-0.38
0.05	-0.09	-0.09	-0.33	-0.38
0.03	-0.09	-0.09	-0.33	-0.38
0.01	-0.09	-0.08	-0.33	-0.38

Table 23: Sensitivity analysis - Own-price elasticity (wages) - Physical Medicine and Rehabilitation