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ALLOCATIVE INEFFICIENCY AND ITS COST: THE CASE OF THE SPANISH PUBLIC HOSPITALS

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Abstract: In this paper we present a new empirical model based on an input distance function from which allocative inefficiency can be obtained avoiding the "Greene Problem". Well known in the literature, this problem refers to the difficulty in practice of separating economic efficiency in its two components, technical and allocative inefficiency, using a cost system. Moreover, we develop a procedure to calculate the cost of allocative inefficiency. Using a panel of the Spanish public hospital sector to apply our methodology, we find evidence of *systematic* allocative inefficiency in the employment of all variable inputs. Moreover, since inputs are generally poor substitutes, the cost of this allocative inefficiency is high.

Keywords: allocative inefficiency cost, Spanish public hospitals, duality theory, Greene problem, Morishima elasticities of substitution.

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1. Introduction

In this paper we develop and estimate a model to analyse the inefficiency of resource allocation in Spanish public hospitals and the cost associated with this inefficiency. That is, we test the hypothesis that hospital inputs, given technology and prices, are not being optimally used in the sense that costs are not minimised. To do this, we present an empirical model that allows us to calculate the allocative inefficiency of input use in two ways: an error components approach and a parametric approach. In both approaches the general procedure involves the estimation of a system of equations formed by an input distance function and the associated input cost share equations. With this model, we avoid the Greene Problem and we allow allocative inefficiency to be *systematic*, and we incorporate this possibility into our empirical model. This specification distinguishes our study from other studies that concern themselves with the calculation of allocative efficiency and allows unbiased estimates of the allocative efficiency to be obtained (e,g, Grosskopf and Hayes, 1993).

Using duality theory, we propose a methodology based on Shephard's (1953) input distance function, which has certain advantages over production and cost functions. Unlike a production function, a distance function is valid for several outputs. In contrast to a cost function, it does not require the assumption of cost minimising behaviour. These advantages are especially important when we consider some characteristics of the Spanish public hospital sector: a) it provides a wide range of services, and b) public ownership and a lack of price competition mean that cost control is not a survival condition.

The paper is organised as follows. In Section 2 we describe the relevant characteristics of Spanish public hospitals. In Section 3 we outline our empirical model that allows us to identify if there exists a costly misallocation of resources in the provision of health care. In Section 4 we discuss the econometric specifications and a number of econometric issues related to the specifications, as well as the data set used in the estimation. In Section 5 we present and discuss our empirical findings. Briefly, we find a pattern of systematic input misallocation. We find that this misallocation has increased cost by approximately 14% over minimum cost. In the final Section we summarise our findings.

2. The Spanish public hospital sector

In 1986 the Spanish health system began a process of transformation from being a system of Social Security to a National Health System (NHS), whose basic principles are universal coverage with free access to all citizens and financing by means of taxes.

Until 1992, the Spanish hospitals run by INSALUD g*estión-directa*[1] had retrospective budgets with little or no delegation of responsibilities. The resulting lack of effective control mechanisms provided an incentive to increase expenses. In order to improve the delegation of responsibilities, the *Contratos-Programa* (Management Contracts) were designed to replace the retrospective budgets. Whereas the latter were based on historical expenses, the *Contratos-Programa* were based on budgets by objectives, with these objectives quantified in advance, in both activity and financial terms. The new budgetary system began in 1992, and in 1993 the *Contratos-Programa* began to be applied to the INSALUD *gestión-directa* hospitals.

The difficulty of finding a solution to reduce resource misallocation in the sector is implicit in the nature of the hospital system. In the first place, the absence of a profit motive in the hospitals weakens the incentives to act in a cost-minimising manner. In the second place, the agents administering hospital activities enjoy a significant asymmetry of information in their dealings with the sponsor. Thus, the organisation of these hospitals can be placed within the framework of a bureaucratic structure (Niskanen, 1968), where the hypothesis of cost minimisation is questionable. The economics literature devoted to the study of these organisations has adopted the hypothesis that they may behave in a manner out of keeping with the traditional objective of profit maximisation. Profit maximisation is replaced by alternative objectives such as the maximisation of the personal utility of the bureaucrats (Niskanen, 1968; Migué and Bélanger, 1974; Spicer, 1982), thereby allowing for a persistent costly misallocation of resources in the provision of health care. In the following sections, we develop an empirical model which permits to analyse this inefficiency and its cost.

[1] Until 2002, INSALUD *gestión-directa* was the public agency that has administered the provision of health care in those Spanish regions without control over health care. In 2000 it included 10 of the 17 Spanish regions and accounted for around 40% of public health expenditure.

3. The empirical model

We now present the methods that permit the calculation of allocative efficiency. Atkinson and Cornwell (1994) group them into two broad approaches: a) an error components approach, and b) a parametric approach. We demonstrate that the inclusion of an input distance function can overcome the main drawbacks of each approach.

3.1. The Error Components Approach

This approach is based on the familiar system of equations

$$\ln C = \ln C(y, w) + v + u \tag{1}$$

$$\frac{x_i w_i}{C} = \frac{\partial \ln C(y,w)}{\partial \ln w_i} + v_i + A_i, \tag{2}$$

where C = wx is total cost and C(y,w) is a minimum cost frontier. The error components v and v_i represent statistical noise, and are assumed to be distributed as multivariate normal with zero mean and constant variance. The error component u ≥ 0 represents the cost of inefficiency (technical as well as allocative). In principle the error component u can be decomposed into two terms, $u_A \geq 0$ capturing the cost of allocative inefficiency, and $u_T \geq 0$ capturing the cost of technical inefficiency. In practice this has proved difficult. The error components A_i >=< 0, i = 1,…,n, represent allocative inefficiency. The difficulty with the error components approach, denoted by Bauer (1990) as the "Greene problem," is finding a relationship between u_A and the A_i. Schmidt and Lovell (1979) solved the problem by using a self-dual Cobb-Douglas functional form to derive an exact relationship between u_A and the A_i. Greene (1980) used a translog functional form, but avoided the problem by making the (very restrictive) assumption of independence between u_A and the A_i. Schmidt (1984), Bauer (1985), Ferrier and Lovell (1990) and Kumbhakar (1991) suggested somewhat less restrictive relationships between u_A and the A_i. Kumbhakar (1997) used a translog functional form to derive an exact (and extremely complicated) relationship between u_A and the A_i. Despite (or perhaps because of) its analytical elegance, Kumbhakar's formulation remains to be implemented empirically.

In light of the difficulties associated with the use of a cost frontier system to estimate allocative efficiency, we modify the model by formulating an input distance function system. This system is

$$\ln 1 = \ln D_I(y, x) + v + u \tag{3}$$

$$\frac{w_i x_i}{C} = \frac{\partial \ln D_I(y, x)}{\partial \ln x_i} + v_i + A_i. \tag{4}$$

where D_I is the input distance function: $D_I(\bar{y}, x) = \max_{\delta}\{\delta \geq 1 : x/\delta \in L(\bar{y})\}$, where $L(\bar{y}) = \{x \in R_n^{+}: x \text{ can produce } \bar{y} \in R_m^{+}\}$. For $x \in L(\bar{y})$, $D_I(\bar{y}, x) \geq 1$, with $D_I(\bar{y}, x) = 1 \Leftrightarrow x$ is technically (but not necessarily allocatively) efficient for $\bar{y}$.

As in the cost stochastic frontier system (1) - (2), the error components v and v_i represent statistical noise, and the error components A_i >=< 0 represent allocative inefficiency, here represented by the difference between actual and stochastic shadow input cost shares.

However in sharp contrast to (1), the error component u in (3) represents the *magnitude* of *technical* inefficiency, rather than the *cost* of *technical and allocative* inefficiency. Thus the great advantage of estimating the input distance function system (3) - (4) instead of the cost frontier system (1) - (2) is that the error component u in (3) does not include the cost of allocative inefficiency, and so u and the A_i are inherently independent, and the "Greene problem" disappears.

3.2. The Parametric Approach

In this approach firms are assumed to minimise the shadow cost of producing a given output vector for some shadow input price vector w^s, and so

$$C(y, w^s) = \min_x \{w^s x : x \in L(y)\}. \tag{5}$$

Firms minimise shadow cost by equating marginal rates of substitution with shadow input price ratios, which may diverge from market input price ratios. The estimation of these shadow price ratios, and their comparison with the market price ratios, enables the calculation of allocative inefficiency.

Starting with Toda (1976), a line of research has been developed in which these shadow price ratios have been calculated. Initially these studies were based on the estimation of a cost-based system of equations from which expressions for actual cost and actual input cost shares are obtained from shadow cost and shadow input cost shares (Atkinson and Halvorsen, 1986, Eakin and Kniesner, 1988, Oum and Zhang, 1995). This system of equations had the property of establishing a relationship between shadow input price ratios and market input price ratios, using parametric corrections k_{ij} >=< 1 to market input price ratios sufficient to satisfy the cost minimisation condition.

Ideally the parametric corrections to market input price ratios would be input- and firm-specific. However if only cross-section or time series data are available, a drawback of this approach is that the method is unable to estimate specific k_{ij}s for each observation. A second drawback is the need to assume technical efficiency. To solve the first problem, Atkinson and Halvorsen (1990) and Bhattacharyya *et al*. (1995) defined the allocative inefficiency parameters as functions of different variables that vary across firms, thereby obtaining estimates of firm-specific k_{ij} values. As Atkinson and Cornwell (1994) point out, however, this has the risk that the estimates will be inconsistent if the functions are incorrectly specified. Fortunately these problems disappear when panel data are available. Panel data have the advantage of allowing us to obtain firm-specific estimates of both technical and allocative efficiency. This approach, used by Atkinson and Cornwell (1994), does not completely solve the problem, however, as it is assumed that technical efficiency and the k_{ij} coefficients of each firm are constant throughout the sample period. Balk and Van Leeuwen (1997) relaxed this assumption by normalising on a particular firm. However, as they recognise, parameter estimates are not invariant to the choice of the reference firm.[2]

Färe and Grosskopf (1990) modified this approach by using an input distance function, rather than a shadow cost function, to represent technology. Their approach makes it possible to obtain estimates of k_{ij} for each firm in each time period. Thus in a shadow price model where firms are assumed to minimise shadow cost as in (5), we start from the dual Shephard's lemma:

$$\frac{\partial D_I(y,x)}{\partial x_i} = w_i^s(y,x) = \frac{w_i^s}{C(y,w^s)}\,, \qquad (6)$$

to obtain the shadow price ratios:

[2] For a comparison between the approaches of Atkinson and Cornwell (1994) and Balk and Van Leeuwen (1997), see Maietta (1998).

$$\frac{\frac{\partial \mathrm{D_I}(y,x)}{\partial \mathrm{x_i}}}{\frac{\partial \mathrm{D_I}(y,x)}{\partial \mathrm{x_j}}} = \frac{\mathrm{w_i^s}}{\mathrm{w_j^s}}. \tag{7}$$

If the cost minimisation assumption is satisfied, these normalised shadow price ratios coincide with market price ratios. However if expense preference behaviour causes allocative inefficiency, the two price ratios differ. To study the magnitude and direction of such deviations, a relationship between the normalised shadow prices (obtained through the distance function) and the market input prices is introduced by means of the parametric price corrections

$$\mathrm{w_i^s} = \mathrm{k_i}\ \mathrm{w_i}. \tag{8}$$

Dividing (8) by the corresponding expression for input j we obtain

$$\frac{\mathrm{w_i^s}}{\mathrm{w_j^s}} = \mathrm{k_{ij}} \frac{\mathrm{w_i}}{\mathrm{w_j}}, \tag{9}$$

where $k_{ij} = k_i/k_j$.

Thus from (9) the degree to which shadow price ratios differ from market price ratios is calculated. Moreover, we can obtain the direction of such inefficiency as follows: (a) if $k_{ij} = 1$, there is allocative efficiency; (b) if $k_{ij} > 1$, input *i* is being under-utilised relative to input *j*; (c) if $k_{ij} < 1$, input *i* is being over-utilised relative to input *j*.

Numerous studies have applied the approach of Färe and Grosskopf (1990) as a means of estimating the extent of allocative inefficiency in production, examples being Färe *et al*. (1990) and Grosskopf *et al.* (1995). To estimate the k_{ij} coefficients it is also possible to estimate the distance function jointly with the shadow input share equations, thereby improving efficiency in estimation. To do this, one estimates the system (3) - (4) and then obtains estimates of the k_{ij} coefficients using equations (7) - (9). Grosskopf and Hayes (1993) used this equation system to estimate technical and allocative inefficiency in Illinois municipalities. Atkinson and Primont (1998) and Atkinson *et al.* (1998) estimated this system of equations to obtain indices of technical and allocative efficiency for American electric utilities and railroads, respectively.

However these three papers simplify the model (3) - (4) by assuming that the A_is have zero means, which has the important drawback of introducing the assumption that allocative inefficiency is random rather than systematic. As the objective of this research is precisely to determine whether persistent allocative inefficiency exists in the Spanish hospital sector, this issue is of particular relevance. In the following Section we modify the model of Grosskopf and Hayes (1993) to allow for the existence of *systematic* allocative inefficiency. We specify an empirical model formed by an input distance function and the shadow input cost share equations to analyse allocative efficiency in the Spanish public hospital sector using two approaches: the error components approach and the parametric approach.

4. Econometric specification and data description

We now consider how to estimate the system (3) - (4). However when carrying out the estimation of the system, there are a number of econometric issues to be considered.

a) *Functional form*

We have chosen a flexible functional form, a translog short run multiproduct input distance function. In the hospital sector the translog functional form (Vita, 1990; Carey,1997) has supplanted the Cobb-Douglas functional form used in early empirical research (Feldstein, 1967; Vitaliano,1987). Thus the short-run input distance function is specified as:

$$\ln 1 = B_0 + \sum_{r=1}^{m}\alpha_r \ln y_{rht} + \frac{1}{2}\sum_{r=1}^{m}\sum_{s=1}^{m}\alpha_{rs}\ln y_{rht}\ln y_{sht} + \sum_{i=1}^{n}\beta_i \ln x_{iht} + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\beta_{ij}\ln x_{iht}\ln x_{jht} +$$

$$\xi_f \ln xf_{ht} + \frac{1}{2}\xi_{ff}\ln xf_{ht}^2 + \sum_{r=1}^{m}\sum_{i=1}^{n}\rho_{ri}\ln y_{rht}\ln x_{iht} + \sum_{i=1}^{n}\xi_{fi}\ln xf_{ht}\ln x_{iht} + \sum_{r=1}^{m}\xi_{fr}\ln xf_{ht}\ln y_{rht} +$$

$$\sum_{t=1}^{T-1}\gamma_t T + \varepsilon_{ht} \qquad (10)$$

The associated variable input cost share equations are

$$\frac{x_{iht}w_{iht}}{C_{ht}} = \beta_i + \sum_{j=1}^{n}\beta_{ij}\ln x_{jht} + \sum_{r=1}^{m}\rho_{ri}\ln y_{rht} + \xi_{fi}\ln xf_{ht} + \mu_{iht} \qquad (11)$$

where $y = (y_1,\ldots,y_m)$ is an output vector, $x = (x_1,\ldots,x_n)$ is a variable input vector, xf is a quasi-fixed input, T is a time dummy, h = 1,…, H denotes hospitals, and ε_{ht} and μ_{iht} are disturbance terms.

b) Homogeneity of degree +1 in variable inputs

In order to be able to carry out the estimation we impose homogeneity of degree +1 in variable inputs, which is a property of an input distance function. This condition requires that $\sum_{i=1}^{n} \beta_i = 1$; $\sum_{j=1}^{n} \beta_{ij} = 0$; $\sum_{r=1}^{m} \rho_{ri} = 0$; $\sum_{f=1}^{F} \xi_{fi} = 0$. We also impose the symmetry conditions $\alpha_{rs} = \alpha_{sr}$, $\xi_{fi} = \xi_{if}$, $\rho_{ri} = \rho_{ir}$ and $\beta_{ij} = \beta_{ji}$.

c) The error structure

Here we are concerned with the disturbance terms in (10) - (11). We assume that the disturbance term in (10) has the structure

$$\varepsilon_{ht} = \eta_{ht} + \delta_h \qquad h = 1,..., H; \quad t = 1,...,T, \tag{12}$$

where η_{ht} ~ iid N(0, σ^2) is a random disturbance term, and the δ_h are hospital-specific disturbances that capture unobserved heterogeneity. Since hospital technology is highly complex, it is unlikely that an econometric distance function will fully encompass all the elements that affect it. If these hospital-specific differences exist and are not explicitly picked up in the model, a problem of omitted variables exists and the estimated coefficients of the included variables are biased. As Carey (1997) points out, the main advantage of using panel data instead of cross-section data when dealing with the hospital sector is that it is possible to capture unobserved systematic differences among hospitals (for example, quality of services and severity of illnesses).

In the efficiency literature these fixed effects δ_h are traditionally interpreted as indices of the technical inefficiency of each firm. However these fixed effects capture not only variation in technical efficiency but also the influence of other variables that have not been fully incorporated into the model and which do not change over the period considered, such as service quality or the geographic configuration of each hospital. This will have an effect on the indices of technical efficiency, which are picked up in these fixed effects.

Turning to the disturbance term in (11), we assume it has the structure

$$\mu_{iht} = \eta_{iht} + A_i \qquad i = 1,...,N, \tag{13}$$

where η_{iht} is normally distributed with zero mean. The existence of contemporaneous correlation is permitted among the η terms. This is made possible by the combined estimation of the system of equations, and it constitutes an advantage over the estimation of single equation models, since it allows us to assume that stochastic factors exist that can affect the disturbance terms of the different equations in a period of time.

The A_i terms in (13) can be interpreted as measures of allocative inefficiency. As we have explained in Section 2, allocative inefficiency could be systematic in the Spanish public hospital sector. In other words, the A_is could have nonzero means. We therefore assume that the A_is have means a_i, and we propose the following transformation of the error term, inspired by Ferrier and Lovell [11],

$$\frac{x_i w_i}{C} = (\beta_i + a_i) + \sum_{j=1}^{n} \beta_{ij} \ln x_{jht} + \sum_{r=1}^{m} \rho_{ri} \ln y_{rht} + \xi_{fi} \ln xf_{ht} + (A_i - a_i) + \eta_{iht}, \quad (14)$$

where the transformed error terms (μ_{iht} - a_i) have zero means.

d) Endogeneity of variable inputs

Given the special characteristics of Spanish public hospitals, we assume that hospital management may have incentives to choose hospital inputs following criteria other than cost-minimisation (Lee, 1971; Spicer, 1982). If this is so, the variable input regressors could be endogenous, and for this reason we use an instrumental variables (IV) approach. Each variable input is regressed on a vector of variables that is expected to be correlated with the variable input but uncorrelated with the error term. The predicted values are used in the estimation of (10) - (14).

e) Corrections for autocorrelation and heteroscedasticity

We introduce intra-equation intertemporal effects by permitting the error terms to follow first-order autoregressive processes. Although equal across firms, we specify that the first order autoregressive parameter in the distance function disturbance term differs from that in the share equation disturbance terms. To ensure consistency in summation, however, we also specify that the autoregressive parameter for each share equation is equal across shares (Berndt *et al*., 1993). Heteroscedasticity is corrected by using White's (1980) method.

4.1. The Data

The data have been obtained from the Spanish Ministry of Health and Consumption. With the objective of homogenising the sample, we have excluded specialised hospitals that cannot be classified as general hospitals, and hospitals having fewer than 100 beds.[3] Moreover, during the sample period several hospitals have merged. To deal with this, we have treated a merged hospital as a new hospital. As a result, the final sample is an unbalanced panel consisting of 318 observations on 67 general hospitals of the INSALUD g*estión-directa* over the period 1987-94.

To estimate the model (10) - (14) we need data on variable and quasi-fixed inputs, outputs and operating expenses. Table 1 provides definitions of the variables used in the analysis.

Following Feldstein 1967,we approximate outputs with the number of treated cases in various classifications. As the data do not directly take into account treated cases, we use the number of hospital discharges as a proxy. We classify hospital discharges into medicine (MED), surgery (SUR), obstetrics (OBS), paediatrics (PED) and intensive care (UIC). Apart from these primary hospital activities, other activities such as outpatient visits (first and successive visits) and emergencies are carried out in most of the sample hospitals. These complementary activities are gathered into an aggregate variable (AM), each of the activities being weighted in accordance with the UPA[4] classification.

The variable inputs include care graduates (G); care technicians (T); other non-assistant personnel (RES) and supplies (S). Since S is contaminated by the effect of price variation, both temporal and spatial, we deflate this variable.[5]

We include a quasi-fixed input, which we approximate by the number of beds in the

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[3] Burgess and Wilson (1995) and Carey (1997), provide evidence that hospitals with fewer than 100 beds have cost structures that are distinctly different from those of larger hospitals.

[4] The UPA weights hospital activities according to resource consumption. The weights are: inpatient days in medicine (1); surgery (1.5); obstetrics (1.2); paediatrics (1.3); intensive care (5.8); first outpatient visit (0.25); successive outpatient visit (0.15) and emergencies (0.3).

[5] We deflate the supplies variable by the consumer prices index of the National Statistics Agency (INE), taking into account the group of goods to which each supply type belongs and the differences in prices that exist between the different regions.

hospital (BED). Although this is clearly not the most suitable measure, it is commonly used since the data relating to capital and its amortisation are not reliable.

To account for expenses on personnel we use salaries, wages and overtime reported in the different categories. In this sense the unit cost of each personnel category is considered (which is a result of upgrading manpower, system productivity, labour schedules and other fringe benefits). Expenses on supplies include purchases of disposable goods.

We also include a teaching variable (EDU) in an attempt to capture the differences in complexity across hospitals. This variable is defined as the number of students carrying out their studies in a hospital. In the literature on the hospital sector it has been common to introduce this variable, since teaching hospitals are generally the biggest and most complex, as well as being located in metropolitan areas and having a relatively high investment in technology. These hospitals also have as an additional mission of the professional training of medical students.

Finally we include a dummy variable (D_t) for each sample year. This vector represents variables that, in their temporal evolution, affect all hospitals in the same way.

5. Empirical results

To estimate the system (10) - (14) we use an iterative seemingly unrelated regressions (ITSUR) procedure, with instruments for the endogenous variables. As instruments, we employ the exogenous variables of the model and the following three variables that we also consider to be exogenous: childbirths, childbirths where the child weighs less than 2.5 kilograms, and the endowment of X-ray rooms of each hospital.[6] Because the cost shares sum to unity, one of the share equations is deleted. Results are invariant to the choice of equation to be deleted.

[6] To test the validity of using IV estimation, we calculate the Hausman [36], test of exogeneity. The value of the test statistic corresponding to the null hypothesis $\beta_{GLS} = \beta_{IV}$ is 1113, which exceeds the critical value of the *chi*-square distribution for 46 degrees of freedom at any reasonable significance level (the critical value at 0.01 level is 71.2). The result of this test confirms the appropriateness of an IV approach.

The variables are divided by their geometric means, so that the estimated distance function is a Taylor series approximation to the true but unknown distance function at the mean of the data. The estimated distance function satisfies the requisite regularity conditions at the sample means: it is non-decreasing and concave in inputs and decreasing in outputs.[7] The AR1 parameter that we introduce in each share equation to correct for first-order autocorrelation is statistically significant.[8] The parameters estimated from the system of equations are presented in Table 2.

5.1. The Error Components Approach

The indices of allocative efficiency estimated using the error components approach (a_i) are presented in Table 3. These parameters indicate the *systematic* allocative inefficiency arising from the use of the corresponding input in a non-cost minimising mix. All parameter estimates differ significantly from zero, which implies that, at the sample mean, the proportion in which the inputs are being used is *systematically* inefficient. The proportion in which care graduates and supplies are used is above optimum, while that of care technicians and other personnel is below optimum. Thus too much is spent on care graduates and supplies, and too little is spent on care technicians and other personnel.

The coefficients of the time dummies show the effect on the distance function of unobserved variables that, in their evolution through time, affect all hospitals equally. We can determine how these time effects influence the distance function from one year to the next through the expression

$$TC_{t+1,t} = \gamma_{t+1} - \gamma_t. \qquad (15)$$

A positive (negative) value of $TC_{t+1,t}$ indicates an upward (downward) shift in the distance function (Färe and Grosskopf, 1995), which is typically associated with technical change. The indices obtained from (15) are presented in Table 4. From 1988 through 1992, $TC_{t+1,t} < 0$, indicating that hospital performance deteriorated during this period. This trend began to reverse beginning in 1992-93. This pattern may reflect the

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[7] A likelihood ratio test of the Cobb-Douglas restriction on the translog functional form yields a test statistic of 259.56, which exceeds the critical value of the *chi*-square distribution for 66 degrees of freedom at the usual levels of significance. Thus for these data the translog distance function is a better representation of the production technology than the Cobb-Douglas function.

[8] The autoregressive parameter estimate in the distance function is –0.0147 with a t-statistic of -0.696. Since it is not significantly different from zero, we set this autocorrelation coefficient to zero.

increased control over hospital administrators created by the implementation of the management contracts in INSALUD hospitals beginning in 1992. González and Barber (1996) find similar results.

5.2. The Parametric Approach

We now analyse allocative efficiency by means of the parametric approach. Although it is possible to apply this approach by estimating only the input distance function, we opt for its joint estimation with the cost share equations with the objective of improving efficiency in estimation. Applying the parameters estimated in (10) - (14) to (7) and (9), we obtain indices of allocative inefficiency *for each observation* according to the expression

$$k_{ij} = \frac{w_{jht} x_{jht} \left[\hat{\beta}_i + \sum_{j=1}^{n} \hat{\beta}_{ij} \ln x_{jht} + \sum_{r=1}^{m} \hat{\rho}_{ri} \ln y_{rht} + \hat{\xi}_{fi} \ln xf_{fht} \right]}{w_{iht} x_{iht} \left[\hat{\beta}_j + \sum_{i=1}^{n} \hat{\beta}_{ij} \ln x_{iht} + \sum_{r=1}^{m} \hat{\rho}_{rj} \ln y_{rht} + \hat{\xi}_{fj} \ln xf_{fht} \right]} \quad . \qquad (16)$$

It is important to distinguish these measures of allocative efficiency from those obtained from the error components approach, in which the a_i coefficients represent the systematic allocative inefficiency *for each input*. In the parametric approach the k_{ij} coefficients indicate the allocative inefficiency *for each pair of inputs*. Moreover, in the error components approach, behind the a_i coefficients lies the assumption that there is an *additive* relationship between w_i and w_i^s. In the parametric approach a *multiplicative* relationship between w_i and w_i^s is specified, yielding coefficients k_{ij} as indexes of allocative inefficiency.

Finally, with the error components approach we can only estimate allocative inefficiencies at the sample mean. This drawback does not appear in the parametric approach. In contrast to the a_i coefficients, individual estimates of the k_{ij}s for each observation can be identified. Once the parameters of the system are estimated, we can obtain firm- and time-specific measures of allocative inefficiency from the k_{ij} coefficients, since these coefficients depend on input quantities and input prices.

The mean values of the k_{ij} coefficients obtained from (16), together with their t-statistics, are presented in Table 5.[9] We also use bootstrap techniques (Efron and

[9] We have analysed the pattern of the estimated k_{ij} coefficients across hospitals of differing

Tibshirani, 1986) to obtain the confidence intervals of the k_{ij}. In this way we can determine if these coefficients are robust to small changes of the model specification. From the results we conclude that both care graduates and supplies are significantly over-utilised relative to care technicians and other personnel, and that supplies are insignificantly over-utilised relative to care graduates. These findings demonstrate the typical bureaucratic behaviour of preference for supplies and highly qualified personnel (Lindsay and Buchanan, 1970; Lee, 1971; Spicer, 1982).

In summary, we have tried in Sections 5.1 and 5.2 to determine the extent and nature of allocative inefficiency in Spanish public hospitals. To do this, we have used *two different approaches*. While at the beginning of this Section we detailed the differences between the two approaches, it is also important to emphasise the *relationship* that exists between them. As we have already pointed out when discussing the empirical model, if systematic efficiency exists (that is, if the a_i terms have mean values significantly different from zero), their inclusion is necessary if the estimated parameters, and consequently the estimated k_{ij}s, are to be unbiased. This specification differentiates the present study from others that have analysed allocative efficiency in a bureaucratic setting. By not allowing allocative inefficiency to be systematic, their estimated k_{ij}s may be biased. Our findings provide empirical evidence that persistent allocative inefficiency exists in this sector. This in turn supports the hypothesised bureaucratic model, and implies that the inclusion of the parameters a_i in the empirical model is indispensable in order to obtain unbiased estimates of the k_{ij}s.

The results indicate that the proportion in which variable inputs are allocated is, at the mean, inefficient, and costs could therefore be reduced through a more efficient allocation of inputs. The next logical step in the investigation is to determine the extent to which the technology allows substitution among variable inputs. This analysis reveals how costly allocative inefficiency is. If allocative inefficiency exists, it is not very costly if variable inputs are good substitutes, but it is very costly if they are poor substitutes. Since the input distance function describes the technology, we can analyse the degree of substitutability among the variable inputs by means of Morishima elasticities of substitution. These elasticities are defined as

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complexity and size, and have found no important differences. We also have analysed the time path of the k_{ij} and have not found important trends.

$$
\begin{aligned}
&M_{ij}(y,x) = -\mathrm{d}\ln\left[(D_i(y,x/x_i)/D_j(y,x/x_j)\right]/\mathrm{d}\ln\left[x_i/x_j\right] = \\
&x_i D_{ij}(y,x)/D_j(y,x) - x_i D_{ii}(y,x)/D_i(y,x) = \\
&E_{ij}(y,x) - E_{ii}(y,x)
\end{aligned} \tag{17}
$$

where the terms E_{ij} are cross shadow price elasticities indicating whether the input pairs are net substitutes or net complements, and the terms E_{ii} are direct shadow price elasticities. Estimated Morishima substitution elasticities M_{ij} and their two components E_{ij} and E_{ii} are provided in Tables 6 and 7.

The estimated Morishima elasticities M_{ij} suggest very limited possibilities for substitution among the different pairs of inputs. All point estimates are numerically small, and most are significantly less than unity. The same patterns hold for the estimated cross shadow price elasticities E_{ij}. These findings imply that the estimated allocative inefficiency is likely to be very costly.

5.3. The Cost of Allocative Inefficiency

It is possible to estimate the cost of allocative inefficiency. To do this, we define an input vector x^* that fulfils the cost minimisation conditions. Then, starting from the dual Shephard's lemma (6), *at the optimum* we have

$$
\frac{\partial D_I(y,x)}{\partial x_i^*} = \frac{\partial \ln D_I(y,x)}{\partial \ln x_i^*}\frac{D_I(y,x)}{x_i^*} = \frac{w_i}{C(y,w)}, \tag{18}
$$

and for any two inputs,

$$
\frac{\dfrac{\dfrac{\partial \ln D_I(y,x)}{\partial \ln x_i^*}}{\dfrac{\partial \ln D_I(y,x)}{\partial \ln x_j^*}}}{\dfrac{w_i}{w_j}} = \frac{x^*_i}{x^*_j}. \tag{19}
$$

If we define a multiplicative input quantity correction z_i such that $x_i^* = z_i\, x_i$, we can write (19) as:[10]

[10] This approach, which is inspired by Kopp and Diewert (1982), is also a parametric approach, but it is expressed in terms of input quantities rather than input prices.

$$\frac{\frac{\frac{\partial \ln D_I(y,x)}{\partial \ln x_i^*}}{\frac{\partial \ln D_I(y,x)}{\partial \ln x_i^*}}}{\frac{w_i}{w_j}} = \frac{z_i x_i}{z_j x_j} \Rightarrow \frac{\frac{\frac{\partial \ln D_I(y,x)}{\partial \ln x_i^*}}{\frac{\partial \ln D_I(y,x)}{\partial \ln x_i^*}}}{\frac{x_i w_i}{x_j w_j}} = \frac{z_i}{z_j}. \qquad (20)$$

This is a simultaneous system of n-1 nonlinear equations in n variables z. However since share equations are homogeneous of degree zero in inputs, we can normalize by some arbitrarily chosen $z_j x_j$. In this way we obtain z_{ij} parameters ($z_{ij}=z_i/z_j$), such that $x_i^* = z_{ij}\ z_j\ x_i$. From the calculated values of z_{ij} it is possible to deduce directly z_j by substituting the z_{ij} values into the estimated distance function to obtain

$$\ln 1 = \ln D_I\,[(y,\ (z_{ij}\, z_j\, x_i)] \qquad i = 1,...,n. \qquad (21)$$

Finally, deriving the remaining z_i parameters ($i \neq j$) is easy, because $z_i = z_{ij}\ z_j$.

Calculated parametric corrections to the optimal input quantities at the sample mean are:[11] $z_{supplies} = 0.678$, $z_{graduates} = 0.907$; $z_{other\ personnel} = 0.962$; and $z_{technicians} = 1.01$. Thus to correct allocative inefficiency of input quantities, it is necessary to decrease utilisation of supplies, graduates and other personnel by 32.2%, 9.3% and 3.8%, respectively, and to increase utilisation of technicians by 1%. Once the optimal input quantities have been calculated, the effect of allocative inefficiency on the cost of production can be evaluated by comparing actual cost with optimal cost. The results reported in Table 8 indicate that allocative inefficiency has increased cost by 14% at the sample mean. The primary source of cost inefficiency is the excessive use of supplies.

6. Summary and conclusions

In this paper we propose an empirical model to evaluate allocative inefficiency. It consists of estimating an equation system, formed by an input distance function and the cost share equations for each factor, that allow us to obtain allocative inefficiency in two ways: analysing the error terms of the share cost equations and using a parametric approach. In this way, we avoid falling into the well known “Greene

[11] To perform the optimisation we use the mathematical program MATLAB. The initial values of z_{ij} chosen are (1,1,1).

problem" and we can assume that the employment of an input in a proportion different from that which would minimise cost could be systematic, and incorporate this possibility into our empirical model. This specification allows us to obtain unbiased estimates of the allocative efficiency.

We provide an empirical application of this model to the study of allocative efficiency in Spanish public hospitals, based on an unbalanced panel consisting of 67 general hospitals observed over the period 1987-94. The analysis of the sector reveals a bureaucratic structure characterised by information asymmetry and by a lack of incentives on the part of the agents who manage public hospital activities to adopt the criterion of cost minimisation.

According to our results, allocative efficiency does not exist. We find statistically significant evidence of allocative inefficiency, which takes the form of systematic over-utilisation of supplies and care graduates relative to care technicians and other personnel. We also find very limited possibilities for input substitution, which implies that input misallocation is costly. We estimate the cost of the misallocation to be 14% of actual cost. These findings provide quantitative support for our initial hypothesis that cost-minimising behaviour does not characterise the operation of Spanish public hospitals.

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Table 1. Definitions of variables used in the analysis

Variable	Type	Description
MED	Output	Discharges in general medicine, psychiatry, tuberculosis, long stay, rehabilitation and others.
SUR	Output	Discharges in surgery, paediatric and gynaecological surgery.
OBS	Output	Discharges in obstetrics.
PED	Ouput	Discharges in paediatric medicine and neonatology.
UIC	Output	Discharges in units of intensive care, burns and intensive neonatals.
AM	Output	Weighted sum of first and successive visits and emergencies
G	Input	Care graduates (doctors, pharmacists and other graduates).
T	Input	Care technicians (nurses, matrons and others)
RES	Input	Other personnel (directive personnel, administration managers, qualified and non-qualified personnel).
S	Input	Deflated expenses on sanitary material, drugs, food, clothing, fuels and others.
BED	Quasi-fixed input	Number of beds.
EG	Cost	Expenses on assistant graduates.
ETEC	Cost	Expenses on assistant technicians.
ERES	Cost	Expenses on non-assistants and other personnel.
ESU	Cost	Expenses on supplies.
EDU	Var. Complexity	Number of medical students.
D_t	Time	Time dummy variable

Table 2: Input distance function parameter estimates

Variable	Coefficient[(a)]	t-statistic		Variable	Coefficient[(a)]	t-statistic	
L(MED)	-0.1542	-5.3477	**	L(OBS).L(PED)	0.0235	1.5317	
L(SUR)	-0.0488	-1.6671	*	L(OBS).L(UIC)	0.0081	2.1984	**
L(OBS)	-0.0262	-1.8475	*	L(OBS).L(AM)	0.0071	0.3039	
L(PED)	-0.0558	-2.7190	**	G(OBS).L(G)	-0.0015	-0.8080	
L(UIC)	-0.0049	-1.0734		L(OBS).L(T)	0.0004	0.2653	
L(AM)	-0.0385	-2.0527	**	L(OBS).L(RES)	0.0039	1.6820	*
L(G)	0.1350	3.6200	**	L(OBS).L(S)	-0.0028	-1.3965	
L(T)	0.3262	6.9419	**	L(OBS).L(BED)	-0.0874	-2.5544	**
L(RES)	0.3833	7.0838	**	L(PED).L(UIC)	-0.0072	-1.8208	*
L(S)	0.1553	5.0237	**	L(PED).L(AM)	-0.0204	-0.6921	
L(BED)	0.1161	2.3272	**	L(PED).L(G)	0.0045	1.6891	*
L(EDU)	-0.0166	-3.8721	**	L(PED).L(T)	0.0006	0.2969	
L(MED).L(MED)	0.2285	3.1937	**	L(PED).L(RES)	-0.0023	-0.7113	
L(SUR)·L(SUR)	0.2304	1.6526	*	L(PED).L(S)	-0.0029	-0.9881	
L(OBS)·L(OBS)	0.0055	1.0369		L(PED).L(BED)	-0.0264	0.6297	
L(PED)·L(PED)	-0.0002	-0.0254		L(UIC).L(AM)	0.0064	1.2038	
L(UIC)·L(UIC)	-0.0019	-0.8067		L(UIC).L(G)	-0.0005	-0.4034	
L(AM)·L(AM)	-0.0558	-0.9885		L(UIC).L(T)	-0.0005	-0.4775	
L(G).L(G)	0.1099	3.7168	**	L(UIC).L(RES)	0.0008	0.5173	
L(G).L(T)	-0.0662	-2.9103	**	L(UIC).L(S)	0.0002	0.1628	
L(G).L(RES)	-0.0232	-0.7834		L(UIC).L(BED)	-0.0329	-3.2697	**
L(G).L(S)	-0.0203	-1.0777		L(AM).L(G)	-0.0023	-0.2197	
L(G).L(BED)	0.0044	0.3430		L(AM).L(T)	0.0144	1.5405	
L(T)·L(T)	0.0920	2.3420	**	L(AM).L(RES)	0.0115	0.8392	
L(T)·L(RES)	0.0057	0.1621		L(AM).L(S)	-0.0235	-2.0122	**
L(T).L(S)	-0.0314	-1.6950	*	L(AM).L(BED)	0.3368	4.7580	**
L(RES).L(S)	-0.0587	-2.3929	**	L(T).L(BED)	-0.0211	-1.9629	**
L(RES).L(RES)	0.0762	1.5453		L(RES).L(BED)	0.0001	0.0068	
L(S).L(S)	0.1105	4.5014	**	L(S).L(BED)	0.0165	1.2165	
L(BED).L(BED)	0.0952	0.6391		L(EDU).L(EDU)	-0.0007	-0.2370	
L(MED).L(SUR)	0.1655	2.6105	**	L(MED).L(EDU)	-0.0483	-3.8651	**
L(MED).L(OBS)	0.0028	0.1001		L(SUR).L(EDU)	-0.0435	-2.4635	**
L(MED).L(PED)	-0.0030	-0.0845		L(0BS).L(EDU)	-0.0014	-0.3026	
L(MED).L(UIC)	0.0033	0.4017		L(PED).L(EDU)	-0.0015	-0.2969	
L(MED).L(AM)	-0.1895	-3.1729	**	L(UIC).L(EDU)	0.0061	4.1820	**
L(MED).L(G)	0.0124	1.4051		L(AM).L(EDU)	-0.0030	-0.3127	
L(MED).L(T)	0.0179	2.3935	**	L(G).L(EDU)	-0.0024	-1.1355	
L(MED).L(RES)	-0.0072	-0.6688		L(T).L(EDU)	-0.0023	-1.3326	
L(MED).L(S)	-0.0231	-2.3784	**	L(RES).L(EDU)	-0.0002	-0.0855	
L(MED).L(BED)	-0.0632	-0.7497		L(S).L(EDU)	0.0049	2.1730	**
L(SUR).L(OBS)	0.0540	3.0476	**	L(BED).L(EDU)	0.0784	4.4009	**
L(SUR).L(PED)	0.0023	0.0774		AR1	0.4396	16.0545	**
L(SUR).L(UIC)	-0.0001	-0.0233		γ_{89}	-0.0424	-3.8708	**
L(SUR).L(AM)	-0.0448	-0.6458		γ_{90}	-0.1235	-9.9131	**
L(SUR).L(G)	-0.0252	-2.0202	**	γ_{91}	-0.1947	-14.5330	**
L(SUR.L(T)	-0.0109	-1.0387		γ_{92}	-0.2090	-13.4983	**
L(SUR).L(RES)	0.0025	0.1658		γ_{93}	-0.2029	-12.4191	**
L(SUR).L(S)	0.0336	2.4493	**	γ_{94}	-0.1885	-10.6124	**
L(SUR).L(BED)	-0.3298	-3.2306	**				

[(a)] Standard error estimates employ the White (1980) heteroscedasticity-robust computation.

* statistically significant at 10% — Number of observations= 318

** statistically significant at 5% — Number of hospitals= 67

Table 2 (cont.): Statistics of the Model

Equation	R-squared	DW	S.E. regression
Distance function	-	1.7454	0.0403
Share graduates	0.4124	1.5282	0.0392
Share technicians	0.3321	1.6253	0.0330
Share other personnel	0.3612	1.3909	0.0476
Share supplies	0.4813	1.6227	0.0435

Table 3. Mean Values of Systematic Allocative Inefficiencies

Variable	Coefficient	t-statistic
$a_{graduates}$	0.0880	2.3463 **
$a_{technicians}$	-0.1031	-2.1884 **
$a_{supplies}$	0.1394	3.3018 **
$a_{other\ personnel}$	-0.1243	-2.2884 **

** statistically significant from zero at 5%.

Table 4. Time Effects

Period	TC[(a)]	t-statistic
88-89	-0.0424	-3.8708 **
89-90	-0.0811	-7.6770 **
90-91	-0.0711	-7.6899 **
91-92	-0.0143	-1.4876
92-93	0.0061	0.6806
93-94	0.0143	1.6372 *

[(a)] Evaluated at the means of the data using parameter estimates of (17) - (21).
* statistically significant from zero at 10%
** statistically significant from zero at 5%

Table 5. Coefficients k_{ij}

Coefficients	Mean[(a)]	t-statistic
k graduates, technicians	0.4414 (0.37-0.58)	9.3106 **
k graduates, other personnel	0.4568 (0.36-0.57)	9.1760 **
k graduates, supplies	1.2720 (0.91-1.63)	1.3317
k technicians, other personnel	1.0553 (0.86-1.20)	0.0756
k technicians, supplies	2.9465 (2.32-3.15)	2.5693 **
k other personnel, supplies	2.9759 (2.43-3.43)	2.5005 **

[(a)] Evaluated at the means of the data using parameter estimates of (17) - (21).
** statistically significant different from one at 5% level
Note: Confidence intervals of k_{ij} obtained from bootstraping are in parentheses. To obtain it the percentile method has been used. The reestimation of the system (17)-(21) with the pseudo-data generated was repeated 100 times.

Table 6. Estimated Morishima Substitution Elasticities M_{ij}

	Mean[(a)]	t-statistic		Mean[(a)]	t-statistic
$M_{\text{graduates, ,technicians}}$	-0.0155	-0.5838	$M_{\text{technicians, graduates}}$	0.2211	1.7851 *
$M_{\text{graduates, other personnel}}$	0.1276	14.6371**	$M_{\text{other personnel , graduates}}$	0.6387	4.7887 **
$M_{\text{graduates, supplies}}$	0.0571	2.0979**	$M_{\text{supplies, graduates}}$	0.1451	0.6598
$M_{\text{technicians, other personnel}}$	0.7345	3.6204**	$M_{\text{other personnel , technicians}}$	0.8206	3.7837 **
$M_{\text{other personnel , supplies}}$	0.4244	1.6841*	$M_{\text{supplies, other personnel}}$	0.1427	0.5710
$M_{\text{technicians, supplies}}$	0.5233	2.5761**	$M_{\text{supplies, technicians}}$	0.1995	0.8373

Table 7. Estimated Cross and Direct Price Elasticities E_{ij} and E_{ii}

	Mean[(a)]	t-statistic		Mean[(a)]	t-statistic
$E_{\text{graduates, technicians}}$	-0.0682	-2.3266 **	$E_{\text{technicians, graduates}}$	-0.1715	-3.4995 **
$E_{\text{graduates, other personnel}}$	0.0745	8.6833 **	$E_{\text{other personnel , graduates}}$	0.2201	3.9012 **
$E_{\text{graduates, supplies}}$	0.0040	0.1458	$E_{\text{supplies, graduates}}$	0.0045	0.1417
$E_{\text{technicians, other personnel}}$	0.3419	3.2745 **	$E_{\text{other personnel , technicians}}$	0.4019	3.3260 **
$E_{\text{other personnel , supplies}}$	0.0057	0.0303	$E_{\text{supplies, other personnel}}$	0.0022	0.0302
$E_{\text{technicians, supplies}}$	0.1307	0.9342	$E_{\text{supplies, technicians}}$	0.0589	0.9075
$E_{\text{graduates, graduates}}$	-0.0530	-22.7467 **	$E_{\text{technicians, technicians}}$	-0.3926	-3.2475 **
$E_{\text{other personnel , other personnel}}$	-0.4187	-3.1733 **	$E_{\text{supplies, supplies}}$	-0.1405	-0.7016

[(a)] Evaluated at the means of the data using parameter estimates of (17) - (21).
* statistically significant from zero at 10%
** statistically significant from zero at 5%

Table 8. The Cost of Allocative Inefficiency per Hospital per Year (Thousands of euros)

	Actual Cost [(*)]	Optimal Cost[(*)]	Allocative Inefficiency Cost[(*)]	Allocative Inefficiency Cost (%)
Graduates	6,493.71	5,890.45	603.27	9.3
Technicians	6,701.21	6,762.86	-61.65	-1
Other Personnel	8,029.70	7,723.77	305.93	3.81
Supplies	10,162.01	6,889.85	3,272.17	32.2
TOTAL	**31,386.64**	**27,266.93**	**4,119.72**	**14**

[(*)] cost per hospital and year.