ALLOCATIVE INEFFICIENCY AND ITS COST: THE CASE OF 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 estimates of allocative inefficiency and its cost can be obtained. The model avoids the "Greene problem," which refers to the difficulty in practice of using a cost system to separate economic inefficiency into its technical and allocative components. We also develop a procedure to calculate the cost of allocative inefficiency. Using a panel of Spanish public hospitals to apply our methodology, we find evidence of *systematic* allocative inefficiency in the employment of variable inputs. 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, parametric input distance function.

JEL classification: C33, D24, D73, I12, L32

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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. We test the hypothesis that, given technology and prices, hospital inputs are not optimally allocated in the sense that costs are not minimised. To do this, we develop a model that allows the unbiased estimation of 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. 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 estimation of allocative inefficiency.

Using duality theory, we propose a methodology based on a parametric Shephard's [1] input distance function, which has certain advantages over production and cost functions. Unlike a production function, a distance function allows 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 competition mean that cost control is not a survival condition. Thus, the absence of a profit motive weakens incentives to act in a cost-minimising manner thereby allowing for a persistent and costly misallocation of resources in the provision of health care. In this study we develop a model that enables us to analyse this misallocation and its cost.

The paper is organised as follows. In Section 2 we outline a model that allows us to determine if there exists a costly misallocation of resources in the provision of health care. In Section 3 we discuss the two econometric specifications and a number of econometric issues related to the specifications. In Section 4 we present and discuss our empirical findings. Briefly, we find a pattern of systematic input misallocation that has increased cost by approximately 14% over minimum cost. In the final Section we summarise our findings.

2. THE EMPIRICAL MODEL

We present two methods that permit the calculation of allocative efficiency. Atkinson and Cornwell [2] identify the two methods as an error components approach and a parametric approach. We demonstrate that replacing the usual cost frontier with an input distance function can overcome the main drawbacks of each approach.

2.1. The Error Components Approach

This approach is based on the cost frontier system of equations

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

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

where C is the cost; y is the output vector; x is the input vector; w is the input prices vector 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 $u \geq 0$ 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 $A_i \gtreqless 0$, $i = 1,\ldots,n$, represent allocative inefficiencies, and so u_A cannot be independent of the A_i. The difficulty with the error components approach, denoted by Bauer [3] as the "Greene problem," is specifying a tractable relationship between u_A and the A_i. Kumbhakar [4] used a translog functional form to derive an exact (and extremely complicated) relationship between u_A and the A_i, but his 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 formulate a dual input distance function system as

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

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

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

As in the cost frontier system (1) - (2), the error components v and v_i represent statistical noise, and the error components $A_i \gtreqless 0$ represent allocative inefficiencies, represented by the difference between actual and stochastic input cost shares. However in 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.

2.2. 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

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

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

Starting with Toda [5], 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. This system of equations had the property of establishing a relationship between shadow input price ratios and market input price ratios, using parametric corrections $k_{ij} \gtreqless 1$ to market input price ratios sufficient to satisfy the cost minimisation conditions.

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, this method must assume technical efficiency, and it is unable to estimate specific k_{ij}s for each observation without endogenising the k_{ij}s. The availability of panel data allows us to obtain firm-specific estimates of both technical and allocative efficiency. This approach, used by Atkinson and Cornwell [2], does not completely solve the problem, however, as it is assumed that technical efficiency and the k_{ij}s are time-invariant for each firm. It is possible to relax this assumption by normalising on a reference firm (Balk and Van Leeuwen [6]), although parameter estimates are not invariant to the choice of the reference firm.[1]

Färe and Grosskopf [8] modified this approach by using an input distance function, rather than a shadow cost function, to represent technology.[2] This makes it possible to estimate k_{ij} for each firm in each time period. Thus in a shadow price model (5) where firms are assumed to minimise shadow cost, the dual Shephard's lemma

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

yields the shadow price ratios:

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

[1] For a comparison of the approaches of Atkinson and Cornwell [2] and Balk and Van Leeuwen [6], who normalised on a reference firm, see Maietta [7].

[2] On the other hand, it is possible to calculate output shadow prices using an output distance function (see for example Reig-Martínez *et al*. [9])

If the cost minimisation assumption is satisfied, these shadow price ratios coincide with actual 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 shadow price ratios in (7) and the actual price ratios is introduced by means of the parametric price ratio corrections

$$\frac{w_i^s}{w_j^s} = k_{ij}\frac{w_i}{w_j}. \qquad (8)$$

The degree to which shadow price ratios differ from actual price ratios is calculated from (8). If $k_{ij} = 1$, there is allocative efficiency; if $k_{ij} > 1$, input *i* is under-utilised relative to input *j*; if $k_{ij} < 1$, input *i* is over-utilised relative to input *j*.

Numerous studies have used input distance functions to estimate the extent of allocative inefficiency. However it is preferable to estimate the input 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}s using (7) - (8) (Grosskopf and Hayes [10], Atkinson and Primont [11]).

However in the system (3) - (4) the A_is are typically assumed to 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 allocative inefficiency is systematic in the Spanish hospital sector, this issue is of particular relevance. In the next Section we modify the system (3) – (4) to allow for *systematic* allocative inefficiency, and we use two approaches, the error components approach and the parametric approach.

3. ECONOMETRIC SPECIFICATION

We now consider how to estimate the system (3) - (4), how to deal with a number of econometric issues.

a) *Functional form*

We have chosen a flexible functional form, a translog short run multiproduct input distance function. This functional form has supplanted the Cobb-Douglas functional form used in early hospital research (Feldstein [12]). The short-run input distance function is specified as:

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

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

$$\sum_{t=1}^{T-1}\gamma_t T + \varepsilon_{ht} \qquad (9)$$

The associated variable input cost share equations are

$$\frac{x_{iht}w_{iht}}{C_{ht}} = \beta_i + \sum_{j=1}^{n}\beta_{ij}\ln x_{jht} + \sum_{r=1}^{m}\rho_{ri}\ln y_{rht} + \xi_{fi}\ln xf_{ht} + \mu_{iht} \qquad (10)$$

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. Homogeneity of degree +1 of the input distance function in variable inputs is enforced by imposing the restrictions $\sum_{i=1}^{n}\beta_i=1$, $\sum_{j=1}^{n}\beta_{ij}=0$, $\sum_{i=1}^{n}\rho_{ri}=0$ ($\forall$

r=1,..m), $\sum_{i=1}^{n} \xi_{fi}=0$. We also impose the symmetry conditions $\alpha_{rs} = \alpha_{sr}$, $\beta_{ij} = \beta_{ji}$, $\xi_{fi} = \xi_{if}$, $\xi_{fr} = \xi_{rf}$, $\rho_{ri} = \rho_{ir}$.

b) The error structure

We assume that the disturbance term in (9) has the structure

$$\varepsilon_{ht} = \eta_{ht} + \delta_h \qquad h = 1,..., H; \; t = 1,...,T, \qquad (11)$$

where η_{ht} ~ iid $N(0, \sigma^2)$ 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 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 [13] points out, the main advantage of using panel 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).

The fixed effects δ_h are traditionally interpreted as indices of the technical inefficiency of each firm. However these fixed effects capture not just variation in technical efficiency but also the influence of other variables that have not been fully incorporated into the model and that do not change over the sample period, such as service quality and the geographic location 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 (10), we assume it has the structure

$$\mu_{iht} = \eta_{iht} + A_i \qquad i = 1,\ldots,N, \qquad (12)$$

where η_{iht} is normally distributed with zero mean. The existence of contemporaneous correlation among the ηs is made possible by the estimation of a system of equations, and it constitutes an advantage over the estimation of a single equation, 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 (12) are interpreted as measures of allocative inefficiency, which 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 (10), inspired by Ferrier and Lovell [14],

$$\frac{x_{iht} w_{iht}}{C_{ht}} = (\beta_i + a_i) + \sum_{j=1}^{n} \beta_{ij} \ln x_{jht} + \sum_{r=1}^{m} \rho_{ri} \ln y_{rht} + \xi_{fi} \ln xf_{ht} + (A_i - a_i) + \eta_{iht}, \qquad (13)$$

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

c) *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, [15]; Spicer, [16]). 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 inputs but uncorrelated with the error term. The predicted values are used in the estimation of (9) - (13).

d) 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 allow the autoregressive parameter in the distance function disturbance term to differ from that in the share equation disturbance terms. To ensure consistency in summation, however, we impose equality of share equation autoregressive parameters across shares (Berndt *et al*. [17]). Heteroscedasticity is corrected using White's [18] method.

4. EMPIRICAL RESULTS

To estimate the system (9) - (13) we use an iterative seemingly unrelated regressions (ITSUR) procedure, with instruments for the endogenous variables. In Appendix A we describe our data set used in the estimation.[3] 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.

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 mean: it is non-decreasing and concave in inputs and decreasing in outputs.[4] The AR1 parameter that we introduce in each share equation to correct for

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[3] To test the validity of using IV estimation, we calculate the Hausman [19] 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.

[4] 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.

first-order autocorrelation is statistically significant.[5] The parameters estimated from the system of equations are presented in Appendix B.

4.1. The Error Components Approach

The indices of allocative efficiency estimated using the error components approach are presented in Table 1. 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 input mix 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.

(INSERT TABLE 1 ABOUT HERE)

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. The influence of the passage of time is given by the expression

$$TC_{t+1,t} = \gamma_{t+1} - \gamma_t. \quad (14)$$

A positive (negative) value of $TC_{t+1,t}$ indicates an upward (downward) shift in the distance function, which is typically associated with technical change. The indices obtained from (14) are presented in Table 2. From 1988 through 1992, $TC_{t+1,t} < 0$, indicating that hospital performance deteriorated during this period. This trend began to

[5] 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.

reverse beginning in 1992-93. This pattern may reflect the increased control over hospital administrators created by the implementation of the management contracts in INSALUD hospitals beginning in 1992.[6] González and Barber [20] find similar results.

(INSERT TABLE 2 ABOUT HERE)

4.2. The Parametric Approach

We now analyse allocative efficiency using 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 to improve efficiency in estimation. Applying the parameters estimated in (9) - (13) to (8), we obtain indices of allocative inefficiency *for each observation* according to the expression

$$k_{ij} = \frac{w_{jht} x_{jht} \left[\hat{\beta}_i + \sum_{j=1}^{n} \hat{\beta}_{ij} \ln x_{jht} + \sum_{r=1}^{m} \hat{\rho}_{ri} \ln y_{rht} + \hat{\xi}_{fi} \ln xf_{fht} \right]}{w_{iht} x_{iht} \left[\hat{\beta}_j + \sum_{i=1}^{n} \hat{\beta}_{ij} \ln x_{iht} + \sum_{r=1}^{m} \hat{\rho}_{rj} \ln y_{rht} + \hat{\xi}_{fj} \ln xf_{fht} \right]} \quad . \qquad (15)$$

It is important to distinguish these measures of allocative inefficiency from those obtained from the error components approach, in which the a_is represent the systematic allocative inefficiency *for each input*. In the parametric approach the k_{ij}s indicate the allocative inefficiency *for each pair of inputs*. Moreover, in the error components approach, behind the a_is lies the assumption of an *additive* relationship between w_i and

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[6] Prior to 1992 the hospitals run by INSALUD g*estión-directa* 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.

w_i^s. In the parametric approach a *multiplicative* relationship between w_i and w_i^s is specified, yielding the coefficients k_{ij} as indexes of allocative inefficiency.

Finally, with the error components approach we can only estimate allocative inefficiencies at the sample mean. The parametric approach avoids this drawback. 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}s, since these coefficients depend on input quantities and input prices.

The mean values of the k_{ij}s obtained from (15), together with their t-statistics, are presented in Table 3.[7] We use bootstrap techniques (Efron and Tibshirani [21]) to obtain confidence intervals for the k_{ij}s. 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 are consistent with the typical bureaucratic behaviour of preference for supplies and highly qualified personnel (Lee [15], Spicer [16]).

(INSERT TABLE 3 ABOUT HERE)

We have used *two different approaches* to determine the nature of allocative inefficiency in Spanish public hospitals. We have discussed the differences between the two approaches, but it is also important to emphasise the *relationship* that exists

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

between them. As we have pointed out, if systematic inefficiency exists (that is, if the a_is 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 inefficiency 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 systematic 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.

4.3. The Cost of Allocative Inefficiency

The results indicate that the variable input mix is inefficient at the mean, and costs could therefore be reduced through a more efficient allocation. The next logical step in the investigation is to determine the extent to which the technology allows substitution among variable inputs. 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

$$\begin{aligned} & \mathrm{M_{ij}}(y,x) = -\mathrm{d}\ln\left[(\mathrm{D_i}(y,x/\mathrm{x_i})/\mathrm{D_j}(y,x/\mathrm{x_j})\right]/\mathrm{d}\ln\left[\mathrm{x_i}/\mathrm{x_j}\right] = \\ & \mathrm{x_i D_{ij}}(y,x)/\mathrm{D_j}(y,x) - \mathrm{x_i D_{ii}}(y,x)/\mathrm{D_i}(y,x) = \\ & \mathrm{E_{ij}}(y,x) - \mathrm{E_{ii}}(y,x) \end{aligned} \qquad (16)$$

where the E_{ij}s are cross shadow price elasticities indicating whether the input pairs are net substitutes or net complements, and the E_{ii}s are direct shadow price elasticities.

Estimated Morishima substitution elasticities M_{ij} and their two components E_{ij} and E_{ii} are provided in Tables 4 and 5.

(INSERT TABLES 4 AND 5 ABOUT HERE)

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.

To estimate the cost of allocative inefficiency, 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

$$\frac{\partial D_I(y,x)}{\partial x_i^*} = \frac{\partial \ln D_I(y,x)}{\partial \ln x_i^*} \frac{D_I(y,x)}{x_i^*} = \frac{w_i}{C(y,w)} \qquad (17)$$

and for any two inputs,

$$\frac{\dfrac{\dfrac{\partial \ln D_I(y,x)}{\partial \ln x_i^*}}{\dfrac{\partial \ln D_I(y,x)}{\partial \ln x_j^*}}}{\dfrac{w_i}{w_j}} = \frac{x^*{}_i}{x^*{}_j}. \qquad (18)$$

If we define an input quantity correction z_i such that $x_i^* = z_i \, x_i$, we can write (18) as:[8]

[8] This approach, which is inspired by Kopp and Diewert [22], is also a parametric approach, but it is expressed in terms of input quantities rather than input prices.

$$\frac{\dfrac{\dfrac{\partial \ln D_I(y,x)}{\partial \ln x_i^*}}{\dfrac{\partial \ln D_I(y,x)}{\partial \ln x_j^*}}}{\dfrac{w_i}{w_j}} = \frac{z_i x_i}{z_j x_j} \Rightarrow \frac{\dfrac{\dfrac{\partial \ln D_I(y,x)}{\partial \ln x_i^*}}{\dfrac{\partial \ln D_I(y,x)}{\partial \ln x_j^*}}}{\dfrac{x_i w_i}{x_j w_j}} = \frac{z_i}{z_j} \qquad (19)$$

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 derive z_j directly by substituting the z_{ij} values into the estimated distance function to obtain

$$\ln 1 = \ln D_I\,[(y, (z_{ij}\, z_j\, x_i)] \qquad i = 1,\ldots,n. \qquad (20)$$

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:[9] $z_{supplies} = 0.678$, $z_{graduates} = 0.907$; $z_{other\ personnel} = 0.962$; 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 cost can be evaluated by comparing actual cost with minimum cost. The results reported in Table 6 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.

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

(INSERT TABLE 6 ABOUT HERE)

5. 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 (n-1) input cost share equations, that allows us to estimate allocative inefficiency in two ways: analysing the error terms of the share cost equations and using a parametric approach. Both enable us to avoid the "Greene problem", and to incorporate the possibility that the employment of an input in a proportion different from one that would minimise cost could be systematic. This specification allows us to obtain unbiased estimates of allocative inefficiency.

We provide an empirical application of this model to the study of allocative inefficiency in Spanish public hospitals sector, based on an unbalanced panel consisting of 67 general hospitals observed over the period 1987-94. This sector is characterised by a lack of incentives on the part of the agents who manage public hospitals to adopt the criterion of cost minimisation.

Our results confirm that resource allocation is not allocatively efficient. 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.

6. REFERENCES

[1] Shephard, R. W., 1953, *Cost and Production Functions* (Princeton: Princeton University Press.)

[2] Atkinson, S. E. and Cornwell, C., 1994, Parametric Estimation of Technical and Allocative Inefficiency with Panel Data, *International Economic Review* 35, 231-43.

[3] Bauer, P. W., 1990, Recent Developments in the Econometric Estimation of Frontiers, *Journal of Econometrics* 46, 39-56.

[4] Kumbhakar, S. C., 1997, Modelling Allocative Inefficiency in a Translog Cost Function and Cost Share Equations: an Exact Relationship, *Journal of Econometrics* 76, 351-56.

[5] Toda, Y., 1976, Estimation of a Cost Function when Cost is not a Minimum: the Case of Soviet Manufacturing Industries, 1958-1971, *Review of Economics and Statistics* 58, 259-68.

[6] Balk, B. M. and Van Leeuwen, G., 1999, Parametric Estimation of Technical and Allocative Efficiencies and Productivity Changes: a Case Study, in S. Biffignandi, ed., Micro- and Macro-Data of Firms: Statistical Analysis and International Comparison (Heidelberg: Physica-Verlag).

[7] Maietta, O. W., 2002, The Effect of the Normalisation of the Shadow Price

Vector on the Cost Function Estimation, *Economics Letters* 77, 381-85.

[8] Färe, R. and Grosskopf, S., 1990, A Distance Function Approach to Price Efficiency, *Journal of Public Economics* 43, 123-26.

[9] Reig-Martínez, E., Picazo-Tadeo, A. and Hernández-Sáncho, F., 2001, The Calculation of Shadow Prices for Industrial Wastes using Distance Functions: an Analysis for Spanish Ceramic Pavements Firms, *International Journal of Production Economics* 69, 277-285.

[10] Grosskopf, S. and Hayes, K., 1993, Local Public Sector Bureaucrats and their Input Choices, *Journal of Urban Economics* 33, 151-66.

[11] Atkinson, S. E. and Primont, D., 2002, Stochastic Estimation of Firm Technology, Inefficiency, and Productivity Growth Using Shadow Cost and Distance Functions, *Journal of Econometrics* 108, 203-25.

[12] Feldstein, M. S., 1967, Economic Analysis for Health Service Efficiency: Econometric Studies of the British National Health Service (Amsterdam: North-Holland).

[13] Carey, K., 1997, A Panel Data Design for Estimation of Hospital Cost Functions, *Review of Economics and Statistics* 79, 443-53.

[14] Ferrier, G. and Lovell, C. A. K., 1990, Measuring Cost Efficiency in Banking: Econometric and Linear Programming Evidence, *Journal of Econometrics* 46, 229-45.

[15] Lee, M. L., 1971, A Conspicuous Production Theory of Hospital Behavior, *Southern Economic Journal* 38, 48-58.

[16] Spicer, M. W., 1982, The Economics of Bureaucracy and the British National Health Service, *Milbank Memorial Fund Quarterly / Health and Society* 60, 657-72.

[17] Berndt, E. R., Friedlaender, A. F., Chiang, J. S. W. and Vellturo, C. A., 1993, Cost Effects of Mergers and Deregulation in the U.S. Rail Industry, *Journal of Productivity Analysis* 4, 127-44.

[18] White, H., 1980, A Heterokedasticity-Consistent Covariance Matrix and a Direct Test for Heterokedasticity, *Econometrica* 48, 721-46.

[19] Hausman, J. A., 1978, Specification Tests in Econometrics, *Econometrica* 46, 1251-71.

[20] González, B. and Barber, P., 1996, Changes in the Efficiency of Spanish Public Hospitals after the Introduction of Program-Contracts, *Investigaciones Económicas* 20, 377-402.

[21] Efron, B. and Tibshirani, R., 1986, Bootstrap Methods for Standard Errors, Confidence Intervals, and Other Measures of Statistical Accuracy, *Statistical Science* 1, 54-77.

[22] Kopp, R. J. and Diewert, W. E., 1982 The Decomposition of Frontier Cost Function Deviations into Measures of Technical and Allocative Efficiency, *Journal of Econometrics* 19, 319-31.

TABLES

Table 1. 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 2. 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 (9) - (13).
*   statistically significant from zero at 10%
** statistically significant from zero at 5%

Table 3. 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 (9) - (13).

** 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 (9)-(13) with the pseudo-data generated was repeated 100 times.

Table 4. 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 5. 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 (9) - (13).
* statistically significant from zero at 10%
** statistically significant from zero at 5%

Table 6. 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.

APPENDIX A: 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 (Carey [13]). During the sample period several hospitals have merged, and 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 (9) - (13) we need data on variable inputs, quasi-fixed inputs, outputs and operating expenses. Table A.1 provides definitions of these and other variables used in the analysis.

Table A.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

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 and emergencies are carried out in most of the sample hospitals. These two complementary activities are merged into an aggregate variable (AM), each of the activities being weighted in accordance with its UPA classification. The UPA weights hospital activities according to resource consumption. The weights are: first outpatient visit (0.25); successive outpatient visit (0.15) and emergencies (0.3).

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 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.

We include as a quasi-fixed input the number of beds in the 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 unreliable.

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. 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. It has become common to include this variable, since teaching hospitals are generally the largest 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 the professional training of medical students.

Finally we include a dummy variable (D_t) for each sample year, in an effort to reflect variables that, in their temporal evolution, affect all hospitals in the same way.

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.

APPENDIX B

Table B.1: System of Equations Estimated Parameters

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 [19] heteroscedasticity-robust computation.

* statistically significant at 10% Number of observations= 318

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

Table B.1 (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