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HOSPITAL INDUSTRY RESTRUCTURING AND INPUT SUBSTITUTABILITY: EVIDENCE FROM A SAMPLE OF ITALIAN HOSPITALS

MASSIMILIANO PIACENZA, GILBERTO TURATI, DAVIDE VANNONI

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Hospital Industry Restructuring and Input Substitutability: Evidence from a Sample of Italian Hospitals

Massimiliano Piacenza

Italian National Research Council, Ceris-CNR, Collegio Carlo Alberto
via Real Collegio 30,10024 Moncalieri (TO), ITALY; e-mail: m.piacenza@ceris.cnr.it.

Gilberto Turati *

University of Torino, Department of Economics and Finance "G. Prato"
Corso Unione Sovietica 218bis, 11034 Torino, ITALY; e-mail: turati@econ.unito.it.

Davide Vannoni

University of Torino, Department of Economics and Finance "G. Prato"
Corso Unione Sovietica 218bis, 11034 Torino, ITALY; e-mail: vannoni@econ.unito.it.

Abstract. In this paper we investigate the economic rationality of the bed downsizing process characterising the hospital industry worldwide in the last decades, providing new evidence on the factor substitutability in the production of hospital services. We consider a sample of Italian regional producers and – differently from other studies – estimate a general cost function model, namely the *Generalised Composite*, firstly introduced by Pulley & Braunstein (1992). Alternative cost function specifications (included Translog) are estimated jointly with their associated input cost-share equations. For all models we derive Allen, Morishima and Shadow elasticities of substitution between input pairs, obtaining a fairly consistent picture across all specifications and elasticity concepts. More precisely, our results suggest a very limited degree of substitutability between factors in the production of hospital services (in particular, between beds and medical staff). These findings, consistent with previous evidence in the literature, suggest that a restructuring policy of the hospital industry which is confined to limiting the number of beds could not be a viable strategy for controlling the increase in public health care expenditure.

Keywords: Public health care expenditure, Hospital industry downsizing, Input substitutability

JEL Codes: D24, I18, L32

1. Introduction

A huge process of reorganisation invested hospital industries worldwide in the last decades. At a macro level, in order to curb the presence of excess capacity, public producers' number of beds has been reduced by Central or Regional governments almost anywhere (e.g. Kroneman and Siegers, 2004; Hensher *et al.*, 1999). At a micro level, a number of M&As - interesting both private and public hospitals - has been observed in several countries, not only as a response to bed reduction, but also to exploit scale and scope economies, and improve effectiveness and quality of care. The process has been originated on two basic premises: on the one hand, the need to contain public health care expenditure imposed governments to find new ways on how to improve the efficiency (and the effectiveness) in the provision of health services. As expenditure for hospital services represented (and still represent) a significant share of total health expenditure, it is not surprising that hospitals were clearly at the core of policies aimed at controlling expenditure growth. On the other hand, the perception that an ageing population would have different needs (especially chronic illnesses) with respect to past years caused traditional hospitals – which focus typically on acute care – not to be tailored to answer these structural changes in the epidemiological context.

This massive ongoing reshaping of the hospital industry raises of course a number of questions, that only in recent years the academic literature has started to ask. A first problem to address is to understand whether M&As are justified both from an efficiency and an effectiveness point of view. In this perspective, as discussed in Posnett (1999), results are somewhat mixed. As for efficiency, for instance, studying the Canadian Province of Ontario, Preyra and Pink (2006) find large scale unexploited gains from consolidation in the hospital sector, while Bilodeau *et al.* (2002), concentrating on Québec, show the presence of both economies and diseconomies of scale, with some establishments operating at constant returns to scale. As for effectiveness, for example, focusing on U.S. surgical procedures, Birkmeyer *et al.* (2002) find that mortality rates are lower the higher the volume of patients treated, whereas Grilli *et al.* (1998) challenge this view, by surveying literature on cancer patients. A second question to focus on is the strategic reply of hospitals to bed reductions implemented by Central and Regional governments. For instance, Kroneman and Siegers (2004) find that behavioural responses are related to the hospital financing system: in particular, in global budget systems, occupancy rates appear to decline after a reduction in hospital bed supply, while in per diem financing systems, admission rates did not drop following bed downsizing. In both systems, no effects are detected on average length of stay.

In this framework, in order to understand the potential role of industry restructuring on health expenditure growth, an important issue to be discussed concerns workforce management after bed reductions. In the U.S., where the share of private producers is higher than elsewhere, bed downsizing has been sometimes accompanied also with staff reductions, with no clear effects on hospital performance. Chadwick *et al.* (2004) find for example that Human Resource Management practices are important determinants of successful downsizing, of both beds and the workforce. In particular, looking at financial performance of hospitals, they find a positive impact of consideration for employees' morale and welfare during downsizing (like more extensive communication and advance notice, respectful treatment of laid off employees, attention to survivors' concerns on job security). Somewhat contrary to this view, Aiken *et al.* (2002a, 2002b) find that better staffing is positively associated with higher nurse-assessed quality of care, lower risk-adjusted and failure-to-rescue rates, lower level of dissatisfaction and burnout, hence suggesting a deterioration of performance following downsizing. However, in other countries, especially in Europe, where the share of public producers is higher, the restructuring of the industry has been limited in most cases to bed downsizing, while workforce management and planning has been conducted using fixed ratio relationships (e.g. physicians to patients) that have no empirical validity (e.g. Bloor and Maynard, 2003). Of course, this one-factor restructuring process has caused a consistent change in the input-mix, in particular an increase in medical staff per bed.

Several factors can help explain observed variations in input-mix. For instance, a higher need of labour can be related to a higher severity of illness in acute care patients. This might be linked to the increase in patients turnover and the reduction in average length of stay (endogenously determined by clinicians), which characterised hospital industries in countries that adopted a Prospective Payment System. Or it might be a signal of the increase in the quality of services, both perceived by nurses or measured in terms of mortality rates (e.g. Aiken *et al.*, 2002a, 2002b).

In this paper, we aim at understanding whether this change in input-mix is economically rational, by focusing on the production technology of hospital services. We estimate different cost function models and derive factors elasticity of substitution, considering a sample of regional Italian hospitals. Like other countries, Italian hospital industry experienced a wide restructuring process. However, downsizing has been limited mostly to bed, while workforce reduction has been tackled only blocking turnover, causing a large increase in medical staff per bed. Besides uncovering potential inefficiencies which can limit the impact of hospital restructuring on health expenditure, the estimation of input elasticities of substitution is important *per se*, since very few studies have addressed this issue in the economic literature, and none of these has tested different functional forms for the hospital cost function.

The remainder of the paper is structured as follows: Section 2 surveys economic literature on input substitutability in the production of hospital services. Our empirical exercise is in Section 3, where we describe our sample, the functional forms and the estimation procedures, and the results. Section 4 concludes.

2. Input substitutability in the production of hospital services

While estimation of production and cost functions and efficiency analysis have received considerable attention in the literature on the hospital industry, economic studies working out also input substitutability in the production of hospital services are quite rare. A pioneering study is that by Bothwell and Cooley (1982), focusing on Health Maintenance Organizations in the U.S.. They distinguish four inputs (administrative services, hospital services, medical professional staff services, and capital expenses for maintaining a health centre), and find that administrative services are complements to all the other inputs, but that there is substitution between all other input pairs. In particular, Allen elasticity of substitution between medical staff and capital expenses (the input pair we are most interested in, to understand the observed change in input-mix), is estimated to be 0.638, which suggest small substitution possibilities. Jensen and Morrisey (1986), studying the U.S. short-term general acute care hospitals, confirm this result, estimating that elasticity of substitution of medical staff with beds ranges between 0.247 (for non-teaching hospitals) to 0.303 (for teaching ones), and elasticity of substitution between nurses and beds ranges between 0.189 and 0.305 (respectively, for the same type of hospitals). These estimates are even lower adjusting output for case-mix. The same difficulties in substituting between inputs is found also for medical staff and nurses, with estimated elasticities close to 0.35 for both types of hospitals. This last result is in contrast with Cowing and Holtmann (1983). Considering New York State hospitals and computing Allen elasticities, they find substantial substitutability between nurses and other types of workers in the short-run, but no estimates are provided for substitution between labour and capital.

More recent studies include e.g. Bilodeau *et al.* (2002) and Okunade (2003). Considering hospitals in Québec, the former study estimates an hospital cost function with five inputs (labour, drugs, food, supplies, and energy). While not reporting punctual estimates of Allen elasticities, the authors interpret substitutability of supplies and energy with labour as the hospitals' general ability to substitute capital for labour. A more complete analysis of input substitutability – considering Allen, Morishima, and shadow measures of elasticities - is provided by Okunade (2003) for Health Maintenance Organizations in the U.S.. The general conclusion – based on the preferred Morishima conceptual measure – is that HMOs production technology is characterised by significant but limited factor substitutions. More specifically, estimated Morishima elasticity of substitution between capital and medical staff given a change in the price of capital is 0.5124, while given a change in the wages of professional inputs is 0.667. These estimates imply that: a 10% increase in the price of capital, will cause the ratio of medical staff to capital to raise to about 5.12%; a 10% increase in the wages of medical staff, will lift the capital/professional inputs by about 6.7%.

Taken together, available evidence on factor substitutability in the production of hospital services seem to suggest that substitution is possible between capital and medical staff (both physicians and nurses), but is rather limited. In the next sections, we provide additional evidence on this point, by considering different functional forms and different concepts of elasticity of substitution.

3. Empirical analysis

3.1. The sample

As discussed in the previous sections, the aim of the paper is the study of the technological characteristics of hospital services supply, and the exploration of substitution possibilities among the different inputs involved in the productive process, especially between the number of beds and medical staff (both physicians and nurses). The data used in the econometric analysis have been obtained by the Piedmont Region (a highly industrialised area in the North-Western part of Italy), and are relative to the productive activity and the cost structure of all the hospitals operating in one of the 27 Local Health Units (LHU) active during the period 2000-2004. LHU are vertically integrated organisations funded by the Region, and responsible of a whole array of hospital and community services (e.g. France *et al.*, 2005). The sample includes two types of hospitals: those directly managed by the LHU (ASL from now on), and other major hospitals that have been hived off from the LHU and transformed into independent enterprises called *Aziende Ospedaliere* (AO from now on).

This unique dataset includes all the publicly owned firms involved in the provision of hospital services in the Piedmont Region. The time span covered by the data follows the (still unfinished) reform process of the National Health Service (NHS), so that our units are affected by the downsizing policy of the industry, which has been pursued during the 90s, and which is still regarded as one of the primary areas of intervention to control health expenditure. Planning at the regional level of health care provisions (as envisaged in the recent Piedmont Socio-Health Plan for the years 2006-2010) foresees a reorganisation of the regional hospital network, with the aim of increasing the quality and the effectiveness of services. This would imply a reduction of the required number of beds, due to the planned reduction of average length of stay, and a parallel increase in outpatient treatments, home care services, consultancy and day hospital treatments.

Information on the number of beds and on the quantity and complexity of the services provided (number of patients, average DRG weight, number of inpatient days) have been collected for each single hospital within a LHU and for each AO. The total number of beds, both ordinary and for day-hospital, are then computed for each ASL by aggregating the values of the different hospitals which belong to the same LHU. Unfortunately, disaggregated information on the costs and on the labour force are available only for AO, but are not available for each hospital within each LHU. This limitation can represent a problem for ASL units, since staff costs can be related also to community services, rather than hospital services. For such units, considering all costs as relative to the core hospital activity would be inappropriate, so that caution must be put in choosing which type of costs can be included in the study. To that purpose, the different types of costs have been selected and reorganised so as to obtain a measure of operating cost with a composition that can be comparable for ASL and AO structures. First, financial costs, extraordinary and atypical costs have been subtracted. The breakdown of the remaining costs is shown in table 1. As can be easily seen, the cost structure is rather different between ASLs and AOs. If labour costs (in particular medical staff) represent 50% of total operating costs for AO, in the case of ASL their share is only 35% in 2000-2002 and 25% in the last two years of observation. On the other hand, a large portion of costs of ASL structures is relative to outsourced services (more than 60% in 2004), a category that is not so important (less than 10% of costs) for AOs. The share of the costs of drugs is about 3% for ASLs and 6.5% (increasing up to 8.3% in 2004) for AOs. The relative importance of operating services given out by contract (such as food services, cleaning and laundry) is different among the two types of hospitals too: it is about 2% for ASLs, and 4-5% for AOs. Finally, depreciation and administrative expenditures weight less for the former than for the latter.

[TABLE 1 HERE]

The figures in table 1 clearly confirm that the two types of hospitals are not performing identical tasks. Since our aim is to identify an operating cost structure which is as much homogeneous as possible, we selected the costs items that are more closely related to the core activity of hospitals, that is the provision of health care services. We come out with a final aggregation named operating hospital costs (*OHC*, the dependent variable in our econometric model) which is the sum of the costs of the following inputs: labour, drugs, capital (the measure of which is proxied by the total number of beds)[1]. As shown in table 2, for what concerns the relative weight of the different cost categories, the two types of hospitals are now much more similar. Labour costs are about 86% of operating hospital costs, while the weights of drugs and depreciation are respectively 9.6% and 4.4%. *OHC* has an average value of 79 million euro for ASLs (average yearly growth rate of 3.6%) and 122 million euro for AOs (average yearly grow rate of 4.8%).

[TABLE 2 HERE]

3.2. Explanatory variables of the cost model

Exploiting the informative content of the database, we have obtained the following explanatory variables to be included in the estimation of the cost function: output, complexity of provided services (case-mix), input prices. The full sample is a panel of 29 productive units which are observed over a period of 5 years, for a total of 145

[1] Such a restricted cost aggregate corresponds on average to 32% of total operating costs for ASL (65% for AOs).

observations. As an index of production volume (Y) we opted for the total number of patients per year (ordinary and in day-hospital). In addition, in order to keep into account the severity of illnesses, a control variable of the average DRG weight (*DRGW*) has been added. Such a variable should reflect the differences in the production mix, i.e. the average degree of complexity of the services provided by the hospital structures[2].

As the labour input is concerned, a distinction has been made between medical staff (*MS*, including physicians and nurses) and administrative staff (*AS*); the average price for the two categories (P_{MS} and P_{AS}, respectively) has been obtained by dividing costs by the effective number of employees. As a proxy for the price of drugs (P_D) we used the ratio between the corresponding cost and the total number of in-patients days per year. Finally, the average price of the capital input (P_K) has been computed by dividing depreciation costs by the total number of beds. A time trend that should reflect the effect of technical progress has been added to the model (*TREND*). Its coefficient can be interpreted as a growth (or reduction) rate of costs due to an Hicks-neutral technological change.

[TABLE 3 HERE]

Table 3 reports the descriptive statistics of the variables used in the estimation. There is a high variability in the level of operating costs and in the output levels, which is partially due to the fact that our sample of hospitals is very heterogeneous in size, but can be also explained by the above mentioned differences among ASL and AO units[3].

3.3. Functional form and estimation procedure

The bulk of empirical works on hospital costs adopted the well-known Translog specification. Given the complexity of hospital services production process, we do not impose *a priori* restrictions on the functional form and estimate a more general model, namely the *Generalised Composite* cost function, which has been first introduced by Pulley and Braunstein (1992, PB_G). The PB_G model reads as follows:

[2] For example, a tonsillectomy is a typical operation with a low degree of complexity (DRG weight 0.27), while thyroid and cardiovascular operations have an average (DRG weight 1.04) and a high degree (DRG weight 2.40) of complexity, respectively.

[3] The sample consists of 7 small units (average number of beds ≤ 368), 15 units of an average size (368<average number of beds ≤ 621) and 7 big units (average number of beds > 621).

$$OHC^{(\phi)} = \left\{ \exp\left[\left(\begin{array}{l} \alpha_0 + \alpha_Y Y^{(\pi)} + \alpha_{DRGW} DRGW^{(\pi)} + \frac{1}{2}\alpha_{YY} Y^{(\pi)} Y^{(\pi)} + \frac{1}{2}\alpha_{DRGWDRGW} DRGW^{(\pi)} DRGW^{(\pi)} \\ + \alpha_{YDRGW} Y^{(\pi)} DRGW^{(\pi)} + \sum_r \delta_{Yr} Y^{(\pi)} \ln P_r + \sum_r \delta_{DRGWr} DRGW^{(\pi)} \ln P_r \end{array} \right)^{(\tau)} \right] \right. \quad (1)$$

$$\left. \cdot \exp\left[\sum_r \beta_r \ln P_r + \frac{1}{2}\sum_r \sum_l \beta_{rl} \ln P_r \ln P_l \right] \right\}^{(\phi)}$$

where the superscripts in parentheses π, ϕ and τ represent Box-Cox transformations (for example $Y^{(\pi)} = (Y^{\pi} - 1)/\pi$ for $\pi \neq 0$ and $Y^{(\pi)} \to \ln Y$ for $\pi \to 0$). *OHC* is the long-run production cost of hospital services, *Y* is the output, *DRGW* is the average degree of complexity of the service provided, and P_r indicates factor prices (with *r* = *MS*, *AS*, *D* and *K*). By applying the *Shephard's Lemma*, the associated input cost-share equations are:

$$S_r = \left[\begin{array}{l} \alpha_0 + \alpha_Y Y^{(\pi)} + \alpha_{DRGW} DRGW^{(\pi)} + \frac{1}{2}\alpha_{YY} Y^{(\pi)} Y^{(\pi)} + \frac{1}{2}\alpha_{DRGWDRGW} DRGW^{(\pi)} DRGW^{(\pi)} \\ + \alpha_{YDRGW} Y^{(\pi)} DRGW^{(\pi)} + \sum_r \delta_{Yr} Y^{(\pi)} \ln P_r + \sum_r \delta_{DRGWr} DRGW^{(\pi)} \ln P_r \end{array} \right]^{\tau - 1} \cdot \left(\delta_{Yr} Y^{(\pi)} + \delta_{DRGWr} DRGW^{(\pi)} \right) \quad (2)$$

$$+ \beta_r + \sum_l \beta_{rl} \ln P_l$$

The *Composite* specification (PB_C) is obtained by setting $\pi = 1$ and $\tau = 0$. In a similar vein, the well-known *Generalised Translog* (GT) and *Standard Translog* (ST) models, as well as the *Separable Quadratic* (SQ) functional form, can be estimated by imposing simple restrictions on the system (1)-(2)[4].

The PB cost functions originate from the combination of the log-quadratic input price structure of the ST and GT specifications with a quadratic structure for outputs.[5] The relatively few studies which employed the PB specifications referred to the banking, telecommunications, multi-utilities and electricity sectors. Overall, the composite model has consistently proved to be successful in obtaining more stable and reliable estimates than the alternative functional forms (see Fraquelli *et al.*, 2005, for more details). The PB_G model proposes to transform both sides of the cost function – from *OHC* = *C*(*Y*, *P*) to $OHC^{(\phi)} = [C(Y, P)]^{(\phi)}$ – in order to enlarge the set of plausible empirical

[4] More precisely, the GT model is obtained by setting $\phi = 0$ and $\tau = 1$, while the ST model requires the further restriction $\pi = 0$. The SQ model is obtained from the PB_C specification by adding the restrictions $\delta_{Yr} = 0$ and $\delta_{DRGWr} = 0$ for all *r*.

[5] The log-quadratic input price structure can be easily constrained to be linearly homogeneous. To be consistent with cost minimization, (1) must satisfy symmetry ($\beta_{rl} = \beta_{lr}$ for all couples *r*, *l*) as well as the following properties: *a*) non-negative fitted costs; *b*) non-negative fitted marginal costs with respect to outputs; *c*) homogeneity of degree one of the cost function in input prices ($\Sigma_r\beta_r = 1$ and $\Sigma_l\beta_{rl} = 0$ for all *r*, as well as $\Sigma_r\delta_{Yr} = 0$ and $\Sigma_r\delta_{DRGWr} = 0$); *d*) non-decreasing fitted costs in input prices; *e*) concavity of the cost function in input prices.

specifications. The optimal value of ϕ can be estimated resorting to standard non-linear least squares routines. The comparison between the general PB_G specification and the nested models (i.e. PB_C, SQ, GT, and ST) can be made by LR tests using the estimated log-likelihood values for the system (1)-(2).

All the specifications of the multi-product cost function are estimated jointly with their associated input cost-share equations. In our four-inputs case, to avoid the singularity of the covariance matrix of residuals, the equation for administrative staff (S_{AS}) was not included in each of the estimated systems. Prior to estimation, all variables were standardized on their respective sample means. Parameter estimates were obtained via a non-linear GLS estimation (NLSUR), which ensures estimated coefficients to be invariant with respect to the omitted share equation.

3.4. Results: the cost function

The results of the NLSUR estimations for the ST, GT, SQ, and PB models are presented in table 4. By looking at the summary statistics (last five rows), one can observe that computed R^2 for the cost function is rather high and identical across specifications, while R^2 associated to the factor-share equations are not dissimilar except from the SQ model, for which are much lower (in particular for capital input). The poor ability of the SQ specification to fit the observed factor-shares is not surprising, given that it assumes a strong separability between inputs and outputs. McElroy's (1977) R^2 can be used as a measure of the general goodness of fit for the NLSUR system. The results suggest that the fit is almost identical for the different functional forms, and between 83% and 86%. However, LR tests comparing PB_G and the restricted specifications (see table 5) always lead to favour the *Generalised Composite* model (at the 5% significance level) with respect to PB_C, SQ, GT, and ST alternative functional forms.

[TABLE 4 AND 5 HERE]

The first six rows of table 4 present the estimates of first-order coefficients for output, average DRG weight and factor prices, which are all highly significant and show the expected sign. Since the results are similar across specifications, we comment only on the estimated parameters for the PB_G model, which is to be preferred over the alternatives according to LR tests. In particular, we briefly discuss cost elasticities with respect to *Y*, *DRGW*, P_{MS}, P_D and P_K for the average hospital within the industry[6].

As for the output elasticity, the estimate is significantly lower than 1 (around 0.71, Standard Error 0.05), revealing the presence of remarkable scale economies (index of returns to scale about 1.41, SE 0.11) that could be better exploited, for instance, by enlarging the average size of hospitals managed by LHUs. On the *DRGW* side, it emerges a strong impact of the severity of illnesses on *OHC* (about 0.39, SE 0.13), which is consistent with previous empirical literature on the cost structure of hospital services. Finally, as for the estimates of input cost-shares for the average hospital - corresponding to cost elasticities with respect to the price of medical staff (0.66), drugs (0.10), and capital, proxied by beds (0.05) - they are very similar to their respective sample mean values (see S_{MS}, S_D and S_K in table 3), thus confirming the general goodness of fit of the PB_G cost function model.

3.5. Results: the elasticities of substitution

Given the main aim of this study, we computed Allen, Morishima, and Shadow elasticities of substitution for all the estimated models (Chambers, 1988). Ideally, one wants to measure for each couple of inputs the percentage change in the input ratio x_r/x_l due to a percentage change in the input price ratio P_l/P_r. *Allen* elasticities can be considered as *one price-one factor* elasticities, since they measure how the use of an input varies due to changes in the price of another input. They can be computed as $\sigma^A_{rl} = \varepsilon_{rl}/S_l$, where S_l is the l^{th} cost share and ε_{rl} is the derived input-demand elasticity of input x_r with respect to price P_l ($d\ln x_r/d\ln P_l$). While they have been criticized to a great extent in that they clearly are inappropriate measures of elasticities of substitution, Allen elasticities are still widely used in applied analysis. *Morishima* elasticities represent *two factor-one price elasticities* and are closer proxies to the desirable measure. They are computed as $\sigma^M_{rl} = \varepsilon_{rl} - \varepsilon_{ll}$ and measure how the *r*,*l* input ratio responds to a change in P_l. There is a useful link between Morishima and Allen elasticities:

$$\sigma^M_{rl} = (\sigma^A_{rl} - \sigma^A_{ll})S_l \qquad (3)$$

It is straightforward to notice than when inputs are Allen substitutes, they must be also Morishima substitutes (since σ^A_{ll} is always negative) but the converse does not hold, so

[6] The *average* LHU (the point of normalization) corresponds to a hypothetical LHU operating at an average level of production and degree of complexity, and facing average input prices.

that inputs can well be Allen complements and Morishima substitutes. Finally, *Shadow* elastiticities of substitution are a weighted average of Morishima elasticities and, as such, they are *two factor- two price* elasticities:

$$\sigma^{S}{}_{rl} = \frac{S_r}{S_r + S_l}\sigma^{M}{}_{rl} + \frac{S_l}{S_r + S_l}\sigma^{M}{}_{lr} \tag{4}$$

After some computation, Allen elasticities can be written as:

$$\sigma^{A}{}_{rl} = \frac{\frac{\partial S_r}{\partial P_l}P_l + S_r S_l}{S_r S_l} \tag{5}$$

Thus, in order to compute such elasticities for our different cost function models, it is important to compute the partial derivative $\partial S_r / \partial \ln P_l$.[7]

[TABLE 6 HERE]

As can be seen in table 6, except from Allen elasticities for the input pair drugs-capital, all inputs are substitutes, but the low estimated values suggest that substitution possibilities are in general very limited. As an example, in the PB_G specification, $\sigma^{M}{}_{MS,K}$ = 0.13, suggesting that a 10% increase in the price of capital implies only a 1.3% change in the *MS/K* ratio. The higher figures are recorded for the input pairs involving *AS,* suggesting that the other three inputs (medical staff, drugs and capital) are particularly responsive to increases in the price of administrative staff ($\sigma^{M}{}_{r,AS}$ are higher than $\sigma^{M}{}_{AS,r}$ for all *r*). The results are remarkably stable across specifications for almost all input pairs, and are broadly consistent with the ones previously appeared in the empirical literature. As discussed in Section 2, e.g. Jensen and Morrisey (1986) found substitution elasticities equal to 0.25 for the pair medical staff/beds and equal to 0.19 for the pair nurses/beds. Bilodeau *et al.* (2002) found that labour and drugs were substitutes with substitution elasticities lower than 1. As far as capital is concerned, the substitution possibilities with other inputs are lower, i.e. the values of $\sigma^{M}{}_{r,K}$ are lower than all the other $\sigma^{M}{}_{r,l}$ couples and the values of $\sigma^{M}{}_{K,r}$ are lower than all the other $\sigma^{M}{}_{l,r}$ couples.

[7] In the ST, GT and SQ specifications, such derivative *trivially corresponds to the coefficient* β_{rl}, while in the other two specifications (PB_G and PB_C) its computation is much more complicated, as it can be seen from a close inspection at equation (2).

Our results can be affected by two potential sources of distortions. On the one hand, since we estimate a cost function, we use the implicit assumption of cost minimization. By taking into account the inefficiency in the provision of health care services, how will the results on input substitutability be affected? Unfortunately, we are not able to estimate jointly a system of cost functions and related cost share equations in a stochastic frontier framework. Without the inclusion of the information on input cost shares the results coming from one equation frontier models, as far as input substitutability is concerned, are in generally very poor[8]. However, some past studies found that there are no substantial differences among technological estimates coming from average and frontier cost functions for hospitals (e.g. Eakin and Kniesner, 1988).

The second issue is that, even if one remains confined within a cost function analysis, our sample of firms is affected by a regulatory intervention aimed at hospital downsizing by means of the reduction in the number of beds. It turns out that our estimates of substitution elasticities are computed without taking into account the constrained environment in which hospitals are operating. Unfortunately, the constraints are imposed at the regional level (i.e., the target of reducing the number of beds must be reached for the whole Piedmont region), so that we cannot include the constraint in our specification of the cost function. However, we are confident that the presence of constraints is not seriously biasing the estimates for input elasticities. For example, Granderson and Lovell (1998) were able to introduce a firm-specific variable accounting for rate of return regulation in the gas industry and found that such regulation increased the estimates of elasticity of substitution of $\sigma^{M}_{K,r}$ pairs and reduced those of $\sigma^{M}_{r,K}$ pairs. Since in our case the constraint pushes toward the reduction of beds, it is reasonable to assume that in an unregulated framework one should observe higher values for $\sigma^{M}_{r,K}$ couples and lower values for $\sigma^{M}_{K,r}$ pairs. Looking at the figures in table 6, this means that the values of such pairs should get closer the ones to the others, thus making Morishima elasticities more symmetrical and leaving almost unchanged the values of Shadow elasticities.

[TABLE 7 HERE]

[8] Very recently, Kumbakhar and Tsionas (2005) showed how to estimate cost (technical and allocative) inefficiency by recurring to simulation-based Bayesian inference procedures in a well-specified Translog system including the cost frontier and related cost-share equations.

Table 7 presents the estimates of Shadow elasticities of input substitutability when the productive scale (Y) and the DRG weight (*DRGW*) of the average hospital of our sample are increased (and reduced) proportionally, focusing on the cost function model best fitting the data, i.e. the PB_G specification. Parameters λ_Y and λ_{DRGW} refer to the coefficients used to scale down ($\lambda_Y = 0.25, 0.5$; $\lambda_{DRGW} = 0.5$) and up ($\lambda_Y = 2, 3$; $\lambda_{DRGW} = 2$) the average values of the output (Y = 22,072 patients) and DRG weight ($DRGW$ = 1.12), respectively. First, notice that for almost all input pairs (with the notable exception of *MS-AS*), it emerges a certain degree of complementarity only by scaling down the average producer. Even if estimated elasticities are always insignificant at the usual confidence levels, this result suggests a higher rigidity in managing inputs for small-scale low-complexity generalist community hospitals, for instance because they need to respect exogenously given standards for staff and beds, which are binding given their volumes of output. Clearly enough, this rigidity helps explain the findings of unexploited scale economies for very small hospitals. Second, note that by scaling up the average hospital, both with respect to output volume and with respect to output complexity, substitution possibilities (and statistical significance) increase, but substitutability remain fairly small and significantly less than unity. These results hold even scaling up contemporaneously the average hospital in the two mentioned directions. For instance, concentrating on the most interesting of these input pairs for us (*MS-K*), by doubling the DRG weight and tripling output volume, elasticity of substitution rises from 0.14 to 0.30 only. Notice also that – for the *MS-K* pair – holding constant output volume at $\lambda_Y = 3$, it emerges a slight decrease of substitution possibilities when increasing complexity of output. This last result shows up also for almost all other couples of inputs, and suggests that – at high volumes – substitution between factors becomes increasingly difficult when also complexity of treated patients increase. This finding is consistent with a high rigidity of the production process starting from high levels of output. Results are more ambiguous when holding DRG weights fixed at $\lambda_{DRGW} = 2$: increasing the levels of output ease substitutability for the *MS-K*, *D-K*, and *K-AS* pairs, while substitutability worsens for the remaining couples of inputs. Finally, note that for the *MS-AS* input pair, estimated elasticities are invariant both to scaling with respect to output volume and to scaling with respect to output complexity, being consistently close to unity (and statistically significant). Besides showing that these two inputs are the more substitutable in the production process of hospitals, this result suggests that Administrative Staff is not probably a source of production economies. Overall, our findings confirms then previous estimates in the literature, validating the difficulties for hospitals in substituting between input pairs, in particular between medical staff and beds.

4. Concluding remarks

The hospital industry in many countries has undergone an unprecedented process of restructuring, aimed at reducing excess capacity and increasing the appropriateness of care. The process has been characterised by bed downsizing, while the management and planning of workforce has been conducted using fixed ratio relationships with no empirical validity, often causing a change in the input-mix used in the production of hospital services. In this paper we investigate the economic rationality of this change, providing new evidence on the factor substitutions characterising hospitals' technology. We consider a sample of regional producers located in Piedmont, a region in the North-Western part of Italy. As in other countries, also in this case the hospital industry has been (and still is) marked by a wide reduction in the number of beds, while no significant decrease has been observed for medical staff (including both physicians and nurses). Differently from other studies, we do not impose *a priori* restrictions on the functional form of the hospital cost function, and estimate a more general model, namely the *Generalised Composite*. The multi-product cost functions are estimated jointly with their associated input cost-share equations. For all the models, we derive Allen, Morishima and Shadow elasticities of substitution between input pairs, obtaining a fairly consistent picture across all specifications and elasticity concepts. In particular, confirming previous findings in the literature, our results suggest a very limited degree of substitutability between factors in the production of hospital services. This is particularly true for beds and medical staff. Given this evidence, one can notice that putting restrictions on bed capacity, without keeping into account the limited possibility of substitution of this factor with the other ones, might imply an inefficient use of resources and severely limit the possibility to control public health expenditure by restructuring the hospital industry.

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Table 1. Breakdown of total operating costs for ASL and AO units

	2000	2001	2002	2003	2004
			ASL		
Labour	36.1%	34.6%	33.4%	25.2%	25.0%
Medical Staff	28.0%	26.7%	25.8%	19.5%	19.2%
Materials and services	59.5%	62.2%	63.2%	72.1%	72.3%
Materials	9.0%	8.6%	10.7%	7.2%	7.2%
Drugs	2.7%	2.8%	3.1%	2.9%	3.1%
Operating Services Contracted Out	2.1%	2.2%	2.1%	1.7%	1.7%
Other Outsourced Services	46.6%	49.0%	48.4%	61.4%	61.8%
Administrative Costs	2.3%	1.0%	1.1%	0.9%	1.0%
Depreciation	1.4%	1.5%	1.6%	1.2%	1.1%
Other costs	0.7%	0.7%	0.7%	0.6%	0.6%
Total Operating Costs (10^3 €)	190,086	205,150	216,115	295,099	311,600
			AO		
Labour	59.4%	56.8%	56.4%	53.0%	52.8%
Medical Staff	45.3%	43.1%	43.3%	40.9%	40.3%
Materials and services	32.9%	36.1%	36.3%	40.1%	40.0%
Materials	19.3%	20.1%	20.5%	21.0%	23.2%
Drugs	6.5%	6.5%	6.9%	7.3%	8.3%
Operating Services Contracted Out	4.2%	5.2%	5.3%	5.0%	5.3%
Other Outsourced Services	6.5%	7.1%	6.6%	9.9%	7.4%
Administrative Costs	3.4%	2.1%	2.1%	2.2%	2.3%
Depreciation	2.8%	3.2%	3.4%	3.2%	3.1%
Other costs	1.4%	1.8%	1.8%	1.6%	1.8%
Total Operating Costs (10^3 €)	163,013	175,424	188,420	203,450	208,720

Table 2. Breakdown of operating hospital costs (OHC) for ASL and AO (average 2000-2004)

	ASL	AO
Labour	87.6%	84.7%
Medical Staff	67.4%	64.8%
Drugs	8.5%	10.6%
Depreciation	3.9%	4.7%
Operating hospital costs (10^3 €)	78,628	121,558

Table 3. Descriptive Statistics

	Mean	St. Dev.	Min	Median	Max
Operating Hospital Cost (10^3 €)					
Labor + Drugs + Capital cost	88,990	42,985	29,262	86,495	309,694
Production data					
Total number of patients (Y)	22,072	13,237	639	19,728	68,715
Average DRG weight ($DRGW$)	1.12	0.20	0.64	1.06	1.93
Total in-patients days	142,171	83,617	18,400	131,396	576,810
Total number of beds (K)	521	294	62	485	1,848
Input prices					
Medical Staff (€ per *MS* worker)	46,181	2,133	41,665	46,319	55,572
Administrative Staff (€ per *AS* worker)	26,544	1,841	22,053	26,310	31,170
Drugs (€ per in-patients day)	63	31	21	57	200
Capital (€ per bed)	8,051	3,715	3,016	7,170	22,859
Input cost-shares					
Medical Staff (S_{MS})	0.67	0.04	0.57	0.67	0.75
Administrative Staff (S_{AS})	0.20	0.03	0.14	0.20	0.30
Drugs (S_D)	0.09	0.03	0.03	0.09	0.20
Capital (S_K)	0.04	0.01	0.02	0.04	0.09

Table 4. NLSUR parameter estimates for the *Generalised Composite* (PB_G), *Composite* (PB_C), *Separable Quadratic* (SQ), *Generalised Translog* (GT) and *Standard Translog* (ST) models

REGRESSORS [a]	PB_G MODEL	PB_C MODEL	SQ MODEL	GT MODEL	ST MODEL
Constant	1.004***	0.995***	1.003***	-0.021	0.982***
Y	0.717***	0.638***	0.683***	0.622***	0.638***
DRGW	0.391***	0.479***	0.553***	0.367***	0.441***
$\ln P_{MS}$	0.658***	0.658***	0.661***	0.660***	0.658***
$\ln P_D$	0.100***	0.101***	0.095***	0.098***	0.100***
$\ln P_K$	0.046***	0.046***	0.043***	0.044***	0.046***
TREND	0.003	0.002	0.004	0.011	0.008
Y^2	-0.321	-0.113	-0.136**	-0.241	0.187*
$DRGW^2$	0.322	0.031	0.002	-0.141	-0.560
Y DRGW	0.526	0.613***	0.587***	0.272	0.214
$Y \ln P_{MS}$	-0.013	-0.011	0	-0.016*	-0.010
$Y \ln P_D$	0.019***	0.018***	0	0.021***	0.017***
$Y \ln P_K$	0.012**	0.011**	0	0.012**	0.010*
$DRGW \ln P_{MS}$	-0.025**	-0.024*	0	-0.035**	-0.034**
$DRGW \ln P_D$	0.037***	0.037***	0	0.048***	0.048***
$DRGW \ln P_K$	0.012	0.012	0	0.015	0.015
$\ln P_{Ms} P_{AS}$	0.010	0.007	-0.004	0.005	0.006
$\ln P_{Ms} P_D$	-0.046***	-0.046***	-0.043***	-0.044***	-0.044***
$\ln P_{Ms} P_K$	-0.029***	-0.028***	-0.023***	-0.027***	-0.027***
$\ln P_{As} P_D$	-0.010	-0.009	0.001	-0.004	-0.006
$\ln P_{As} P_K$	0.004	0.002	0.007	0.006	0.003
$\ln P_D P_K$	-0.012**	-0.012***	-0.017***	-0.014***	-0.013***
Box-Cox ϕ	-0.446*	-0.260	-0.260	0	0
Box-Cox π	1.219***	1	1	0.563***	0
Box-Cox τ	0.015	0	0	1	1
System log-likelihood	1406.581	1402.422	1315.912	1385.590	1377.424
System R^2 [b]	0.863	0.859	0.832	0.849	0.858
- Cost function R^2	0.921	0.918	0.916	0.918	0.916
- S_{MS} *equation* R^2	0.514	0.507	0.446	0.528	0.512
- S_D *equation* R^2	0.769	0.771	0.581	0.766	0.782
- S_K *equation* R^2	0.571	0.592	0.073	0.518	0.570

[a] The dependent variable is Operating Hospital Costs (*OHC*).
[b] The goodness-of-fit measure used for NLSUR systems is McElroy's (1977) R^2.
*** significant at 1 % level, ** significant at 5 % level, * significant at 10 % level (two-tailed test).

Table 5. Comparing *Generalised Composite* (PB_G) against restricted models by LR tests

Restricted model [a]	χ^2-statistic	P-value
PB_C MODEL ($\pi = 1$, $\tau = 0$)	8.318	0.016
SQ MODEL ($\pi = 1$, $\tau = 0$, $\delta_{Yr} = \delta_{DRGWr} = 0$ for all r)	181.338	0.000
GT MODEL ($\phi = 0$, $\tau = 1$)	41.983	0.000
ST MODEL ($\phi = 0$, $\pi = 0$, $\tau = 1$)	58.314	0.000

[a] The restrictions with respect to PB_G model are reported in parentheses.

Table 6. Estimates of input substitutability elasticities (at mean values of output, average DRG weight and input prices) for different cost function models [a]

Allen elasticities (1 factor, 1 price)	PB_G MODEL	PB_C MODEL	SQ MODEL	GT MODEL	ST MODEL
MS, *K*	0.02 (0.27)	0.09 (0.25)	0.17 (0.25)	0.06 (0.26)	0.10 (0.26)
MS, *D*	0.31 (0.13)	0.31 (0.12)	0.32 (0.12)	0.31 (0.12)	0.33 (0.13)
MS, *AS*	1.08 (0.30)	1.05 (0.30)	0.87 (1.23)	1.04 (0.28)	1.05 (0.30)
D, *K*	-1.62 (1.16)	-1.56 (1.01)	-3.30 (0.59)	-2.26 (0.85)	-1.94 (1.00)
D, *AS*	0.50 (0.57)	0.52 (0.54)	1.06 (0.38)	0.78 (0.47)	0.67 (0.53)
K, *AS*	1.39 (1.33)	1.22 (1.18)	1.85 (0.95)	1.66 (1.06)	1.38 (1.22)
Morishima elasticities (2 factors, 1 price)	PB_G MODEL	PB_C MODEL	SQ MODEL	GT MODEL	ST MODEL
MS, *K*	0.13 (0.13)	0.14 (0.11)	0.18 (0.10)	0.15 (0.11)	0.15 (0.12)
K, *MS*	0.26 (0.18)	0.30 (0.17)	0.34 (0.17)	0.28 (0.18)	0.31 (0.18)
MS, *D*	0.26 (0.05)	0.20 (0.05)	0.31 (0.06)	0.29 (0.06)	0.29 (0.06)
D, *MS*	0.45 (0.09)	0.44 (0.09)	0.44 (0.09)	0.45 (0.09)	0.46 (0.09)
MS, *AS*	1.04 (0.28)	1.01 (0.28)	1.00 (0.43)	1.03 (0.26)	1.02 (0.28)
AS, *MS*	0.95 (0.25)	0.93 (0.25)	0.81 (0.86)	0.92 (0.24)	0.93 (0.25)
D, *K*	0.05 (0.10)	0.07 (0.11)	0.03 (0.11)	0.05 (0.12)	0.05 (0.12)
K, *D*	0.06 (0.13)	0.08 (0.08)	-0.03 (0.07)	0.04 (0.08)	0.06 (0.08)
D, *AS*	0.92 (0.29)	0.90 (0.28)	1.04 (0.22)	0.99 (0.25)	0.95 (0.29)
AS, *D*	0.28 (0.09)	0.29 (0.09)	0.38 (0.08)	0.34 (0.09)	0.33 (0.09)
K, *AS*	1.10 (0.40)	1.04 (0.38)	1.20 (0.29)	1.16 (0.32)	1.09 (0.38)
AS, *K*	0.19 (0.18)	0.16 (0.15)	0.25 (0.13)	0.22 (0.14)	0.20 (0.17)
Shadow elasticities (2 factors, 2 prices)	PB_G MODEL	PB_C MODEL	SQ MODEL	GT MODEL	ST MODEL
MS, *K*	0.14 (0.12)	0.15 (0.10)	0.19 (0.10)	0.16 (0.10)	0.16 (0.12)
MS, *D*	0.28 (0.05)	0.29 (0.05)	0.33 (0.06)	0.31 (0.06)	0.31 (0.06)
MS, *AS*	1.02 (0.27)	0.99 (0.27)	0.95 (0.53)	1.01 (0.25)	1.00 (0.28)
D, *K*	0.06 (0.10)	0.07 (0.09)	0.01 (0.09)	0.05 (0.10)	0.06 (0.10)
D, *AS*	0.50 (0.14)	0.50 (0.14)	0.59 (0.11)	0.55 (0.13)	0.54 (0.15)
K, *AS*	0.36 (0.21)	0.36 (0.18)	0.41 (0.15)	0.39 (0.16)	0.37 (0.20)

[a] Estimated asymptotic standard errors in parentheses. *MS* = Medical Staff, *AS* = Administrative Staff, *D* = Drugs, *K* = Capital (number of beds).

Table 7. Estimates of Shadow elasticities of input substitutability by scaled values of the average output and DRG weight (PB_G model, average input prices) [a]

	Scaling procedure for the output (Y)	Scaling procedure for DRG weight ($DRGW$) λ_{DRGW} = 0.50		λ_{DRGW} = 1 (average value)		λ_{DRGW} = 2	
MS, *K*	λ_Y = 0.25	-1.20	(1.52)	-0.34	(0.51)	0.26	(0.32)
	λ_Y = 0.50	-0.42	(0.54)	-0.05	(0.22)	0.26	(0.23)
	λ_Y = 1 (average value)	0.00	(0.24)	0.14	(0.12)	0.26	(0.16)
	λ_Y = 2	0.23	(0.16)	**0.26**	**(0.11)**	**0.28**	**(0.16)**
	λ_Y = 3	**0.39**	**(0.19)**	**0.34**	**(0.15)**	0.30	(0.19)
MS, *D*	λ_Y = 0.25	-0.75	(0.53)	0.04	(0.14)	**0.48**	(0.16)
	λ_Y = 0.50	-0.19	(0.18)	**0.18**	(0.08)	**0.45**	(0.11)
	λ_Y = 1 (average value)	0.12	(0.08)	**0.28**	(0.05)	**0.42**	(0.08)
	λ_Y = 2	**0.30**	(0.07)	**0.36**	(0.05)	**0.40**	(0.09)
	λ_Y = 3	**0.41**	(0.12)	**0.41**	(0.09)	**0.41**	(0.12)
MS, *AS*	λ_Y = 0.25	**1.01**	(0.22)	**1.01**	(0.24)	**1.02**	(0.29)
	λ_Y = 0.50	**1.01**	(0.24)	**1.02**	(0.26)	**1.02**	(0.29)
	λ_Y = 1 (average value)	**1.02**	(0.25)	**1.02**	(0.27)	**1.02**	(0.29)
	λ_Y = 2	**1.02**	(0.28)	**1.02**	(0.28)	**1.02**	(0.29)
	λ_Y = 3	**1.03**	(0.31)	**1.02**	(0.30)	**1.02**	(0.29)
D, *K*	λ_Y = 0.25	-1.61	(1.33)	-0.45	(0.43)	0.22	(0.29)
	λ_Y = 0.50	-0.64	(0.43)	-0.14	(0.17)	0.22	(0.21)
	λ_Y = 1 (average value)	-0.14	(0.19)	0.06	(0.10)	0.21	(0.15)
	λ_Y = 2	0.14	(0.14)	**0.19**	(0.11)	0.22	(0.16)
	λ_Y = 3	**0.31**	(0.19)	**0.27**	(0.16)	0.24	(0.20)
D, *AS*	λ_Y = 0.25	-0.57	(0.58)	0.25	(0.20)	**0.68**	(0.18)
	λ_Y = 0.50	0.00	(0.25)	**0.39**	(0.15)	**0.65**	(0.15)
	λ_Y = 1 (average value)	**0.33**	(0.17)	**0.50**	(0.14)	**0.63**	(0.15)
	λ_Y = 2	**0.52**	(0.16)	**0.57**	(0.15)	**0.62**	(0.17)
	λ_Y = 3	**0.63**	(0.19)	**0.63**	(0.18)	**0.62**	(0.19)
K, *AS*	λ_Y = 0.25	-1.00	(1.58)	-0.13	(0.57)	0.50	(0.36)
	λ_Y = 0.50	-0.21	(0.60)	0.17	(0.29)	**0.50**	(0.27)
	λ_Y = 1 (average value)	0.21	(0.31)	**0.36**	(0.21)	**0.50**	(0.23)
	λ_Y = 2	**0.46**	(0.24)	**0.49**	(0.20)	**0.51**	(0.24)
	λ_Y = 3	**0.62**	(0.26)	**0.58**	(0.23)	**0.53**	(0.27)

[a] Estimated asymptotic standard errors in parentheses. Bold typeface values indicate 10% (or lower) significance level. *MS* = Medical Staff, *AS* = Administrative Staff, *D* = Drugs, *K* = Capital (number of beds).