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HOSPITAL INEFFICIENCY AND THE FORM OF MANAGERIAL CONTRACT

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Abstract

This paper explores potential realization of efficiency gains by hospitals that are managed on a day-to-day basis by external organizations under formal contracts. It draws from the incentives literature, which postulates that managers of firms where ownership is separated from control will employ an input mix that deviates from cost minimization. While this status applies to hospitals generally, we hypothesize that specialized managerial expertise, coupled with the threat of non-renewal, will improve efficiency in hospitals that opt for contract. Secondary data obtained from the AHA Annual Surveys (1991-1998) are applied to examine 'expense preference' parameters for all contract management adopters both pre- and post-adoption. These are contrasted with two control groups of hospitals drawn from the same years and using propensity score methods to control for selectivity bias. Results reveal allocative inefficiency among both adoption and control groups but a significantly lower change in the efficiency parameter pre- and post-adoption associated with a staffing preference. This suggests that changes in incentive contracts are one important strategy hospitals are using to cope with competitive pressures.

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Introduction

While there is considerable literature on the impact of managed care and networking in U.S. hospitals, other profound organizational changes affecting the industry have been largely overlooked. In particular, the last two decades have seen a dramatic growth in "contract-management" arrangements, to the point where nearly 20 percent of acute care hospitals now fall within this category (see Figure 1). Under this arrangement an independent firm is contracted to provide day-to-day management services in lieu of a salaried CEO. This organizational form may be viewed as occupying an intermediate position between system acquisition in which ownership is relinquished entirely and that of the freestanding hospital that maintains full administrative and operational control. These hospitals venture to attain the management, administrative, and operational benefits of the more tightly integrated system hospitals while retaining the advantages of organizational autonomy. Specialized managerial expertise, coupled with the threat of non-renewal, are expected to improve efficiency in hospitals that opt for contracts. Despite the importance of this phenomenon, there is a paucity of evidence on the efficiency gains from contract adoption.

In this study we attempt to fill the gap by tracking changes in performance of adopters and non-adopters over time. To derive an empirical test, we turn to the incentives literature, which postulates that managers of firms where ownership is separate from control will employ an input mix that deviates from cost minimization. While separation of ownership from control applies in both our cases, we hypothesize that allocation of inputs to the production process will be more efficient under contracted managers. Our test is a generalization of the method found in Mester (1989), whereby an 'expense preference' parameter associated with one of the firm's inputs enters its cost function in a highly non-linear fashion. Unlike Mester, we allow this parameter to vary across inputs, after deriving an appropriate functional form. We derive a system of non-linear equations that consists of the cost function and the input demand functions for capital and labor, and estimate them jointly by method of non-linear seemingly unrelated regressions. Our model is more robust than an earlier generalization due to Dor et al. (1997) since we further impose constraints on the inefficiency parameters that are consistent with linear homogeneity. It offers an alternative to panel data estimations of hospital cost functions that identify managerial disparities through hospital effects which confound them with other factors such as quality of care and unmeasured case severity (Carey, 1997). Moreover, our quasi-experimental sample design allows us to explicitly test for the stability of inefficiency parameters over time.

We hypothesize that hospital behavior under management contract will reveal a more efficient allocation of inputs to the hospital production process. Contract management has continued to grow, and so have external constraints and accountability facing the hospital industry. Better understanding of the behavior of this form of structural reorganization is an important research direction in the ongoing study of organizational change in the health care sector.

Background

Institutional contract management involves the daily running of the hospital by an external organization under formal contract. The managing organization reports directly to the board of trustees or owners of the hospital, which retains ownership of assets as well as legal rights and responsibilities. The management firm supplies an administrator and often a management team as well as other support services that may provide marketing, recruitment, strategic planning, legal, and/or financial expertise. Contract management in the hospital industry is dominated by a handful of large firms, some of which manage dozens of hospitals at any given time (Scott, 1994).

Institutional contract management is not limited to the hospital industry. In the realm of education, recent interest has appeared in the management of public schools by for-profits and entrepreneurship is growing among education companies. In the 1997-1998 school year, approximately 60 publicly funded elementary and secondary schools were run by for-profit firms.

Prior literature has been anecdotal or descriptive, involving small samples only. Rundall and Lambert (1984) and Alexander and Rundall (1985) looked at matched samples before and after adoption, and reported lower proportions of expenses due to payroll in public hospitals under contract management. Wheeler and Zuckerman (1984) studied pre- and post-adoption samples for 21 contract-managed hospitals. They found a reduction in number of employees per occupied bed in the post-test sample, as well as reduction in the variability of this measure, suggesting enhanced control over staffing patterns as well as improved organizational stability. Together these studies at least suggest that labor should be treated as a 'preferred' input by less efficient managers. Other descriptive studies suggested that efficiency gains from contract adoption might be more general. For instance Dor (1994) found lower expenses per admission, per bed, and per FTE following contract adoption in the late 1980's. One reason cited was the importance of efficiency from a financial standpoint for the purpose of gaining access to managed care contracts.

However these latter studies lacked a comparison group again making it difficult to rule out the possibility that some historical event other than adoption itself was responsible for the change. A more comprehensive work that accounted for paired comparisons both pre- and post-adoption is that of Kralewski, Dowd, Pitt, and Biggs (1984). This study showed no difference in changes in staffing ratios or payroll expenses between the two groups. It did show improved financial health related to markups of services by contract managers but no evidence of efficiency improvement following from decreases in expenses. Thus to date, the evidence remains inconclusive.

To derive a more complete test we build from the incentives literature, which postulates that when ownership of the firm is removed from control, managers may not be driven by profit maximization. Rather they may be motivated to maximize utility, and consequently have a positive preference for expenditures on items such as more staff and higher managerial wages. While separation of ownership from control applies to hospitals in general, we hypothesize that allocation of inputs to the production process will be more efficient under contracted management arrangements rather than under conventional salaried administrators.

The issue of separation of management and control of the firm has been examined more widely in the empirical literature, where results have been mixed. Edwards (1977) developed an early 'intercept' test for expense preference tied to specific inputs. He found that salaried managers opted for higher expenditures on labor compared with manager-owners. Hannan and Mavinga (1980) applied this test to other institutional settings in the banking industry, and found similar results. Awh and Primeaux (1985) developed a model applicable to the electric utility industry; their results provided evidence contrary to expense preference. Blair and Placone (1988) and Mester (1989) tested the hypothesis in the savings and loan industry, and found no evidence of expense preference behavior in mutuals, compared with lending institutions with shareholders who are presumed to exercise tighter control of management. However, Mester's study represented a major methodological shift from the earlier body of work, as she was critical of the notion that preferences could be revealed from an intercept term in the firm's input demand function. She suggested that preferences would permeate the production process as a whole. Thus, she derived a more general test in which an input-specific inefficiency parameter appears as a highly nonlinear argument in the firm's cost function. As with Edward's original work, she associated expense preference behavior with labor demand. Dor, Duffy, and Wong (1997) provide a further generalization of Mester's model, whereby the firms' cost function is estimated jointly with the demand function for the input hypothesized to be preferred. While their model did not yet develop the full set of constraints appropriate for the system of non-linear equations, it demonstrated that results could change quite dramatically depending upon the particular input being studied.

In this study, we rectify the constraints problem, and present more robust estimation. We again use the setting of contract management, but for a more recent and longer time-series than previously considered. We further expand earlier work by incorporating all contract-managed hospitals and contrasting them with a comparison group of hospitals that never adopted, but have the same longitudinal distribution. Moreover, the current sample design allows us to explicitly test for the stability of the inefficiency parameter over time. Finally, we recognize that hospitals may not randomly enter into contract management and control for selection effects using propensity score methods in drawing the control group.

Methods

In this section we detail the development of our empirical test of input-specific inefficiency. Let C* = cost under cost-minimization, and S_i^* = optimal share of input *i* in total cost. Then

$$C^* = \sum_{i=1}^{J} W_i^* X_i^*$$

$$S_i^* = \frac{W_i^* X_i^*}{C^*}$$

Where W_i^* is the market determined input price for the *i*'th input, and X_i^* is the level of input *i* if cost-minimization is satisfied. For convenience we will assume that there is only one preferred input, which managers may choose to allocate inefficiently. Let X_i^* denote the preferred input, using the operator $X_j = (1+z_j)X_j^*$ to denote deviations from the optimal level[1]; substituting and rearranging yields:

$$C = C^*(1+z_j.S_j^*) \qquad [1]$$

$$S_j = S_j^* \cdot \frac{1+z_j}{(1+z_j S_j^*)} \qquad [2]$$

Where C and S_j are the observed costs and input share, and z_j is an inefficiency parameter to be estimated. A number of observations can be made. First, from [1] and [2] it is immediately obvious that the following condition applies

$$\textit{If } z_j = 0, \textit{ then } S_j = S_j^*, \textit{ and } C = C^*$$

Evaluating the limits of equation [2] we get

$$\lim_{z_j \to \infty} S_j = 1$$

$$\lim_{z_k \to -1} S_k = 0$$

The first condition states that if $z_j=0$, i.e. no expense preference occurs, then the observed cost and the observed input shares are equal to their respective optimal values. The second condition states that if expense preference is 'absolute', i.e., approaches infinity, then the preferred input becomes the only input in the cost function. Further note that as the share of the preferred input increases, the share of the alternative input *k* necessarily declines. Evaluating the limits for the relevant

[1] Note that this is simply the parameterization of the more general results $X_j \geq X_j^*$. The profit maximizing firm will set inputs such that $P \cdot MP_{j,}$. For the utility maximizer such that $U=U(\pi, X_j)$ where π is profit, wage exceed marginal product value of the 'preferred' input.

preference parameter z_k implies that it can take on small negative values, up to the cut off points $z_k > -1$. We will refer to preference parameters at that range as 'non-preference' values[2]. While C^*, S_j^* and consequently the z's are unobservable to the researcher, it is possible to parameterize these in terms of existing variables using well-known functional forms[3]. A general form is given by the translog cost function:

$$\ln C = \alpha_0 + \alpha_1 \ln Y + \alpha_2 (\ln Y)^2 + \sum_{i=1}^{n} \beta_i \ln w_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \ln w_i \ln w_j + \sum_i \gamma_i \ln w_i \ln Y \quad [3]$$

where Y = output and w_i is the factor price of the i'th input. By Shephard's lemma, the share of input i in costs is given by its elasticity. Hence

$$S_j = \frac{\partial \ln(\mathrm{C})}{\partial \ln w_j} = \beta_j + \beta_{jj} \ln w_j + \sum_{i \neq j}^{n} \beta_{ij} \ln w_i + \gamma_j \ln Y \quad [4]$$

Equations [3] and [4] can be estimated jointly by method of seemingly unrelated regression (e.g., Berndt and Christensen, 1973). Note that with multiple inputs, equation [4] can itself be regarded as a vector of equations. In any event, one input share equation is omitted from the estimation since $\sum S_i = C$.

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[2] It can easily be shown that the same boundary condition, $-1 \leq z < \infty$, applies to multiple inputs (n>2), for any z_i , provided that one of the preferred inputs approaches infinity faster than other inputs. A special case arises when all z_i move at the same rate. In this case, for any input we have $S_j = S_j^*$, but $C > C^*$. Since all relative shares remain the same, this can be interpreted to mean that allocative inefficiency may not occur. At the same time, since all inputs are equally overused, technical inefficiency occurs, with total costs exceeding the least cost optimum.

[3] This is akin to multiple cause-multiple indicator models. See Van Vliet and Van Praag (1987).

Substituting these into equation [1] and equation [2]

[3']

$$\ln C = \alpha_0 + \alpha_1 \ln Y + \alpha_2 (\ln Y)^2 + \sum_{i=1}^{n} \beta_i \ln W_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \ln W_i \ln W_j + \sum_{i=1}^{n} \gamma_i \ln W_i \ln Y$$

$$+ \ln \left[1 + \sum_{j=1}^{n} z_j \left(\beta_j + 2\beta_{jj} \ln W_j + \sum_{i \neq j}^{n} \beta_{ij} \ln W_i + \gamma_j \ln Y \right) \right]$$

$$S_j = \frac{(1+z_j)\left(\beta_j + 2\beta_{jj} \ln W_j + \sum_{i \neq j}^{n} \beta_{ij} \ln W_i + \gamma_j \ln Y \right)}{1 + \sum_{j=1}^{n} z_j \left(\beta_j + 2\beta_{jj} \ln W_j + \sum_{i \neq j}^{n} \beta_{ij} \ln W_j + \gamma_j \ln Y \right)} \qquad [4']$$

Equations [3'] and [4'] present a constrained optimization problem. The translog cost function and corresponding input share are nested within this problem. Thus the usual constraints of linear homogeneity and homotheticity apply (see Table 2). Combining the limiting cases from [1] and [2] we have the further constraint that $z > -1$.

An important observation is that equation [3'] is virtually identical to the model presented in Mester [1989]. However, Mester did not consider the relationship between the cost function and input shares equations in this highly non-linear setting. From an examination of [3'] and [4'] it is immediately obvious that the z's are determined simultaneously by these equations. Estimates can be obtained by the method of iterative seemingly unrelated non-linear regressions. Gallant (1987) has shown that this method is equivalent to maximum likelihood estimation. Note that in the 2 input case [3'] and [4'] are greatly simplified when one z_j is estimated each time, as would necessarily be the case when only two inputs are considered. This is summarized in Table 1.

Data and Sample Design

The majority of data for this study come from the American Hospital Association (AHA) Annual Survey Database for the years 1991-1998. The dependent variable is total hospital expenditures. The AHA data isolates labor costs but not capital costs[4]. This allows us to incorporate two inputs into the models: labor and non-labor[5]. While input prices are not available directly from the data, we constructed measures of these by dividing labor costs by full-time equivalent employees and non-labor costs by the number of facility beds. Output is measured as adjusted inpatient days. The patient variable is the number of inpatient admissions with outpatient services transformed into inpatient unit equivalents using a known formula and loaded onto inpatient variables[6]. We did this in order to fully account for the hospitals' output, while keeping the specification as parsimonious as possible to ensure model convergence. In order to control for product heterogeneity, we entered the Medicare diagnosis related group (DRG) case-mix index obtained from the Centers for Medicare and Medicaid Services (formerly Health Care Financing Administration) public use files. Average length of stay is also entered to control for variation in output not captured by the adjusted patient days and case mix variables. Finally, we include three binary variables that have been shown to explain cost variation among hospitals and/or by which adopters appear to differ from non-adopters: rural location, government control, and nonprofit status. Descriptive statistics are listed in Table 2. All financial variables are converted to 1998 dollars.

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[4] Labor costs are defined as the sum of total facility payroll expenses and total facility employee benefits. Unfortunately the survey does not provide a breakdown of expenses by type of labor, so that this category covers registered nurses, licensed practical nurses, and administrative staff.

[5] Capital expenditures are a small part of the residual input. Depreciation plus interest accounted for eight percent of total expenses in 1993, the latest year for which the AHA data reported on capital expenditures. Labor costs made up 54 percent of the total for 1993.

[6] The AHA adjusted discharges variable is the product of discharges and the ratio of total revenue to inpatient revenue.

Our methods involve examining expense preference behavior for contract managed hospitals and comparing them to those with conventional management structures. To that effect, we created four hospital samples. Two contain contract-managed hospitals. The first of these includes data on hospitals for the year falling two years before they first reported being contract-managed (pre-contract sample). The second contains information for the year coming two years following first reporting, allowing the hypothesized behavior of contract-adopting hospitals a period of adjustment (post-contract sample). Because results of models estimated on these samples are conditional on hospitals that eventually adopted contract management, we also created two control groups of hospitals that never reported being contract-managed, corresponding to the same time periods (pre-control and post-control samples).

One thousand three hundred and sixty-five hospitals reported being contract-managed during one or more of the years 1991-1998. Since the sample design calls for information on pre-contract hospitals for two years prior to the adoption year, that sample includes those 278 hospitals that adopted contract management during the period 1993-1998, for which a full set of data was available. Hence the pre-contract sample spans the years 1991-1996. The post-contract sample contains data for the 215 hospitals whose apparent adoption year was between 1992 and 1996 and for which all data elements were non-missing. The post-contract sample represents the years 1994-1998, or two years following adoption. One hundred and fifty-eight hospitals appear in both samples. Because specialty hospitals produce different services and have distinct technologies, the four samples were limited to nonfederal hospitals classified as general medical and surgical.

For the pre-control and post-control groups, we chose random samples without replacement of non-adopters numbering three times the numbers of adopters. Because the sampling strategy involves drawing all hospitals that adopted contract management, and because those hospitals differ in profile from internally managed hospitals, the drawing of a simple random sample was likely to introduce selectivity bias. More specifically, as seen below, a relatively high proportion of contract-managed hospitals are rural. These hospitals are also more likely to be government-affiliated hospitals, less likely to be not-for-profit, are lower in case-mix index, and have longer lengths of stay.

In order to account for these various differences, we used propensity scores to reduce selectivity bias in the comparisons. Propensity score methods are commonly used in observational studies in which the experimental unit of interest lacks the benefits of randomization. Consequently, the ‘treatment’ group and the randomized control group may differ systematically across a number of covariates (Rosenbaum and Rubin 1984; D’Agostino 1998; Imbens 2000). The propensity score, defined here as the conditional probability of adopting contract management, can be used to balance the distribution of covariates between the contract and control groups. Because the propensity score is a scalar function of the covariates, it overcomes a significant drawback to standard techniques of adjustment through stratification, which can use only a limited number of covariates in the adjustment. By summarizing information into a scalar, stratification on it alone can match the distribution across many covariates. (Refer to Appendix for further discussion.)

Results

The full set of parameter values for the model including the labor input equation is reported in Table 3. The estimation procedure incorporated two empirical themes. First, we attempted to look at the effect of contract adoption on hospital efficiency. To this end, we obtain separate estimates of the input-specific preference parameter in the pre-contract and post-contract period, for hospitals that ultimately ended up adopting contracts. Second, we aim to verify that the findings were not related to technological changes that occurred over time, independently of contract adoption. We therefore repeat the estimation for a matched control group with an identical longitudinal distribution, and compare the inefficiency parameter in the simulated 'pre' and 'post' periods. In addition, we implemented the same estimation strategy for the non-labor input. Parameter estimates were similar, with the important exception of the preference parameters, which by construction must take on smaller values. To avoid redundancy, we do not present the full set of results here. Rather we summarize the results for all the z_{tj} parameters in Table 4. All of the regression models were estimated by method of non-linear iteratively seemingly unrelated regressions (non-linear ITSUR). Start values were obtained from linear ITSUR models in which the parameter z_{tj} is set to zero. All models converged within 3-4 iterations.

It is immediately apparent from an examination of Table 3 that labor is a preferred input, with all $z_{tj} > 0$. For contract adopters the values of this parameter fell from 0.98 in the pre-contract period to 0.71 in the post-contract period, indicating a reduction in labor-specific inefficiency due to adoption of the contract. The results become even more pronounced in comparison with the matched control group. For this group, z rises from 0.54 in the pre-period to 1.13 in the post-period. Thus in the absence of contract adoption the degree of inefficiency would have actually increased over the same time span[7].

Table 4 summarizes these results as well as results for the inefficiency parameters of the residual input. The latter set of estimates were always negative, but within the permissible range.

[7] The notion that excess staffing occurs in hospitals has also appeared in related literature (e.g. Mobley and Magnussen, 2002). Recently the trade literature has began to focus on the problem of nurse 'shortage" in hospitals, suggesting that hospitals tend to underdeploy nurses (Green and Nordhause-Bike, 1997) However this concern is limited to certain high-end specialties of registered nurses, and does not seem to apply to licensed practical nurses, nurse aids and the like. Moreover, even for registered nurses as a whole the national trend been that of increased employment in hospitals during most of the period observed in our data (Buerhaus and Staiger, 1999).

The table further demonstrates that when there is a decrease (increase) in the value of inefficiency for the ‘preferred’ input, there is a concomitant decrease (increase) in the value of ‘non-preference’ for the residual input. The interpretation of these results should be treated with caution. These results pertain to a summation of non-labor inputs categories that could not be identified in the data, due to changes in the AHA survey in the 1990’s. It is possible that for some specific activities subsumed into this category positive values would have been found for corresponding inefficiency parameters. For instance, capital investments, known anecdotally to comprise about 7-8 percent of total spending in U.S. hospitals, is a likely ‘preferred’ input. The significance Table 4 is in demonstrating how our estimation procedure conforms to the boundary conditions defined in the previous section.

We next investigate the significance of the difference in z between contract managed hospitals pre- and post-adoption controlling for extraneous historical factors. This task is complicated by the large number of hospitals that are common to both the pre-contract and post-contract samples. While the contract-managed and control groups are entirely distinct, there are 158 hospitals that appear in both the pre-contract and post-contract samples and 299 hospitals in both the pre-control and post-control samples. We are unable to apply the two-sample t-test for the difference in parameters across regressions due to unknown covariances among the pre- and post-parameter estimates.

As an alternative strategy, we solve [4’] for z_j (in the case of one preferred input) yielding

$$z_{jh} = (S^*_{jh} - S_{jh}) / S^*_{jh}(S_{jh} - 1)$$

where

$$S^*_{jh} = \beta_j + 2\beta_{jj} \ln W_{jh} + \beta_{jk} \ln W_{kh} + \gamma_j \ln Y_h \qquad [5]$$

Where h indexes the hospital. Calculation of [5] yields the distribution of hospital specific values of z. Our interest lies in the equation for which labor is the preferred input. Table 5 describes z for this model. To facilitate comparisons across regressions, the hospitals common to both the pre-contract and post-contract samples and to the pre-control and post-control samples are separated, producing 158 and 299 matched pairs of hospital specific zs, respectively.

We wish to evaluate the significance of a 'management' effect, or whether z differs for contract-managed hospitals between pre- and post-adoption years, after netting out a trend effect. For the hospitals represented in panel A, the first step in this evaluation is calculation of the changes in the zs for each set of matched pairs. The result of the paired t-test performed on the change in z before and after contract adoption, appears in column (1) of Table 6. The average difference, -0.28, is significant. Since z represents inefficiency, this suggests an efficiency gain for these hospitals. Next, the second column shows that applying the paired t test to the difference in z for the control groups results in a highly significant average difference of 0.58, indicative of a decrease in efficiency. The third column compares the difference in the changes in the means by application of the two sample t test to the two sets of changes in z. Under the assumption of unequal variances, the difference of –0.96 is, not surprisingly, highly significant. This final result provides strong evidence of the existence of a 'management' effect in which contract adoption results in improved efficiency after controlling for other factors affecting hospital efficiency over time.

In the case of the hospitals contained in the independent samples of Panel B, the 'management' effect can be expressed as

$$\Delta = [(\mu_{11} - \mu_{01}) - (\mu_{10} - \mu_{00})] \qquad [6]$$

or the difference in z between pre- and post-adoption minus trend. In order to test the significance of this effect, a two way analysis of variance is performed on binary variables M (1 = contract management; 0 = control), P (1 = post period; 0 = pre-period) and interaction $M * P$ according to the following regression:

$$z = \beta_0 + \beta_1 M + \beta_2 P + \beta_3 M * P + \varepsilon . \qquad [7]$$

The management effect, which is equivalent to $\mu_{11} - \mu_{01} - \mu_{10} + \mu_{00}$, can then be expressed as

$$(\beta_0 + \beta_1 + \beta_2 + \beta_3) - (\beta_0 + \beta_1) - (\beta_0 + \beta_2) + \beta_0 = \beta_3 . \qquad [8]$$

This demonstrates that the significance of the management effect turns on β_3, or the coefficient on interaction $M * P$. Table 7 displays the regression results of equation [7]. The highly significant negative term on the interaction effect points once again to the finding that netting out the trend effect, the decrease in inefficiency for contract adopting hospitals is highly significant. While a less powerful assessment than the case of matched pairs, analysis of the independent samples still offers strong support for the hypothesis of improved efficiency associated with contract management adoption.

Discussion

In this study, we develop a general estimator of input-specific inefficiency that is well suited for settings in which there are varying degrees of separation of ownership and control. Unlike previous studies, which focused on either the cost function of the firm or on its input demand functions, our approach is to estimate the two types of functions jointly. This imposes added structure, allowing the highly non-linear estimator to converge quickly and efficiently. Moreover, our analysis demonstrates that the degree of inefficiency depends critically on the particular input suspected of being ‘preferred’. In our particular setting of adoption of contract management arrangements, there is an added longitudinal dimension to the problem, since contract adoptions occur in different years. To address this we create a matched control group of non-adopters with the same longitudinal distribution.

Turning to our results for U.S. hospitals, we find that labor is consistently a preferred input. However, preference for labor declines after the adoption of a contract declines significantly. In comparison, there is a marked increase in labor-specific inefficiency for non-adopters during the same ‘simulated’ period. At the very least it can be stated that contract-managed hospitals did not experience the increase in labor-specific inefficiency that occurred elsewhere in the industry. Combined, these results suggest that contract-management firms are indeed able to introduce efficiencies over conventional, salaried managers. These results have implications for other service industries as well, particularly education, where contract management arrangements are becoming more prevalent. It would appear that third-party contracts are a way by which boards of predominantly non-profit institutions can impose greater market discipline on the institutions they govern.

As for the particular setting of hospitals, our results also pose new questions regarding the process by which contract-managers capture efficiency gains. In particular, with the data available to us we were unable to separate out specific activities such as capital investment from the residual ‘non-labor’ expense category. To gain a better understanding of this process, it will be useful to focus on more narrowly defined services that are at managerial discretion albeit at a more descriptive level. We leave this to future research. Nevertheless, the example of contract-management provided a useful application for our model, whereby a robust inefficiency parameter for an input can be identified from a system of expenditure equations.

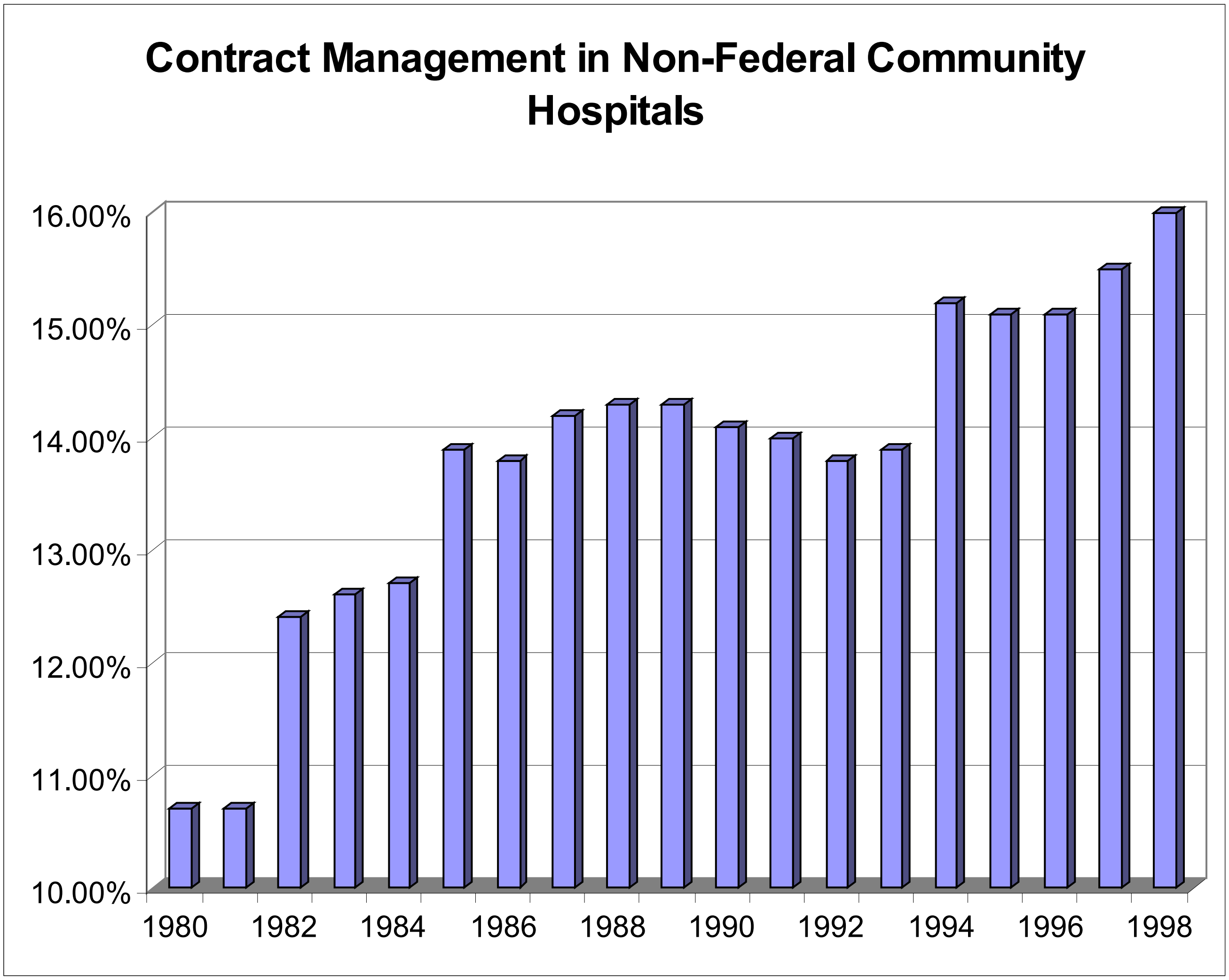
Contract Management in Non-Federal Community Hospitals
16.00%
15.00%
14.00%
13.00%
12.00%
11.00%
10.00%
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998

Figure 1

Table 1. Parameter Restrictions in Empirical Model

<u>Coefficients</u>	Equation 1: ln(COST)	Equation 2: ($Share_1$)	Restrictions:
	Independent Variables (moments)		(cross-equation restrictions follow immediately from the table)
α_0	Constant	--	
α_1	lnY	--	
α_2	lnY * lnY	--	
β_1	$\ln W_1$	constant	
β_2	$\ln W_2$	--	$\beta_1+\beta_2 = 1$
β_{11}	$\ln W_1 * \ln W_1$	$2*\ln W_1$	
β_{22}	$\ln W_2 * \ln W_2$	$\ln W_2$	
β_{12}	$\ln W_1 * \ln W_2$	--	$\beta_{11}+\beta_{22}+\beta_{12} = 0$
γ_1	$\ln Y * \ln W_1$	lnY	
γ_2	$\ln Y * \ln W_2$	--	$\gamma_1+\gamma_2 = 0$
Hedonic Descriptors			
δ_1	CMI	--	
δ_2	LOS	--	
δ_3	RURAL	--	
δ_4	GOV	--	
δ_5	NPROF	--	
	z	*z*	$-1 \leq z \leq +\infty$

Table 2. Descriptive Statistics: Means and Standard Deviations (in parentheses) Variables in Regression Models

Variable	Definition	Contract Pre	Contract Post	Matched Control Pre	Matched Control Post
Dependent					
ln(cost)	ln(total hospital cost)	16.24 (1.200)	16.19 (1.066)	16.41 (1.251)	16.43 (1.100)
$share_1$	Labor expenses/total cost	0.55 (0.074)	0.54 (0.080)	0.55 (0.066)	0.55 (0.066)
$share_2$	Non-labor expenses/total cost	0.45 (0.074)	0.46 (0.080)	0.45 (0.066)	0.45 (0.066)
Independent					
LnY	ln(adjusted patient days)	9.93 (1.077)	9.89 (1.027)	9.89 (1.115)	9.92 (0.994)
lnW_1	ln(labor expenses per FTE)	10.42 (0.288)	10.40 (0.289)	10.44 (0.265)	10.45 (0.247)
lnW_2	ln(capital expenses per bed)	11.15 (0.764)	11.26 (0.697)	11.32 (0.692)	11.41 (0.668)
CMI	Medicare case-mix index	1.12 (0.181)	1.13 (0.161)	1.15 (0.192)	1.15 (0.175)
LOS	Average length of stay (days)	14.69 (19.969)	14.54 (21.570)	10.92 (19.342)	11.94 (24.189)
RURAL	Binary indicator of rural status (= 1 if rural; otherwise = 0)	0.72 (0.450)	0.77 (0.424)	0.72 (0.448)	0.76 (0.43)
GOV	Binary indicator of local government ownership of hospital (= 1 if yes; otherwise = 0)	0.46 (0.499)	0.44 (0.497)	0.45 (0.498)	0.42 (0.494)
NPROF	Binary indicator of nonprofit status (= 1 if yes; otherwise = 0)	0.47 (0.500)	0.50 (0.501)	0.50 (0.500)	0.52 (0.500)

Table 3. ln(cost) , Share 1: Nonlinear ITSUR Regressions [a]
(standard errors in parentheses)

Coefficient[b]	Variable[b]	Contract Adoptors		Control Group	
		Pre	Post	Pre	Post
α_0	Constant	5.205***	1.987	3.897***	2.537***
		(0.9351)	(1.4951)	(0.4362)	(0.9197)
α_1	lnY	-0.897***	-0.253	-0.598***	-0.3934**
		(0.1957)	(0.3107)	(0.089)	(0.1841)
α_2	lnY * lnY	0.081***	0.046***	0.067***	0.052***
		(0.0101)	(0.016)	(0.0047)	(0.0093)
β_1	$\ln W_1$	0.040	0.273**	0.059	0.092
		(0.1082)	(0.1385)	(0.0698)	(0.0694)
β_2	$\ln W_2$	0.960***	0.727***	0.941***	0.908***
		(0.1082)	(0.1385)	(0.0698)	(0.0694)
β_{11}	$\ln W_1 * \ln W_1$	0.053***	0.049***	0.049***	0.041***
		(0.0058)	(0.007)	(0.0039)	(0.0037)
β_{22}	$\ln W_2 * \ln W_2$	0.019***	0.028***	0.014***	0.011***
		(0.0055)	(0.0068)	(0.0034)	(0.0035)
β_{12}	$\ln W_1 * \ln W_2$	-0.072***	-0.077***	-0.063***	-0.052***
		(0.0057)	(0.0067)	(0.0035)	(0.0038)
γ_1	$\ln Y * \ln W_1$	0.004	-0.002	0.005***	-0.002
		(0.0030)	(0.0036)	(0.0017)	(0.0020)
γ_2	$\ln Y * \ln W_2$	-0.004	0.002	-0.005***	0.002
		(0.0030)	(0.0036)	(0.0017)	(0.0020)
δ_1	CMI	0.722***	0.942***	0.681***	0.993***
		(0.1123)	(0.1752)	(0.0651)	(0.0913)
δ_2	LOS	-0.007***	-0.005***	-0.008***	-0.001***
		(0.0009)	(0.0013)	(0.0006)	(0.0003)
δ_3	RURAL	-0.090**	-0.099*	-0.109***	-0.147***
		(0.040)	(0.0544)	(0.021)	(0.0299)
δ_4	GOV	-0.107*	0.011	-0.083**	-0.079
		(0.0572)	(0.0871)	(0.0347)	(0.0483)
δ_5	NPROF	-0.062	0.010	-0.073**	-0.088*
		(0.0555)	(0.0831)	(0.0336)	(0.0468)
z_1		0.977***	0.709**	0.544***	1.129***
		(0.2552)	(0.2978)	(0.0997)	(0.1961)
Adj. R^2 (ln cost)		0.962	0.927	0.969	0.952
Adj. R^2 ($share_1$)		0.441	0.452	0.404	0.376

[a] Models omit the capital share equation ($share_2$);
[b] Variable labels and coefficients are reported as specified in the cost function;
* 0.05 < p-value ≤ 0.1;
** 0.01 < p-value ≤ 0.05;
*** p-value ≤ 0.01.

	Table 4 **(z_{tj})**	
	Contract Adopters	Control Group
Labor		
pre	0.977*** (0.255)	0.544*** (0.131)
post	0.709** (0.298)	1.129*** (0.245)
Residual		
pre	-0.682*** (0.072)	-0.469*** (0.056)
post	-0.611*** (0.125)	-0.643*** (0.049)

Standard errors in parenthesis

Table 5. Values of z: Labor input case

	PANEL A: matched pairs		PANEL B: independent samples	
	Contract Adopters	Control	Contract Adopters	Control
PRE	$\mu_{01} = 1.03$ $\sigma_{01} = .466$ N = 158	$\mu_{00} = .619$ $\sigma_{00} = .344$ N = 299	$\mu_{01} = 1.03$ $\sigma_{01} = .464$ N = 120	$\mu_{00} = .578$ $\sigma_{00} = .540$ N = 535
POST	$\mu_{11} = .788$ $\sigma_{11} = .436$ N = 158	$\mu_{10} = 1.20$ $\sigma_{10} = .480$ N = 299	$\mu_{11} = .669$ $\sigma_{11} = .279$ N = 57	$\mu_{10} = 1.18$ $\sigma_{10} = .595$ N = 346

Table 6. Comparison of Mean Values of z (matched pairs): labor input case

(1) Difference[a] t-value	(2) Difference[a] t-value	(3) Difference[b] t-value
Contract Adopters	Control	Contract Adopters vs. Control
-0.28	0.58	-0.96
(-6.97)	(27.73)	(-18.87)

[a] The differences in means were calculated by subtracting pre-adoption values from post-adoption values. Significance of the difference was determined via the paired t-test.

[b] The difference in the changes in the means was calculated by subtracting the comparison group mean from the contract adopter mean. Significance of the difference was determined using the two sample t-test.

Table 7. Regression Results for z (independent samples): labor input case

Variable	Parameter Estimate	t-value
Intercept	.578	24.7
Management	.455	8.34
Time	.606	16.3
Management * Time	-.970	-10.3
$R^2 = .2140$		
N = 1058		

Appendix: Propensity Scores Calculation through Stepwise Logistic Regression

Propensity scores, or conditional probabilities of adopting contract management, were estimated for each hospital using logistic regression. We performed two regressions corresponding to the 'pre' and 'post' groups. The first regression included all available observations for the adoption years 1993-1998 and the second included those for adoption years1992-1996. We considered all variables used to explain variation in cost as potential covariates in the logit regression. Table A1 shows the results of these regressions. Some interesting results emerge. What matters in the distinction of contract adopters is ownership form and locality. Contract management is on the order of two times as likely to be found among hospitals with government control, non-profit status, or rural location.

Using calculated propensity scores based on the regression results, stratification proceeded by dividing the propensity scores into quintiles. In practice, stratum boundaries can be based either on the propensity scores from the entire merged sample or else from the adoption group alone. Following D'Agostino (1998), we based the stratum boundaries on quintiles of the estimated propensity scores from the combined groups.

Stratification also took into account the distribution of the contract-managed hospitals over time. The control groups were finally drawn randomly within propensity score quintile-year cells. We produced two control groups each containing three times the number of contract adopters that matched the adopter groups' distributions by propensity score quintile and year. Table A2 shows the propensity score distributions.

Table A1. Propensity Score Model (logit)

	Pre-contract Sample		Post-contract Sample	
Variable	Coefficient (Standard error)	Odds Ratio	Coefficient (Standard error)	Odds Ratio
Adjusted patient days (000)	-.109 (6.34E-3)	.896	-.100 (7.72E-3)	.905
Labor expenses per FTE (000$)	-.014 (2.14E-3)	.982	-.013 (2.33E-3)	.987
Non-labor Expenses per BED (000$)	4.46E-8 (3.04E-7)	1.00	7.25E-7 (3.77E-7)	1.00
Case-mix index	8.80E-3 (.042)	.929	-.735	.480
Average length of stay	2.98E-3 (8.40E-4)	1.00	1.39E-3 (8.93E-4)	1.00
Rural	.667 (.049)	1.77	.580 (.054)	1.78
Government	1.02 (.082)	2.36	.822 (.087)	2.28
Nonprofit	.702 (.079)	1.73	.589 (.087)	1.80
Intercept	-1.87 (.126)	--	-.991 (.219	--
N	24,792		21,732	
Likelihood ratio (Chi-Square)	2,207		1,816	

Table A2. Propensity score distributions by quintile

	Pre-contract	Post-contract
Quintile1	13	3
Quintile2	36	20
Quintile3	33	38
Quintile4	75	69
Quintile5	121	85
Total	278	215

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