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UNCERTAIN DEMAND, THE STRUCTURE OF HOSPITAL COSTS, AND THE COST OF EMPTY HOSPITAL BEDS

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ABSTRACT

One of the fundamental facts of the environment hospitals face is uncertainty over demand for their services. This uncertainty leads hospitals to hold excess standby capacity to avoid turning away patients. In this paper we reformulate the theory of cost and production to take account of this uncertainty.

We then use this model to calculate the cost of empty hospital beds. Utilized capacity in the hospital industry, as measured by the inpatient hospital bed occupancy rate, has gradually declined since 1980 and was approximately 65 percent in 1992. Congress and the Administration are concerned that the costs associated with empty beds represent wasteful expense and some have proposed an adjustment to Medicare payment rates which will penalize hospitals with low occupancy rates.

We estimate a short run cost function for a hospital facing uncertain demand using data from a national sample of over 5000 hospitals for the years 1983-1987. The traditional cost model is strongly rejected in favor of the reformulated model. We calculate the cost of an empty hospital bed as $61,395 in 1987 dollars. We estimate that a one percent decrease in the number of hospital beds would decrease hospital costs by slightly over one-half of one percent. These costs are substantial, but smaller than some others have indicated.

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I. INTRODUCTION

One of the fundamental aspects of the environment hospitals face is uncertainty over demand for their services. The number of patients arriving in any given time period is subject to substantial variability, a considerable portion of which is unpredictable. Hospitals prefer not to turn away patients because of lack of capacity. This may be due to an explicit mission of caring for everyone who appears at their doors or concerns over decreased future revenues through an effect on reputation (Joskow, 1980; Mulligan, 1985; Friedman and Pauly, 1981). Consequently, models of hospitals' capacity decisions have assumed hospitals have a target probability of turning away patients and hospitals choose capacity to reach that target (Joskow, 1980; Mulligan, 1985; Shonick, 1970; 1972).

These choices have important implications for the structure of hospital costs. The standard theory of cost and production requires that production be technically efficient, i.e., that production occur on the boundary of the production possibilities set (also known as the production "frontier"). For firms facing stochastic demand who desire (near) universal provision of service, this property does not hold. In this paper we reformulate the theory to derive a cost function which is consistent with this description of a hospital's environment and its goals. This formulation is substantially different from that implied by the standard theory of cost and production. We then estimate the cost function using data from a national panel of hospitals and use the estimates to calculate measures of the cost of an empty hospital bed.

The cost of excess capacity in the hospital industry has reemerged in the 1990s as an important policy issue. In the 1970s and early 1980s, the cost of empty hospital beds was an important justification for the health planning program. With the elimination of federal funding for health planning, interest in the issue waned. Meanwhile, utilized capacity in the hospital industry, as measured by the inpatient hospital bed occupancy rate, began declining around 1980 and stood at approximately 65 percent in 1992.[1] While the costs of excess capacity are borne privately in other industries, in the hospital industry a large portion of these costs are publicly paid, due to the presence of Medicare, Medicaid, and other public programs.[2] Initially, the exclusion of capital costs from Medicare's prospective reimbursement for hospitals,

[1]This represents a decrease of approximately 11 percentage points from an average occupancy rate of 76 percent in 1980.

[2]For example, revenues from Medicare constitute 30 percent of a hospital's total revenues, on average.

combined with the dramatic decline in occupancy rates, reestablished the cost of empty hospital beds as an important public policy issue. As capital becomes included in the Medicare prospective payment rate over a ten year period, Congress and the Administration continue to be concerned that the costs associated with empty beds represent wasteful expense.[3] An adjustment to Medicare payment policy has been proposed which will penalize hospitals with low occupancy rates. Hospitals, on the other hand, have indicated that the costs of empty hospital beds are low and that occupancy adjustments are unnecessary.[4]

The evidence on this topic is mixed. Previous estimates of the cost of an empty bed range from $4,398 (Friedman and Pauly, 1981), $6,439-$10,274 (Friedman and Pauly, 1983), $6,926-$18,855 (Pauly and Wilson, 1986), $6,850-$28,768 (Schwartz and Joskow, 1980), $46,437 (Institute of

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[3]For example, Representative Fortney "Pete" Stark, Chairman of the House Ways and Means Subcommittee on Health, has been quoted as saying "Low occupancy is a symptom of the indulgent spending spree the country's hospitals have been on.", and Gail Wilensky, former Administrator of the Health Care Financing Administration, has indicated that 4 out of every 10 empty staffed hospital beds should be reduced (Healthweek News, July 30, 1990, p. 9).

[4]Healthweek News, op.cit., p.9.

Medicine, 1976) $83,564-$98,632 (State of Michigan, 1979) to $92,336 (Keeler and Ying, 1993).[5] The differences in the estimates may be due to differences in time periods covered, hospital samples, or cost estimation methods.

The early estimates, however, may not be representative of the current cost of an empty hospital bed. First, many structural changes have occurred since most of these analyses were done. Medicine has recently been characterized by rapid technological change which has substantially changed the technology of production. Inpatient stays have decreased, while outpatient visits and complex diagnostic testing have increased. In addition, the introduction of Medicare's Prospective Payment System (PPS) in 1983 was intended to give hospitals incentives to be more efficient, and thus may also have affected the structure of costs. Changes in market structure and the spread of selective contracting have changed incentives for efficiency and

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[5]All figures have been converted to 1987 dollars using the implicit GNP deflator unless indicated otherwise. There is little difference if the HCFA hospital input price index (Freeland, Anderson, and Schendler, 1979) is used instead, e.g., the figure in 1987 dollars for Friedman and Pauly (1981) is $4,251. The figure for Keeler and Ying (1993) was calculated using the estimates reported in the paper and mean cost and bed size from our data.

quality. Thus the cost of an empty bed may differ substantially from estimates for earlier time periods. Second, many of the analyses were based on data which are not necessarily representative of the population of hospitals in the U.S.[6] Last, most of these estimates are derived in a rather ad hoc fashion. The exceptions are Friedman and Pauly (1981, 1983) and Pauly and Wilson (1986), which are based on a cost function derived for a hospital facing uncertain demand, and more recently, Keeler and Ying (1993), who base their estimates on a conventional cost function.

In order to provide more current and representative estimates of the cost of empty hospital beds we estimate our model of costs for a firm facing uncertain demand using data from a national sample of over 5000 hospitals for the years 1983-1987. Our estimates indicate that the cost of an empty bed is $61,395. This falls in roughly the third quartile of the previous estimates. In our sample this amounts to approximately $10.08 per admission (in 1987 dollars).

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[6]For example, Pauly and Wilson used data for 176 hospitals in the state of Michigan from 1979-1982, and Friedman and Pauly used data for 871 hospitals from 1973-1978.

The rest of the paper is as follows: Section II contains a derivation of the model, Section III discusses the measurement of the cost of an empty bed, specification is discussed in Section IV, a description of the data is contained in Section V, Section VI discusses econometric issues, Section VII contains the empirical results, Section VIII contains the results for the cost of an empty hospital bed, and a summary and conclusions are contained in Section IX.

II. THE MODEL

In this section we derive a cost function for a hospital facing stochastic demand. The model is a modification of that proposed by Duncan (1990), and is similar to that of Friedman and Pauly (1981).[7] While there has been a great deal of theoretical attention devoted to the effect of uncertain demand on firm behavior (e.g., Holtausen, 1976; Leland, 1972; Sheshinski and Dreze, 1976), there has been very little empirical work on this topic (see Friedman and Pauly, 1981, 1983; Pauly and Wilson, 1986; and Koop and Carey, 1991 for exceptions).

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[7]Duncan's model has also been used for hospitals by Koop and Carey (1991).

There have been numerous studies of the structure of hospital costs (see Breyer, 1987; Vitaliano, 1987; Cowing, Holtmann, and Powers, 1983; Vita, 1990 and Ellis, 1991 for reviews).[8] The vast majority of these studies treat demand as known to the hospital. As Friedman and Pauly (1981) point out, not only is this assumption unrealistic, but it does not allow the researcher to uncover the nature of hospital costs. Indeed, one of the areas in which Cowing, Holtmann, and Powers (1983) call for development of modeling techniques is demand uncertainty. Service firms with high fixed costs have a service capacity which is fixed over the short or medium run. This means that if demand exceeds capacity at any given point in time, the excess demand cannot be served. In certain industries it is important that firms have sufficient capacity to keep the probability of excess demand below some desired level. Fire departments have more fire engines and fire fighters than are necessary to control the expected level of fires. Telephone companies have enough lines and switching equipment to keep the probability of a customer being unable to get a line to a low level. Hospitals have enough beds, equipment operating rooms, and staff to treat many more patients than flow to

[8]Ellis (1991) estimates that over 3,500 articles and books have been written on hospital costs in the last 5 years.

them on average over the course of a year. This is also important in transportation, water supply and energy generation and transmission.[9]

In other words, hospitals not only provide direct, anticipated patient care, but also standby capacity to ensure that treatment is available if someone should unexpectedly need care. This represents a demand for insurance, or option demand which is a service provided by the hospital. Not taking this insurance aspect of hospital services into account when estimating hospital costs will make hospitals appear inefficient.[10] It will appear as if they are operating below minimum optimal scale, when in reality they may be at minimum optimal scale considering the standby capacity they are producing as a service.

Let the hospital's production function be represented by the relationship

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[9]See, e.g. Keeler (1974), Winston et al. (1990), Ying and Keeler (1991) and Friedlaender et al. (1991), for studies of this issue in transportation.

[10]It will not generally be true that inputs were hired to minimize the cost of the level of output observed. Hospitals will optimally choose factor combinations which are ex ante optimal, given expected demand, but are not ex post efficient, given realized levels of demand.

$$y_t = f(x_t), \tag{1}$$

where y_t is output in period t and x_t is a vector of inputs. Since this is a service, the product is not storable, and there is no excess supply. Assume that demand for the hospital's output is a random variable, d_t, with conditional distribution function

$$G(d_t | d_{t-k}),\ k = 1, \ldots, t, \tag{2}$$

where G represents the distribution of demand conditional on realizations in previous periods. This will allow a hospital to predict the probability of turning away patients, given its information set.[11]

We assume that the hospital does not want to deny patients care due to excess demand, so that the "turn-away probability" is kept below some

[11]Of course, there may be information available to the hospital other than the sequence of past realizations of demand. We assume that this sequence adequately summarizes all the relevant information about demand, i.e., it is a sufficient statistic for demand.

target level, α. This may be due to motives for community service (especially if this is a community hospital with local citizens on its board) or due to concerns for market share, reputation and future demand. This is consistent with, although more general than, Friedman and Pauly's (1981) model. In that model hospitals let quality deteriorate when demand exceeds capacity and suffer an unobserved cost or penalty associated with this. Thus, hospitals wish to avoid situations of excess demand.

The probability that demand exceeds capacity and patients are turned away is

$$\Pr[d_t \geq y_t | d_{t-k}] = \Pr[d_t \geq f(x_t) | d_{t-k}] = 1 - G(f(x_t) | d_{t-k}) \qquad (3)$$

The hospital's problem is to minimize costs subject to the production relation and the constraint that the turnaway probability not exceed the target level, α.

Before proceeding to the derivation of the cost function, first consider the fixity of various kinds of inputs for the hospital. Divide inputs into three categories: fixed, quasi-fixed, and variable. Fixed inputs are those factors which are immobile over long periods of time. In the case of hospitals, bricks and mortar, usually measured as the number of beds, are fixed for long periods of time. Treating beds as fixed leads to a variable cost function, e.g., as in

Vita (1990). Quasi-fixed inputs are factors which cannot be readily varied in response to unexpected realizations of demand. Contracts render much of a hospital's labor force fixed for fairly long periods of time. Last, variable inputs are factors which can be purchased in spot markets and varied instantaneously (or nearly so) in response to realizations of demand. Utilities, some categories of labor, and supplies fall into this category. Thus, quasi-fixed and variable inputs are chosen ex ante before demand is realized, but variable inputs can be adjusted ex post to realizations of demand.

Call the three inputs k for capital, x_q for quasi-fixed, and x_v for variable. Then re-write the production function as

$$y_t = f(x_{vt}, x_{qt}, k_t). \qquad (4)$$

Now consider the hospital's problem. Capital, k_t, is fixed. The hospital chooses quasi-fixed inputs and variable inputs before demand is realized. This is the standard cost minimization problem with the added constraint that demand can exceed supply on average only α percent of the time,

$$\min_{x_{vt}, x_{qt}} \quad w_v x_{vt} + w_q x_{qt} \tag{5}$$

$$\text{s.t.} \quad 1\text{-}G[f(x_{vt}, x_{qt}, k_t) \mid d_{t\text{-}k}] = \alpha. \tag{6}$$

Assume that G is one-to-one. Then the constraint can be written more conveniently as

$$f(x_{vt}, x_{qt}, k) = G^{-1}[1\text{-}\alpha \mid d_{t\text{-}k}]. \tag{7}$$

This results in input demand functions for the variable and fixed inputs,

$$x_{vt} = x_v(G^{-1}[1\text{-}\alpha \mid d_{t\text{-}k}], w_v, w_q, k_t) \tag{8}$$

$$x_{qt} = x_q(G^{-1}[1\text{-}\alpha \mid d_{t\text{-}k}], w_v, w_q, k_t). \tag{9}$$

Now suppose that the firm can adjust its variable inputs in the spot market once demand is realized. Let $\dot{x}_v$ be the adjustment to the variable input. Thus $\dot{x}_v$ can be positive or negative. The firm minimizes the cost of the variable input, conditional on the ex ante input demands, and subject to the production constraint,

$$\min w_v \{\dot{x}_v + x_v(G^{-1}[1-\alpha | d_{t-k}], w_v, w_q, k_t)\} \quad (10)$$

s.t.

$$y_t = f(\dot{x}_v + x_v(\bullet), x_q(\bullet), k_t) \quad (11)$$

This determines ex post variable costs, which are a function of realized output, the turnaway constraint, input prices, and capital,

$$C_v = C_v(y_t, G^{-1}[1-\alpha | d_{t-k}], w_v, w_q, k_t). \quad (12)$$

These are the costs which are observable, and thus this is the cost function to be estimated. The difference between this reformulated cost function and a conventional cost function is the presence of target standby capacity ($G^{-1}[1-\alpha]$) as one of the arguments. As we will indicate later, this provides the basis for a specification test of the hypothesis that uncertainty in demand affects the structure of hospital costs.

This cost function has all of the usual properties, excepting duality and independence of demand and cost. Since the firm is constrained to have the capacity to meet randomly fluctuating demand with some probability, it will not generally be producing on the efficient frontier of the production possibilities set. This means that duality between cost and production does not obtain. We can estimate a cost function with all the usual properties but the parameter estimates do not inform us about the structure of production. The turnaway constraint also introduces a dependence between cost and demand, since the firm produces a probability that demand is larger than output.

This implies that an analysis of hospital costs must take account of the randomness of demand and the desire to avoid turning away patients. Omitting this behavior may lead to potentially serious mis-specification problems.

III. THE COSTS OF EMPTY HOSPITAL BEDS

In the case of hospitals, fixed capacity is represented by the number of hospital beds. If a bed is expectedly unoccupied, the variable costs associated with output and the quasi-fixed costs associated with predicted output are avoided, but the fixed costs which vary with the number of available beds are not. In the context of our model, the cost of an empty bed which is expected to be unoccupied will be less than that of an unexpectedly empty bed, since the quasi-fixed costs associated with the expectedly empty bed can be avoided. Thus, the cost of an (expected) empty hospital bed is the fixed cost associated with that bed. This is arguably the relevant cost of an empty bed, since unexpectedly empty beds do not represent permanent excess capacity (assuming rational forecasts). We will use the estimates of the cost function for a hospital facing uncertain demand to calculate the magnitude of these costs.

IV. SPECIFICATION

The model in the previous section implies that variable costs will be a function of actual output, the capacity output which meets the desired turnaway probability, the prices of variable inputs, and the levels of fixed factors. The actual model to be estimated differs from the theory in a number of details. We employ two measures of hospital output, the number of inpatient admissions and the number of outpatient visits. Further, it is commonly recognized that hospital output is captured only incompletely by measures of physical quantity. In order to control more completely for unmeasured aspects of output such as severity, complexity or mix of case types we include measures of case mix and of hospital teaching status. Indicators for whether the hospital is for-profit or public are also included to proxy for unmeasured characteristics of output. They may also capture differences in objectives between these organizational forms. Finally, bed size is also likely correlated with severity or complexity.

The theoretical measure of standby capacity is the capacity output which keeps the hospital's turnaway probability at or below its target level. However, we don't know the firm's desired turnaway probability. Nonetheless, we can describe the distribution of demand, and thus encompass all the relevant information about target capacity. $G[d_t | d_{t-k}]$ is the distribution of demand, conditional on past realizations. If G is a two-parameter distribution, then the conditional mean and variance completely describe the distribution, i.e., they are a sufficient statistic for G. Thus, although we cannot observe the turnaway probability, we can use the mean and variance of demand conditional on past values to describe desired capacity output for all turnaway probabilities. For example, for small target turnaway probabilities in the tail of the distribution, if the mean of the distribution increases (with no change in variance) a higher capacity output will be required to maintain the same turnaway probability. The same is true of an increase in the variance (with no change in the mean). Thus, we can say that desired capacity output is increasing in the mean or variance of the distribution of demand, for small values of the turnaway probability.

We also include the inverse of the hospital's inpatient occupancy rate in the cost function. This measures the extent of excess capacity. It also controls for another dimension of output, average length of stay in the hospital. As the inverse occupancy rate increases, the relative share of fixed factors increases, thus the coefficient on the inverse occupancy rate will measure the cost of excess capacity, and allow us to calculate the cost of an empty hospital bed. Thus, we write the variable cost function to be estimated as

$$C_{vt} = C_v(y_t, E[y_t | y_{t-k}], Var[y_t | y_{t-k}], w_t, k_t; \theta_t) \qquad (13)$$

where y_t is actual, realized output, $E[y_t | y_{t-k}]$ is the mean of output conditional on past values, $Var[y_t | y_{t-k}]$ is the variance of output conditional on past values, w represents input prices, k represents fixed factors such as bedsize as inverse occupancy rate, and θ is a vector of other characteristics such as case mix, teaching status, etc.[12]

Since theory provides no guide to the form of the cost function, we employ the translog functional form, which is a flexible functional form. The translog has the usual properties of a cost function, plus it allows for flexible substitution properties and locally approximates any arbitrary function. The model we estimate is

$$
\begin{aligned}
\ln C_v = {} & \beta_1 \ln Y + \tfrac{1}{2}\beta_2 (\ln Y)^2 + \beta_3 \ln \hat{Y} + \tfrac{1}{2}\beta_4 (\ln \hat{Y})^2 + \beta_5 \ln V + \tfrac{1}{2}\beta_6 (\ln V)^2 \\
& + \beta_7 \ln W + \tfrac{1}{2}\beta_8 (\ln W)^2 + \beta_9 \ln B + \tfrac{1}{2}\beta_{10} (\ln B)^2 + \tfrac{1}{2}\beta_{11} \ln \hat{Y} \ln Y + \beta_{12} \ln Y \ln B \\
& + \beta_{13} \ln Y \ln W + \tfrac{1}{2}\beta_{14} \ln Y \ln V + \beta_{15} \ln Y \ln B + \beta_{16} \ln \hat{Y} \ln W + \tfrac{1}{2}\beta_{17} \ln \hat{Y} \ln V \\
& + \beta_{18} \ln B \ln W + \beta_{19} \ln B \ln V + \beta_{20} \ln W \ln V + + \beta_{21} \ln(\sigma_Y) + \beta_{22} \ln(1/\text{Occupancy}) \\
& + \beta_{23} \ln(\text{Case Mix}) + \beta_{24} \text{Teach} + \beta_{25} \text{Public} + \beta_{26} \text{For-Profit} \\
& + \mu + \tau + \varepsilon, \qquad (14)
\end{aligned}
$$

where Y is actual admissions, $\hat{Y}$ is predicted admissions, V is outpatient visits, W is hospital wages, B is beds, 1/Occupancy is the inverse of the occupancy

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[12]We have not specified quality as part of this model. If there is significant variation in unobserved quality, then the model is actually a reduced form, since the structural parameters on the observed variables (output, input prices, etc.) cannot be identified separately from the quality effects. The model is strictly speaking structural only under the assumptions of product homogeneity and (constrained) cost minimization.

rate, Case Mix is the case mix index, Teach, Public and For-Profit indicate hospital characteristics, σ_y is the standard error of predicted admissions, μ are hospital specific fixed effects, and τ are time fixed effects.[13,14]

V. DATA

A. Sources

We used data from the American Hospital Association's (AHA) Annual Survey of Hospitals for each of the years 1983 through 1987. This is an annual survey of the universe of hospitals in the United States. It contains data on costs, payments to inputs, output, hospital characteristics, and other factors. A Medicare case mix index for each hospital was obtained from the U.S. Health Care Financing Administration.[15] Data on socioeconomic and

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[13]To economize on the number of higher-order terms to be estimated, inverse occupancy and the standard error of predicted admissions are restricted to enter only as first-order terms.

[14]The hospital specific fixed effects condition out all time invariant omitted hospital-specific factors. Thus, any aspects of hospital-specific quality, objectives, or severity which do not vary over time are captured by the fixed effects. In addition, hospital teaching status and ownership form may capture some differences in firm objectives if they exist.

[15] See Anderson and Lave (1986) for more detail.

demographic characteristics of the county in which the hospital was located were obtained from the Area Resource File, the Health Interview Survey, the Current Population Survey, and the Health Care Financing Administration.[16] Hospitals were deleted if we could not match AHA and Medicare identification numbers, if the hospital did not exist for all five years, or if the hospital did not report information to the AHA for all five years or if the hospital could not be matched with a county.[17] The estimation sample contained complete data for 5260 hospitals in 1983, 5263 in 1984, 5266 in 1985,[18] and 5267 in 1986 and 1987. The number of hospitals varies by year due to missing data for some variables.

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[16]We are grateful to David Salkever for generously sharing data on county health insurance coverage and Medicare enrollment with us.

[17]This process excluded hospitals which shut down within this period. Since these hospitals are the most likely to have high variable costs relative to capacity, this may lead our results to be somewhat understate the effect of excess capacity on variable costs.

[18] These represent 92% of short-term community general hospitals in 1985.

B. VARIABLES

Dependent Variable

The dependent variable is total operating cost, measured in real terms. The implicit GNP deflator was used to convert all money figures to 1983 dollars. **Independent Variables**

The independent variables are actual inpatient admissions, predicted admissions, the standard error of predicted admissions, outpatient visits, the inverse of the occupancy rate, the number of hospital beds, the wage rate, the Medicare case mix index, a dummy variable indicating whether the hospital is for-profit, a dummy variable indicating if the hospital is public, and a dummy variable indicating if the hospital is a teaching hospital (if there are any interns or residents). Descriptive statistics for all the variables are displayed in Table 1.

Actual admissions are the number of inpatient admissions to the hospital in a year. Predicted admissions are the econometric forecast of output for the hospital, as in Friedman and Pauly (1981).[19] This is our measure of

[19]AHA data covering the period 1980-1987 were used for the purposes of forecasting expected admissions. The model used three lags, thus there were forecasted values for 1983-1987.

the expectation of the hospital's conditional distribution of demand.[20] Since we had a relatively short time series for each hospital (eight years), we were unable to forecast expected output for each hospital using pure time series methods as Friedman and Pauly did. Rather we exploited the cross-sectional as well as the time series variation in the data to generate forecasts for expected output for each hospital by grouping the hospitals by geographic area.[21] Hospitals which were in the following categories were pooled together: hospitals in the same Metropolitan Statistical Area (MSA), hospitals in the same urban area, or hospitals in rural areas in the same state.[22] There were 365 such areas. The forecasting equation used three lags for admissions, a time trend, and hospital specific dummies. The hospital specific intercepts allowed us to generate forecasts for each hospital even though the forecasting equation was estimated for pooled sets of hospitals. The fits for the

[20]Since we have only annual data, within year fluctuations in demand are ignored, which may be quite important. Thus our results probably understate the importance of demand fluctuations for hospitals.

[21]Since hospitals in the same area share common shocks specific to their market, perhaps not too much is violated by pooling hospitals in this manner for the purpose of forecasting.

[22]MSAs or urban areas with only one hospital were combined with rural hospitals in the same state. There were 14 such areas.

forecasting equations were excellent, with R^2s in the range of 0.97 to 0.99. Examples for three MSAs are reported in Appendix Table A1. The standard error of predicted admissions is the measure of the second moment of the conditional distribution of demand faced by the hospital.

Outpatient visits are another output produced by hospitals. Since they have been growing in importance over the 1980s, we include them as well as inpatient admissions. They are measured as the total number of outpatient visits to the hospital in a year.

The inverse of the occupancy rate is a proxy for fixed capacity. Assuming that fixed costs are positively related to capacity, average fixed costs will depend positively on the inverse of the occupancy rate. In addition, the number of inpatient beds is allowed to shift the cost function. This variable may proxy for unmeasured severity of illness associated with large size or perhaps economies of scale or scope (Anderson and Lave, 1986).

There are no reported data on wages (or other input prices) by hospital, therefore we used reported payroll per full time equivalent (FTE) employee as a proxy for hospital wages.[23] This undoubtedly captures variation in the composition of the labor force across hospitals as well as the true wage rate. An alternative would have been to use a hospital wage index constructed by HCFA for the purpose of Medicare reimbursement, but this index is area, rather than hospital specific. The Medicare case mix index measures the complexity of a hospital's Medicare cases in any given year in terms of their relative costliness and is frequently used as a proxy for overall hospital case mix.[24] It is constructed by HCFA for the purposes of Medicare reimbursement (see Pettengill and Vertrees (1982) for details). Last, the ownership form of the hospital and teaching status are control variables for hospital characteristics which may affect cost. A hospital is defined as a teaching hospital if it has any interns or residents.

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[23]Labor is the chief input in the production of hospital services. Expenditures on labor constitute approximately 70% of hospital costs (Freeland, Anderson, and Schendler, 1979).

[24]We assume this is a reasonable proxy for the hospital's non-Medicare case mix, which may or may not be the case. Case mix indices have been rightly criticized as a means of aggregating outputs. We use it here as a proxy for severity.

VI. ECONOMETRIC ISSUES

Since we employ panel data, with repeated measures for each hospital, the model was estimated by the method of fixed effects, or least squares with dummy variables.

Our major hypothesis is that randomness in demand affects hospitals' input choices, and hence their costs. This is embodied in the terms for expected demand and the standard error of expected demand. The null hypothesis that these terms do not affect costs is inconsistent with our model. If these terms are jointly significant then we can reject the null hypothesis that demand uncertainty doesn't matter. The test result is reported in Table 2. The terms involving predicted demand and its variance are jointly significant at better than 1% level, thus clearly uncertainty over demand affects hospital input choices and costs.

Since the cost function we estimate has not been derived from a specific production technology, there is no particular functional form which is indicated. As indicated previously we employ the translog functional form, since it is a flexible functional form which is an arbitrary local approximation to any functional form. The simpler Cobb-Douglas functional form is nested in the translog, thus the significance of the higher order terms is a test of the

Cobb-Douglas as the null specification. The test is reported in Table 2. The F-statistic for the joint significance of all the higher-order terms equals 176.27, which is significant at better than the 1% confidence level. Thus we can reject the Cobb-Douglas in favor of the translog functional form.

There were two other salient issues to consider concerning the econometric specification: exogeneity and heteroskedasticity. It is possible that the measures of output; admissions and outpatient visits, could be endogenous. The fixed effects condition hospital-specific fixed factors out of the error term, but endogeneity could still result due to remaining time varying factors. The inverse occupancy rate could also be endogenous, since it is a function of the number of admissions and average length of stay. The case mix index could also be endogenous if hospitals affect not only the number of patients coming to them, but also their type.

We employed the test of Hausman (1978) and Wu (1973) to test for the exogeneity of these variables.[25] Exogeneity was rejected at the 1% level for admissions and at the 5% level for the occupancy rate. We could not reject the exogeneity of outpatient visits or the case mix index at conventional

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[25]We tested for the exogeneity of these variables and all the higher order terms in which they were involved.

levels.[26] The values of the test statistics are displayed in Table 2.

Consequently we treated admissions and the occupancy rate and all their interaction terms as endogenous and employed instrumental variables. We utilized county level socioeconomic and demographic variables which plausibly affect demand as instruments. These were: the number of physicians per capita in the county, county per capita income, the proportion of population in the county with any private insurance coverage, the number of HMOs, the number of Medicare beneficiaries, population, the number of deaths, the percent of the population which is non-white, the percent younger than 15, the percent older than 65, the unemployment rate, and the hospital Herfindahl index. These are variables which affect the demand faced by a hospital through the level of health or through market structure, but not its costs. The first-stage estimates are reported in Appendix Table A2.

It is often alleged that the errors in hospital cost regressions are

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[26]The test statistic for outpatient visits was significant at the 12% confidence level, however we chose not to use the instrument for outpatient visits because the fit in the first-stage was so poor (R^2=0.05, F-statistic for joint significance of excluded variables = 2.6). A number of papers have shown that the use of instruments when there is a poor fit in the first-stage can seriously bias results and is worse than OLS (Nelson and Startz, 1990a,b; Buse, 1992; Maeshiro, 1979; Staiger and Stock, 1993; Bound et al., 1993).

heteroskedastic. For that reason we employed Koenker's (1981) robust version of the Breusch-Pagan (1979) LaGrange multiplier test for heteroskedasticity of an unknown form.[27] The test statistic is reported in Table 2 and rejects homoskedasticity at the 1% level. Hence we calculated heteroskedasticity consistent standard errors using White's (1980) method.

VII. RESULTS

Table 3 contains the fixed effects estimates of the cost function. The estimates of the individual hospital and time fixed effects are not reported. Most of the parameter estimates are consistent with expectations. Both predicted admissions and the variance of predicted admissions have a significant impact on total costs. This is consistent with our theory of a hospital facing uncertain demand. Higher expected demand raises costs as hospitals must devote more resources to maintaining capacity sufficient to meet their target turnaway probability. Higher variance in demand also leads to higher costs as hospitals hire more quasi-fixed inputs to avoid the probability of turning away patients at a high realization of demand.

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[27]Breusch and Pagan's test statistic is not robust to non-normality.

Actual admissions are positive and significant, indicating that firms do engage in costly input adjustments in response to actual realizations of demand. Costs also increase with the number of outpatient visits. The inverse of the occupancy rate is also positive and significant, consistent with its interpretation as a proxy for fixed capacity costs. The first-order coefficient on bed size is negative, but the total effect is positive. This result is consistent with the findings in most studies of hospital costs that larger bed size is associated with higher costs. The wage rate and case mix index have a positive impact on costs, as expected. For-profit hospitals are not significantly more costly, and public hospitals cost less, than not-for-profit hospitals. The only surprising result is that teaching hospitals are not significantly more costly than non-teaching hospitals. This may be due to the measure of teaching status employed, or because teaching status doesn't vary enough for individual hospitals to identify its impact separately from the hospital-specific fixed effects.

Table 4 contains the estimates of output cost elasticities and marginal costs. All of the elasticities seem reasonable. Predicted admissions have a larger impact than actual admissions, as they should, underscoring the importance of demand uncertainty for hospital costs. This is consistent, a la

Friedman and Pauly, with a model in which quality deteriorates when there is excess demand.[28] In this case, the marginal cost of an actual (unexpected) admission should be less than that of an expected admission, since quality was allowed to fall for the unexpected admission. We cannot identify whether this truly is a quality effect,[29] but the result is consistent with the uncertainty model regardless. The standard deviation of predicted admissions also has a large effect on costs.[30] The measures the impact of uncertainty on costs. The greater the uncertainty, the more hospitals try to hedge by holding excess capacity, and the higher are costs. Outpatient visits have an elasticity of 0.4, but a relatively small marginal cost of $220.53 for an additional visit.

We calculated ray economies of scale as suggested by Caves et al. (1981),

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[28]This is essentially an interpretation of quality as service intensity, i.e., the volume of quasi-fixed inputs per admission.

[29]For example, the hospital could simply be shifting the costly unexpected patients to other hospitals and retaining the minor illnesses, thus leading to lower marginal costs for unexpected admissions. We are indebted to an anonymous referee for bringing the quality issue and these interpretations to our attention.

[30]The marginal cost of the standard error of predicted admissions measures the effect of a one standard deviation charge. The standard deviation is 136.58 admissions. Thus, the per admission marginal cost is $449.84.

$$S = \left(1 - \frac{\partial \ln C_v}{\partial \ln B}\right) \div \left(\Sigma_i \frac{\partial \ln C_v}{\partial \ln y_i}\right).$$

That is, we evaluated the expression for ray scale economies at the observed value of beds. Since this observed value is not likely to be the optimal long run value, this is a measure of short-run economies of scale.[31] The estimate of S equals 1.23, indicating increasing returns to scale. This is what we would expect, given that hospitals are holding excess capacity.

VIII. WHAT IS THE COST OF AN EMPTY BED?

In this section we report calculations of the costs associated with empty beds based on the estimates reported in Table 3. We report the total fixed cost per bed, and the cost elasticity of the occupancy rate.

The cost of an expectedly empty bed is the estimate of total fixed costs per bed. Since the inverse of the occupancy rate represents fixed capacity, its marginal impact on cost represents the marginal cost of an increase in fixed capacity (a decrease in the occupancy rate). Multiplying by

[31]Although in principle it is possible to calculate long run economies of scale from the short run cost function (Braeutigam and Daughety, 1983), this requires accurate data on the price of the fixed factor. Since we do not have such data, we calculate the short run measure.

the inverse occupancy rate gives the total cost of fixed unused capacity at that point. Dividing by total beds generates the total fixed cost per bed, or the cost of an empty bed.

The cost of an empty bed is $54,332 ($61,395 in 1987 dollars). This estimate is roughly in the mid-range of previous estimates, although it is larger than those produced by previous methods which accounted for uncertain demand (Friedman and Pauly and Pauly and Wilson). This may be due to changes in the hospital production process which may have led to higher fixed costs (e.g., the diffusion of capital intensive new technologies such as magnetic resonance imaging), actual diseconomies associated with lower occupancy rates (i.e., movement "back up" the average cost curve), changes in the character or quality of the product, or changes in incentives under the Prospective Payment System. Thus, it is difficult to discern whether the cost of an empty bed is truly "higher" than previously estimated by this method, or whether the production of hospital services has changed in important but unmeasurable ways.[32]

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[32]Our estimate of the cost of an empty hospital bed measures cost at the level of average quality in the sample. If there is significant variation in quality, this cost could vary widely for hospitals. The net benefit associated with reducing the number of beds would depend on what, if any, quality

We also calculated the impact of changing the occupancy rate on hospital costs. The local effect of changing the occupancy rate is simply its cost elasticity. This equals 0.42. Thus a one percent increase in the occupancy rate would decrease hospital costs by approximately 0.42 percent. If we consider decreasing hospital bed size to increase the occupancy rate, (holding admissions and length of stay constant), then the local effect is the sum of the cost elasticities of occupancy and beds. This equals 0.55, thus a one percent decrease in the number of beds would decrease costs by a little over one-half of one percent. The global effects of a decrease in the number of empty beds could be quite large in absolute terms, depending on the optimal number of empty beds.[33]

IV. Summary and Conclusions

In this paper we have investigated the consequences of the uncertain environment hospitals face for the structure of hospital costs. We derived a

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response hospitals had to such a program.

[33]The optimal number of beds, of course, depends not just on the cost of an empty bed, but also on the benefit of an empty bed, i.e., the social value placed on having beds available when needed.

cost function for such a firm and estimated the parameters using data for a national panel of hospitals for the years 1983-1987.

We strongly reject the hypothesis that demand uncertainty does not affect hospital costs. Thus we conclude that uncertainty has important effects on hospital behavior and that failure to control for this may bias estimates of cost function parameters.

We use the cost function estimates to calculate local measures of the cost of empty hospital beds. We find that the cost of an empty hospital bed is $61,395 in 1987 dollars, which is significant, but quite a bit smaller than some others have indicated. The local effects of decreases in bed size are quite small; a one percent decrease in bed size decreases costs by just over one-half of one percent. The global effects of larger decreases could be quite a bit larger. Figures like these need to be combined with measures of the social benefit of excess capacity in hospitals in order to calculate the optimal occupancy rate and hence the optimal number of excess beds.

There are a number of limitations to this research, however. In particular, we used an aggregate output for hospital inpatient care, we had only one input price, we estimated short run as opposed to long run costs, and we had only imperfect controls for quality. Perhaps these are areas in which future research could lead to improvements.

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TABLE 1

Variable Descriptive Statistics[a]

Variables	Mean	Standard Error
Total operating Cost	22,129,469.06	31,987,936.30
Actual Admissions	6,092.62	6,611.85
Predicted Admissions	6,092.41	6,585.69
Standard Error of Predicted Admissions	115.26	136.58
Outpatient Visits	40,139.44	68,959.54
Number of Beds	170.16	177.94
Inverse of the Occupancy Rate	1.88	1.14
Wage Rate	16,838.31	11,550.96
Case Mix Index	1.094	0.14
Teaching Hospital	0.16	0.37
For-Profit Hospital	0.13	0.34
Public Hospital	0.29	0.45
Physicians per 100,000 Population in the Hospital's County	1,340.59	3,399.28
Number of HMOs in the Hospital's County	1.24	2.90
Total Enrollment in Medicare Part A, Hospital's County	65,842.94	147,079.68
Total Number of Deaths in the Past Year, Hospital's County	4,830.84	11,222.93
Per Capita Income, Hospital's County	11,809.22	2,957.58

[1a]All monetary figures are in 1983 dollars.

TABLE 1 (Cont'd.)

Variable Descriptive Statistics[a]

Variables	Mean	Standard Error
Percent of the County Population with Private Coverage for Hospitalization	82.75	10.09
Percent of the County Population Non-white	12.61	13.60
Percent of the County Population Less Than Age 15	22.03	2.81
Percent of the County Population Greater Than Age 65	13.25	3.99
Herfindahl Index Based on Number of Beds, Hospital's County	0.45	0.37
Unemployment Rate, Hospital's County	7.81	3.36
County Population	578,405.32	1,406,548.26

[a]All monetary figures are in 1983 dollars.

TABLE 2

Specification Tests[a]

Null Hypothesis	Test	Value of Test Statistic	Reject Null?
Demand uncertainty does not affect hospital behavior	F-statistic for significance of terms involving predicted demand or standard error of predicted demand	F=48.85***	Yes
Cobb-Douglas functional form	F-statistic for significance of all higher order terms	F=176.27***	Yes
Admissions exogenous	Hausman (1978)-Wu (1973) test: F or t-statistic for significance of predicted values of variable added to regression for all first-order and higher-order terms	F=38.05***	Yes
Outpatient Visits exogenous		F=2.6	No
Inverse Occupancy Rate exogenous		t=2.1**	Yes
Case Mix Index exogenous		t=0.29	No
Errors homoskedastic	Koenker's (1981) robust version of Breusch and Pagan's (1979) LM test $LM \sim \chi^2_{30}$	LM=349.81***	Yes

[a]** denotes significance at the 5% confidence level, and *** denotes significance at the 1% confidence level.

TABLE 3

Fixed Effects Estimates of Variable Cost Function[a,b,c]

Dependent Variable

Ln(Total Operating Cost)

Independent Variables	Parameter Estimates
Ln(Actual Admissions)[d]	1.68***
	(0.31)
Ln(Predicted Admissions)	0.15***
	(0.06)
Ln(Standard Error of Predicted Admissions)	0.32***
	(0.005)
Ln(Outpatient Visits)	0.32***
	(0.09)
Ln(Beds)	-0.55
	(0.35)
Ln(Wage Rate)	4.31***
	(0.18)
Ln(Inverse Occupancy Rate)[d]	0.42***
	(0.07)
Ln(Case Mix Index)	0.31***
	(0.03)
Teaching Hospital	0.004
	(0.004)
Public Hospital	-0.04**
	(0.01)
For-Profit Hospital	-0.03
	(0.02)
[Ln(Actual Admissions)]^{2}[d]	2.49***
	(0.07)
[Ln(Predicted Admissions)]^{2}	2.81***
	(0.04)
[Ln(Beds)]^{2}	0.61***
	(0.04)
[Ln(Wage Rate)]^{2}	0.29***
	(0.01)
[Ln(Outpatient Visits)]^{2}	0.007***
	(0.0009)

TABLE 3 (Cont'd.)

Fixed Effects Estimates of Variable Cost Function[a,b,c]

Independent Variables	Parameter Estimates
Ln(Actual Admissions)x Ln(Predicted Admissions)[d]	-2.75*** (0.04)
Ln(Actual Admissions)x Ln(Outpatient Visits)[d]	0.07*** (0.004)
Ln(Actual Admissions)x Ln(Beds)[d]	-1.32*** (0.02)
Ln(Actual Admissions) xLn(Wage Rate)[d]	0.71*** (0.02)
Ln(Predicted Admissions) xLn(Outpatient Visits)	-0.007 (0.004)
Ln(Predicted Admissions) xLn(Beds)	1.25*** (0.003)
Ln(Forecasted Admissions) xLn(Wage Rate)	-0.68*** (0.03)
Ln(Outpatient Visits) xLn(Beds)	-0.03*** (0.005)
Ln(Outpatient Visits) xLn(Wage Rate)	-0.04*** (0.01)
Ln(Beds) xLn(Wage Rate)	-0.16*** (0.03)
R^2	0.70
F	2082.422***
Number of Observations	26323

[a]The parameter estimates for the hospital specific and time dummies are not reported.
[b]Heteroskedasticity-consistent standard errors are in parentheses below the estimates.
[c]***-Significant at 1% confidence level; **-significant at 5% confidence level.
[d]Instrumental variable.

TABLE 4

Cost Elasticities and Marginal Costs

Variable	Cost Elasticity	Marginal Cost
Actual Admissions	0.31	$962.91
Predicted Admissions	0.40	$1,261.94
Standard Error of Predicted Admissions	0.32	$61,438.75
Outpatient Visits	0.40	$220.53

APPENDIX

TABLE A1

Forecasting Hospital Admissions-Three Examples[a,b,c]

Dependent Variable

Hospital Admissions

Independent Variables	Area: Baltimore, MD	Appleton-Oshkosh-Neenah, WI	Amarillo, TX
Intercept	417.83 (365.47)	98.15 (350.13)	-462.70 (797.66)
Admissions Lagged 1 Year	1.21*** (0.09)	0.60*** (0.20)	1.41*** (0.31)
Admissions Lagged 2 Years	-0.52*** (0.13)	0.23 (0.26)	-0.54 (0.47)
Admissions Lagged 3 Years	0.31*** (0.10)	0.11 (0.23)	0.14 (0.31)
Time Trend	-100.63 (64.31)	-37.92 (65.59)	70.87 (149.80)
R^2	0.98	0.99	0.98
F	1632.17***	754.63***	285.45***
Number of Observations	120	35	25

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[a]The parameter estimates for the hospital specific dummies are not reported.
[b]Standard errors are in parentheses below the estimates.
[c]***-Significant at 1% confidence level.

APPENDIX

TABLE A2

First-Stage Instrumental Variable Regressions[a,b,c]

Independent Variables	Ln (Admissions)	Ln (Occupancy Rate)	Ln (Case Mix Index)	Ln (Outpatient Visits)
Ln(Beds)	0.17*	-0.89***	0.03	1.26***
	(0.086)	(0.12)	(0.03)	(0.31)
Ln(Wage Rate)	0.27***	0.32***	-0.095***	0.39*
	(0.056)	(0.074)	(0.018)	(0.20)
Teaching Hospital	-0.0014	0.009	-0.00075	0.0015
	(0.0044)	(0.006)	(0.0014)	(0.016)
Public Hospital	0.006	-0.05***	-0.00025	-0.017
	(0.008)	(0.01)	(0.00025)	(0.028)
For-Profit Hospital	-0.05***	0.009***	0.0016	-0.07**
	(0.0098)	(0.01)	(0.003)	(0.035)
$Ln(Beds)^2$	0.014	-0.095***	0.017***	0.036
	(0.012)	(0.015)	(0.0037)	(0.042)
$Ln(Wage Rate)^2$	-0.005*	0.005	0.003***	-0.13
	(0.0029)	(0.004)	(0.0009)	(0.010)
Ln(Predicted Admissions)	0.73***	0.40***	0.17***	-0.45
	(0.081)	(0.11)	(0.026)	(0.29)
Ln(Standard Error of Predicted Admissions)	0.03***	-0.05***	-0.0035**	-0.02
	(0.0043)	(0.006)	(0.0014)	(0.015)
$Ln(Predicted Admissions)^2$	0.14***	-0.15***	-0.014	0.125***
	(0.0043)	(0.006)	(0.014)	(0.015)
Ln(Predicted Admissions) x Ln(Beds)	-0.15***	0.19***	-0.029***	-0.097***
	(0.007)	(0.009)	(0.0022)	(0.025)

APPENDIX

TABLE A2

First-Stage Instrumental Variable Regressions[a,b,c]

Independent Variables	Ln (Admissions)	Ln (Occupancy Rate)	Ln (Case Mix Index)	Ln (Outpatient Visits)
Ln(Predicted Admissions) x Ln(Wage Rate)	-0.06***	-0.05***	0.0027	-0.0004
	(0.008)	(0.011)	(0.0026)	(0.03)
Ln(Beds) x Ln(Wage Rate)	0.055***	0.021*	0.011***	-0.052*
	(0.0087)	(0.012)	(0.0028)	(0.03)
Physicians Per Capita	0.062***	-0.063***	0.017***	0.055
	(0.0097)	(0.013)	(0.003)	(0.035)
HMOs	0.002	0.16***	0.021***	-0.003
	(0.004)	(0.005)	(0.0013)	(0.014)
Any Insurance Coverage	-0.21***	0.12***	-0.033***	0.255***
	(0.015)	(0.02)	(0.0047)	(0.053)
Medicare Enrollment, Part A	-0.27***	0.37***	0.13***	0.07
	(0.063)	(0.083)	(0.02)	(0.23)
Total Number of Deaths	0.072***	-0.103***	0.004	-0.04
	(0.013)	(0.017)	(0.004)	(0.045)
Per Capita Income	-0.24***	0.43***	0.12***	0.19***
	(0.017)	(0.022)	(0.005)	(0.06)
Total Population	0.43***	-0.17***	0.096***	0.66**
	(0.056)	(0.022)	(0.018)	(0.20)
Percent Non-White	-0.12***	0.18***	0.043***	0.12**
	(0.014)	(0.02)	(0.0046)	(0.05)
Percent Less Than Age 15	0.45***	-1.49***	0.017	-0.75**
	(0.087)	(0.12)	(0.027)	(0.31)

APPENDIX

TABLE A2

First-Stage Instrumental Variable Regressions[a,b,c]

Independent Variables	Ln (Admissions)	Ln (Occupancy Rate)	Ln (Case Mix Index)	Ln (Outpatient Visits)
Percent Greater Than Age 65	-0.32***	0.27***	0.04	0.41
	(0.08)	(0.11)	(0.025)	(0.29)
Herfindahl Index, Beds	0.03	-0.07	-0.004	-0.18
	(0.03)	(0.044)	(0.01)	(0.12)
Unemployment Rate	-0.15***	0.16***	0.019***	0.044**
	(0.006)	(0.008)	(0.002)	(0.02)
R^2	0.52	0.34	0.39	0.046
F-statistic	970.07***	469.53***	580.88***	43.57***
Number of Observations	26323	26323	26323	26323

[a]Standard errors reported in parentheses below parameter estimates.

[b]*-significant at 10% confidence level; **-significant at 5% confidence level; ***-significant at 1% confidence level.

[c]Estimates for hospital-specific dummies and time dummies are not reported.