

A New Approach to Hospital Cost Functions and Some Issues in Revenue Regulation

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An important aspect of hospital revenue regulation at the State level is the use of retroactive allowances for changes in the volume of service. Arguments favoring non-proportional allowances have been based on statistical studies of marginal cost, together with concerns about fairness toward non-profit enterprises or concerns about various inflationary biases in hospital management. This article attempts to review and clarify the regulatory issues and choices, with the aid of new econometric work that explicitly allows for the effects of transitory as well as expected demand changes on hospital expense. The present analysis is also novel in treating length of stay as an endogenous variable in cost functions.

We analyzed cost variation for a panel of over 800 hospitals that reported monthly to Hospital Administrative Services between 1973 and 1978. The central results are that marginal cost of unexpected admissions is about half of average cost, while marginal cost of forecasted admissions is about equal to average cost. We obtained relatively low estimates of the cost of an "empty bed." The study tends to support proportional volume allowances in revenue regulation programs, with perhaps a residual role for selective case review.

Introduction

During the last decade, hospitals have become subject to increased regulation of revenue and expenses. The Federal Economic Stabilization Program (ESP) of the early 1970s attempted to limit price increases for all hospitals. Subsequently, regulatory agencies at the State level, affecting about one third of community hospitals, have implemented more detailed rules for allowable revenue increases. Ginsburg and Wilson (1979) and Hamilton *et al* (1980) have usefully described the rules and procedures used in selected States.

In theory, regulation of hospital revenue is justified by the growth of cost-based, third-party reimbursement insurance which, unlike indemnity insurance, lowers the user price of service below social opportunity cost. This justification for market intervention differs from the more traditional concerns about monopoly exploitation which underlie economic regulation of communication, electric power, and

other "utilities." In practice, a major feature of current hospital revenue regulation that differs from public utility pricing is the following: hospital rates are generally not fixed independently of the volume of service that is actually realized. For example, a hospital which experiences a 10 percent increase (decrease) in admissions may be retroactively allowed only a 5 percent increase (decrease) in revenue.

This paper reviews, criticizes, and clarifies some of the arguments used in prospective and, especially, retrospective adjustment of allowable revenue. These policy discussions rely on statistical evidence that the marginal cost of hospital care is less than the average cost. We use a novel approach and present new evidence on cost behavior which explicitly recognizes transitory and expected volume changes. This research implies that retrospective volume adjustments, even if ideally implemented, are primarily suited to canceling windfall financial gains and losses for individual hospitals, rather than controlling growth of volume or total expense. However, we find the concerns about transitory gains and losses to be less than compelling. Finally, we present new and much lower estimates of the costs of empty hospital beds that are expected to remain unused.

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Policy Issues

More than a dozen published studies of hospital cost variation may be cited for evidence that marginal cost (MC) of a hospital admission or inpatient day is less than average cost (AC). Lipscomb, Raskin, and Eichenholz (1978) compiled results of such studies, suggesting a ratio MC/AC near .9 in cross-sectional data, compared to .5 when time-series data are used. One influential study by Lave and Lave (1970), using a pooled time-series of individual hospitals, found MC/AC in a range around one-half.

Lipscomb *et al* argue on the basis of these results that the ESP during 1972-1974 "created strong incentives for volume expansion." The principal regulation of the ESP was that hospitals could not obtain revenue increases greater than 6 percent due to price changes. Maintaining a constant revenue per day of care was allowable, so it appears that a typical hospital faced $MR > MC$ for additional days of care to charge-paying patients.

The validity and practical importance of the argument by Lipscomb *et al* are open to serious doubts. On the basis of the cost function studies, it appears that at a breakeven price (equal to average cost), hospitals would always have a financial incentive to expand in volume, since price would exceed marginal cost. This incentive would occur even in the absence of the price regulation.¹ Regulation may increase the incentive to generate inpatient volume if third-party agencies such as Blue Cross and Medicare, who now pay on the basis of *ex post* reasonable cost, would be forced to pay regulated charges set equal to average financial requirements *ex ante*.² The ESP did not force such a change, nor do some of the State programs reviewed by Hamilton *et al*.

There are reasons to suspect that volume growth incentives may not be of much practical importance in affecting total hospital expenses. For one thing, growth in volume has played only a small part in past cost increases. The growth rate of inpatient days *per capita* for short-stay hospitals was 1.30 percent per year for 1966-1971, up only modestly from the longer-run average rate of 1.08 percent for 1946-1966. Occupancy rates peaked in 1968 and have declined steadily to the present. Most recently, between 1976 and 1979, inpatient days *per capita* and beds have grown remarkably slowly at -.09 percent and .18 percent per year, respectively.³ These small increases oc-

¹The generation of volume of service discussed here is not due to price or quality inducements. Instead, the argument envisions such practices as discretionary admitting of emergency and clinic patients for overnight observation.

²According to Bauer (1978), one of the reasons hospitals have supported mandatory revenue controls is the expectation of obtaining more favorable reimbursement from the cost-based payers.

³These data are based on Table 1 in A.H.A. *Hospital Statistics*, 1980 Edition.

curred even though the passage of Medicare and Medicaid probably made it easier for hospitals to raise total revenue by increasing volume. Growth in the volume of patients served has never been a major factor in the alarming inflation of inpatient expenses, and its aggregate importance has been declining, probably regardless of revenue regulation.

Two other arguments for retrospective adjustment of allowable revenue deal with the non-profit status of most hospitals. The first argument is concerned with issues of fairness. Since there are no shareholders earning a return for taking risks, it may seem fair to insulate hospital employees and customers from temporary losses and consequent dislocations due to volume declines. As a corollary, it would then seem fair to reclaim financial gains from hospitals that experience increased volume when $P > MC$. Even if volume cannot be manipulated directly (that is, by means other than price and quality of offered service), demand changes are somewhat foreseeable and only partly unexpected. The fairness argument applies most readily to unexpected demand changes. The econometric analysis of the next section shows that the cost effects of expected and unexpected changes in demand can indeed be distinguished for research purposes. However, in the practice of regulation, these distinctions present a difficult problem which will receive more attention toward the end of the paper.

A second argument is concerned with incentives in non-profit hospitals. Suppose a hospital has a financial gain due to volume increase when $P > MC$. Since there are no shareholders to receive dividends or to appreciate a build-up of reserves, the non-profit firm might "splurge" these gains on tangible goods and services which increase future costs of operation. This process may contribute to a historical growth of costs as volume increases slowly but steadily. When volume declines, however, the result may not be symmetrical. The threat that a hospital may close due to insolvency is likely to generate public sympathy and rescue attempts. The net effect of these responses to volume change would be a sort of "ratchet" movement toward higher cost per patient. (In other words, there would be some sporadic movement upward, but no offsetting declines.)

If the ratchet hypothesis is valid, it implies that cost per patient is inefficiently high, not necessarily that the volume of patients is too high. Controlling the financial impact of changes in volume may reduce the ratchet effect. However, some changes in volume are more permanent and foreseeable than others. Regulators concerned about aggregate cost and aggregate volume will not want to prevent competitive changes in market share or redistribution due to differential population growth. We will return to the discussion of regulatory strategy after developing relevant conceptual and empirical foundations.

Model of Hospital Cost Variation

A satisfactory model of hospital cost behavior should explain the puzzle resulting from past empirical studies—namely, that short-run marginal cost, SMC, appears to be well below average cost at all levels of output, while in cross-sectional studies which approximate the long run, marginal cost (LMC) is more nearly equal to AC. The problem is this: since less input variation is possible in the short run, SMC cannot always be less than LMC.

The puzzle can be resolved by recognizing a rational response to demand uncertainty when even variable inputs such as labor are essentially fixed over meaningful intervals of time. A hospital may adapt to periods of unusually high demand by permitting the quality of service and/or worker morale to deteriorate. Quality reductions would be reflected by crowding or by delays in responding to patient requests for service. Worker morale may fall as the pace of work increases or vacations and days off are canceled. Such declines would eventually have unfavorable consequences to the enterprise, such as a lower price obtainable for a given average demand level, reduction in physician "good will," or a "shortage" of workers at current wage rates.

If there are these unobservable "latent penalties," hospitals would maintain what appears to be short-run excess capacity, and use this capacity to reduce the level of such penalties. However, demand changes over time would cause hospitals to gradually revise their expectations, leading to a shift of the short-run cost curves. Comparing hospitals with permanently different average levels of demand will therefore indicate higher marginal costs than comparing costs over time for hospitals subject to unexpected or transitory demand variations.

For econometric purposes, one may not assume that inputs were hired to produce, at lowest cost, the particular levels of output actually observed. Instead, one might assume that inputs have been hired to minimize *ex ante* expected costs, averaging over all possible demand levels, and including the latent penalties when demand exceeds a planned level. The problem of qualitative deterioration appears applicable beyond hospitals, but it has not received much attention in the general economics literature. The authors (1981) have tested the latent penalty model for hospitals successfully against an alternative traditional model in which firms pay high prices in "spot markets" for inputs to prevent quality deterioration when demand is unusually high.

The present paper offers more detail on the methods used to implement the latent penalty model and provides substantial new results by considering the length of inpatient stay to be an endogenous variable of interest. It will be assumed that cost depends on a forecasted level of admissions, as well as on the actual level of admissions and other influences such as

bed size class, case-mix, service mix, and input prices. Since the market area of the hospital was not identified in the data set, market-level demand variables could not be used to make admissions an endogenous variable subject to "smoothing" by hospital managers. This sort of smoothing behavior will be tested, however, in the variation of length of stay.

The following definitions are needed to develop the econometric model, with subscripts *i* pertaining to a particular hospital and *t* pertaining to a particular time interval.

- TC_{it} = total cost incurred
- B_{it} = inpatient beds
- Q_{it} = forecasted admissions
- q_{it} = actual admissions
- S_{it} = average length of stay in days
- W_{it} = wage rate of non-physician workers
- P_{it} = price index for other hospital inputs
- X_{it} = vector of service-mix characteristics
- μ_i = hospital-specific real costliness due to unobserved variables, constant over time
- e_{it}, U_{it}, V_{it} = random disturbances

In this study, we will not observe the diagnostic mix of patients. Following Lave and Lave (1970, 1978), we use multiple time-series observations. This permits us to estimate a separate constant term for each hospital as a control for case-mix and other unobserved cost determinants. Also, we assume that the unobserved determinants affect real inputs used per case treated. Therefore we estimate deflated average cost functions of the following form:

$$\frac{TC_{it}}{P_{it} \cdot q_{it}} = \mu_i + f(B_{it}, Q_{it}, q_{it}, S_{it}, W_{it}/P_{it}, X_{it}) + U_{it}$$

More specifically, we assume that purely fixed cost, deflated, is proportional to the capacity for ad-

missions, $\frac{B_{it} \cdot d}{S_{it}}$ where *d* is the number of days in

the time interval, and S_{it} is exogenous. Note that average fixed cost is therefore proportional to the inverse of the occupancy rate. Quasi-fixed costs, fixed for one period only, are proportional to Q_{it} . Therefore, letting $IOCC_{it}$ be the inverse of occupancy rate, average deflated cost in the simplest case is

$$(1) \quad ADC_{it} = \mu_i + \alpha \cdot IOCC_{it} + \beta \cdot Q_{it}/q_{it} + \gamma \cdot \frac{W_{it}}{P_{it}} + \delta \cdot X_{it} + U_{it}$$

Because latent penalties of a high level of admissions relative to the forecasted level cannot be observed, the statistical average cost is not "U-shaped." The principal extension of this model will be to include S_{it} as a jointly determined variable. Also, the bed capacity B_{it} will be added as a separate variable shifting the average cost function. Unchanging characteristics of the hospital such as affiliation with medical schools or urban location need not be specially addressed when the hospital-specific term μ_i is included.

The method used for estimating equation (1) is known as the "demeaned" regression technique. The mean of equation (1) for hospital i is subtracted from each observation before calculating the regression coefficients. With a relatively large number of time periods, this method converges to the variance-components method of Balestra and Nerlove (1966). We do not, however, take the further step of actually calculating μ_i for each hospital because these constants serve no further conceptual purpose.

Using equation (1), we estimate marginal cost as follows. We multiply both sides of the equation by q_i to give total cost. SMC is the derivative of this function with respect to q , holding Q constant. By contrast, LMC is the total derivative with $dq = dQ$, meaning that the actual output variation is accurately foreseen. Therefore, it is easily shown that

$$\begin{aligned} \text{SMC} &= \text{AC} - \alpha \cdot \text{IOCC} - \beta \cdot Q/q; \\ \text{LMC} &= \text{SMC} + \beta \cdot Q/q. \end{aligned}$$

These marginal costs will be calculated at the means of the variables and expressed as a percentage of AC.

There is more than one way to consider the cost of bed capacity in this model. The difference between LMC and AC is a measure of purely fixed capacity costs, including beds and other determinants of fixed cost. This amount, divided by the number of beds per admission, gives an average fixed cost per bed. However, bed capacity may also shift the variable cost function (either up or down). This type of cost of an extra bed may be calculated by differentiating TC with respect to B . We refer to this calculation as the "annual cost impact" of a bed.

Data Resources

The principal data source for this project is a file of monthly reports by 870 hospitals to Hospital Administrative Services (HAS), a commercial service of the American Hospital Association (AHA). The data set contained 72 monthly reports for each hospital, covering the entire six years from 1973 to 1978. The *HAS Guide for Uniform Reporting (1977)* published a description of the coding of the monthly reports. We supplemented the HAS data for each hospital with information on geographic region, SMSA size, teaching status, and ownership status.

Hospitals contract voluntarily for the HAS program, and, moreover, we selected only hospitals with complete reporting for the entire six year period. For these reasons, the sample of 870 hospitals is not random or representative of hospitals in the nation. After inspection of basic characteristics of the sample, we find the sample conducive to a variety of important econometric tasks. Major features of the sample are described in tables in Technical Note A.

Table A1 shows that our sample includes relatively more non-profit and relatively fewer investor-owned hospitals than are found in the general AHA survey. It may be that the investor-owned hospital group has sharply different managerial behavior and case-mix. Proprietary institutions also tend to be smaller in bed capacity. To the extent that we do not fully capture the technology and case-mix differences in measured variables, our results may not be applicable to proprietary hospitals.

Table A2 shows that the sample is not distributed across geographic regions with the same relative frequencies as the entire industry. The sample is somewhat more concentrated in the northern region of the Midwestern States (closer to AHA headquarters!) and somewhat less concentrated in the West and Southwest. Nevertheless, the sample size in each region is large enough to suggest that the effects of regional location can be adequately controlled for econometric analysis.

Table A3 shows that the sample includes relatively more large hospitals and fewer small hospitals than the general industry. Again, because the sample includes meaningful numbers of small hospitals, we can adequately study differences in behavior depending on size.

The sampling issue most difficult to fully resolve is the issue of self-selection. By subscribing to HAS, a hospital reveals that it has the managerial capability for extensive data reporting and fruitful use of HAS publications comparing categories of hospitals. These hospitals may differ from others in the way they perceive and respond to volume changes, inflation, technology and case-mix. One suspects that these hospitals are more effective in attaining their organizational goals. In particular, they may perceive more accurately and adapt more rapidly to permanent changes in demand. If such is the case, operating costs for these hospitals as compared to the industry should, for example, rise more strongly with permanent increases in output and more weakly with transitory increases. The policy implication of this sample self-selection is by no means disturbing—a sample with relatively more competent management is appropriate for developing standards in reimbursement.

Detailed edit checks on 320 data items revealed many cases of missing entries, negative numbers, and large "jumps" over time. These problems appeared to result as hospitals corrected errors or omissions in one month by making alterations in the next month's data. Since a month is probably shorter than the period of contractual commitments anyway, these problems largely disappeared when we aggregated from months to quarters and aggregated cost and service categories. We also excluded particular variables from further analysis.* The following examples

*We only rejected 40 hospitals due to unreliable data. Region, ownership, and size of these hospitals were not significantly different from the overall sample.

are indicative of the editing process. We effectively smoothed occasional large entries in catch-all categories such as "employee benefits" by aggregating from months to quarters. We reduced discrepancies among hospitals in accounting for their hours and expense by aggregating categories of expense and hours. The measure of "laboratory workload units" involves many unexplainable missing entries. Therefore, we could not use this variable.

Because hospitals may differ substantially in the degree to which physician services are included in the budget, we created cost measures in two variants—either including or excluding the physician cost entries. All cost measures exclude the service categories for education and non-operating activities (categories 39, 40, 55 in the *Guide*) but include reported capital costs.

We used the following variables to study the explicit effect of service mix on hospital costs.

- ICU = days in intensive care units as a proportion of total days of care
- SURG = visits to the operating suite per admission
- OUTP = outpatient clinic visits per admission
- RAD = radiation procedures per admission
- SPEC = selected specialty service per admission, including dialysis, respiratory therapy, and physical therapy.

We computed an internal wage index (WAGE) for each hospital and deflated both total cost and WAGE by HCFA's national input price index (reported in Freeland, Anderson, and Schendler, 1979). We made quarterly interpolations using a constant ratio to CPI quarterly rates.

Volume Forecasts

In general, one would expect the time series of quarterly admissions to display seasonal variation, autocorrelated random disturbances, and perhaps a deterministic time trend. There are various methods to untangle these influences to forecast demand, and, in addition, there are some models of expectation formation that have useful applications in research. Of course, the method used by each hospital for its own planning is not observed.

Our present approach is to assume that forecasted demand is obtained by fitting a simple structural model to experience and extrapolating with a method of minimum average prediction variance. Nelson (1973) is a useful reference on this topic. In this approach we avoid the more rigid "adaptive expectations" models which used fixed-weighted averages of past output levels. We still assume that the only information available and relevant for demand forecasting is demand experience. Such an assumption is defensible for a stationary random process over a relatively short period of time.

Define S_t as the seasonal factor for sample quarter t , so that

$$S_t = \sum_{j=1}^4 f_j D_{jt}$$

where each D_{jt} is a dummy variable corresponding to one of the seasons and is zero unless quarter t belongs to season j . Then for a stationary process,

$$q_t = qS_t + U_t$$

where U_t is a normally distributed random variable, and q is constant over time.

We assume a first-order autocorrelation in the error term, that is,

$$U_t = \rho U_{t-1} + e_t$$

where ρ is less than unity in absolute value, and e_t is the random noise component. The autocorrelation process is an effective way to capture what appears to be trend or drift in the demand series over time. Including a deterministic time trend offers little extra insight into the demand process.

We first fit the simple structure just described to a random sample of 25 hospitals, including a wide range of hospital size and geographic region. The results are presented in Table A4 in the Technical Note. The diversity among the estimates was striking, so we could not justify pooling the observations. Even within geographic regions, the sign and size of seasonal factors were not uniform. The autoregressive parameter varied widely, although in 15 cases it exceeded 0.6 in value. Compared to the winter quarter, seasonal differentials exceeding 5 percent were quite common, and eight institutions had some seasonal differentials of 10 percent or more. Although these parameters could be estimated with relatively acceptable standard errors, it would appear that the pure noise component is typically 20 to 40 percent of demand variance. For these reasons, we employed a procedure that would estimate different demand parameters for each hospital.

The best forecast using the structural model described above is the following:

$$E[q_t] = qS_t + \rho(q_{t-1} - qS_{t-1})$$

where the autocorrelation of disturbances is explicitly used to project future discrepancies from seasonally adjusted average volume. Table 1 presents an example of this forecasting for a 295 bed hospital.

TABLE 1
Illustration of Demand Fluctuation and Fitted
Stochastic Model

Hospital Characteristics: Non-Governmental,
 Non-Profit, New England, 295 Beds

Observation		Actual Admissions (q)	Expected Admissions (Q)	q-Q/Q
1	1973:1	2,602		
2		2,625	2,514	4.4%
3		2,488	2,492	-.2
4		2,476	2,540	-2.5
5	1974:1	2,564	2,571	.3
6		2,424	2,479	-2.2
7		2,390	2,309	3.5
8		2,417	2,451	-1.4
9	1975:1	2,424	2,517	-3.7
10		2,382	2,352	1.3
11		2,322	2,270	2.3
12		2,324	2,389	-2.7
13	1976:1	2,498	2,432	2.7
14		2,433	2,419	.6
15		2,160	2,317	-6.7
16		2,252	2,241	.5
17	1977:1	2,330	2,367	-1.6
18		2,215	2,266	-2.3
19		2,070	2,118	-2.3
20		2,225	2,159	3.1
21	1978:1	2,293	2,342	-2.0
22		2,171	2,232	-2.7
23		1,921	2,078	-7.6
24	1978:4	2,068	2,023	2.2

Fitted Model

Seasonals: Spring = -4%, Summer = -8%,
 Autumn = -2%
 Autocorrelation Coefficient = .92
 R² = .84
 Standard error of noise component = 74

The fit of the demand process model for this particular hospital is better than the average of 25 sample hospitals. But even so, prediction errors of 2 to 3 percent are relatively common, and there are two cases of error greater than 5 percent. The size of these errors and the changes in demand from quarter to quarter are large enough, in comparison with net revenue margins of hospitals, to warrant serious attention.

Cost Function Results

The initial results in Table 2 are estimates of regression equation (1). The most striking result is the large size of the "quasi-fixed" cost coefficient ($\beta = 526$) relative to purely fixed costs and average total cost of 872. Since the value of β is the difference between SMC and LMC, the striking size of the estimated coefficient reconciles some of the differences in past research.

While the purely fixed cost appears low, there is evidence of a small but statistically significant effect of beds on variable costs. Hospitals with more beds had slightly higher average cost. Inclusion of this variable also helps control for the rather well-understood association of large hospitals with both high occupancy rates and more costly mix of services and diagnoses. Separate cost functions within bed-size classes (for example, 100 to 200 beds) are available from the authors, who found some minor differences in coefficients.

The coefficient of the wage index is quite low in Table 2. Other price indexes vary over time, but not among the particular hospitals. When ordinary regression is used without separate constant terms, the wage coefficient exceeds 100. It appears, therefore, that the coefficient of WAGE in the demeaned method may not be appropriate for use out of this context.

TABLE 2
Hospital Cost Function with Exogenous Length of Stay
 (Dependent Variable: Deflated Average Cost per Admission, 1972 Dollars, Mean 872)
 (All coefficients are significant at the .01 level unless starred.)

Independent Variables	Variable Mean	Regression Coefficient "Demeaned" Method
Forecast/Actual		
Admissions	1.008	526
IOCC	1.40	9
BEDS	251	.37
WAGE, deflated	3.23	5
ICU	.04	409
SURG	.46	104
OUTPAT	2.63	1.6
RAD	3.91	*
SPEC	3.68	2.5
Time in Quarters		8.8
		R ² = .49
		d.f. = 18244

IOCC is the inverse of the occupancy rate; WAGE is the payroll expense per manhour, deflated by a national hospital input price index varying over time; ICU is the proportion of total days spent in intensive care units; SURG is the number of operating room procedures per admission; OUTPAT is the number of clinic visits per admission; RAD is the number of radiation procedures per admission, and SPEC is the number of specialty services per admission, including such services as dialysis treatments and respiratory therapy.

The results show a substantial pure time trend. The service intensity and real wage variables all incorporate trends of their own, but the independent time trend is about 4 percent per year. This represents growth in real inputs that is industry-wide, such as sophisticated monitoring equipment, disposable supplies to prevent spread of infection, employees with more training, etc. A cost function analysis cannot explain such secular changes. We observed that the HCFA input price index was not as volatile as the CPI over the sample period. However, when we substituted the CPI in the regression analysis, the strong independent time trend remained.

An important purpose of this paper is to determine if estimated marginal cost of an admission is affected by the statistical treatment of length of stay. The mean stay is a characteristic of hospital service which may be varied in response to changing admission demands in relation to capacity and staffing levels.

We formulated a model with endogenous mean stay S as follows:

$$(2a) \text{ ADC} = f(\text{IOCC}, Q/q, S, \dots) + U$$

$$(2b) S = h(Q/q, Z) + V$$

where IOCC has been recalculated to measure fixed cost with non-varying S .⁵ Also, U and V are random disturbances, and Z is a vector of exogenous variables that do not shift the cost function.

In equation (2b) we expect a negative effect of q on S and therefore a positive coefficient of Q/q . This reflects either rationing of space, revenue stabilization behavior, or both. Alternative motives could be tested with market area data allowing demand to be held constant. If the random components U and V are uncorrelated, the model is recursive, and each equation may be estimated separately by ordinary least squares. The recursive model results for equation (2a) appear in the left column of Table 3.

In the more general case of simultaneous determination of ADC and S , equation (2a) can be identified from the data if there are appropriate instrumental variables denoted Z in equation (2b). We developed the following instrumental variables: share of obstetrical admissions in total admissions, ratio of outpatient revenue to total revenue in ancillary departments, and emergency and clinic revenue per visit. We used these variables in a two stage least squares estimation reported in the right column of Table 3.

The marginal cost of a day of care differs substantially between the two methods. If one has confidence in the instrumental variables, then the TSLS results are more valuable because they allow for unobserved correlated shocks to both cost and days of care. The problem is that almost any variable postu-

TABLE 3

Average Cost with Endogenous Length of Stay
(Demeaned Regression Method, All Coefficients
Significant at .01 Level Unless Starred)
Dependent Variable: Deflated Average Cost per Ad-
mission (1972 Dollars, Mean 872)

Independent Variables	Recursive	
	Model ¹	TSLS ²
IOCC ³	*	48
Forecast/Actual		
Admissions	402	300
Mean Stay	58	84
BEDS	.1	*
WAGE	5	6
ICU	433	429
SURG	72	64
OUTPAT	1.4	1.2
RAD	*	-.01
SPEC	1.2	8.2
Time in Quarters	10	10.2
R ²	.55	
d.f.	18243	

¹In the recursive model, mean stay affects average cost, but the converse does not hold. Moreover, random components of the two variables are assumed independent.

²Two-stage least squares; the average cost function is identified by the absence of variables affecting mean stay, such as obstetrical admissions.

³This variable is computed using the 24 quarter average mean stay rather than the actual level in each period.

lated to affect S may arguably affect cost per case—for example, obstetrical admissions might be cheaper.

Other results differ remarkably between the two columns. Fixed costs are relatively higher in the TSLS column, and "quasi-fixed" costs are correspondingly less. A direct effect of beds on variable cost appears in one case but not the other. We presently view the TSLS results as slightly superior from a methodological standpoint⁶

Table 4 presents a summary of the major implications of the regression analyses. Treating the length of stay as endogenous has a substantial effect on perceived short-run cost of an admission but little effect on LMC. This is a strong indication of the smoothing effect of changes in stay. The various implications about fixed cost are least plausible in the recursive model results. In either case, the marginal cost ratio for days of care is rather close to the SMC ratio for admissions. This is somewhat unexpected, since a marginal admission could have some high initiation costs, such as for tests and supplies and specialist employee time, while a marginal day at the end of a stay is presumed to be much less resource intensive.

⁵The variable IOCC measures the capacity to treat admissions of the normal type experienced. Since the effect of varying S will be picked up as a separate variable, "capacity" is defined by the average S experiences over the whole time period.

⁶The separate regression for length of stay is not reported here in detail. The major finding was an elasticity of .4 for the effect of Q/q on S . Other contributing influences had much smaller effect.

TABLE 4
Marginal Cost for Admissions or
Days of Care as a Proportion of Average Cost
and Pure Bed Capacity Costs
 (All computations are made at sample mean values.)

	Mean Stay		
	Exoge- nous	Recursive Model	TSLs
Cost of Admissions			
SMC/AC	.38	.54	.58
LMC/AC	.98	1.00	.92
Cost of Day of Care			
MC/AC		.47	.69
Annual Fixed Cost per Bed ¹	\$631	0	2432
Annual Cost Impact of a Bed ²	\$3818	909	2432

¹Dollar values are in terms of 1972 HCFA input price index.

²Defined in text by the derivative of total cost with respect to beds.

The final quantitative implications pertain to the cost of an empty bed, where the "cost impact," calculated by the total derivative method described earlier, includes the effect of beds on variable cost as well as fixed cost. Ruling out the recursive model results as implausible, a result in the range of \$2,400 to \$3,800 appears dramatically lower than the estimate of \$17,210 (both figures in 1972 values) endorsed by the National Academy of Sciences (1976).

We have discussed the cost of an empty bed in the context of regulatory decisions to close facilities or restrict new construction. Our estimates, using existing institutions and reported historically-based costs, are relevant to the question of the gain from closing beds in current facilities. These gains may not be very much, and the costs, including reduced safety margins and competition, should not be overlooked. However, our cost data are less relevant to decisions on restricting new construction or entry into the market.

Concluding Thoughts on Regulatory Policy

Two simple options for revenue regulation are either to treat all volume changes as transitory by using an allowance of 40 to 60 percent of average cost for changes in admissions or to permit a full proportional allowance.

The proportional method is administratively simpler, allows hospitals to eventually accommodate rising demand at constant quality, and encourages speedy adjustment to lasting declines in demand. The non-proportional method cancels financial windfall gain or loss, but lasting increases in demand may then be met by lower quality, while lasting declines permit higher quality.

A more complete model of hospital management could be used to explore these options, in conjunction with other programs. For example, the major thrust of cost containment is to restrain cost per patient below what it would be in response to insurance coverage and technical change. If this restraint is vigorous, the ratchet effect of transitory demand change becomes less important, because it is more difficult to translate temporary gains into permanent changes in reimbursable expense.

We recognize that many authorities continue to posit "demand creation" as a costly phenomenon to be addressed by a variety of regulations and by stimulation of prepaid physician risk-sharing plans. A selective case review method would be direct and relatively neutral in its effect on managerial response to changing market conditions. Our view is that if hospital revenue regulation is continued, non-proportional volume adjustments constitute a relatively unattractive method of addressing concerns about inappropriate utilization.

This paper has employed one method of sorting out transitory from expected changes in demand. In practice, hospital managers and regulators may develop more sophisticated forecasts and approved targets. The direct method of asking hospitals to give a demand estimate for the purpose of setting prospective prices may lead to strategic misrepresentation. In view of our findings of nearly proportional cost change for expected demand changes, the simple alternative of proportional volume adjustment allows some short-run gains or losses, but these are essentially unexpected amounts having no incentive effect on resource allocation.

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Technical Note

TABLE A1
Control of Hospital, Relative Frequency

	Sample (Size 871)	AHA, 1976
		Annual Survey
Government, Non-Federal	21.2%	30.8%
Non-Government, Non-Profit	78.3%	56.5%
Investor-Owned	.5%	12.6%

Source: A.H.A., *Hospital Statistics 1977 Edition*.

TABLE A2
Census Region of Hospitals, Relative Frequency

	AHA, 1976	
	Sample	All Non-Federal
New England	6.3%	5.5%
Middle Atlantic	11.4	12.3
South Atlantic	16.3	13.9
East North Central	28.1	15.6
East South Central	4.7	7.7
West North Central	13.5	12.9
West South Central	7.7	13.5
Mountain	6.2	5.8
Pacific	5.7	12.6

TABLE A3
Hospital Bed Capacity, Relative Frequency

	AHA, 1976	
	Sample	All Community Hospitals
Under 100 Beds	19.7%	48.8%
100-199	24.3	23.3
200-299	19.7	12.1
300-399	14.7	6.4
400-499	9.0	3.9
500 and Over	12.4	5.2

TABLE A4
Stochastic Model of Demand, Fitted to 25 Hospitals

Hospital	Region	Beds	P	Seasonal Factors			R ²
				Spring	Summer	Autumn	
1	1	302	.91	-.05	-.03	-	.90
2	1	297	.92	-.04	-.08	-.02	.84
3	2	275	.45	-.07	-	+	.35
4	2	262	.93	-.03	-.03	+.03	.93
5	2	174	.53	-.09	-.07	+	.56
6	2	530	.76	-.06	-.02	+	.75
7	3	130	.81	-.03	+.03	+	.71
8	3	80	.65	-	+	+	.48
9	3	139	.51	-.08	-	-	.49
10	3	140	.65	-.11	-	-	.60
11	4	475	.90	-.03	+	+.04	.80
12	4	319	.17	-.05	-.07	-	.47
13	4	166	.40	-.03	+	+.03	.59
14	4	213	.44	-.09	-.08	-.06	.58
15	4	157	.84	+	-	+	.70
16	4	382	.46	-.06	+	+	.57
17	4	79	.82	-.10	-.06	-.07	.72
18	4	290	.81	-.05	-	-.04	.61
19	5	60	.42	-.14	-.09	-	.67
20	6	128	.03	-.16	-.14	-.13	.73
21	6	517	.79	-	.04	+	.62
22	6	25	.62	-.10	-	-	.44
23	6	25	.08	-	-.10	-.13	.16
24	7	95	.84	-.05	.10	+	.86
25	7	130	.81	-.15	-	-.10	.68

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