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2

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Hospital Utilization: An Analysis of SMSA Differences in Occupancy Rates, Admission Rates, and Bed Rates

> *. . . The national surplus of hospital beds by no means contradicts the fact that there are frequent shortages in particular communities at particular times.*
>
> The New York Times, *Editorial, August 26, 1971*

ABSTRACT: This study examines the determinants of regional differences in the utilization of short-term general hospitals in Standard Metropolitan Statistical Areas (SMSAs) in 1967. Three interrelated dependent variables are used: the bed rate (the number of beds per thousand population), the occupancy rate (the proportion of days in the year the average bed is occupied), and the admission rate (the number of admissions per thousand population). ¶ The analyses of the occu-

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pancy rate and the bed rate are largely based on the existence of short-run (stochastic) variations in the demand for hospital care. Because of the costs of constructing and maintaining rarely used capacity and the costs associated with delayed treatment due to insufficient capacity, the randomness of demand for care is an essential ingredient in hospital planning. The empirical analysis indicates that the hospital sector appears to respond to the short-run variations in demand, to the cost of delayed treatment, and to a positive income elasticity of demand for available hospital beds. ¶ Beds in different hospitals are now imperfect substitutes for each other. Hospital facilities could be used more efficiently by coordinating admissions among hospitals in an SMSA and by removing artificial barriers to admission in particular hospitals (e.g., veteran status). With the existing stock of beds, a coordinated admissions policy would give the average SMSA an excess bed capacity in all but one week in about thirteen years. This would appear to represent "too much" capacity. ¶ The analysis indicates that hospital admission rates are greater in SMSAs where there is more hospital and surgical insurance coverage, more unused capacity (lower occupancy rate, greater bed rate), more surgeons per capita, an absence of HMOs, and more nonwhites. The presence of nonsurgical MDs is apparently not related to hospital admissions.

[1] INTRODUCTION AND SUMMARY

Introduction

The level and distribution of hospital services are a matter of continued public interest. Concern stems from such considerations as the adverse effects of delayed treatment arising from insufficient hospital bed capacity, on the one hand, and the cost of maintaining unused beds, on the other.[1]

Utilization of nonfederal short-term general and specialty hospitals in the United States has been in an uptrend in the post-World War II period, as shown in Table 1. Admissions jumped from one for every 10 persons in the population during the late 1940s to one for every 6.7 persons by the early 1970s. At the same time the number of beds in such hospitals increased dramatically relative to the population. Hospital bed occupancy rates (the proportion of days in the year the average bed is occupied) continued a steady postwar rise, generating fears of shortages, till 1969, after which they started a downward trend, partly because of a decline in the average length of stay.[2] This increase in hospital utilization is of especially great interest because hospital costs have been growing rapidly over time: the American Hospital Association reported that the average daily cost of

TABLE 1 Utilization of Short-Term General and Specialty Nonfederal Hospitals, Selected Years, 1946 to 1974

Year	Admissions (per thousand population)	Beds (per thousand population)	Occupancy Rate (percent)	Average Length of Stay (days)
1946	96.6	3.4	72.1	9.1
1950	109.9	3.3	73.7	8.2
1955	115.6	3.5	71.7	7.8
1960	127.1	3.6	74.6	7.6
1965	136.2	3.8	76.0	7.8
1967	135.8	4.0	77.7	8.3
1970	142.8	4.1	78.0	8.3
1974	155.5	4.4	75.3	7.8

SOURCES: 1946 to 1960: *Historical Statistics of the United States from Colonial Times to the Present.* U.S. Bureau of the Census, 1965, Series A-1, B-198, 208, 251, 252.
1965 to 1970: *Statistical Abstract of the United States, 1972.* U.S. Bureau of the Census, 1972, Tables 2, 104, 107.
1974: American Hospital Association.

NOTE: The same definitions are used throughout the time series.

caring for patients in short-term general hospitals was $105 in 1972, or nearly double the 1966 cost.[3]

Average values for the United States mask substantial regional differences in the parameters of hospital utilization (see Table A-4 in the appendix). For example, among the forty-eight coterminous states in 1971, the number of admissions to nonfederal short-term general hospitals per thousand population was less than 125 in five states (Delaware, Idaho, Maryland, New Jersey, Rhode Island) and in excess of 185 in three states (Montana, North Dakota, and West Virginia).[4] There was also substantial variation in the relative number of nonfederal short-term general hospital beds—seven states had 3.5 or fewer beds and ten states had 5.0 or more beds per thousand population. Occupancy rates for these beds ranged from a low of 61 percent in Wyoming to a high of 83 percent in New York. Although hospital bed occupancy rates are declining nationally, alleged regional maldistributions and political and economic pressures still exist to induce or retard hospital construction.[5]

Summary

This study develops an economic framework for analyzing the utilization of short-term general hospitals in a region.[6] The three interrelated dimensions of utilization explicitly under study are the annual occupancy rate (OR), the annual admission rate (admissions per thousand population, ADMS*), and the bed rate (beds per thousand population, BEDS*).[7] The theoretical equations for explaining regional differences in hospital utilization are discussed in section 2 and estimated empirically in section 3.

In the empirical analysis, Standard Metropolitan Statistical Areas (SMSAs)[8] serve as my unit of observation for two reasons. First, SMSA borders are designed to represent population centers and are clearly better suited for this purpose than city, county, or state boundaries. It seems reasonable that this is also true for "health" regions. Potential patients, doctors, and hospital administrators are presumably concerned more with "reasonable commutation distances" than with city or county boundaries.[9] Second, the data needed for this study are generally available on an SMSA basis and form a sufficiently large sample (192 observations). To my knowledge this is the first time SMSAs are used as units of observation in an econometric analysis of several interrelated parameters of short-term hospital utilization. Individuals (microdata), hospitals in a particular geographic area, or states have served, instead, as units of observation in previous U.S. studies.

The model assumes that hospitals vary neither the direct money fees they charge patients nor their total bed capacity in response to short-run variations in the demand for admissions, but that they do take these variations into account when determining the long-run level of prices, beds, and occupancy rates. Costs are incurred from constructing and maintaining beds that are unoccupied (excess capacity). In addition, there are also costs of a different nature from delaying or denying admissions because of a lack of unoccupied beds. The latter costs include the greater pain and suffering, increased probability of death or permanent disability, and greater curative costs arising from delayed treatment. Other things being the same, the greater the proportion of unoccupied beds, the smaller the probability of an admission being denied because of hospital crowding. This means that there is an efficient level below 100 percent for the average annual bed occupancy rate.

The randomness of the short-run demand for admissions is an essential aspect of the analysis of occupancy rates and bed rates. If there is an increase in the relative fluctuations around the expected level of the short-run demand for admissions, the probability that a desired admission will be denied can remain the same if the average occupancy rate is smaller and the bed rate greater. Using the binomial theorem, it is shown that the short-run fluctuations in demand for hospital care are greater relative to the average demand the lower the admission rate, the smaller the size of the population, and the lower the substitutability of beds among hospitals.

Empirically, the average occupancy rate is positively related to the admission rate. A 10 percent higher admission rate is associated with a 2.4 percent higher occupancy rate. Similarly, we find that more populous

SMSAs do maintain higher occupancy rates and have fewer beds per capita—they appear to make more efficient use of hospital facilities. For example, a fourfold increase in the population from 300,000 (Albuquerque, New Mexico) to 1.2 million (Denver) would lead to a 7.7 percent increase in occupancy rates without increasing the probability that a desired admission will be delayed or denied. This can come about through increased admissions, a longer length of stay, or a reduction in the bed rate.

Beds can be viewed as perfect substitutes for each other in the same hospital, but as less than perfect substitutes for beds in other hospitals because of limited physician affiliations and imperfect communication of bed vacancies, among other reasons. This suggests that for the same number of beds, the larger the number of hospitals is in an SMSA the lower the average substitutability of beds for each other and the lower the occupancy rate will be.

If hospitals in an SMSA coordinated their admissions and acted as if they were one, the occupancy rate in the average SMSA could be increased by 3.5 percent, with no increase in the probability of denying an admission. This would permit a higher rate of utilization of the existing facilities or a reduction in the bed rate. However, the appropriate policy need not be the physical merging of hospitals, since there may be diseconomies of scale and additional transportation costs associated with one large central hospital compared with several small neighborhood hospitals. What is suggested, instead, is that the substitutability of beds in different hospitals could be increased by a coordinated information system on bed vacancies and admissions. Current computer technology is adequate for this coordinating function, and multiple hospital affiliations among doctors make it a realistic procedure.

Institutional barriers to patient entry also tend to reduce the substitutability of beds in different hospitals. For example, an artificial distinction exists between federal and nonfederal (state and local, proprietary and voluntary) hospitals because of special requirements for the use of the former (e.g., veteran status). If these requirements were eliminated, the number of beds per capita could be reduced.

The hospital sector apparently does respond to the cost of delaying admissions. With admission rates held constant, SMSAs with a greater proportion of emergencies in their case mix—heart attacks, strokes, accidents, et cetera—appear to maintain a greater number of beds per capita.

What is the probability that all the hospitals in an SMSA will be at full capacity and will have to deny some admissions? According to our estimates the probability that a weekly hospital occupancy rate will reach 100 percent in an SMSA is 0.15 percent, or one week out of about thirteen years. Although an optimal rate is not computed, this estimate seems very low. If it is not biased, it suggests that the 1967 levels of occupancy may have been below an efficient level, possibly because of the poor communication of bed availability among hospitals in an SMSA. For the United States as a whole, average bed occupancy rates fell from 78 percent in 1967 to 75 percent in 1974 (see Table 1), suggesting even greater inefficiency in hospital utilization.

The analysis of hospital admissions assumes that potential patients are responsive to the price of hospital care. Hospital admission rates are higher where there is more insurance coverage for hospital and surgical care, presumably because insurance lowers the direct cost to the patient of hospital expenses. The presence of an HMO (Health Maintenance Organization) reduces the admission rate in an SMSA, perhaps because of the incentive on the part of the HMO physicians and administrators to substitute less costly out-of-hospital care and to engage in less surgery than physicians in a fee-for-service practice. It appears that HMOs may go hand in hand with fewer hospital beds per capita through affecting the admission rate, rather than through a more direct route.

More surgeons per capita are associated with a higher admission rate, possibly for the following reasons: surgeons migrate to regions with a higher demand for their services, the presence of more surgeons reduces the price of operations, and surgeons create a demand for their own services because of poor information on the part of patients. By contrast, the presence of nonsurgical physicians appears to be unrelated to the volume of hospital admissions.

Hospital administrators and physicians tend to deal with short-run variations in the demand for admissions on the basis of the urgency of "need" for hospitalization rather than on the basis of money price. Empirically, we find that admission rates are lower when hospitals are more crowded, that is, when the occupancy rate is higher or when there are fewer beds per capita for the same occupancy rate (elasticity 0.34).

Climate is an important determinant of the demand for hospital care. For example, the higher mean January temperature in Washington, D.C. (37° F) compared to Boston (30° F) can account for a 7.6 percent lower admission rate, and a 1.6 percent shorter length of stay.

The income or wealth of an area also plays a role in its health sector. Hospital admission rates are lower in wealthier SMSAs (elasticity −0.7), possibly because of better health or the greater purchase of preventive medicine or out-of-hospital care. Yet, with admission rates held constant, there is a positive income elasticity of demand for a lower probability of a denied or delayed admission. This is reflected empirically in a higher bed rate in wealthier areas (income elasticity +0.25).

The analysis provides a confirmation of "Roemer's Law"—that an increase in the stock of beds results in these beds being occupied. An exogenous 10 percent increase in beds raises the admission rate by 3.4 percent and the length of stay by 4.9 percent, and reduces the occupancy rate by 1.7 percent. Thus, 83 percent of the expanded bed capacity becomes occupied.

The analysis can also be used to examine the relation between the presence of nonwhites in an SMSA and the parameters of hospital utilization. Nonwhites have a higher admission rate and a longer length of stay than whites, presumably because of their poorer health and their greater use of public hospitals where length of stay is longer. However, there is apparently no relation between the percent nonwhite in an SMSA and the bed rate. As a result, hospitals are more crowded in areas with a greater proportion of nonwhites. At this stage of research it is not known, unfortunately, whether this greater crowding is shared equally by the whites and the nonwhites in these areas.

[2] THE THEORY

Introduction

A theoretical model for explaining regional differences in the utilization of short-term general hospitals is developed. Three measures of hospital utilization are explicitly treated as endogenous or dependent variables: the annual occupancy rate, the annual admission rate, and the bed rate. The annual occupancy rate (OR) is the proportion of days in the year in which the average hospital bed in the area (SMSA) is occupied. That is, it is the ratio of the total number of patient days of hospital care divided by the product of 365 and the number of beds (OR = PD/(365) BEDS). The annual admission rate and the bed rate are the number of hospital admissions per year and the number of hospital beds, per thousand of population in the area, respectively.

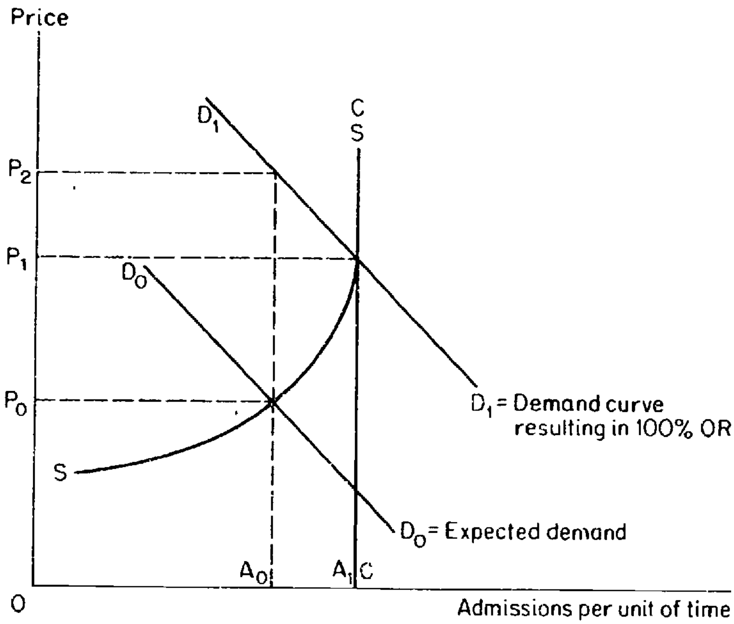
The Framework

Our analysis of hospital utilization assumes the existence of both short-run and long-run markets for hospital care. In the short run the bed rate in an SMSA is assumed to be inelastic because of the large fixed costs of adding bed capacity. However, in the long run the supply curve of hospital beds in an SMSA is assumed to be perfectly elastic in the relevant range.[10]

Figure 1 shows the short-run supply and demand for hospital admissions in an SMSA with a fixed number of beds.[11] The price of an admission to the patient is not just the fees for the room, board, and other services provided by the hospital. It encompasses a broad price concept, including the value of the extra discomfort, loss of earnings, and curative costs caused by a delayed admission and the poorer quality of service that may arise from crowded hospital conditions. At a higher price fewer admissions are demanded.

The height of the short-run market demand curve in an SMSA *at a moment in time* is a function of systematic and random elements. The systematic variables include the demographic characteristics of the population, the extent of health insurance coverage, et cetera. At a moment in time, at each price of admission, each individual has a probability of "demanding" an admission. The random element in the short-run demand for admissions is due to the aggregation across individuals of the outcome of this random process. Thus, the short-run market demand curve fluctuates randomly about its expected value. The curves D_0D_0 and D_1D_1 in Figure 1 are two short-run demand curves.

FIGURE 1 Short-Run Supply and Demand for Hospital Admissions



NOTE: SS = short-run supply curve
D_0D_0 and D_1D_1 = short-run demand curves
CC = hospital capacity (100% OR)
$\frac{OA_0}{OC}$ = supply occupancy rate at price P_0

If it is assumed that the bed rate and average length of stay are constant in an SMSA in the short run, the price-inelastic line CC in Figure 1 represents a 100 percent occupancy rate—capacity utilization—of hospital beds. If there were no fluctuations in the demand for hospital admissions, hospitals could maintain a 100 percent bed occupancy rate each day. Then CC would be the short-run supply of admissions. However, a 100 percent daily occupancy rate need not be efficient if there are fluctuations in demand and if there are costs associated with a delayed or denied hospital admission. The larger the relative random fluctuation in the demand for admission and the relative cost of a delayed or denied admission are, the greater the efficient amount of unused capacity is on the average day so as to satisfy the demand for admissions in all but 100α percent of the time periods.

Hospital administrators and doctors are assumed to respond to a rise in the short-run demand curve for admissions by increasing the number of admissions and hence the occupancy rate. However, higher bed occupancy rates are costly—the marginal cost of providing hospital care increases as the hospitals approach capacity utilization. Hence, the short-run supply curve is upward rising and is assumed to be perfectly inelastic at a 100 percent bed occupancy rate.[12]

Suppose, for example, the short-run demand curve is D_0D_0 in Figure 1 and the short-run shadow price and number of admissions are P_0 and A_0, respectively. Because of random factors the short-run demand curve shifts to D_1D_1. For the same number of actual admissions A_0, the new demand curve implies a higher shadow price of an admission P_2. The higher shadow price would arise from the greater proportion of potential patients who are denied, or given a delayed, admission.[13] However, at this high shadow price hospitals will supply more admissions and increase the occupancy rate. The new equilibrium in response to the increase in the short-run demand curve to D_1D_1 is at P_1, A_1, which represents a higher price and quantity of admissions than in the initial equilibrium.

An occupancy rate equation is developed later (see equation 21 and Table 2) in which SMSA differences in occupancy rates are specifically related to SMSA differences in the factors that result in fluctuations in the short-run demand for admissions. An admission rate equation is also developed (see Table 3) to analyze the effects of SMSA variations in the systematic factors determining the demand for admissions.

In the long run the bed rate in an SMSA is not constant. The demand curve for hospital beds in an SMSA is a function of two aspects of the demand for admissions. The first is the demand for beds to satisfy the long-run systematic demand for admissions. The second is the demand for beds to satisfy the randomly fluctuating short-run demand for admissions in all but 100α percent of time periods ($\alpha < .50$). At a higher shadow price

TABLE 2 Occupancy Rate Equation (dependent variable: the natural log of the occupancy rate, lnOR)

Explanatory Variable	Symbol	Predicted Sign
Randomness model variables		
1. Admission rate	ADMS'	+
2. Square root of inverse of population	$\sqrt{\frac{1}{POP}}$ = SPOP	–
3. Square root of number of hospitals	SQHOSP	–
Bed stock variable		
4. Bed rate	BEDS'	–
Length of stay variables		
5. Percent nonwhite	%NWHT	+
6. Percent change in population	%CHPOP	–
7. Mean January temperature	JANTEMP	–

of admission fewer admissions and hence fewer beds are demanded (see Figure 2). For the reasons indicated above, the long-run supply of hospital beds in an SMSA is assumed to be perfectly elastic. Thus, in the long run, the observed bed rate is a function of the long-run systematic demand for hospital admissions, the amplitude of the short-run fluctuations in the demand for admissions around the long-run expected level, and the height of the horizontal supply curve for hospital beds. The equation for the long-run demand for beds is developed below (see equation 25 and Table 4).

Randomness of Demand for Admissions The maintenance of a hospital bed and its auxiliary equipment and personnel is costly. If a known constant number of beds were demanded each day in each hospital, occupancy rates of less than 100 percent would represent wasted resources. Since there is fluctuating demand for hospital services, however, the presence of "unused capacity" on the average day in an area may be efficient—up to a point, vacant beds *are* a productive resource. The extent to which hospital utilization rates do, in fact, respond to fluctuations in the demand for admissions is a major aspect of our analysis.

Other studies, to be sure, have used the randomness of admissions as a basis for analyzing hospital occupancy rates.[14] This study, however, differs from the others in terms of (1) the specification of the randomness model (including the effects of population size and number of hospitals), (2) the treatment of the admissions variable as endogenous rather than exogenous,

TABLE 3 **Admission Rate Equation (dependent variable: admissions per thousand population, ADMS*)**

Explanatory Variable	Symbol	Predicted Sign[a]
Supply shift variables		
1. Natural log of occupancy rate	lnOR	–
2. Bed rate	BEDS*	+
Insurance variable		
3. Hospital and surgical insurance per capita	HI	+
Income variable		
4. Median family income	INC	?
Medical sector variables		
5. Nonsurgical MDs per thousand population	GENMD*	?
6. Surgical MDs per thousand population	SURG*	+
7. Insurance-nonsurgical MD interaction	(HI)(GENMD*)	?
8. Insurance-surgical MD interaction	(HI)(SURG*)	?
9. HMO	HMO	–
10. Medical students per hundred thousand population	MST*C	+
State of health variables		
11. Mean January temperature	JANTEMP	–
12. Percent of the population nonwhite	%NWHT	+
13. Mortality per thousand population	MORT*	+
14. Demographic variables (age and sex)		

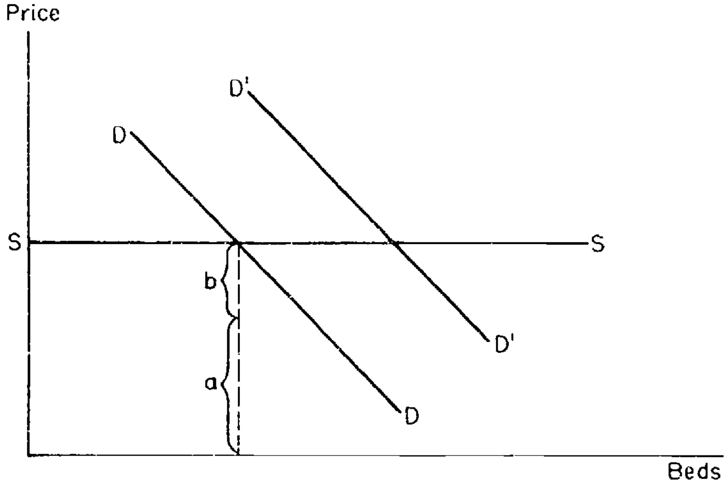
[a]Question mark indicates ambiguous sign.

and (3) the application of the model to regional differences in hospital utilization rather than to hospital differences within an area.

Let us specify an accounting period of D days, where D days may be one day, seven days, or 365 days. In the time period of D days an individual is either admitted to a hospital or he is not.[15] That is, "admission to a hospital" is a dichotomous variable for an individual. Let N_t designate the observed number of admissions in an area in time period t, and POP designate the size of the population. Then, N_t/POP is the observed admission rate in the area for the time period t, D days in length.

Let p designate the long-term admission rate in the area, that is, the admission rate in the statistical universe. The expected number of admissions is E(N) = p(POP). The observed number of admissions in any one

FIGURE 2 Long-Run Supply and Demand for Hospital Beds



NOTE: SS = long-run supply curve
DD and D'D' = long-run demand curves
a = demand for beds to "satisfy" expected number of admissions
b = demand for beds to "satisfy" all but 100α percent of the fluctuating short-run demand for admission

time period, N_t, is a random variable which forms a distribution around the mean E(N).

The number of patient days (PD_t) of hospital care in the time period is the sum across patients of all of the lengths of stay. The number of patient days (PD_t) can be thought of as the average length of stay (LS_t) multiplied by the number of admissions (N_t). If the mean length of stay does not vary across time periods, the expected number of patient days is

$$(1)\quad E(PD) = E[(LS)(N)] = \overline{LS}(p)(POP)$$

Using the binomial formula, the variance across time periods in patient days is

$$(2)\quad Var(PD) = (\overline{LS})^2(POP)(p)(1-p)$$

The coefficient of variation, a commonly used measure of relative variation, is the ratio of the standard deviation to the mean of a variable. The coefficient of variation in patient days is

$$(3)\quad CV(PD) = \frac{SD(PD)}{E(PD)} = \frac{\overline{LS}\sqrt{POP(p)(1-p)}}{\overline{LS}(POP)p} = \sqrt{\frac{1}{(POP)}\,\frac{(1-p)}{p}} = \sqrt{\frac{1}{POP}\left(\frac{1}{p}-1\right)}$$

TABLE 4 Bed Rate Equation
(dependent variable: beds per thousand population, BEDS*)

Explanatory Variable	Symbol	Predicted Sign
A. Expected admissions		
1. Admission rate	P	+
B. Stochastic effect—coefficient of variation		
2. V[a]	V	+
Income variable		
3. Median family income	INC	+
Health sector variables		
4. Percent of beds in federal hospitals	%FEDBED	+
5. HMO	HMO	−
6. Medical students per hundred thousand population	MST*C	+
Demographic variables		
7. Emergency deaths per thousand population	EMERG*	+
8. Percent nonwhite	%NWHT	−
9. Percent change in population	%CHPOP	?[b]

[a] $V = \sqrt{\frac{HOSP}{POP}\left(\frac{1}{p} - 1\right)}$

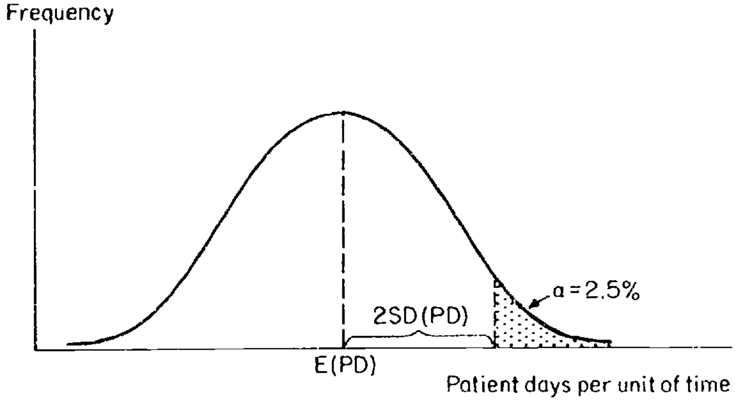
[b] Question mark indicates ambiguous sign.

The relative variation in the number of patient days of hospital care demanded is smaller, the larger the size of the population (POP) and the greater the rate of admission (p).[16]

Using the central limit theorem, if the demand for an admission by one individual were independent of that by others, the demand for patient days in a large area would be normally distributed across time periods, as is shown in Figure 3.[17]

Suppose, however, that individual demands for admission were positively correlated—the probability is higher that Jones will enter a hospital if Smith enters a hospital. This situation arises in the course of epidemic diseases or natural disasters. For the same expected number of admissions the variance in the number of patient days of hospital care demanded is greater (smaller) if individual demands for admission are positively (negatively) correlated. The frequency distribution of patient days is no longer normally distributed, although it may still be symmetric around the mean. With a decline over time in the relative importance of infectious diseases as a cause of hospitalization, there has presumably been a decline in the correlation among individual demand curves for medical care.

FIGURE 3 Frequency Distribution of Patient Days of Hospital Care



NOTE: f = normal frequency distribution
$Z_\alpha = 1.96 \approx 2.0$, for $\alpha = 0.025$
$2\,SD(PD) \approx Z_\alpha SD(PD)$

Let us make the simplifying assumption that individual demands for hospital admissions are statistically independent of each other. Then the variation across time periods in the number of patient days demanded is normally distributed. In order to have a sufficient number of beds to satisfy demand for admission for, say, 97.5 percent of the time periods, the number of beds in an SMSA should exceed the mean number of patient days by approximately twice the standard deviation of patient days.[18] Although during the average period of D days there are "unused" beds, these beds are fully used (occupied) during about 2.5 percent of the time periods.

Let us designate α as the probability that the number of patient days of hospital care demanded in the time period of D days exceeds the capacity (number of beds times the number of days in the time period) of the hospitals.[19] The standardized normal variate $Z\alpha$ indicates that the number of beds is sufficient for all but 100α percent of occurrences. Here, and in Figure 3, $\alpha = 0.025$ and $Z_\alpha \approx 2.0$.

The number of beds a community requires to satisfy the demand for patient days, in 100α percent occurrences is

$$(4) \quad B = [E(PD) + Z_\alpha SD(PD)]\,\frac{1}{D}$$

That is, for only 100α percent of occurrences will the number of patient days demanded in the time period D exceed

$$E(PD) + Z_\alpha SD(PD)$$

Factoring out E(PD) and rearranging terms,

$$(5) \quad \frac{BD}{E(PD)} = 1 + Z_\alpha CV(PD)$$

The expected bed occupancy rate (OR) equals $\frac{E(PD)}{(B)(D)}$ if the number of beds is assumed fixed. Then,

$$(6) \quad OR = \frac{E(PD)}{(B)(D)} = \left[\frac{1}{1 + Z_\alpha CV(PD)} \right]$$

Taking natural logs and using the relation that $\ln(1 + a) \approx a$ when a is small,[20]

$$(7) \quad \ln OR = -(Z_\alpha) CV(PD)$$

Substituting equation (3) into equation (7),

$$(8) \quad \ln(OR) = -Z_\alpha \sqrt{\frac{1}{POP} \left(\frac{1}{p} - 1\right)}$$

According to equation (8), the occupancy rate is positively related to the size of the population, the admission rate, and the proportion of occurrences in which the demand exceeds the supply of beds (α).[21] This provides us with two measurable explanatory variables for inter-SMSA differences in occupancy rates: population size and the admission rate.

When a bed is vacated it is not always immediately reoccupied by another patient, even if there is queuing for beds. The bed may be vacated too late in the day for the next patient to arrive, or the bed may be reserved for a day or two for a patient who is expected to arrive.[22] The "use rate" of a hospital bed shall be defined as the occupancy rate plus the proportion of days of potential occupancy lost because of a late discharge or bed reservation. Data on bed use rates do not exist. However, the concept of "use" without occupancy may influence the relation between the admission rate and the occupancy rate.

The total number of bed days used in an SMSA in a year is the sum of the bed days of occupancy and the bed days "consumed" by lags between successive occupancies. That is, in time period t,

$$(9) \quad USE_t = N_t \overline{LS}_t + N_t LG_t$$

where LG_t is the lag in filling a bed per admission. The use rate (UR) is obtained by dividing equation (9) by (365)(B), or

$$(10) \quad UR_t = \frac{USE_t}{365(B)} = OR_t + \frac{N_t LG_t}{365(B)}$$

Since $N_t = (p_t)(POP)$, and at full capacity the use rate equals unity, differentiating UR_t with respect to p_t at full capacity when B is constant,

$$(11) \quad \frac{\partial UR}{\partial p} = \frac{\partial OR}{\partial p} + \frac{POP}{(365)(B)} \left(p \frac{\partial LG}{\partial p} + LG_t\right) = 0$$

Rearranging the terms, the marginal effect of the admission rate on the occupancy rate is

$$(12) \quad \frac{\partial OR}{\partial p} = \frac{-POP}{(365)(B)} LG_t(1 + e)$$

where e is the elasticity of the lag per admission (LG_t) with respect to the admjssion rate (p_t).

If on average a lag between admissions exists ($LG_t > 0$) and if this lag is invariant with respect to admission ($e = 0$), at "full capacity" the measured occupancy rate will be less than 100 percent, and a higher admission rate implies a lower occupancy rate. As long as the elasticity of the lag with respect to admissions is larger in algebraic value than minus unity (i.e., $e > -1$, so that $(1 + e) > 0$), at full capacity occupancy rates decrease with an increase in admissions.

Thus, it is hypothesized that, ceteris paribus, occupancy rates rise with increases in the admission rate up to a very high level of occupancy, beyond which further increases in the admission rate may have no effect, or a negative effect, on the occupancy rate.

Returning to equation (5), by rearranging terms we can write

$$(13) \quad B = \frac{E(PD)}{D} [1 + Z_\alpha CV(PD)]$$

and after taking natural logarithms and using the approximation $\ln(1 + a) \approx a$,

$$(14) \quad \ln B = \ln\left(\frac{E(PD)}{D}\right) + Z_\alpha CV(PD)$$

Substituting for the expected value and coefficient of variation in patient days,

$$(15) \quad \ln\left(\frac{B}{POP}\right) = \ln\left(\frac{LS}{D}\right) + \ln(p) + Z_\alpha \sqrt{\frac{1}{POP}\left(\frac{1}{p} - 1\right)}$$

The first two terms on the right hand side of equation (15) show the relationship between the systematic variables and the bed rate B/POP, while the last term shows the relationship between the randomness of admissions and the bed rate.

Coordination among Hospital Beds Thus far, the model has implicitly assumed that all hospital beds in an area (here an SMSA) are equally good substitutes for each other. This assumption of the absence of segmentation in the hospital sector is unrealistic for several reasons.

First, there may be differentiation among hospitals in the demographic characteristics of the patients they will admit. For example, short-term general hospitals are differentiated on the basis of age (children, geriatrics), sex, and veteran status.

Second, patients may view beds in different hospitals as being imperfect substitutes for each other. This would arise because of real or perceived differences among hospitals in social and physical amenities, religious affiliation, distance from the home of the patient or his relatives, et cetera.

Third, hospital beds may be imperfect substitutes for one another because physicians have a limited number of hospital affiliations. Patients tend to "choose" a hospital on the basis of their physician's affiliations rather than choose a physician on the basis of his hospital affiliations.

The less-than-perfect substitutability among hospital beds has an implication for the utilization of hospital resources. It can be shown theoretically that, ceteris paribus, the smaller the substitution among hospital beds, the less efficient the utilization of hospitals will be as measured by a lower occupancy rate and a higher bed rate.

Suppose two SMSAs have the same population, admission rate, and desired α. The communities differ, however, in that SMSA A has one hospital ($H_A = 1$), whereas SMSA B has k identical hospitals ($H_B = k$), one for each of the k demographic groups and each serving 100/k percent of the population. By substituting equation (3) into equation (13) for community A,

$$(16)\quad B_A(D) = E(PD)\,(1 + Z\,CV(PD)) = E(PD)\left(1 + Z\sqrt{\frac{1}{POP}\left(\frac{1}{p} - 1\right)}\right)$$

For community B,

$$(17)\quad B_B(D) = k\left[\frac{E(PD)}{k}\left(1 + Z\sqrt{\frac{1}{\frac{POP}{k}}\left(\frac{1}{p} - 1\right)}\right)\right]$$

$$= E(PD)\left(1 + (\sqrt{k})Z\sqrt{\frac{1}{POP}\left(\frac{1}{p} - 1\right)}\right)$$

where $k > 1$. Thus, B_B is larger than B_A. Recalling equation (8), the natural log of the occupancy rate for community A is

$$(18)\quad \ln OR_A = -Z\sqrt{\frac{1}{POP}\left(\frac{1}{p} - 1\right)}$$

Therefore, for community B,

$$(19)\quad \ln OR_B = -Z\sqrt{\frac{1}{\frac{POP}{k}}\left(\frac{1}{p} - 1\right)} = (\sqrt{k})(-Z)\sqrt{\frac{1}{POP}\left(\frac{1}{p} - 1\right)} = (\sqrt{k})\ln OR_A$$

Since the natural log of a number smaller than unity is negative and $OR_A < 1.0$, $OR_B < 1.0$, and $k > 1$,

$$\left.\begin{aligned} &\ln OR_B < \ln OR_A \\ \text{or}\quad & \\ (20)\quad & OR_B < OR_A \end{aligned}\right\}$$

That is, ceteris paribus, because of less efficient pooling of beds, the bed rate would be higher and the occupancy rate lower in the SMSA with more hospitals.

This finding need not imply that there would be efficiency gains from merging all of the hospitals in an area into one hospital. If this merging were done all other factors would not be held constant. It is not clear whether the merging of several small neighborhood hospitals into one central hospital would entail additional social costs. First, there may be an increase in the average distance traveled to and from the hospital by physicians, patients, and also the patient's visitors.[23] These costs should be evaluated not solely on the basis of increased opportunity cost (time cost) of travel to the hospital, but also on the basis of the cost of delay in receiving emergency medical treatment.[24] Second, there is evidence that larger hospitals, other variables held constant, are less efficient in coordinating the myriad of medical and nonmedical tasks performed within hospitals.[25] And there is the frequently asked, but perhaps unanswerable, question of the optimal hospital size in terms of minimum average cost.[26] Finally, there has been a development of capital-intensive but often little-used forms of diagnosis, monitoring, and treatment. Substantial economies may accrue from concentrating this equipment in a small number of large hospitals rather than keeping a proliferation of expensive but underused equipment in many smaller hospitals.

The model developed here does not explicitly address itself to the optimal hospital size. It is, however, addressed to the coordination (communication) among hospitals. Modern data processing techniques can be used to anticipate hospital demands and coordinate admissions so as to reduce bed vacancies.

Occupancy Rate Equation We can now develop the theoretical equations for analyzing regional differences in hospital bed occupancy rates. Combining the models for the randomness of demand for admissions and the imperfect substitution among beds in different hospitals generates the equation for the *ith* SMSA,

$$(21)\quad \ln OR_i = -Z_{\alpha,i}V_i$$

where

$$V = \sqrt{\frac{HOSP}{POP}\left(\frac{1}{p} - 1\right)}$$

and HOSP is the number of short-term general hospitals in the SMSA. The parameter Z_α is the standardized normal variate for the proportion (α_i) of instances in which the demand for beds exceeds the available supply of beds in the *ith* SMSA. Although $Z_{\alpha,i}$ is not directly measurable for an

SMSA, the average value of Z_0 can be estimated by a regression of lnOR on V.[27]

The partial effects on the occupancy rate of each of the measurable components of V can be estimated by regressing lnOR as a linear function of these variables. This formulation (as shown in Table 2) facilitates the inclusion of additional variables in the analysis of occupancy rates.

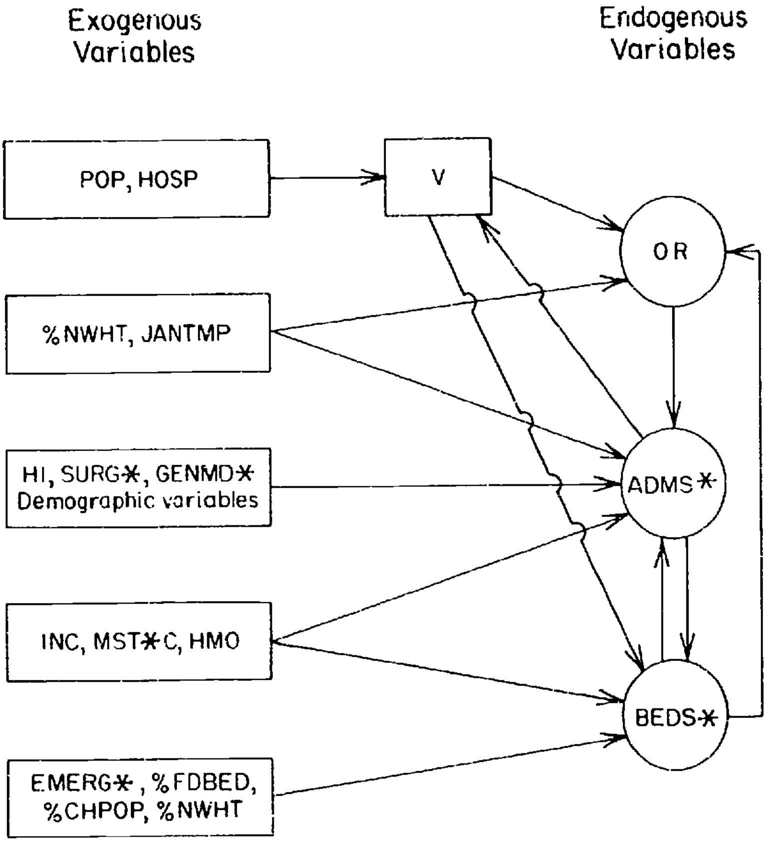
If an SMSA experiences an increase in its bed rate (beds per thousand population), and the SMSA's admission rate and average length of stay remain constant, the occupancy rate will fall.[28] The exogenous increase in the bed rate also tends to increase the admission rate. Therefore, SMSAs with higher bed rates may have higher admission rates and lower occupancy rates.[29] If the bed rate is not held constant, we could observe a spurious negative partial effect of admissions on occupancy rates. Thus, the bed rate (BEDS*) is entered into the occupancy rate equation and is hypothesized to have a negative partial effect.

With the admission rate and bed rate held constant, the occupancy rate is, by definition, a function of the average length of stay. It would be useful to examine the effects on occupancy rates of several variables that may influence the average length of stay. There is, for example, considerable public interest in racial differences in the pattern of utilization of hospital resources. Blacks tend to have a longer average length of stay than whites.[30] This may be due to such factors as poorer health, a greater use of public hospitals because of a lower level of income and wealth, and less desirable housing conditions that make the home a less satisfactory substitute for the hospital in the recuperation period. Then, with the admission rate and bed rate held constant, populations with a greater proportion of nonwhites (%NWHT) would have a higher bed occupancy rate.[31]

Climate is another factor of interest. With the admission rate held constant, SMSAs in colder winter climates are expected to have longer lengths of stay for two reasons. First, since admission rates are higher in colder winter climates,[32] the case mix is expected to be more heavily weighted toward serious cases where the mean January temperature is lower, and more serious cases have longer average lengths of stay. Second, with case mix held constant, patients are likely to be kept in the hospital longer the less amenable the nonhospital environment is to recuperation. Nonhospital care is presumably less productive than hospital care for recuperative purposes in a colder winter climate than in a warmer climate. The partial effect of mean January temperature (JANTEMP) on occupancy rates is hypothesized to be negative.

Finally, the model can be used to test whether more rapidly growing SMSAs (greater annual percent change in population, %CHPOP) have lower occupancy rates. The shorter length of stay may be due to the better health of migrants and the greater attractiveness to migrants of healthier environments.

FIGURE 4 Flow Diagram of the Hospital Utilization Equations



SOURCE: Equations (21) and (25) and Tables 2, 3, and 4.

Table 2 and Figure 4 summarize the theoretical regression equation for the analysis of SMSA differences in short-term general hospital occupancy rates. (A more detailed definition of the variables and data sources are presented in the appendix.) The hypothesized signs for the partial effects of the variables are presented. All of the explanatory variables, except for the admission rate, may be viewed as being caused independently of the dependent variable, the natural log of the occupancy rate.

The admission rate is an endogenous explanatory variable, since it is, in part, a function of the occupancy rate. Given fixed capacity in the short run, the cost of admitting a patient to fill a bed includes the cost associated with the higher probability that a patient with a greater demand for admission (e.g., with an illness in more urgent need of hospital care) will be subject to a delayed or denied admission. The increase in the probability of delaying a more serious case because of a particular hospital admission is zero for low levels of occupancy, but rises as the occupancy rate increases. This results in a more selective admissions policy during periods of higher occupancy rates. That is, less serious cases form a smaller proportion of a hospital's case mix during periods of high occupancy rates.[33]

Since the admission rate is an endogenous variable, it is not appropriate to use ordinary least squares regression analysis for estimating the occupancy rate equation. Instead, the equation is estimated on the basis of two-stage least squares and a predicted admission rate.

Admission Rate Equation Economic, demographic, and institutional variables are used to explain regional differences in the admission rate of short-term general hospitals.

The cost of admitting a patient to a hospital includes the value associated with the increased probability that this admission will delay the potential admission of a patient with a stronger demand for hospital care. it is for this reason that hospitals appear to be more selective in the cases they admit when they are crowded. Medical conditions for which delay in treatment or alternative treatments are less costly are put lower down on the admissions queue during periods of high occupancy rates. Some of those persons whose initial request for an admission is denied will not be admitted subsequently because they receive an alternative form of medical care, have a spontaneous cure (including the discovery that there was no medical problem), or die. Alternative forms of medical care include treatment in the home, specialized hospitals, nursing homes, and hospitals outside the SMSA.[34]

Thus, we expect a negative partial effect of the occupancy rate, an index of hospital crowding, on the admission rate. In addition, with the occupancy rate held constant, more beds per capita in an SMSA imply a larger absolute number of vacancies per capita and hence a lower shadow price for an admission—which results in a larger number of admissions. To test a "beds effect," the bed rate (BEDS*) is entered as an explanatory variable, and is hypothesized to have a positive partial effect on admissions.

It could be argued, however, that a positive partial correlation between the admission rate and the bed rate is not due to more beds causing more admissions, but, rather, to a higher demand for admissions causing more hospital beds to be constructed. This suggests that the bed rate should be viewed as an endogenous variable (determined within the model), not an exogenous variable (determined outside of the model) in an analysis of hospital admissions.

In the short run the bed rate is viewed as fixed, and the hospital admission and occupancy rates are interrelated. In the long run, the bed rate is not fixed and the three variables are interdependent. As the number of beds adjusts to long-run conditions, the occupancy rate may lose some of its variability. (A model is developed below for analyzing SMSA differences in the bed rate.) The analysis of interregional differences in admissions is performed for both a "short-run" model, using a predicted occupancy rate and the observed bed rate as explanatory variables, and a "long-run model," using a predicted bed rate.

It is often argued that the effect of more extensive hospital and surgical insurance coverage is to lower the patients' direct cost of incremental units of medical services and thereby to increase their incentive to purchase more medical services. This increased purchase may be done directly by the patient either through requesting more services or by searching for a doctor who will prescribe these services. It may also occur if the doctor, seeing the lowered direct price to the patient, suggests or provides more medical care. This additional medical care may show up, in part, as a higher rate of hospital admission. Thus, greater hospital and surgical insurance coverage per capita (HI) is expected to be associated with a higher rate of hospital admission.[35]

In some states medical care can be privately purchased on a basis which is not fee-for-service. A health maintenance organization (HMO) provides prepaid group practice services. In consideration for a fee paid in advance (without fee-for-service), an HMO assures the delivery of a broad range of health services, including physician and hospital care.[36]

Since there is no fee-for-service, the clients of an HMO have an incentive to demand more services, including hospital services, than otherwise. The HMO, on the other hand, has an incentive to use the least costly methods of improving its clients' health and to discourage the use of services—subject to the constraint that dissatisfied clients need not renew their HMO subscription. It has been alleged, therefore, that HMO clients receive a higher level of preventive care, greater out-of-hospital curative care, and less in-hospital curative care than those who rely on the fee-for-service system.

This suggests the hypothesis that hospital admission rates are lower, ceteris paribus, in SMSAs in which a larger proportion of the population is in an HMO, but the relevant data are not available. We can, however, construct a dichotomous explanatory variable, HMO, which takes the value of unity for an SMSA in a state in which an HMO exists, and a value of zero if there is no HMO. This HMO variable is hypothesized to have a negative partial effect on the admission rate in an SMSA.

There are several reasons for a relationship between the number of physicians per capita in an SMSA and hospital admissions. First, the greater the relative number of physicians, with demand for their services held constant, the lower the cost and consequently the greater the use of their services.[37] Second, if the supply schedule of physicians' services is held fixed, communities with a higher demand for health care have a larger number of physicians per capita.[38] Finally, it has been alleged that physicians create their own demand. The more physicians per capita, the more medical care received per capita; on the one hand, physicians wish to "fill up" their day, and, on the other, patients place considerable faith in the physician's advice as to the amount and type of medical care that should be purchased.

The effect on hospital admissions of a larger number of physicians depends on whether physicians' services are complementary to or substitutable for hospital services. Surgeons' services are hospital-using. However, it is not clear a priori whether hospital services are substitutes for or complements to the medical care provided by nonsurgical out-of-hospital physicians. Thus, the number of surgeons per thousand population (SURG*) is hypothesized to have a positive partial effect on admissions, but the partial effect of nonsurgical out-of-hospital physicians per thousand population (GENMD*) is not clear a priori. One might ask the question, Does the effect of the presence of a larger number of physicians depend on the extent of hospital insurance coverage? In order to answer it, two linear interaction variables are provided for hospital insurance and physicians—(HI)(MD*) and (HI)(SG*).

The variable median family income (INC) is also included in the analysis. Income may be a proxy variable for health status.[39] Further, it is not clear a priori whether hospital admissions increase or decrease with income, with an initial level of health held constant.[40] At any given level, if preventive or early curative care are less hospital-using than cure at later stages, patients with higher incomes may have a lower admission rate. On the other hand, there may be a positive income elasticity of demand for hospital-using curative medicine. Thus, no prediction is offered as to the effect of median family income on the admission rate.

Hospital admission rates appear to be seasonal; they tend to be higher in the fall and winter than in the spring and summer.[41] Thus, if all other variables that influence hospital admissions are held constant, communities with more severe winters will tend to have higher admission rates. Mean January temperature (JANTEMP) is used as a measure of the severity of the winter and is hypothesized to have a negative partial effect on the admission rate.

Our dependent variable—the admission rate—is defined as the number of admissions in the short-term general hospitals located in a particular SMSA in 1967 divided by the population of the SMSA. An admission rate obtained in this manner is a biased estimate of the hospital admission rate of the resident population of the SMSA. To obtain the population's true admission rate, the admissions of nonresidents who used the SMSA's hospitals should be eliminated while those of residents who entered short-term general hospitals outside the SMSA should be included in the data. Unfortunately, however, it is not possible to make these adjustments. An alternative procedure is to obtain a proxy for the net in-migration of patients. On the assumptions that the net in-migration would be greater the more the SMSA is used as a health center and that an SMSA is more likely to serve as a health center if it has a medical school—especially a large one—the number of medical school students per hundred thousand population (MST*C) is used here as a control variable.

Finally, the probability of hospitalization in a year is related to a person's demographic characteristics—age, sex, and race. Thus, admission rates by SMSA will vary with the demographic composition of the population, and variables are included in the study to capture these effects: the percentage of the population that is female (%FEMAL), the percentages of males and females separately in the age groups 10 to 39, 40 to 54, and 55 years of age and over, the live birth rate (LBR), and the percent of the population that is nonwhite (%NWHT). It would also be desirable to hold constant a measure of the "healthiness" of the SMSA's environment; the mean January temperature captures some of this effect. With family income and demographic composition of the SMSA held constant, the health status of the environment may be highly correlated with the mortality rate (MORT*).

Table 3 and Figure 4 present the admission rate equation and indicate the hypothesized effect of each variable. (A more detailed definition of the variables and data sources are presented in the appendix.)

Bed Rate Equation The models developed above provide a framework for analyzing SMSA differences in the number of short-term general hospital beds. Recall that the model for the randomness of demand for admission to a hospital and the model for the lack of coordination among hospitals (see equations 13 and 17) indicated that we can write[42]

(22) $B(D) = E(PD)(1 + Z_a V)$,

where

$$V = \sqrt{\frac{HOSP}{POP}\left(\frac{1}{p} - 1\right)}$$

Since $E(PD) = (\overline{LS})(p)$, dividing both sides of equation (22) by (D)(POP), taking natural logarithms, and using the relation $\ln(1 + ZV) \approx ZV$,

(23) $\ln(BEDS^*) = \ln\left(\frac{\overline{LS}}{D}\right) + \ln(p) + Z_a V$

where BEDS* is the bed rate. The bed rate is now expressed as the sum of two effects: the demand for beds due to the average (systematic) demand for admissions,

$$\ln\left(\frac{\overline{LS}}{D}P\right)$$

and the demand for beds due to the randomness of admissions, $Z_{\alpha}V$. The demand for beds due to the systematic demand for admissions is smaller the lower the admission rate and the shorter the length of stay. The demand for beds due to stochastic admissions is smaller the higher the admission rate, the larger the size of the population, the smaller the number of hospitals, and the greater the desired proportion of occurrences in which demand for beds exceeds the number of beds available (α).

If we can postulate a relation that explains SMSA variation in α, we can develop additional variables for explaining SMSA variations in the bed rate. What factors, then, could be postulated as being associated with a smaller probability (α) that admissions will have to be delayed because of excessive crowding?[43] It seems reasonable that there would be a positive income or wealth elasticity of demand for a smaller probability of a delayed admission. In addition, greater wealth in a community would facilitate charity capital fund raising and decrease the cost to the community of borrowing funds for the addition of hospital beds. Thus, it is hypothesized that α is a negative function and Z_{α}, therefore, a positive function of median family income in the SMSA. The more important the role emergencies play in an SMSA case mix, the greater the expected cost from a delayed or denied admission. Thus, ceteris paribus, the more important the emergencies, the smaller the desired α and, consequently, the higher the bed rate.[44]

With the admission rate held constant, it can be hypothesized that an SMSA serving as a medical center would prefer a lower probability of rejecting an "interesting" (exotic) case because of a scarcity of beds. In addition, the case mix is likely to contain a higher proportion of more serious illnesses, which have a longer length of stay. The extent to which an SMSA serves as a medical center, measured by the number of medical students per hundred thousand population (MST*C), is hypothesized to be positively related to the bed rate.

The variable for the number of hospitals (HOSP) embodied in the composite explanatory variable V may not fully capture the effect on utilization of differences among hospitals. If beds under different administrative control (government, voluntary, proprietary) were equally good substitutes for one another, the fraction of beds under a given administration should have no effect on the SMSA's overall bed rate. However, if only veterans can use federal short-term general hospitals, the addition of federal hospital beds has a smaller and indirect effect on bed availability for nonveterans than for veterans. The addition of federal hospital beds in an SMSA is expected to increase the total number of beds in the SMSA, but by less than the increase in the number of federal beds. State and local government short-term general hospital beds are good substitutes for beds in voluntary hospitals. Although proprietary hospitals charge higher fees than nonprofit hospitals, there are no other special barriers to patient entry. The proportion of proprietary beds in the total bed census is so small that it is unlikely that SMSA variations in proprietary hospital beds could have a statistically significant effect on the overall bed rate.[45] Thus, it is hypothesized that the "veterans effect" results in a positive relation between the proportion of short-term general hospital beds in federal hospitals (%FEDBED) and the bed rate.

The parameter Z_α can be hypothesized as a function of several other variables. Roemer and Shonick suggest that clients in HMOs have a lower admission rate because HMOs use a "shortage" of beds as a mechanism for restricting hospital admissions.[46] This implies that, with the admission rate held constant, there is a negative relation between our HMO variable and the bed rate.

Since blacks have been subject to discrimination in the provision of other public services,[47] this may be true also of hospital services. In addition, with nonprofit hospitals financed to a large extent by voluntary contributions from wealthy individuals and foundations, any discrimination from these sources against blacks would imply that SMSAs with a larger fraction of the population black or nonwhite (%NWHT) may have a lower bed rate.

Finally, the bed rate in an area is a function of the way its denominator, population, changes. If hospital construction lags behind population growth, the greater the increase in population, the smaller the bed rate. If the community anticipates future demands on the basis of current population growth rates, a positive partial relation would exist between the bed rate and the growth rate of the population (%CHPOP). The population growth rate effect would appear as short-run variations in Z.

The variable Z_α, which is not measurable for individual SMSAs, has been hypothesized to be a function of a set of exogenous explanatory variables. For the sake of simplicity, a linear functional form is postulated,

$$(24) \quad Z = b_0 + b_1 \text{ INC} + b_2 \text{ EMERG}^* + \ldots$$

Substituting equation (24) into equation (23), we can express the bed rate as a function of these exogenous variables:

$$(25) \quad \ln\text{BEDS}^* = \ln\left(\frac{\text{LS}}{\text{D}}\right) + \ln p + b_0 V + b_1 V(\text{INC}) + b_2 (V)(\text{EMERG}^*) + \ldots$$

In equation (25), the partial derivative of lnBEDS* with respect to V, evaluating the other exogenous variables at their means, provides an estimate of Z_α. Since V is positive, the sign of the slope coefficient of the interaction term of V with a variable is the same as the sign of the partial effect of that variable on Z_α and on the bed rate.

Table 4 and Figure 4 present the bed rate equation. (For a detailed definition of the variables and data sources, see the appendix.)

[3] EMPIRICAL ANALYSIS

In the preceding pages structural equations and hypotheses were developed to explain regional differences in short-term general hospital occupancy rates, admission rates, and bed rates. This section presents the empirical estimation of these equations and tests the hypotheses for 1967 hospital utilization data, using SMSAs as units of observation. (The data are described in the appendix.)

Occupancy Rate

The theoretical analysis developed in section 2 of the effect on the occupancy rate of the randomness of the demand for admissions resulted in the equation

$$\ln OR = -Z_\alpha V, \tag{26}$$

where

$$V = \sqrt{\frac{HOSP}{POP}\left(\frac{1}{p} - 1\right)}$$

is measurable, and Z_α is not measurable for individual SMSAs. If the assumptions of the model are valid, the regression of the natural log of the occupancy rate on V will not have an intercept, but will have a negative slope coefficient, the absolute value of which is our estimate Z_α. When the normal distribution is used, the slope coefficient indicates the proportion of occurrences (α) in which the demand for beds in the average SMSA exceeds the available supply of beds.

Table 5 presents the regressions of lnOR on V.[48] The occupancy rate is expressed in ratio form, the mean OR is 0.77, and the admission variable p is the predicted weekly probability of an admission for an individual—that is, the relevant time period is assumed to be D = 7 days. When a linear regression is computed, we cannot reject the null hypothesis that the intercept is zero, which is consistent with our model.

When the regression is forced through the origin, the slope coefficient is negative, is highly significant, and has an absolute value equal to 2.974. With the use of the upper tail of the normal distribution, this value of Z_α

TABLE 5 Analysis of Occupancy Rates (dependent variable: lnOR)

Explanatory Variable	Linear Regression Coefficient	Linear Regression t-Ratio	Regression Forced through the Origin Coefficient	Regression Forced through the Origin t-Ratio
V[a]	−2.409	−6.63	−2.974	−4.43
Constant	−0.051	−1.58	b	b

SOURCE: See appendix.

[a] $V = \sqrt{\frac{HOSP}{POP}\left(\frac{1}{p} - 1\right)}$

where p is the predicted annual admission rate per thousand population divided by 52,000. The admission rate is computed from the reduced form regression with the exogenous variables that enter the admission rate and occupancy rate equations (see Table A-3).

[b] Intercept forced through the origin.

implies $\alpha = 0.0015 = 0.15$ percent. In other words, if an accounting period D of one week is assumed, the demand for beds equals or exceeds the supply of beds, on average, in only 0.15 percent of the weeks.[49]

The value of α can be computed for various time periods (D). For example, on approximately 13 percent of the days some potential patients would be subject to a delayed or a denied admission.[50] These point estimates of α seem reasonable and provide additional support for the model under investigation.

Table 6 presents a linear regression of the natural logarithm of the occupancy rate on the randomness model variables and on four additional variables. The (predicted) admission rate has a significant positive effect on the occupancy rate: the greater the exogenous factors increasing the admission rate are, the higher occupancy rates climb. The elasticity of the occupancy rate with respect to the admission rate is +0.24 at the mean level of admissions.

When hospital admissions are viewed as random events, larger populations have a more stable relative demand for hospital beds and are therefore able to maintain a higher occupancy rate. The variable SPOP, the square root of the inverse of the population of the SMSA in thousands, has a significant negative effect on the occupancy rate. Thus, occupancy rates are higher in more populous SMSAs. As an example, a fourfold increase in the population from 300,000 (Albuquerque, New Mexico in 1970) to 1.2 million (Denver) would lead to a 7.7 percent increase in bed occupancy rates, with no increase in the probability of being denied a hospital admission (α).

The model for imperfect communication of bed vacancies among hospitals predicts that, if beds in different hospitals are not perfect substitutes for each other, the larger the number of hospitals in an SMSA, the lower the

TABLE 6 Two-Stage Least Squares Analysis of Occupancy Rates (dependent variable: lnOR)

Explanatory Variable	Coefficient	t-Ratio
Randomness model variables		
ADMS*[a]	0.0014	2.93
SPOP	-84.511	-5.16
SQHOSP	-0.016	3.26
Bed stock variable		
BEDS*	-0.033	-3.29
Length of stay variables		
JANTEMP	-0.0023	-3.20
% NWHT	0.0014	1.91
% CHPOP	-0.00073	-3.67
Constant	4.671	106.58

SOURCE: The appendix.

[a]ADMS* = predicted annual admission rate per thousand population, computed from the reduced form regression of the admission rate on the exogenous variables in the admission rate and occupancy rate equations. (See Table A-3.)

occupancy rate. The square root of the number of hospitals (SQHOSP) is found to have a significant negative effect on the occupancy rate. If there were perfect communication of bed vacancies, and the hospitals in an SMSA would act as *if* they were one, at the mean (SQHOSP = 3.2) the occupancy rate could be increased by about 3.5 percent without changing the probability of a desired admission being denied.

The same percent increase in the number of hospitals and in the population size leaves unchanged the number of hospitals per capita. The occupancy rate, however, would increase if there were some communication among hospitals as to bed vacancies. Empirically, we find that this is in fact the situation.[51]

To sum up, the statistical significance of the number of hospitals indicates that there is less than perfect substitution of beds among hospitals; on the other hand, the increase in the occupancy rate accompanying a proportionate increase in the population and number of hospitals implies that there is some substitution. Thus, beds in different hospitals appear to be imperfect substitutes for each other.

The bed rate (BEDS*), the number of beds per thousand residents, has a significant negative effect on the occupancy rate. A 10 percent increase in the bed rate decreases the occupancy rate by 1.7 percent. This provides support for Roemer's Law, according to which an increase in the bed rate results in these beds being filled, with little change in the occupancy rate.

The hypothesized negative relation between mean January temperature (JANTEMP) and the occupancy rate is observed. With the predicted admission rate held constant, the colder the winter climate the higher the occupancy rates, presumably due to a longer length of stay. If all other factors were the same, the difference in mean January temperature would imply a 1.6 percent higher annual occupancy rate in Boston (30° F) than in Washington, D.C. (37° F).

The proportion of nonwhites in the SMSAs' population appears to have a weak positive effect on the occupancy rate. This is not due to income effects; when median family income is included in the regression it is not significant and the variable percent nonwhite increases in significance. Nor is it a consequence of a higher nonwhite admission rate, since we control for the effect of nonwhites on the SMSAs' admission rate. It may, however, reflect the longer average length of stay of nonwhites.

Occupancy rates appear to be lower in SMSAs experiencing a more rapid population growth. This may be reflecting a shorter length of stay in more rapidly growing areas.

In summary, our empirical analysis of SMSA differences in hospital bed occupancy rates tends to support the randomness model of the demand for hospital admissions developed in section 2.

Admission Rate Equation

The regression equation developed for explaining SMSA differences in hospital admissions (see Table 3) is estimated simultaneously with the occupancy rate in our "short-run" model—Table 7—and simultaneously with the bed rate in our "long-run" model—Table 8.

Endogenous Explanatory Variable: Occupancy Rate As hypothesized, the regression analysis indicates that the (predicted) occupancy rate has a significant negative effect on the admission rate.[32] A 1 percent increase in the occupancy rate, ceteris paribus, decreases the admission rate by 2 percent (from Table 7, regression 2).

The variable BEDS* also has the expected positive effect on the admission rate. A 1 percent increase in the bed rate is associated with a 0.34 percent increase in the admission rate. Thus, there is a "beds effect"—more beds, ceteris paribus, mean more patients (admissions) to occupy the beds. Since the elasticity is less than unity, the occupancy rate increases or the length of stay decreases in response to an increase in the bed rate. Since it was found above that the elasticity of the occupancy rate with respect to beds is −0.17, the implied elasticity of length of stay with respect to beds is +0.49. Thus, an increase in the number of beds has a 50 percent greater impact on length of stay than on the number of admissions.

The insurance variable (HI)—an estimated (predicted) value of the benefits from hospital and surgical insurance per capita in the SMSA—has a

TABLE 7 Two-Stage Least Squares Analysis of Hospital Admission Rates (dependent variable: ADMS*; N = 192 SMSAs)

Variables	Regression (1) Coefficient	Regression (1) t-Ratio	Regression (2) Coefficient	Regression (2) t-Ratio
Supply shift variables				
lnOR[a]	−324.929	−3.30	338.844	−3.14
BEDS*	11.558	4.36	10.958	4.08
Insurance variable				
HI	2.678	2.44	3.063	2.90
Income variable				
INC	−19.131	−3.43	−19.456	−3.61
Medical sector variables				
GENMD*	−75.026	−.60	b	
SURG*	577.556	2.92	494.515	3.12
HIXMD*	1.858	.78	b	
HIXSG*	−9.799	−2.56	−7.971	−2.69
HMO	−12.796	−1.89	−13.046	−1.91
MST*C	−.067	−.78	b	
State of health variables				
JANTEMP	−1.873	−3.82	−1.862	−3.69
%NWHT	.910	2.22	.891	2.07
%FEMAL	−25.653	−2.53	−26.688	−2.61
MORT*	−3.769	−.93	−3.396	−.82
%M1039	−36.654	−3.43	−37.065	−3.41
%M4054	−51.817	−3.81	−52.166	−3.68
%M55	−30.949	−2.77	−31.873	−2.80
%F1039	37.687	3.41	37.805	3.37
%F4054	54.772	3.70	56.013	3.61
%F55	31.596	2.84	32.197	2.86
Constant	2712.29	3.99	2814.71	4.08

SOURCE: The appendix.
[a]Predicted natural log of the occupancy rate. See Table A-3.
[b]Variable not included.

positive effect on the admission rate.[53] Surgeons (SURG*) have significant positive effects and the insurance-surgeon interaction variable has a significant negative effect. A 10 percent increase in the number of surgeons is associated with a 2 percent higher hospital admission rate.[54] The number of nonsurgical MDs, however, is not correlated with the hospital admission rate. The separate effects of insurance, surgeons, and nonsurgical MDs on admissions are consistent with the model developed in section 2.

The presence of an HMO in the state in which the SMSA is located has a weakly significant negative effect on the hospital admission rate;[55] it reduces the admission rate by 13 (or by 7.6 percent), compared to a mean admission rate of 170 per thousand population. This finding is consistent with the proposition that the different economic incentives of HMO practice have an influence on the admission rate. The variable designed to capture medical center effects on the admission rate—the number of medical students per 100 thousand population (MST*C)—is statistically insignificant.

SMSAs with higher median family income have lower hospital admission rates, with an elasticity at the mean of −0.7. This may reflect the greater efficiency in producing health (for example, via preventive medicine) on the part of those with more education[56] and greater wealth. At the same time, it may also be due to the substitution of less time-consuming out-of-hospital treatment for in-hospital care on the part of those with a higher valuation of time.

A greater proportion of nonwhites in the population of an SMSA is accompanied by a significantly higher hospital admission rate.[57] This finding is consistent with lower levels of health and wealth among nonwhites than among whites—two factors which appear to be associated with a higher hospital admission rate.[58]

Colder winter climates (JANTEMP) are associated with a higher admission rate. A 10 percent drop in the mean January temperature increases the admission rate by 4 percent. The decrease in the mean January temperature from Washington, D.C. (37° F) to Boston (30° F) would raise the admission rate by approximately 13.0 admissions per thousand a year, or by about 7.6 percent of the mean level of admissions. The effects on admissions of climate and the other explanatory variables are not due to regional differences; the partial effects are not significantly altered when regional dummy variables for the South and New England are added to the regression equation.

Eight demographic control variables are included in the regression analysis. SMSAs with a higher proportion of females in the population (%FEMAL) have significantly lower hospital admission rates. The six sex-specific age variables are all statistically significant, but because of multicollinearity the specific coefficients need not be meaningful. The mortality rate (MORT*) in the SMSA appears to have no partial correlation with the admission rate. That is, SMSAs with "sicker" populations—higher death rates, holding the age-sex structure constant—do not appear to have higher admission rates.[59]

Endogenous Explanatory Variable: Bed Rate While it may be appropriate in a short-run model to view the bed rate as exogenous, this is clearly not valid for a long-run model. In the long run the bed rate is hypothesized to be a positive function of the admission rate. Using an observed rather than a predicted bed rate may bias the effect of beds on the admission rate.[60] Table 8 presents the estimated admission rate equation for the long-run model.

The slope coefficient, standard error, and elasticity for the bed rate are nearly identical when the variable is treated as an exogenous variable (Table 7, regression (2)) as when it is treated as an endogenous variable (Table 8). Also, the slope coefficients and t-ratios of the other explanatory variables are hardly changed. In terms of statistical significance, the most important changes are that percent nonwhite becomes insignificant and that the variable HMO becomes strongly significant.

Summary The empirical estimation of the admission rate equation throws light on a number of relationships. It indicates a significant negative effect

TABLE 8 Two-stage Least Squares Analysis of Hospital Admission Rates (dependent variable: ADMS*; N = 192 SMSAs)

Variables	Coefficient	t-Ratio
Supply shift variable		
BEDS*[a]	11.005	4.21
Insurance variable		
HI	1.266	2.07
Income variable		
INC	−16.017	−4.00
Medical sector variables		
SURG*	273.161	2.88
HIXSG*	−3.294	−1.87
HMO	−18.356	−3.47
MST*C	−.073	−1.10
State of health variables		
JANTEMP	−.825	−3.29
%NWHT	.041	.17
%FEMAL	−28.451	−3.65
%M1039	−31.571	−4.00
%M4054	−36.367	−4.03
%M55	−29.300	−3.45
%F1039	28.909	3.67
%F4054	34.295	3.57
%F55	27.102	3.26
Constant	1739.12	4.03

SOURCE: See appendix.
[a]Predicted beds per thousand population. (See Table A-3.)

of the (predicted) occupancy rate on the admission rate and a positive effect of the bed rate on the admission rate. Whether the bed rate is treated as an exogenous or an endogenous variable, the elasticity is approximately +0.34. Thus, admission rates are higher in SMSAs with more vacant beds per capita. However, an exogenous increase in the number of beds has a 50 percent larger impact on length of stay (elasticity +0.49) than on admissions. "Roemer's Law" (that an increase in the stock of beds results in these beds being occupied) is largely substantiated (elasticity +0.83).

Both the "hospital and surgical insurance" variable and the number of surgeons per capita have a positive effect on the admission rate. However, there appears to be no relationship between the number of nonsurgical MDs and the admission rate. The attempt to identify a "medical center" effect was not successful.

Median family income is negatively correlated with admissions, with an elasticity of −0.67. Finally, hospital admission rates are higher in SMSAs with a higher proportion of the population nonwhite, without an HMO, and with colder winter climates. SMSAs with HMOs appear to have annual admission rates that are lower by 7.6 percent or 13 admissions per thousand population. The temperature difference between Boston and Washington, D.C. would imply 13 additional admissions per thousand population per year in Boston.

Bed Rate Equation

Table 9 presents the empirical estimation of the equation developed for explaining SMSA differences in the number of beds per thousand population (bed rate). The variable $\ln \hat{p}$ is the natural log of the predicted weekly probability of an admission.[61] The variable

$$V = \sqrt{\frac{HOSP}{POP}\left(\frac{1}{p} - 1\right)}$$

is our variable for the effect of the randomness of the demand for admissions on the demand for beds. In equation (23) the coefficient of V is Z_α, which is hypothesized to be a linear function of the variables that are interacting with V in Table 9. And, the elasticity of beds with respect to admissions is less than unity because a higher admission rate results in a more stable relative demand for admissions.[62]

Empirically, the log of the admission rate has a significant positive partial effect on the log of the bed rate. However, although its hypothesized value is unity, the estimated coefficient is 0.7—significantly less than unity.[63] This parameter may be biased downward compared to the hypothesized value because of the less than complete adjustment of the stock of beds to

TABLE 9 Two-Stage Least Squares Analysis of SMSA Differences in Hospital Bed Rates (dependent variable: ln(BEDS*); N = 192 SMSAs)

Variables	Regression (1) Coefficient	Regression (1) t-Ratio	Regression (2) Coefficient	Regression (2) t-Ratio
A. Expected admissions				
ln $\hat{p}$	0.704	6.41	0.606	4.69
B. Stochastic effect—coefficient of variation				
V[a]	−17.929	−4.99	−17.667	−4.20
Income variable				
V(INC)	1.314	2.42	1.337	2.02
Health sector variables				
V(%FEDBED)	0.273	7.91	0.277	8.02
V(HMO)	b		−1.928	−1.53
V(MST*C)	0.048	2.79	0.056	3.18
Demographic variables				
(V)(EMERG*)	2.194	5.16	2.432	4.61
V(%NWHT)	b		−0.066	−1.31
V(%CHPOP)	b		0.002	0.15
Constant	5.600	8.68	5.036	6.65

SOURCE: The appendix.

[a] $V = \sqrt{\frac{HOSP}{POP}\left(\frac{1}{\hat{p}} - 1\right)}$

where HOSP = number of hospitals, POP = population, and

$\hat{p} = \frac{ADMS^*}{(1{,}000 \times 52)}$ = predicted weekly admission rate per capita

(See Table A-3.)

[b] Variable not included.

the admission rate. That is, the data may not be reflecting the full long-term adjustment of beds to admissions because of the time involved in expanding (contracting) bed capacity in areas experiencing an increase (decrease) in the demand for admissions. Note, for example, that the data are for 1967 utilization, while Medicare and Medicaid were initiated in 1966. There was too little time for the bed rate to adjust fully to the sudden change in the demand for admissions in response to these new programs.

The *elasticity* of the bed rate with respect to the admission rate is 0.66. This elasticity is composed of a "mean effect" (0.70) and a "randomness effect" (−0.04).[64] It is the apparent downward bias in the mean effect that is responsible for what seems to be a low elasticity of beds with respect to admissions.

The randomness model variable V has the hypothesized positive partial effect on the bed rate. The partial effect, which is also our estimate of Z_α, is 2.437.[65] This is within one standard error of the value of Z_α estimated in the occupancy rate analysis. The implied value of α is 0.73 percent.

Significant interaction between V and other variables is shown in Table 9 for the extent of emergencies in the SMSA's case mix, median family income, the proportion of beds in federal hospitals, and the medical center variable.[66] These four shift variables for Z_α also had significant positive effects on the bed rate when they were entered linearly in a regression containing lnp and V.

It is hypothesized that the more important the emergencies in an SMSA's case mix, the greater the cost of a delayed or denied admission and therefore the larger the optimal Z. The emergency variable has the hypothesized positive effect on the bed rate.

As to income—if, as seems reasonable, there is a positive income elasticity of demand for a smaller probability of delayed or denied admission—SMSAs with higher median family incomes would have a larger Z_α and a higher bed rate.[67] Empirically, median family income has a significant positive direct effect on the bed rate, with an elasticity of +0.25. However, the commodity that is being purchased is not beds *per se*, but, rather, a lower probability of delayed or denied admission.[68]

The variable for the proportion of short-term general hospital beds in federal hospitals (%FEDBED) has a significant positive effect on the bed rate. If federal and nonfederal hospital beds were perfect substitutes for each other, the proportion of beds in federal hospitals would have no effect on the bed rate. If there were no substitution between federal and nonfederal hospital beds, an increase in the number of federal beds would have no effect on the number of nonfederal beds. Empirically, it appears that federal and nonfederal beds are imperfect substitutes for each other—an increase in the number of federal beds increases the total number of beds, but by less than the increase in federal beds.[69]

The medical center variable (the number of medical students per 100,000 population in the SMSA) has a significant positive effect on the bed rate, even though it has none on the admission rate. The effect on beds presumably measures the longer length of stay of medical center patients or a greater Z_α, so that there is a smaller probability of having to turn away an interesting case.

Three other variables included in the regression analysis of Table 9—V(%NWHT), V(%CHPOP), and V(HMO)—have insignificant slope coefficients and show statistically insignificant effects also when entered as linear rather than interaction variables. With the admission rate constant, it had been hypothesized that discrimination against nonwhites in the provision of medical care could result in a lower bed rate in SMSAs with a higher proportion of nonwhites, but, although the partial effect is negative, it is not significant. The HMO variable tests the hypothesis that HMOs maintain a lower bed rate and that this is a means of reducing hospital admissions and medical expenses. Again, although we do find a negative coefficient, it is not statistically significant. Finally, more rapidly growing populations have the same bed rate as those growing less rapidly, other variables remaining constant.

Thus, the analysis indicates that SMSA differences in bed rates can be systematically related to expected admission rates, to random variation in the short-run demand for admissions (V), and to variables that may determine the frequency with which the stock of beds is insufficient for the short-run demand for beds.

APPENDIX

The Data

Table A-1 is a list of the endogenous and exogenous variables used in this study, their symbols, and the data sources.

The unit of observation is a Standard Metropolitan Statistical Area. An SMSA is a county or group of contiguous counties which contain at least one city (or two contiguous cities) of at least 50,000 inhabitants. In New England, however, SMSAs consist of towns and cities rather than counties, and metropolitan state economic areas are defined in terms of whole counties. Thus, in this study, New England metropolitan state economic areas and non-New England SMSAs are the units of observation referred to as SMSAs for simplicity's sake.

Hospital utilization data stem from a 1967 survey of all short-term general hospitals in the country, as reported in *Hospitals: A County and Metropolitan Area Data Book*, National Center for Health Statistics, Department of Health, Education, and Welfare, November 1970. Although data are presented for 201 SMSAs, nine are excluded from the empirical analyses because of evidence that they include long-term care facilities. These nine SMSAs have either a very long average length of stay or an excessively large proportion of beds in federal hospitals.[70] Although only the sample of 192 SMSAs is analyzed here, the findings for the full sample are quite similar.

Data on hospital and surgical insurance coverage or benefits do not exist for SMSAs. An instrumental variables approach is adopted in which state data are used to compute a regression equation to explain state differences in per capita hospital and surgical insurance benefits (HI). States without SMSAs and those across which there is considerable commutation are

TABLE A-1 Hospital Utilization: The Variables (N = 192 SMSAs)

Variable (units)	Symbol	Mean	Standard Deviation	Coefficient of Variation	Source of Data
A. Endogenous variables					
1. Admission rate (admissions per thousand)	ADMS*	169.55	40.38	.24	a,b
2. Occupancy rate (percent)	OR	77.28	6.72	.087	a
3. Natural log of occupancy rate	lnOR	4.34	.091	.021	a
4. Bed rate (beds per thousand)	BEDS*	5.22	1.44	.28	a
B. Exogenous variables					
1. Population of SMSA, 1966 (thousands)	POP 66	641.16	1237.6	1.93	a
2. % change in population, 1950–1960	% CHPPO	33.10	33.34	1.01	c
3. % Nonwhite	% NWHT	10.68	10.50	.98	c
4. Median family income (thousands $)	INC	5.81	.83	.14	d
5. % General hospital beds in state and local government hospitals, 1967	% SLBED	15.82	18.36	1.16	b
6. % General hospital beds in federal hospitals, 1967	% FEDBED	10.64	13.95	1.31	b
7. % General hospital beds in proprietary hospitals, 1967	% PRBED	4.49	8.56	1.91	b

TABLE A-1 (continued)

Variable (units)	Symbol	Mean	Standard Deviation	Coefficient of Variation	Source of Data
8. HMOs in the state (HMO = 1)	HMO	0.54	0.50	0.93	e
9. Square root of the number of hospitals	SQHOSP	3.20	1.92	.60	a
10. Nonfederal general practice MDs and medical specialists in patient care, per thousand population, in 1967	GENMD*	.51	.12	.24	a,f
11. Nonfederal surgical specialists in patient care, per thousand population, in 1967	SURG*	.35	.090	.26	a,f
12. % Males, 10–39, in 1960	%M1039	43.73	3.48	.080	g
13. % Males, 40–54, in 1960	%M4054	17.47	1.67	.096	g
14. % Males, ≥ 55, in 1960	%M55	15.51	3.45	.22	g
15. % Females, 10–39, in 1960	%F1039	43.35	2.84	.066	g
16. % Females, 40–54, in 1960	%F4054	17.44	1.57	.090	g
17. % Females, ≥ 55, in 1960	%F55	17.42	3.68	.21	g
18. % Population, female, 1960	%FEMAL	50.86	1.16	.023	g
19. Mean January temperature, 1960	JANTEMP	36.10	12.03	.33	h
20. Deaths from arteriosclerotic heart disease, incl. coronary, per thousand population	HEART*	2.51	.78	.31	a,i
21. Deaths from vascular lesions affecting nervous system					

21. Deaths from vascular lesions affecting nervous system—strokes per thousand population	STROKE*	1.00	.27	.27	a,i
22. Deaths from motor vehicle accidents per thousand population	MOTOR*	.21	.068	.32	a,i
23. Deaths from other accidents per thousand population	OTHACC*	.29	.061	.21	a,i
24. Suicide per thousand population	SUIC*	.11	.037	.34	a,i
25. Homicide per thousand population	HOMIC*	.050	.037	.74	a,i
26. Deaths from 6 leading emergency situations (sum of variables 20 to 25)	EMERG*	4.16	.93	.22	a,i
27. Total deaths per thousand population	MORT*	8.91	1.64	.18	a,i
28. Number of medical students per 100,000 population	MST*C	14.96	32.53	2.17	a,j
29. Live births per 1,000 women, 17–46, 1967	LBR	93.81	16.06	.17	g,k
30. Square root of 1/population 1966 (actual population)	SPOP	.0019	.00079	.42	a
31. Hospital and surgical insurance benefits per capita (in dollars)	HI	50.51	13.21	.26	a,l,m
32. Insurance × number of surgeons per thousand population [(31) × (11)]	HIXSG*	17.91	6.91	.39	a,f,l

TABLE A-1 (concluded)

	Variable (units)	Symbol	Mean	Standard Deviation	Coefficient of Variation	Source of Data
33.	Insurance × number of nonsurgical out-of-hospital physicians per thousand population [(31) × (10)]	HIXMD*	26.40	10.58	.40	a,f,l

SOURCES:
[a]*Hospitals: A County and Metropolitan Area Data Book.* U.S. Dept. of Health, Education, and Welfare, Public Health Service, November 1970, Table 2.
[b]Ibid., Table 3.
[c]*Census of Population: 1960*, Vol. I, *Characteristics of the Population*, Part I (United States Summary), U.S. Dept. of Commerce, Bureau of the Census, 1964, Table 63.
[d]Ibid., Table 142.
[e]Robert E. Schlenker, Jean N. Quale, and Richard McNeil, Jr., "Socioeconomic and Legal Factors Associated with HMO Presence: An Evaluation of State Data," Interstudy, Minneapolis, Minnesota, October 1973, mimeo.
[f]J. N. Haug and G. A. Roback, "Medical Practice Data by Metropolitan Area," *Distribution of Physicians, Hospitals, and Hospital Beds in the U.S., 1967, by Region, State, County, and Metropolitan Area*, Chicago, American Medical Association, 1968, Table 14.
[g]*Census of Population, 1960*, Vol. I, *Characteristics of the Population*, Parts II–LII (The States), U.S. Dept. of Commerce, Bureau of the Census, 1963, Table 20.
[h]*County and City Data Book, 1962*, U.S. Dept. of Commerce, Bureau of the Census, 1962, Table 6, item 456.
[i]"Deaths from 59 Selected Causes for Standard Metropolitan Statistical Areas of the United States: 1960," *Vital Statistics of the United States, 1960*, Vol. II, *Mortality*, Part B, U.S. Dept. of Health, Education and Welfare, Public Health Service, 1963, Table 9-8.
[j]"Approved Medical Schools and Schools of Basic Medical Sciences," *The Journal of the American Medical Association*, Education Number 210, November 24, 1969, 1462–3, Table 1.
[k]"Live Births by Live-Birth Order and Race, for SMSA's of the U.S., 1967," *Vital Statistics of the United States, 1967*, Vol. I, *Natality*, U.S. Dept. of Health, Education and Welfare, Public Health Service, 1970, Table 1-55.
[l]*County and City Data Book, 1967*, U.S. Dept. of Commerce, Bureau of the Census, 1967, Table 3, items 24, 25, 58, and 60.
[m]Louis S. Reed and Willine Carr, "Private Health Insurance, Enrollment, Premiums and Benefit Expense, by Region and State, 1966," Research and Statistics Note 14, 1968, U.S. Dept. of Health, Education, and Welfare, July 29, 1968.

TABLE A-2 Hospital and Surgical Benefits (per capita)

TABLE A-2 Hospital and Surgical Benefits (per capita)

		Number of Observations, 41 States			
Variable (units)	Symbol	Mean	Standard Deviation	Coefficient of Variation	Source of State and SMSA Data
A. Endogenous variable					
1. Hospital and surgical benefits per capita	HI	41.65	10.69	.26	a,b,c,d
B. Exogenous variables					
1. % of employed in 1960, in manufacturing in 1960	%MANUF	22.81	10.14	.44	e
2. % of employed in 1960, white collar in 1960	%WC	38.92	4.54	.12	e
3. % of employed in 1960, in local					

Table A-2 (concluded)

Variable (units)	Symbol	Number of Observations, 41 States: Mean	Standard Deviation	Coefficient of Variation	Source of State and SMSA Data
government in 1962	%LOCAL	6.79	1.07	.16	g
4. % of employed in 1960, in federal government in 1965	%FED	3.92	2.20	.56	h

C. Weighted Regression (weighted by state's population):

$HI = -32.48 - 2.51(\%LOCAL) + 0.68(\%MANUF) + 2.05(\%WC) - 1.34(\%FED)$

$\bar{R}^2 = 0.71$

SOURCES:

[a] *Census of Population: 1960, Vol. I, Characteristics of the Population,* Part I (United States Summary), U.S. Dept. of Commerce, Bureau of the Census, 1964, Table 9.

[b] *County and City Data Book, 1967,* U.S. Dept. of Commerce, Bureau of the Census, 1967, Tables 1 and 3, items 24, 25, 58, and 60.

[c] *Hospitals: A County and Metropolitan Area Data Book,* U.S. Dept. of Health, Education, and Welfare, Public Health Service, November 1970, Table 2.

[d] Louis S. Reed and Willine Carr, "Private Health Insurance Enrollment, Premiums and Benefit Expense, by Region and State, 1966." Research and Statistics Note 14, 1968, U.S. Dept. of Health, Education, and Welfare, July 29, 1968.

[e] *County and City Data Book, 1967,* U.S. Dept. of Commerce, Bureau of the Census, 1967, Table 3, items 23 and 24.

[f] Ibid., Table 3, items 23 and 25.

[g] Ibid., Table 3, items 23 and 58.

[h] Ibid., Table 3, items 23 and 60.

NOTE: *States Excluded:* (a) No SMSAs: Vermont, Idaho, Wyoming, and Alaska. (b) Substantial commutation across state borders: New York, [illegible] Virginia, Maryland, and District of Columbia.

excluded, leaving a sample of 41. The "best" weighted regression for explaining state differences in HI using a small set of occupation and industry variables is presented in Table A-2. The coefficient of determination adjusted for degrees of freedom is 71 percent. The parameters of this equation and SMSA values for the explanatory variables are used to obtain predicted values of HI for the SMSAs.

Table A-3 lists the exogenous variables in the reduced form equations for the admission rate (ADMS*), the natural logarithm of the occupancy rate (lnOR) and the bed rate (BEDS*), and the explanatory power of these equations.

TABLE A-3 List of Variables in Reduced-Form Equations

A. Exogenous Variables		
Health Sector Variables	Demographic Variables	Other Variables
SQHOSP	SPOP	INC
HMO	%CHPOP	JANTEMP
BEDS*[a]	%NWHT	
HI[b]	%FEMAL	
SURG*	MORT*[e]	
GENMD*[ce]	EMERG*[cd]	
HIXSG*	%M10-39	
HIXMD*[ce]	%M40-54	
MST*[c]	%M55+	
%SLBED[c]	%F10-39	
%PRBED[c]	%F40-54	
%FEDBED[c]	%F55+	

B. Summary Statistics (N = 192)			
	ADMS*	lnOR	BEDS*
R^2	0.73	0.45	0.59
DF	172	166	168

NOTE: The variables are defined in Table A-1.
[a]Not included in the reduced form equation for BEDS*, or for ADMS* when ADMS* enters the bed rate equation.
[b]Predicted from the equation in Table A-2.
[c]Not included in reduced form equation for ADMS*.
[d]Not included in reduced form equation for lnOR.
[e]Not included in reduced form equation for BEDS*.

TABLE A-4 Utilization of Nonfederal Short-Term General Hospitals, By State, 1971

State	Admissions (per thousand population)	Beds (per thousand population)	Occupancy Rate (%)	Average Length of Stay (days)
Alabama	158	4.1	80.4	7.6
Alaska	83	1.9	62.2	5.3
Arizona	131	3.6	74.0	7.5
Arkansas	164	4.1	75.5	6.9
California	142	3.8	69.6	6.8
Colorado	166	4.3	73.5	6.9
Connecticut	128	3.4	81.2	8.0
Delaware	118	3.5	77.2	8.3
Wash., D.C.	248	7.2	76.7	8.2
Florida	150	4.1	76.9	7.7
Georgia	147	3.7	75.4	6.8
Hawaii	113	3.1	78.4	8.0
Idaho	121	4.0	66.1	8.0
Iowa	168	5.5	69.2	8.3
Kansas	169	5.8	71.7	8.9
Kentucky	157	3.9	80.0	7.3
Louisiana	158	4.1	71.3	6.8
Maine	148	4.2	73.4	7.6
Maryland	105	3.0	80.0	8.4
Massachusetts	149	4.5	78.9	8.7
Michigan	131	3.8	79.6	8.4
Minnesota	170	5.8	72.3	8.9
Mississippi	160	4.1	75.3	7.0
Missouri	154	4.7	79.3	8.7
Montana	186	5.4	66.6	7.1
Nebraska	173	6.1	69.4	8.9
Nevada	149	3.9	75.2	7.1
New Hampshire	145	4.0	75.4	7.6
New Jersey	119	3.6	82.7	9.0
New Mexico	136	3.5	62.8	5.9
New York	140	4.6	83.3	9.9
North Carolina	141	3.7	79.3	7.6
North Dakota	196	6.4	64.7	7.8
Ohio	142	4.0	81.8	8.4
Oklahoma	154	4.2	71.5	7.1
Oregon	147	4.0	68.3	6.8
Pennsylvania	144	4.5	80.7	9.3
Rhode Island	124	3.5	82.3	8.6
South Carolina	133	3.6	76.7	7.6
South Dakota	165	5.3	64.2	7.5
Tennessee	171	4.6	79.0	7.8
Texas	157	4.2	72.8	7.1

TABLE A-4 (concluded)

State	Admissions (per thousand population)	Beds (per thousand population)	Occupancy Rate (%)	Average Length of Stay (days)
Utah	144	3.3	74.0	6.1
Vermont	161	4.4	74.6	7.4
Virginia	128	3.6	81.0	8.4
Washington	142	3.3	68.3	5.8
West Virginia	190	5.3	78.8	8.0
Wisconsin	160	5.1	73.0	8.4
Wyoming	171	5.0	61.1	6.5
U.S. Total	146	4.2	76.7	8.0

SOURCE: *Statistical Abstract of the United States, 1973*, Tables 13, 113.

NOTES

1. A sampling of articles from *The New York Times* is illustrative. For discussions of insufficient bed capacity, see the issues of January 21, 1971, p. 29, and of September 12, 1971, section IV, p. 9. Between the publication of these two articles, *The New York Times* reported Elliot Richardson, then Secretary of Health, Education, and Welfare, as citing "an estimate of $3.6 billion as last year's cost of maintaining unused beds all over the country" (*The New York Times*, August 26, 1971, p. 36). The next year, while the General Accounting Office reported the "overbuilding" of hospital facilities in six cities, Congress was passing legislation to promote hospital bed construction (*The New York Times*, September 21, 1972, p. 36, and December 18, 1972, p. 78).
2. See Harry T. Paxton, "Whatever Happened to the Hospital Bed Shortage?" *Medical Economics*, February 28, 1973, p. 33.
3. *The New York Times*, July 31, 1972, p. 36, and January 15, 1973, p. 23.
4. *Statistical Abstract of the United States, 1973*, Tables 13 and 113.
5. Several states have recently passed legislation requiring state approval before a free-standing hospital can be constructed or an existing one's bed capacity increased. The legislation is designed to restrict the growth of "unnecessary" hospital facilities and to encourage the development of hospital facilities in areas with "insufficient" capacity. For analyses of certificate-of-need legislation, see Clark C. Havighurst, ed., *Regulating Health Facilities Construction* (Washington, D.C.: American Enterprise Institute, 1974). This control has been strengthened by the 1972 amendment to the Social Security Act which contains a provision for reducing Medicare and Medicaid payments to health facilities constructed or expanded without the approval of a state planning agency.
6. The theoretical model may be used to analyze one region over time or many regions at a moment in time. Current time series data for the United States involve too few data points and have problems of serial correlation that are too severe for an adequate test of the model, limitations which are not present in a cross-section interregional analysis.
7. Implications concerning length of stay are derived from the identity between overall length of stay and the three measures of utilization. If $\overline{LS}$ is the average length of stay,

$$OR = \frac{(\overline{LS})(ADMS^*)}{365(BEDS^*)}$$

In this study an asterisk (*) as the suffix to a variable name means it is the variable per thousand population while the suffix *C means per 100 thousand population.

8. See the appendix for the definition of an SMSA.
9. For example, Santa Monica, Culver City, and San Fernando are three cities in Los Angeles county and SMSA surrounded by Los Angeles city. Yet these separate cities do not appear to constitute separate health communities since there is considerable mobility across city boundaries. The large proportion of residents in the five counties comprising New York City who seek hospital services outside of their own county suggests that the populace acts as if the city (SMSA) represented a single medical center. States are not ideal as the unit of observation because in many of them there is either little mobility between two or more hospital areas or there is substantial commutation across state borders for the purchase of hospital care.
10. In the long run the factors of production employed in the hospital sector are either highly mobile across SMSAs or the hospital sector employs such a small proportion of the factors within an SMSA that the factor supply curves can be assumed to be perfectly elastic in the relevant range. Even if each hospital in an SMSA has a U-shaped cost curve, by expanding the number of hospitals rather than the size of each hospital, hospital costs may be invariant with the number of beds in the SMSA.
11. For simplicity of exposition it is assumed that the average length of stay is constant for a given case mix.
12. In practice, however, the curve is not perfectly inelastic but steeply upward rising at occupancy rates in excess of 100 percent. Reported occupancy rates can exceed 100 percent when additional temporary beds are added to rooms, hallways, et cetera.
13. That is, the higher shadow price is due to the extra pain and suffering, extra curative costs, and a higher probability of disability and death. An offset is that some conditions may have a spontaneous cure.
14. See, for example, Hyman Joseph and Sherman Folland, "Uncertainty and Hospital Costs," *Southern Economic Journal*, October 1972, pp. 367–373; William Shonick, "A Stochastic Model for Occupancy-Related Random Variables in General-Acute Hospitals," *Journal of the American Statistical Association*, December 1970, pp. 1474–1500; M. Long and P. Feldstein, "Economics of Hospital Systems: Peak Loads and Regional Coordination," *American Economic Review*, May 1967, pp. 119–129; and J. B. Thompson et al., "How Queuing Theory Works for the Hospital," *The Modern Hospital*, March 1960, pp. 75–78.
15. Multiple admissions of an individual in a time period do occur, and are more frequent the longer the time period lasts. Empirically, among SMSA residents in 1968 who had at least one hospital admission, 86.6 percent had one episode, 10.5 percent had two episodes, and 2.9 percent had three or more episodes in that year. (*Persons Hospitalized by Number of Hospital Episodes and Days in the Year, 1968*, Vital and Health Statistics, Series 10, Number 64, National Center for Health Statistics, December 1971, Tables 1 and 7.)

    In our data the annual average number of per capita admissions is 0.170. If multiple admissions are independent events, the probability of at least one admission is 0.145 $\left(\sum_{i=1}^{\infty} (0.145)^i \approx 0.170\right)$. Then the theoretical frequency for those with one admission is 85.3 percent, two episodes, 12.4 percent, and three or more episodes, 2.3 percent. The theoretical and observed distributions are very close to each other, and it will be assumed that successive admissions for an individual are independent events.
16. Similar conclusions emerge if length of stay (LS) is not considered constant over time. Let us assume that across time periods the average length of stay and the number of admissions are independent.

    (a) $\mathrm{Var}(PD) = \mathrm{Var}(LS \cdot N) = (\overline{LS})^2 \mathrm{Var}(N) + \overline{N}^2 \mathrm{Var}(LS) + \mathrm{Var}(LS)\mathrm{Var}(N)$

if LS is independent of N.

Then, since

(b) $\mathrm{Var}(N) = (POP)p(1 - p)$ and $\overline{N} = (POP)p$

we obtain

(c) $\mathrm{Var}(PD) = POP\{[2\,\mathrm{Var}(LS) + (\overline{LS})^2]p - [(\overline{LS})^2 + \mathrm{Var}(LS)]p^2\}$

(d) $CV(PD) = \dfrac{SD(PD)}{E(PD)} = \dfrac{\sqrt{POP\{[2\,\mathrm{Var}(LS) + (\overline{LS})^2]p - [(\overline{LS})^2 + \mathrm{Var}(LS)]p^2\}}}{\overline{LS} \cdot (POP) \cdot p}$

and

(e) $CV(PD) = \sqrt{\dfrac{1}{(POP)}\left[\left(\dfrac{1}{p}\right)(2CV(LS)^2 + 1) - (CV(LS)^2 + 1)\right]}$

CV(PD) is negatively related to population size and the admission rate, and positively related to the coefficient of variation of length of stay across time periods. These general relationships would hold even if length of stay were not statistically independent of the admission rate, although the equation would be far more complicated. (See Leo Goodman, "On the Exact Variance of a Product," *Journal of the American Statistical Association*, December 1960, pp. 708–713.)

17. Annual rates of admission per capita are about 15 percent. Assuming independence of individual admissions, the distribution of admissions for, say, a week approximates the Poisson distribution for a small sample (for example, a household or small work group), but approximates a normal distribution for a large sample (a large factory, census tract, or SMSA). For a binomial distribution, if the proportion of successes (in this case the admission rate, p, multiplied by the sample size, POP) exceeds 10, the number of successes (admissions) approximates a normal rather than a Poisson distribution. For a population of 100,000 and a weekly admission rate of .15/52, admissions = (100,000)(.15)/(52) = 300 and the normal distribution is a close approximation of the binomial distribution.
18. This assumes perfect pooling of beds among the hospitals in the community. The effects of a lack of perfect pooling among hospitals in an area and the time lag in filling a vacant bed are discussed below. For the normal distribution, only 2.5 percent of the observations are more than 1.96 ≅ 2.00 standard deviations above the mean.
19. For simplicity of exposition, it is assumed that there is no private or social cost in shifting patients within the time period of D days.
20. For a population of one million, a daily admission rate of .15/365, and $\alpha = .001$ (i.e., an insufficient number of beds for one-tenth of one percent of occurrences, or $Z = 3.0$),

$$Z_\alpha CV(PD) = Z_\alpha \sqrt{\frac{1}{POP}\left(\frac{1}{p} - 1\right)} = 0.22$$

If the pooling is done over a week, $Z_\alpha CV(PD) = 0.084$. These values of $Z_\alpha CV(PD)$ are sufficiently small for the approximation to apply.
21. The parameter Z_α is smaller the larger α is. Since Z_α is inversely related to lnOR in the equation, α is positively related to lnOR.
22. See, for example, Paxton, "Whatever Happened to the Hospital Bed Shortage?," p. 42.
23. If, as some suggest, physicians run hospitals on the basis of their own economic self-interest, they may tend to prefer smaller neighborhood hospitals so as to reduce their own average commuting time. Mark V. Pauly and Michael Redisch, "The Not-for-Profit Hospital as a Physician Cooperative," *American Economic Review*, March 1973, pp. 87–99.
24. Some SMSAs (e.g., Los Angeles) appear to have addressed this problem by having small

localized emergency treatment centers to supplement the few, but large, county hospitals.

25. In his "Hospital Organizational Performance and Size," *Inquiry*, September 1973, pp. 10–18), David B. Starkweather concludes that "it is the coordination of interdependent parts which is the difficult aspect of hospital operations." Starkweather studied the relation between the efficiency of several tasks (in terms of time delays and errors) and hospital size.
26. Minimum average cost can be defined only after the case mix and mission of the hospital have been specified. For evidence that cost curves for individual hospitals are U-shaped, see Thomas R. Hefty, "Returns to Scale in Hospitals: A Critical Review of Recent Literature," *Health Services Research*, Winter 1969, pp. 267–280.
27. Let us designate Z_i as the value of Z in the *ith* SMSA, the theoretical equation as (a) $\ln OR_i = -Z_i V_i$, and the regression equation as (b) $\ln OR_i = b_0 + b_1 V_i + U_i$, where $U_i = (Z_i - b_1) V_i + U_i^*$, $b_0 = 0$, and U_i^*, is uncorrelated with V_i. Then, b_i is an unbiased estimate of the mean value of $-Z$ if Z_i is not correlated with V_i and V_i^2. This clearly holds if Z_i and V_i are independent. For a proof, see my *Income Inequality* (New York: NBEP, 1974), p. 44.
28. Recall that, since

$$OR = \frac{(N)(LS)}{(365)(BEDS)}, \quad \frac{\partial \ln OR}{\partial \ln BEDS} = -1$$

29. According to "Roemer's Law," exogenous increases in bed rates primarily affect admissions and length of stay, leaving occupancy rates virtually unchanged. That is, patients fill the available supply of beds. See, for example, M. I. Roemer and M. Shain, *Hospital Utilization under Insurance*, Hospital Monograph Series, No. 6 (Chicago: American Hospital Association, 1959).
30. For example, in New York City the average length of stay of whites is shorter than that of blacks.

	Average Length of Stay in Days		
	1964	1966	1968
White (excluding Puerto Ricans)	10.9	11.2	13.4
Black	13.2	11.6	14.5

SOURCE: Donald G. Hay and Morey J. Wontman, "Estimates of Hospital Episodes and Length of Stay, New York City, 1968," February 1972 (mimeo).

31. In the empirical analyses, the percentage of nonwhites in the population is used as the explanatory variable. For the United States as a whole, over 90% of nonwhites are blacks.
32. See Section 3 below.
33. For a time series study of greater admissions selectivity during periods of high occupancy rates, see John Rafferty, "Patterns of Hospital Use: An Analysis of Short-Run Variations," *Journal of Political Economy*, January-February 1971, pp. 154–165. Note that this is analogous to the response of other industries to a fairly fixed short-run capacity but fluctuating demand. The "greater selectivity" occurs through price changes in industries where prices may be used as a rationing device. It is those individuals with the highest or least elastic demand that pay the high price during the peak season. For example, the price of the same room in a Miami Beach hotel can range from $15 to $60, depending on the season.
34. See, for example, my article "The Demand for Nursing Home Care" in *Journal of Human Resources* (Summer 1976).
35. Hospital and surgical insurance coverage per capita is an endogenous variable, and a

predicted rather than an observed insurance variable is used in the empirical analysis. (See the appendix.)

36. For a survey of the literature on HMOs, see Milton I. Roemer and William Shonick, "HMO Performance: The Recent Evidence," *Health and Society, Milbank Memorial Fund Quarterly*, Summer 1973, pp. 271–317.
37. The cost of physicians' services includes the direct price (fee), the waiting room time, and the costs incurred due to a delay in receiving care.
38. This suggests that the number of physicians is an endogenous variable. However, the observed number of physicians is used in the empirical analysis. For an analysis of physician supply, see Victor R. Fuchs and Marcia Kramer, *Determinants of Expenditures for Physicians' Services in the United States*, NBER Occasional Paper 117, 1972.
39. There is evidence that income and "good health" are negatively correlated among whites but positively correlated among nonwhites. See Michael Grossman, *The Demand for Health*, NBER Occasional Paper 119 (New York: NBER, 1972); and Morris Silver, "An Econometric Analysis of Spatial Variations in Mortality Rates by Age and Sex," V. R. Fuchs, ed., *Essays in the Economics of Health and Medical Care* (New York: NBER, 1972), pp. 161–227.
40. With other variables, including measures of health status, held constant, the demand for nursing home care of the aged in an SMSA appears to be a rising function of income. See my "The Demand for Nursing Home Care".
41. For example, see Helen Hershfield Avnet, *Physician Service Patterns and Illness Rates*, Group Health Insurance, Inc., 1967, Table 42, p. 110.
42. Strictly speaking, equation 22 follows from equations 13 and 17 if it is assumed that there is no substitution among hospitals and that all hospitals are of equal size.
43. In some states a certificate of need is now required to add beds to an existing hospital or to establish a new hospital. The data on hospital beds used in this study are for 1967, and only one state (New York, 1964) had certificate-of-need legislation prior to this year. See William J. Curran, "A National Survey and Analysis of State Certificate-of-Need Laws for Health Facilities," in Clark C. Havighurst, ed., *Regulating Health Facilities Construction* (Washington: American Enterprise Institute, 1974).
44. The emergency variable is the sum of deaths from six causes per thousand population (EMERG*). (See the appendix.)
45. Average proportion of short-term general hospital beds under each form of administrative control for 192 SMSAs:

Control	Mean Percentage of Beds
State and local government	15.8
Federal government	10.6
Proprietary	4.5
Voluntary (private,nonprofit)	69.1
	100.0

SOURCE: The appendix.

46. Roemer and Shonick, "HMO Performance: The Recent Evidence."
47. For evidence on discrimination in public school expenditures, see Finis Welch, "Black-White Differences in Returns to Schooling," *American Economic Review*, December 1973, pp. 893–907.
48. In principle, the occupancy rate is bounded by 0.0 and 1.0. Empirically, however, the annual bed occupancy rates in the SMSAs are clearly within the bounds. For this reason OR is not treated as a bounded variable in the empirical analysis.

The ratio of a regression coefficient to its standard error from a two-stage least squares analysis has an asymptotic normal distribution. Thus the t-test applies only to large samples. A sample of 192 observations is sufficiently large for the approximation to be very close.

The mean and standard deviation of V are 0.033 and 0.013, respectively.

49. Since the coefficient is 2.974, with a standard error of 0.671 the 95 percent confidence interval is 2.974 ± 1.315, or from 1.659 to 4.289. Then, the 95 percent confidence interval for α(D = one week) is from 4.85 percent to approximately zero percent.

Using a related model for 116 short-term general hospitals in Iowa (1969), Joseph and Folland estimated Z_α to be 3.22, with a standard error of 0.142. My point estimate is within two standard errors of their value. (Hyman Joseph and Sherman Folland, "Uncertainty and Hospital Costs," *Southern Economic Journal*, October 1972, pp. 267–273.)

50. For a daily admission rate (p*), p* = p/7 and, since p is very small,

$$\frac{1}{p} - 1 \approx \frac{1}{p}$$

and

$$\ln OR = \frac{-2.974}{\sqrt{7}} \sqrt{\frac{HOSP}{POP}\left(\frac{1}{p^*} - 1\right)}$$

or Z_α (D = one day) = 1.12. Then, α(D = one day) ≈ 0.13.

51. $$d\ln OR = \left(\frac{\partial \ln OR}{\partial SPOP}\right) dSPOP + \left(\frac{\partial \ln OR}{\partial SQHOSP}\right) dSQHOSP = -85.5\,(dSPOP) + (-0.016)(dSQHOSP)$$

If the population is increased fourfold from 200,000 to 800,000, and the number of hospitals, from 4 to 16,

$$d\ln OR = (85.5)(.0011 - .0022) + (0.016)(4 - 2) = 0.095 - 0.032 = 0.063$$

52. The explanatory variable is the predicted natural log of the occupancy rate. It is obtained from the reduced form regression of the natural log of the occupancy rate on the exogenous variables that enter the admission rate and occupancy rate equations. (See Table A-3.)

53. The estimation procedure for HI is discussed in the appendix. In principle, the causation could run in the opposite direction: residents in SMSAs with higher hospital admission rates (for a reason other than insurance coverage) might have an incentive to buy more dollars worth of insurance. This effect will not bias the coefficient of HI in this study, since HI is predicted from an interstate regression of state insurance values on several explanatory variables that are exogenous to the hospital sector and the health of the population.

54. For Table 7, regression 2, since $\overline{HI}$ = 50.5,

$$\frac{\partial ADMS^*}{\partial SURG^*} = 494.5 + (-7.971)(\overline{HI}) = 92.0$$

$$\frac{\partial \ln ADMS^*}{\partial \ln SURG^*} = (92.0)\frac{(0.35)}{170.00} = 0.18$$

55. The variable is significant at a 5 percent level but not at a 2.5 percent level under a one-tailed test.

56. For supporting evidence, see Michael Grossman, "The Correlation between Schooling and Health" in Nestor E. Terleckyj, ed., *Household Production and Consumption* (New York: NBER, 1976).

57. Ceteris paribus, an increase in the proportion of nonwhites in the population from zero

to 10 percent raises the admission rate by 8.9 admissions per year per thousand population. The elasticity at the mean is 0.06.

58. There is a third interpretation. Since nonwhites are on the average poorer than whites, two SMSAs will have the same median income if the one with the larger percentage nonwhite has a lower mean and a larger variance of income. A simple nonlinear Engel curve could generate a negative partial effect on admissions for the variable percent nonwhite.

For the *ith* family, let (a) $ADM_i = a_0 + a_1 I_i + a_2 I_i^2$, where $a_0 > 0$, $a_1 > 0$, $a_2 < 0$.

Computing the mean of both sides of the equation, (b) $\overline{ADM} = a_0 + a_1\bar{I} + a_2(\bar{I}^2 + Var(I))$, where Var(I) is the variance of family income. A larger mean income reduces admissions if (c) $\partial ADM/\partial I = a_1 + 2a_2 I < 0$ or if $-a_1 > 2a_2 I$.

The empirical analysis did establish that larger median incomes reduce admission rates, and that mean and median incomes are highly correlated across areas. A larger variance of income (mean constant) reduces admissions as long as $a_2 < 0$.

59. An alternative explanation is that the calculated slope coefficient is biased toward zero because it reflects two offsetting effects: greater sickness (measured by mortality) causes more admissions, and more admissions reduce mortality. These two effects cannot be disentangled without developing a structural equation to explain SMSA variation in mortality.

60. The predicted bed rate is computed from the reduced form regression of the exogenous explanatory variables in the bed rate and admission rate equations. (See Table A-3.)

61. It is the predicted annual admission rate per thousand population divided by 52,000, and is computed from the reduced form regression of ADMS* on the exogenous variables that enter the admission rate and occupancy rate questions. (See Table A-3.)

62. Differentiating equation (23),

$$\frac{\partial \ln BEDS^*}{\partial \ln p} = 1 + Z_\alpha\left(\frac{\partial V}{\partial \ln p}\right) \text{ and } \frac{\partial V}{\partial \ln p} = -\frac{V}{2(1-p)}$$

which is negative.

63. If the null hypothesis is $\beta_1 = 1$, and $b_1 = 0.704$, the observed t-statistic is 2.69.

64. If

$$\text{(a)} \quad \ln BEDS^* = b_0 + b_1 \ln p + V\left(\sum_{j=1}^{r} b_{j+1}X_j\right)$$

then

$$\text{(b)} \quad \frac{\partial \ln BEDS^*}{\partial \ln p} = b_1 + (\Sigma b_{j+1}X_j)\left(\frac{-V}{2(1-p)}\right) = 0.704 + (2.437)(-0.0167) = 0.70 - 0.04 = 0.66$$

The elasticity is calculated at the mean.

65. This is the partial derivative of lnBEDS* with respect to V, evaluated at the mean, lnp* held constant.

66. The elasticities of BEDS and Z_α with respect to these variables are easily calculated. If X_j is the *jth* explanatory variable for Z_α, and

$$\text{(a)} \quad \ln BEDS^* = b_0 + b_1 \ln p + V\left[\sum_{j=1}^{r} b_{j+1}X_j\right]$$

then at the mean

$$\text{(b)} \quad \frac{\partial \ln Z}{\partial \ln X_j} = b_{j+1}\left(\frac{\bar{X}_j}{\Sigma b_{j+1}X_j}\right)$$

and

(c) $\dfrac{\partial \ln BEDS^{*}}{\partial \ln X_j} = b_{j+1}\overline{VX}_j$

67. There appears to be a positive income elasticity of demand for other institutional health facilities, for example, nursing homes. See my "The Demand for Nursing Home Care."

68. The magnitude of the relevant income elasticity depends on how the "good" is specified. If the residents of the SMSA are purchasing a lower probability of a delay with higher incomes,

$$\frac{\partial \ln \alpha}{\partial \ln INC} = \left(\frac{\partial \ln \alpha}{\partial \ln Z}\right)\left(\frac{\partial \ln Z}{\partial \ln INC}\right),$$

where

$$\frac{\partial \ln Z}{\partial \ln INC} = 3.13$$

In the relevant range, $\partial \ln \alpha / \partial \ln Z$ is a large negative number. Then the elasticity of α with respect to INC is a negative number with a very large absolute value (approximately 10 to 15). However, if the residents of the SMSA are purchasing a higher probability of an acceptance, the elasticity with respect to income is positive but much less than unity (approximately 0.1). That is,

$$\frac{\partial \ln(1-\alpha)}{\partial \ln INC} \approx \frac{\partial \alpha}{-\partial \ln Z}\,\frac{\partial \ln Z}{\partial \ln INC}$$

Normal Distribution Table

Z	α
2.50	0.0062
2.75	0.0030
3.00	0.0013

69. If, at the mean, the proportion of beds in federal hospitals were doubled and the number of nonfederal beds held fixed, the bed rate would increase by 10.7 percent. According to the regression equation, a doubling of federal beds increases the *observed* bed rate by 9.6 percent. There is, therefore, a decline in the number of nonfederal beds in response to an increase in federal beds.

70.

	Percentage of Beds in Federal Hospitals	Average Length of Stay
A. Nine SMSAs		
Ann Arbor, Michigan	21.78	12.4
Augusta, Georgia	76.13	22.4
Durham, North Carolina	31.96	11.6
Galveston, Texas	8.71	13.6
Little Rock, Arkansas	60.59	18.8
Providence, Rhode Island	7.30	18.0
Sioux Falls, South Dakota	36.70	10.0
Tacoma, Washington	0.0	23.6
Topeka, Kansas	60.96	22.0
B. 192 SMSAs		
Mean	10.64	8.8
Standard Deviation	13.95	1.9