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How hospital ownership affects access to care for the uninsured

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This article addresses the effect of hospital ownership on the delivery of service to uninsured patients. It compares the volume of uninsured patients treated in for-profit and nonprofit hospitals by regarding hospital ownership and service as endogenous. Instrumental variable estimates are used to predict the percentage of patients who are uninsured, controlling for hospital ownership and service. The study shows that when for-profit and nonprofit hospitals are located in the same area, they serve an equivalent number of uninsured patients, but for-profit hospitals indirectly avoid the uninsured by locating more often in better-insured areas.

1. Introduction

■ Health economics has recently focused on the differences between for-profit and nonprofit hospitals. This attention is partly due to the growth of for-profit hospitals in recent years. According to the American Hospital Association, the number of for-profit hospital beds grew 41% between 1976 and 1986. During that same period the total number of hospital beds declined by 10% (American Hospital Association, 1987).

The increasing proportion of for-profit hospitals relative to other types of hospitals has led to a debate over their relative merits (Gray, 1986). One side of the debate takes the position that the increasing focus on profits has led hospitals to eliminate important community services, such as emergency rooms and free care to the poor, thereby shifting those burdens to other hospitals. The opposing side of the debate maintains that the profit motive has promoted efficiency in an industry plagued by upwardly spiralling costs. In the last ten years this concern with hospital efficiency has inspired dramatic changes in health policy, the most notable being Medicare's shift from cost-based reimbursement to prospective payment for hospitals. More recently, the suggestion has even been made that nonprofit hospitals should lose their tax-exempt status unless it can be shown that they

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provide more service to their communities than for-profit hospitals (Herzlinger and Krasker, 1987; O'Donnell and Taylor, 1990).

To evaluate the relative merits of for-profit and nonprofit hospitals, we conducted a study of their performance in one particular area: the amount of free care provided to uninsured patients. Of the many ways that hospitals can differ, this is one of the most important in terms of public policy. Uninsured Americans have always relied on hospitals to provide free care, and for the 37 million persons without insurance (Short, Monheit, and Beauregard, 1989), access to care is an important issue. Two research questions that affect public policy in this area are whether for-profit hospitals behave differently from nonprofit hospitals in a given environment, and whether for-profit hospitals choose to locate in a different environment from nonprofit hospitals. These two issues have different policy implications. If it is true that for-profit hospitals behave differently from nonprofit hospitals in a given environment, then there may be legitimate concern that the growth in the number of for-profit hospitals will reduce the care to the uninsured. On the other hand, if it is true that for-profit hospitals choose to locate in a different environment from nonprofit hospitals, then the growth of for-profit hospitals is likely to abate as the choice areas become saturated with for-profit hospitals.

Existing studies generally compare the two types of hospitals while controlling for hospital characteristics such as location and services offered (Sloan, Morrisey, and Valvona, 1988). These studies ask a quite specific question: For any given hospital, does ownership affect that hospital's behavior? This approach is inappropriate for a comparison of for-profit and nonprofit hospitals, however, because for-profit hospitals are more often found in certain areas (Ermann and Gabel, 1986). This preference suggests that hospital ownership is related to area characteristics, some of which are not observable by the econometrician. If these unobserved area characteristics also affect the volume of charity care, then hospital ownership is endogenous. Similarly, the services a hospital offers, such as a trauma unit or obstetrics department, are likely to depend on unobserved area characteristics and thus may be endogenous as well.

Our study controls for the endogeneity of hospital ownership and service. We use as instruments measures of the long-run characteristics of the area, and interactions between supply and demand variables that are correlated with hospital ownership and service but not with short-run changes in the uninsured population. We form additional instruments by explicitly modelling charity-care volume and hospital ownership and services, based on the instrumental variable method devised by Dubin and McFadden (1984) (see also Cameron et al. (1988)). This technique uses predicted values from a multinomial logit equation of hospital ownership and service as instruments in a regression of charity-care volume on hospital ownership and service and other exogenous variables. The results obtained are robust to functional form and choice of instruments.

Our study shows that hospital ownership and service are indeed endogenous. This endogeneity produces a negative relationship between for-profit ownership and charity care in least squares estimates. In contrast, consistent estimates of this relationship give no indication of any difference between for-profit and nonprofit ownership. These results suggest that ownership does not affect the level of charity care at any given hospital. Instead, for-profit hospitals self-select into well-insured areas. In other words, for-profit hospitals may be skimming off the cream by locating in well-insured areas, thereby showing a negative correlation between for-profit ownership per se and volume of charity care. If this is correct, then the future growth of for-profit ownership may be limited to relatively affluent areas. Since nonprofit hospitals tend to locate in less insured areas, government policies that subsidize nonprofit hospitals, such as tax subsidies, may be a useful means to promote access to health care for the uninsured.

2. Model of uncompensated care

■ The model of uncompensated care relates the amount of charity care a hospital provides to that hospital's characteristics and the population it serves. Let λ be the probability that a patient is uninsured, conditional on being admitted to a hospital. According to Bayes' law, λ is defined as

$$\lambda \equiv \Pr(UNINSURED \mid ADMIT) = \frac{\Pr(ADMIT \mid UNINSURED) \cdot \Pr(UNINSURED)}{\Pr(ADMIT)}. \quad (1)$$

A patient either does or does not have insurance, so the unconditional probability of admission is defined as

$$\begin{aligned} \Pr(ADMIT) \equiv {} & \Pr(ADMIT \mid UNINSURED) \cdot \Pr(UNINSURED) \\ & + \Pr(ADMIT \mid INSURED) \cdot [1 - \Pr(UNINSURED)]. \end{aligned} \quad (2)$$

The following expression is derived by substituting (2) into (1), dividing by $(1 - \lambda)$, taking logs, and simplifying.

$$\ln\left[\frac{\lambda}{1-\lambda}\right] = \ln\left[\frac{\Pr(UNINSURED)}{1 - \Pr(UNINSURED)}\right] + \ln\left[\frac{\Pr(ADMIT \mid UNINSURED)}{\Pr(ADMIT \mid INSURED)}\right]. \quad (3)$$

Equation (3) indicates that the log-odds of λ (the probability a patient is uninsured conditional on being admitted to a hospital) is determined by two separate terms. The first term is a function only of the unconditional probability of being uninsured. Thus, the first term measures the proportion of the population without insurance, and this is denoted "demand" because the population without insurance largely determines the demand for free care in the hospital's market. The demand for free care depends on the characteristics of the local population that influence insurance coverage, such as income and the extent of coverage by Medicare or Medicaid. Studies have found a strong relationship between demographic characteristics and the probability of being uninsured (Moyer, 1989; Short, Monheit, and Beauregard, 1989; Sloan, Morrisey, and Valvona, 1988). Dranove, White, and Wu (1989) and Luft et al. (1990) have documented that the most important factor determining hospital choice is distance from a patient's home. The demographic composition of the local population is therefore an appropriate measure of the demand for free care in a hospital's market. The demographic factors are denoted as X_{DEMAND}.

The second term on the right-hand side of (3) is the relative probability of admission for an uninsured patient compared to an insured patient. Thus, the second term measures the hospital's willingness to provide charity care relative to paid care; we refer to the second term as "supply." Three factors may influence a hospital's supply of charity care: the hospital's organizational mission, the hospital's service, and the economic environment (denoted X_{ENVIRON}). A hospital that sees its mission as maximizing profits may directly limit charity care, as through preadmission screening, more often than does a hospital that defines its role as community service. This study considers three types of hospitals that claim very different missions: nonprofit, for-profit, and teaching hospitals. A hospital's choice of service also affects supply of charity care because some services are much more heavily used by the uninsured. In particular, obstetric services have been shown to account for a disproportionate share of uninsured admissions (Townsend, 1986; Sloan, Morrisey, and Valvona, 1988). Finally, the economic environment helps to determine the supply of charity care. The existing empirical literature on hospital provision of free care suggests that income effects are small relative to substitution effects in determining a hospital's provision of free care (Frank and Salkever, 1991). Thus, we expect that the marginal cost of care will be the primary economic factor determining a hospital's willingness to provide free care. In particular, input costs, excess capacity, and the amount of competition for patients or physicians may affect the marginal costs of providing free care.

Assumptions about the distributions of Pr(*UNINSURED*), Pr(*ADMIT* | *UNINSURED*) and Pr(*ADMIT* | *INSURED*) conditional on the observed variables (*MISSION*, *SERVICE*, X_{DEMAND}, and X_{ENVIRON}) are necessary for estimation of (3). Pr(*UNINSURED*) is assumed to follow a logit distribution, and Pr(*ADMIT* | *UNINSURED*)/Pr(*ADMIT* | *INSURED*) is assumed to be log-linear, so that

$$\ln\left[\frac{\Pr(UNINSURED)}{1 - \Pr(UNINSURED)}\right] = X_{\text{DEMAND}}\beta_D,$$

and

$$\ln\left[\frac{\Pr(ADMIT \mid UNINSURED)}{\Pr(ADMIT \mid INSURED)}\right] = MISSION\beta_M + SERVICE\beta_S + X_{\text{ENVIRON}}\beta_E.$$

Substituting in (3) and adding an error term ϵ for unobserved variation gives

$$\ln\left[\frac{\lambda}{1 - \lambda}\right] = MISSION\beta_M + SERVICE\beta_S + X_{\text{DEMAND}}\beta_D + X_{\text{ENVIRON}}\beta_E + \epsilon. \tag{4}$$

Therefore, the probability that a patient is uninsured conditional on admission (λ) follows a logit distribution.

In principle, the parameters of (4) can be estimated easily with a regression in which the unit of observation is the hospital and the percentage of patients admitted with no insurance is used as an estimate of λ. This technique is often referred to as "pooled logit" or "minimum chi-square" (Maddala, 1983). Regression estimates of (4) will be biased, however, if they omit demographic or economic variables that are correlated with a hospital's mission and service. There is much evidence to suggest that the demographics of the local population and the economic environment of the hospital determine a hospital's choice of mission and service (Mullner and Hadley, 1984; Alexander, Lewis, and Morrisey, 1985; Ermann and Gabel, 1986; Townsend, 1986). When any of these factors are incorrectly omitted from the regression used to estimate (4), the results are biased; that is, a hospital's mission and service may proxy for omitted demographic or economic characteristics of the hospital's market.

□ **Identification.** The parameters of (4) are estimated using an instrumental variables approach. The instruments must be correlated with a hospital's mission and service, but not with the error term ϵ. The model developed here suggests three strategies for identification: use a nonlinear model of mission and service, use excluded interactions between demand and supply, and use leads and lags of area characteristics. In addition, we considered using instruments such as certificate-of-need regulation and local property tax rates. However, we decided against these variables because certificate-of-need regulation is difficult to quantify meaningfully, and local tax rates are likely to reflect local demographics and would hence be correlated with the dependent variable.

The first strategy uses predicted probabilities of mission and service from a nonlinear model to form instruments and was used first by Dubin and McFadden (1984). Suppose the probability that a hospital has a certain mission and service is a function of demographic and economic factors:

$$\Pr(MISSION, SERVICE) = f(X_{\text{DEMAND}}, X_{\text{ENVIRON}}, W, \gamma), \tag{5}$$

where W denotes variables excluded from (4) and γ is a vector of parameters. The instruments for *MISSION* and *SERVICE* are the predicted probabilities

$$\hat{\Pr}(MISSION, SERVICE) = f(X_{\text{DEMAND}}, X_{\text{ENVIRON}}, W, \hat{\gamma}).$$

A convenient functional form for (5) is the multinomial logit, since the goal is to predict the probability of being one of six types of hospital. This technique requires fairly weak stochastic assumptions. Furthermore, the results are consistent even if (5) is misspecified.

If the multinomial logit model does not include other instruments W, then the identification comes through functional form. The identifying assumption of this strategy is that the independent variables affect the choice of hospital type in a nonlinear way, whereas they affect the log-odds of the percentage of admissions uninsured in a linear way. Because we do not want to rely on functional form for identification, we use two other types of instrument, both in the multinomial logit model and separately.

The second strategy uses excluded interactions to form instruments. An important feature of equation (3) is that the two terms on the right-hand side are additive. This implies that the determinants of the basic demand for free care do not interact with determinants of a hospital's supply of free care relative to paid care. Therefore, interactions between X_{DEMAND} and X_{ENVIRON} in the specification of (4) can be excluded.

The two conditions for instruments can be shown to hold under a simple set of economic assumptions. Suppose that a hospital maximizes an objective function that is the weighted average of utility from insured and uninsured patients.

$$\begin{aligned} \mathrm{U} = {} & [1 - \Pr(UNINSURED)] \cdot f(\Pr(ADMIT \mid INSURED)) \\ & + \Pr(UNINSURED) \cdot g(\Pr(ADMIT \mid UNINSURED)) \end{aligned} \tag{6}$$

where $f(\cdot)$ and $g(\cdot)$ represent the utility of admitting an insured and an uninsured patient. A hospital chooses $\Pr(ADMIT \mid INSURED)$ and $\Pr(ADMIT \mid UNINSURED)$ to maximize (6), according to the first-order conditions $f'(\cdot) = 0$ and $g'(\cdot) = 0$. A hospital's choice therefore depends on factors that influence the marginal utility of admitting an insured or uninsured patient. These factors might include marginal cost and the monetary and non-monetary benefits of admitting a given patient, which in turn may depend on the hospital's mission, service, and economic environment. This model maintains the assumption that there are no income effects (e.g., if the number of uninsured increases, the probability of admission given insurance status is unaffected, even though the hospital's revenues decline). Although this is a strong assumption, it is supported by the empirical literature (Frank and Salkever, 1991).

The objective function given in (6) satisfies the two conditions required for the interactions to serve as valid instruments. The variables X_{DEMAND}, which predict $\Pr(UNINSURED)$, are distinct from variables, X_{ENVIRON} which predict

$$\Pr(ADMIT \mid UNINSURED)/\Pr(ADMIT \mid INSURED).$$

Furthermore, this objective function depends on interactions between $\Pr(UNINSURED)$ and $\Pr(ADMIT \mid INSURED)$ or $\Pr(ADMIT \mid INSURED)$. To the extent that the value of this objective function influences what missions and services are found in the hospital, this implies that interactions between X_{DEMAND} and X_{ENVIRON} should also be related to the missions and services found in the hospital.

The third identification strategy is to use future and past values of the area-demand and environment variables as instruments for the hospital's choice of mission and service. These leads and lags are correlated with the long-run decisions about the mission and service of the hospital. The decisions about the hospital's mission and service were made in the past, taking into consideration the demographic and economic future of the area. The leads and lags are uncorrelated with the short-run fluctuations of the number of uninsured. The hospital's mission and service will not change in response to temporary changes in the number of uninsured, so the leads and lags are potentially good instruments.

In practice, a combination of these three strategies was used to achieve identification. The interaction terms and the leads and lags were included in the multinomial logit (as

W), in addition to X_{DEMAND} and X_{ENVIRON}. These instruments were also used separately. The combined approach yields substantially the same results as any one strategy alone, but with smaller standard errors in the second stage.

□ **Hospital characteristics.** This article addresses differences between for-profit and nonprofit hospitals, so the data used are a subset of the 1981 American Hospital Association annual survey of hospitals. Long-term and special-care facilities, such as psychiatric or tuberculosis hospitals, which inherently attract a select group of patients, are excluded. Also excluded are all government and county controlled hospitals, because they are usually mandated to provide service to the poor or medically indigent. As a result, on average, more than 10% of the patients of these hospitals have no insurance, and they therefore operate under a set of constraints different from those on for-profit and nonprofit hospitals. The final dataset, after dropping observations with missing data, consists of 3,322 short-term general-care hospitals in the continental United States.

The amount of uncompensated care varies greatly across hospitals (see Table 1). The overall mean of the percentage of patients who are uninsured is 6%, but it ranges from zero to 70%. This information comes from a survey of hospitals conducted by the Office of Civil Rights in 1981. That survey, which collected information on insurance coverage for all admissions to hospitals in the United States during a two-week period, is unique in that it provides the only national data that identify the source of payment for each patient. For this reason, this study is also restricted to the year 1981. For purposes of the study, patients are said to be uninsured if they pay no charges or reduced charges, are

TABLE 1 Summary Statistics of Hospital Variables

Variable Description	Mean	Standard Deviation	Minimum	Maximum
Fraction uninsured	.060	.058	0.0	.70
For-profit				
Obstetrics	.077	.26	0.0	1.0
No obstetrics	.070	.27	0.0	1.0
Nonprofit				
Obstetrics	.645	.49	0.0	1.0
No obstetrics	.149	.36	0.0	1.0
Teaching				
Obstetrics	.051	.22	0.0	1.0
No obstetrics	.007	.08	0.0	1.0
Demand				
Mean per-capita income ($1000)	8.4	1.9	3.4	14.7
% on AFDC	4.6	3.0	.04	18.3
% on Medicare	13.2	3.7	3.1	32.3
% White	88.3	12.5	15.1	110.9
Births per 100,000	1580	340	462	4570
Economic environment				
Hospital wage index	13400	2920	5310	20600
% MD specialists	74.9	23.1	0.0	98.2
MDs per 100,000	150	103	8.0	1430
Herfindahl index	.15	.14	.001	1.0
Occupancy rate (%)	72.8	11.4	15.5	106
Regional variables				
Average temperature	54.7	8.0	35.7	75.5
Suburban dummy	.24	.43	0.0	1.0
Urban dummy	.11	.31	0.0	1.0
West region dummy	.17	.38	0.0	1.0
South region dummy	.31	.46	0.0	1.0
Northeast region dummy	.21	.40	0.0	1.0

self-payers, or are covered by the Hill-Burton Act. Under the Hill-Burton plan the government provided money for hospital expansion; in return, the hospital was obligated to provide a certain amount of free medical care (although this obligation was never enforced).

Hospitals can be classified into one of six categories, according to their ownership, teaching status, and provision of obstetric care as indicated in the 1981 American Hospital Association annual survey of hospitals. A hospital is either for-profit, nonprofit, or teaching, and it either has or does not have an obstetrics department. A teaching hospital is defined as a member of the Council of Teaching Hospitals. There are no for-profit teaching hospitals in the study.

Countywide averages are the best available proxies for the characteristics of the area that a hospital serves. The location characteristics at the county level were compiled by Abt Associates from the Area Resource File and the United States Census. A few variables range over 100% because the numerator and denominator come from different data sources.

Five area characteristics are included to measure the underlying demand for free care in the hospital's market area. The demand for free care is presumably lower when the per-capita income is higher, when the percentage white is higher, and when insurance coverage is higher. The demand for free care is presumably higher when births per capita are higher.

Five other area characteristics are included to measure for the cost of providing care. Increased competition among hospitals to attract physicians or patients is likely to increase the cost of providing care and therefore reduce the supply of free care, since hospitals presumably compete using quality rather than price. The number of physicians per capita, the percentage of physicians that are specialists, and a county-level Herfindahl index (based on patient-days) should be inversely related to competition and therefore positively related to the supply of free care. The supply of free care is also presumably higher when the occupancy rate is lower, since the occupancy rate measures excess capacity. Finally, the supply of free care is presumably higher when hospital wages are lower, since lower wages are associated with lower costs of providing care. The hospital wage index comes from the Bureau of Labor Statistics.

Six other area characteristics are included to measure general differences in both the supply of and demand for free care. These measures are intended to capture broad differences in demographics, laws, regulations, and business climates. The measures included are regional dummy variables for three of the four census divisions, a county's 30-year average temperature, and the dummy variables *SUBURBAN* and *URBAN*, which refer to the county's population density. A county with 500 to 2,500 people per square mile is labelled suburban, and a county with higher density is labelled urban.

□ **Hospital ownership, service, and location.** Tables 2 and 3 display the data by type of hospital in order to illustrate the interrelationship between a hospital's ownership type, services, location characteristics, and amount of free care. Hospitals with different ownership have different proportions of uninsured admissions (see Table 2). The overall difference between nonprofit and for-profit is 6.1% compared to 5.2%. Teaching hospitals provide even more care to uninsured patients, at 6.6%. Providing obstetric services is also strongly related to the proportion of uninsured admissions at a hospital. Hospitals with an obstetrics department have nearly twice the percentage of uninsured patients as hospitals without an obstetrics department. In addition, only 52% of the for-profit hospitals have an obstetrics department, as compared to 81% of the nonprofit hospitals and 88% of teaching hospitals.

The fact that for-profit hospitals are much less likely to have an obstetrics department may mean that they avoid uninsured patients by failing to provide certain services. Alternatively, for-profit hospitals may simply be more likely to locate in areas where there is both a limited demand for obstetric services and a small uninsured population. The

TABLE 2 Percentage of Uninsured Patients, by Hospital Type

Type of Hospital	No Obstetrics	Obstetrics	Total
For-profit			
% Uninsured	3.68	6.49	5.15
	(.38)	(.43)	(.30)
# Hospitals	234	257	491
Nonprofit			
% Uninsured	3.91	6.61	6.10
	(.22)	(.12)	(.11)
# Hospitals	494	2143	2637
Teaching			
% Uninsured	3.52	7.00	6.59
	(.57)	(.59)	(.53)
# Hospitals	23	171	194
Total			
% Uninsured	3.82	6.62	5.99
	(.19)	(.12)	(.10)
# Hospitals	751	2571	3322

Standard errors are in parentheses.

location characteristics of hospitals in our sample do, in fact, differ dramatically by hospital ownership and services (see Table 3). For example, for-profit hospitals are found in areas with fewer people on AFDC, more births, and higher wages. There are also large differences between hospitals in the percentage of Medicare, per-capita income, occupancy, and probability of being in one of the four census regions. This evidence supports the hypothesis that different types of hospitals locate in different areas.

Many of the basic relationships illustrated in Tables 2 and 3 are further documented in previous studies. Arrington and Haddock (1990) found that for-profit hospitals provide less free care. Townsend (1986) and Sloan, Morrisey, and Valvona (1988) found that obstetrics services draw a disproportionate number of uninsured patients. Finally, Townsend (1986), Ermann and Gabel (1986), Mullner and Hadley (1984), and Alexander, Lewis, and Morrisey (1985) found that the location of and acquisition of for-profit hospitals are closely related to market factors such as per-capita income and insurance coverage.

Tables 2 and 3 provide further evidence that for-profit and nonprofit hospitals do not, on average, provide the same services or locate in similar areas. These differences suggest that hospital ownership and services depend on the characteristics of the hospital's location. Some of the characteristics of a hospital's location are likely to be unobserved, and they also may affect the demand for free care. Hospital ownership and services are therefore endogenous, and comparisons of the percentage of uninsured by hospital type that do not control for endogeneity (such as those in Table 2) will be biased.

3. Estimation and specification tests

■ Equation (4) was estimated first by ordinary least squares and then by instrumental variables. Both methods used five dummy variables for the different hospital types, omitting the category of a nonprofit hospital with obstetric services. There are sixteen additional right-hand-side variables, of which five are related to demand, five are related to supply, and six are geographic variables that may affect both supply and demand. The dependent variable (log-odds of the percent uninsured, conditional on admission) was not defined for the 7% of the hospitals that had no uninsured patients during the reporting period. A Cox correction was therefore used adding $1/2n$ to both the numerator and denominator, where n equals the number of admissions for that hospital (Maddala, 1983).

TABLE 3 Average Values of Independent Variables for Each Hospital Type

	For-Profit		Nonprofit		Teaching	
Variable	No OB	OB	No OB	OB	No OB	OB
# Hospitals	234	257	494	2143	23	171
Per-capita income ($1000)	9.00	8.01	8.93	8.17	9.41	10.05
	(.13)	(.12)	(.08)	(.04)	(.28)	(.14)
% on AFDC	4.18	3.75	5.53	4.23	8.66	6.97
	(.18)	(.15)	(.16)	(.06)	(.93)	(.30)
% on Medicare	12.6	12.0	12.9	13.5	13.4	12.4
	(.33)	(.26)	(.15)	(.08)	(.44)	(.16)
% White	82.8	86.3	85.8	90.6	78.8	79.0
	(.77)	(.71)	(.57)	(.25)	(2.48)	(1.14)
Births per 100,000	1592	1721	1513	1591	1430	1478
	(21)	(24)	(12)	(7.6)	(36)	(20)
Hospital wage index	15371	13478	14386	12780	15651	15875
	(159)	(195)	(111)	(62)	(344)	(123)
% MD specialists	83.7	72.1	82.4	71.0	93.7	92.0
	(.96)	(1.4)	(.80)	(.53)	(.69)	(.35)
MDs per 100,000	177	130	176	131	344	282
	(5.5)	(4.7)	(4.7)	(1.8)	(54)	(14)
Herfindahl index	.131	.126	.127	.159	.073	.100
	(.010)	(.007)	(.006)	(.003)	(.021)	(.009)
Occupancy rate	73.5	68.9	76.0	71.7	81.9	80.9
	(.52)	(.67)	(.42)	(.26)	(1.0)	(.42)
Temperature	63.3	61.3	55.1	53.0	52.6	53.9
	(.45)	(.42)	(.33)	(.16)	(.93)	(.43)
Suburban dummy	.436	.261	.308	.184	.478	.404
	(.032)	(.027)	(.021)	(.008)	(.106)	(.038)
Urban dummy	.120	.043	.186	.070	.478	.404
	(.021)	(.013)	(.018)	(.005)	(.106)	(.038)
West region dummy	.218	.276	.172	.160	.043	.088
	(.027)	(.028)	(.017)	(.008)	(.043)	(.022)
South region dummy	.671	.642	.249	.252	.174	.146
	(.031)	(.030)	(.019)	(.009)	(.081)	(.027)
Northeast region dummy	.064	.027	.273	.201	.565	.468
	(.016)	(.010)	(.020)	(.009)	(.106)	(.038)

Standard errors are in parentheses.

For the instrumental variables approach, only the demand, supply, and geographic variables were assumed to be exogenous. This assumption required instruments for the five endogenous dummy variables for hospital type. Two sets of variables excluded from (4) were used separately as instruments: 25 interaction terms between demand and supply, and from 22 leads and lags of demand and supply. Eight explanatory variables provided leads and lags for years 1970, 1975, and 1985. Six of the leads and lags were unavailable, but four could be replaced by values from nearby years, leaving a total of 22 leads and lags as instruments. Leads and lags were not relevant for the regional dummy variables and average temperature, and not available for the Herfindahl index and the hospital wage index.

In addition, five predicted values from a first-stage multinomial logit model were used as instruments. The multinomial logit model used the same exogenous variables as in (4), as well as either the 25 interaction terms or the 22 leads and lags. The results from the multinomial logit are neither central to the article nor easy to interpret, and are therefore not reported.

The robustness of these results was checked by running the model with all possible combinations of instruments, including all together. The results were always similar, except that the standard errors were smaller when more instruments were used. Thus, it appears that the results are robust to the functional form of the first stage and that the specification of the probability model is not driving the results.

To examine the specification of the model and the robustness of the results, a series of specification tests was applied to the model. First, equation (4) was checked for heteroskedasticity. A White (1980) test indicated that the errors were heteroskedastic, so standard errors for both ordinary least squares and instrumental variables were computed using White's robust estimator for the covariance matrix. Furthermore, all test statistics of equation (4) use the form that is robust to heteroskedasticity (Wooldridge, 1991).

The differences between the instrumental variable and least squares estimates provide a test of the importance of endogeneity. Wooldrige's (1991) robust regression-based test statistic was used, which under the null hypothesis of no endogeneity has a chi-squared distribution with the number of degrees of freedom equal to five, the number of endogenous variables. The value of the statistic for both specifications rejects the null hypothesis at the 5% level. The values were 18.8 for the specification with interactions terms and 15.1 for the specification with leads and lags, each with five degrees of freedom. This result indicates that the least squares estimates are significantly biased.

Tests of the multinomial logit specification found no evidence of misspecification (see Hausman and McFadden, 1984). The test of the assumption of the independence from irrelevant alternatives compares coefficients of two different multinomial logit models. One is the full model, and the other drops all observations in certain categories. The multinomial logit model was run first on all six categories and then on just hospitals with obstetric services (three categories). The test statistic

$$\mathrm{IIA} = (\hat{\beta}_{\mathrm{ALL}} - \hat{\beta}_{\mathrm{OB}})'[V(\hat{\beta}_{\mathrm{ALL}}) - V(\hat{\beta}_{\mathrm{OB}})]^{-}(\hat{\beta}_{\mathrm{ALL}} - \hat{\beta}_{\mathrm{OB}})$$

is distributed as chi-squared with degrees of freedom equal to the rank of

$$[V(\hat{\beta}_{\mathrm{ALL}}) - V(\hat{\beta}_{\mathrm{OB}})]$$

under the null hypothesis that independence from irrelevant alternatives holds. The test statistic was 4.72 with 84 degrees of freedom for the specification with interaction terms, and 28.95 with 78 degrees of freedom for the specification with leads and lags. Therefore, neither specification rejected the null hypothesis of independence of irrelevant alternatives. Correct specification of the multinomial logit model improves the efficiency of the instrumental variables estimates, although it is not required for consistency in the second stage.

Three specification tests showed that the instruments were in fact good instruments. First, the predicted probabilities from the multinomial logit model were tested to see whether they were correlated with the endogenous dummy variables. If the predicted probabilities are good instruments, then they will be the only significant predictor in a regression of the endogenous dummy variable on the predicted probabilities and all other exogenous variables (including the interaction terms or the leads and lags). Least squares regressions were run of the five dummy variables (nonprofit obstetrics was excluded) on the predicted probabilities, the explanatory variables, and either the interaction terms or the leads and lags. In all these regressions the predicted probability had a coefficient not significantly different from one, and highly significantly different from zero. All the other coefficients were insignificant. Therefore, the multinomial logit model appears to fit the data well.

Second, a check was made to determine whether the remaining instruments are correlated with the endogenous variable by including them in the multinomial logit model as explanatory variables. The multinomial logit model was run both with and without the remaining instruments, and the values of the log-likelihood functions were compared. Under the null hypothesis that the remaining instruments are not jointly significant, the difference in twice the log-likelihood is distributed as chi-squared with degrees of freedom equal to the number of categories minus one multiplied by the number of excluded variables. For the specification with interaction terms, twice the difference in the log-likelihood functions was 156.6, with 125 degrees of freedom, which rejected joint insignificance at the 5% level. For the specification with leads and lags, twice the difference in the log-likelihood functions was 174.0, with 110 degrees of freedom, which rejected joint insignificance at the 1% level. Thus, the remaining instruments are correlated with the endogenous variable.

Third, a test was made of the overidentifying restrictions, using a robust regression-based test (Wooldridge, 1991), which has a chi-squared distribution with the number of degrees of freedom equal to the number of overidentifying restrictions. This test checks for the correlation between the instruments and the error term, e.g., it tests whether the instruments enter (4). The null hypothesis is that the instruments do not enter (4). For the specification with interaction terms, the test statistic was 30.4 with 25 degrees of freedom. This test did not reject, even at the 20% significance level, which supports their use as instruments. For the specification with leads and lags, the test statistic was 46.8 with 22 degrees of freedom. This test did reject. However, leads and lags of only three variables (percentage on Medicare, percentage on AFDC, births per capita) were problematic. When these leads and lags were removed, the test no longer rejected (results are available from the authors), and the change in the instruments had no effect on the substantive results. Thus, a subset of the leads and lags are good instruments.

Combined, these three methods of testing the specification give us confidence that the interaction terms and leads and lags are reasonable instruments, and that the results are quite robust.

4. Results

■ **Results of least squares.** The least squares estimates provide both a basis for comparison to earlier studies and a benchmark for the instrumental variables estimates (see Table 4). Among hospitals with obstetrics, for-profit hospitals serve fewer uninsured patients than nonprofit hospitals (the omitted category) while teaching hospitals serve more. The same pattern is evident among hospitals with no obstetrics department, although the presence of an obstetrics department is associated with more uninsured patients. Differences between the six hospital types are generally significant at high confidence levels. The only differences that are *not* highly significant are: those between teaching hospitals without obstetrics, of which there are only 23, and all other hospital types; and those between for-profit hospitals with obstetrics and nonprofit hospitals without obstetrics.

As an aid to interpretation, the predicted proportions of uninsured patients for the six hospital types are calculated using sample means for the exogenous variables (see Table 5). Having no obstetrics department appears to reduce a hospital's proportion of uninsured patients by roughly one-third, while being a for-profit hospital rather than a nonprofit hospital appears to reduce a hospital's proportion of uninsured patients by roughly one-fifth. Thus, least squares estimates imply that the elimination of an obstetrics department or a change to for-profit ownership will lead to a sizable reduction in care to the uninsured.

The estimated coefficients for the exogenous variables are generally consistent with expectations. Most of the demand variables have the expected sign and are statistically significant. In areas with higher income and where more people are covered by Medicare and Medicaid, hospitals serve fewer uninsured patients. In areas with higher birth rates, hospitals serve more uninsured patients. Contrary to expectations, the coefficient on the percentage of the population that is white is positive and significant.

The variables that proxy for the economic environment of a hospital enter the regression with the expected signs, although only the hospital wage index and the Herfindahl index are significant. Hospitals serve fewer uninsured patients in areas with higher hospital

TABLE 4 **Estimation Results**

Dependent Variable: $\ln\left[\dfrac{\%UNINSURED + (1/2n)}{1 - \%UNINSURED + (1/2n)}\right]$

Variable	OLS	Instrumental Variables: Interactions	Instrumental Variables: Leads and Lags
Mission and service			
Constant (omitted category: nonprofit with OB)	−2.81**	−2.39**	−2.39**
	(.36)	(.43)	(.43)
For-profit			
With OB	−.244**	−.04	.26
	(.064)	(.35)	(.35)
No OB	−.702**	.14	.29
	(.073)	(.40)	(.37)
Nonprofit			
No OB	−.464**	.30	−.39
	(.050)	(.66)	(.45)
Teaching			
With OB	.328**	1.51**	1.28**
	(.089)	(.42)	(.48)
No OB	−.21	−1.31*	−.90
	(.20)	(.72)	(.61)
Demand			
Income measures			
Per-capita income ($1000)	−.028*	−.043**	−.031*
	(.015)	(.018)	(.017)
Insurance measures			
% on AFDC	−.021**	−.030**	−.020*
	(.010)	(.013)	(.012)
% on Medicare	−.0058	−.0044	−.0033
	(.0052)	(.0062)	(.0062)
Demographics			
% White	.0054**	.0063**	.0056**
	(.0023)	(.0025)	(.0026)
Births per 100,000	.000088*	.000146**	.000080
	(.000053)	(.000074)	(.000064)
Economic environment			
Hospital market			
Hospital wage index	−.000054**	−.000072**	−.000072**
	(.000012)	(.000015)	(.000014)
% MD specialists	.0008	.0014	.0018
	(.0012)	(.0013)	(.0013)
MDs per 100,000	.00024	−.00004	−.00003
	(.00026)	(.00036)	(.00037)
Herfindahl index	.24**	.21	.25*
	(.11)	(.14)	(.13)
Occupancy rate	−.0011	−.0006	.0007
	(.0019)	(.0021)	(.0021)
Regional indicators			
Temperature	.0033	−.0050	−.0052
	(.0034)	(.0054)	(.0050)
Suburban dummy	−.206**	−.244**	−.251**
	(.055)	(.066)	(.062)
Urban dummy	−.036	−.12	−.12
	(.087)	(.10)	(.10)
West region dummy	.476**	.511**	.480**
	(.056)	(.063)	(.062)
South region dummy	.411**	.412**	.338**
	(.063)	(.079)	(.076)
Northeast region dummy	.012	−.043	−.043
	(.053)	(.062)	(.058)

Instruments for instrumental variables are as follows.

Interactions: instruments are both the interaction terms and the predicted values from the multinomial logit model, in which the interactions were also included as predictive variables.

Leads and lags: instruments are both the lead and lag terms and the predicted values from the multinomial logit model, in which the lead and lags were also included as predictive variables.

Standard errors are given in parenthesis. All statistics are based on White's robust estimator of the covariance matrix.

* Significant at the 10% level.

** Significant at the 5% level.

TABLE 5 Predicted Proportion of Uninsured Patients

Variable	OLS	Instrumental Variables: Interactions	Instrumental Variables: Leads and Lags
For-profit			
Obstetrics	.0399	.039	.055
	(.0023)	(.011)	(.016)
No Obstetrics	.0256	.046	.057
	(.0017)	(.015)	(.018)
Nonprofit			
Obstetrics	.05038	.0400	.0431
	(.00095)	(.0051)	(.0039)
No Obstetrics	.0323	.053	.030
	(.0014)	(.027)	(.011)
Teaching			
Obstetrics	.0686	.158	.139
	(.0055)	(.052)	(.054)
No Obstetrics	.0414	.0112	.018
	(.0079)	(.0083)	(.011)

These calculations use the coefficient estimates from Table 4, evaluated at the sample means for all exogenous variables given in Table 1. Standard errors are given in parentheses.

wages. Hospitals also serve fewer uninsured patients in areas with more competition, as measured by the Herfindahl index.

The estimated coefficients for the remaining variables are not surprising. Hospitals in the West and South face significantly more uninsured patients, and suburban hospitals face significantly fewer uninsured patients.

□ **Results of instrumental variables.** The instrumental variable results for the exogenous area variables are quite similar in magnitude and significance to the least squares results, but they are strikingly different for the coefficients on the endogenous hospital type variables (see Tables 4 and 5). The effect of having an obstetrics department on uninsured patient volume largely disappears except among teaching hospitals (recall that there are only 23 teaching hospitals without obstetrics). Teaching hospitals with obstetrics now clearly dominate other hospitals in providing care to the uninsured. More interesting, however, is the fact that for-profit hospitals no longer fall below nonprofit hospitals in providing care to the uninsured. In contrast to the least squares results, these estimates do not indicate any systematic difference between for-profit and nonprofit ownership with respect to uninsured patient volume.

Unfortunately, the instrumental variable estimates of the hospital-type coefficients are imprecise relative to the least squares results. Standard errors on these coefficients increase by a factor of three to ten. Thus, the estimates do not imply that nonprofit and for-profit hospitals behave identically given their location. Rather, the instrumental variable estimates simply provide no evidence of any difference.

The instrumental variable results indicate that least squares coefficients are biased downward for for-profit hospitals with respect to nonprofit hospitals. The downward bias implies that there is a negative correlation between for-profit ownership and the error term in equation (4). Thus, for-profit ownership is less likely in areas with many uninsured people. The bias accords with common sense. If for-profit hospitals avoid areas with many uninsured people, then for-profit ownership will proxy for the number of the uninsured and will appear to have a negative effect on charity care.

These results imply two not altogether surprising conclusions. First, for a hospital in a given location, the effect of for-profit versus nonprofit management on charity care is probably smaller than earlier studies indicated. In particular, there is no evidence that for-profit hospitals per se disproportionately limit care to the uninsured or shift the burden of care for the uninsured to nonprofit hospitals. If these findings are correct, then the fear that the growth of for-profit hospitals will lead to a reduction in charity care appears to be unfounded.

The second implied conclusion is that for-profit hospitals self-select into better-insured markets. In other words, for-profit hospitals appear to be skimming off the cream by being positioned to face a relatively low demand for charity care. If this is true, then the growth of for-profit ownership may be limited by the availability of attractive locations. Furthermore, if nonprofit hospitals are left to serve the relatively underinsured areas that for-profit hospitals avoid, then subsidies to nonprofit hospitals, such as tax exemptions, may be justified.

5. Conclusion

■ For-profit ownership is related to the volume of uninsured patients at a hospital; but this type of ownership is not important in the way one might expect. Because for-profit ownership is more likely in better-insured areas, a hospital's ownership is endogenous to the volume of uninsured patients. This endogeneity biases least squares estimates toward the conclusion that for-profit ownership leads to lower levels of charity care. When the endogeneity of ownership is accounted for, there is no evidence that for-profit ownership per se lowers uninsured patient volume at a given hospital.

The implications of these results are twofold. First, they have ramifications for economic research. For-profit hospitals provide adequate community service to the communities they choose to serve, but they also avoid areas with large numbers of uninsured. Nonprofit hospitals provide the community service expected of them by locating in more needy areas. Based on these conclusions, it appears that economists have been focusing on too narrow a question in asking how ownership affects an existing hospital. In the future, in addition to asking this question they should also address how hospital ownership is determined.

Second, from a policy perspective, these results have implications for the current and future role of for-profit ownership in the hospital industry. To the extent that for-profit hospitals avoid underinsured areas while nonprofit hospitals do not, the current tax-exempt status of nonprofit hospitals may be justified. Furthermore, the selective location strategy of for-profit hospitals may limit their future growth and importance in the hospital industry. If this is correct, then policies designed to increase the role of market forces in the hospital industry may be constrained by the continued dominance of nonprofit ownership.

References

ALEXANDER, J., LEWIS, B., AND MORRISEY, M. "Acquisition Strategies of Multihospital Systems." *Health Affairs*, Vol. 4 (1985), pp. 49–66.

American Hospital Association. *Hospital Statistics, 1987 Edition*. Chicago: American Hospital Association, 1987.

ARRINGTON, B. AND HADDOCK, C.C. "Who *Really* Profits from Not-For-Profits?" *Health Services Research*, Vol. 25 (1990), pp. 291–304.

CAMERON, A.C., TRIVEDI, P.K., MILNE, F., AND PIGGOTT, J. "A Microeconomic Model of the Demand for Health Care and Health Insurance in Australia." *Review of Economic Studies*, Vol. 55 (1988), pp. 85–106.

DRANOVE, D., WHITE, W.D., AND WU, L. "An Analysis of Admission Patterns in Local Hospital Markets." Discussion Paper no. 46, The Wharton School, University of Pennsylvania, 1989.

DUBIN, J.A. AND MCFADDEN, D.L. "An Econometric Analysis of Residential Electric Appliance Holdings and Consumption." *Econometrica*, Vol. 52 (1984), pp. 345–362.

ERMANN, D. AND GABEL, J. "Investor-Owned Multihospital Systems: A Synthesis of Research Findings." In B.H. Gray, ed., *For-Profit Enterprise in Health Care*. Washington, D.C.: National Academy Press, 1986.

FRANK, R.G. AND SALKEVER, D.S. "The Supply of Charity Services by Nonprofit Hospitals: Motives and Market Structure." *RAND Journal of Economics*, Vol. 22 (1991), pp. 430–445.

GRAY, B.H., ed. *For-Profit Enterprise in Health Care*. Washington, D.C.: National Academy Press, 1986.

HAUSMAN, J. AND MCFADDEN, D.L. "Specification Tests for the Multinomial Logit Model." *Econometrica*, Vol. 52 (1984), pp. 1219–1240.

HERZLINGER, R.E. AND KRASKER, W.S. "Who Profits from Nonprofits?" *Harvard Business Review*, (January/February 1987), pp. 93–106.

LUFT, H.S., GARNICK, D.W., MARK, D.H., PELTZMAN, D.J., PHIBBS, C.S., LICHTENBERG, E., AND MCPHEE, S. "Does Quality Influence Choice of Hospital?" *Journal of the American Medical Association*, Vol. 263 (1990) pp. 2899–2906.

MADDALA, G.S. *Limited-Dependent and Qualitative Variables in Econometrics*. New York: Cambridge University Press, 1983.

MOYER, M.E. "A Revised Look at the Number of Uninsured Americans." *Health Affairs*, Vol. 8 (Summer 1989), pp. 102–110.

MULLNER, R. AND HADLEY, J. "Interstate Variations in the Growth of Chain-Owned Proprietary Hospitals, 1973–1982." *Inquiry*, Vol. 21 (1984), pp. 144–151.

O'DONNELL, J.W. AND TAYLOR, J.H. "The Bounds of Charity: The Current Status of the Hospital Property-Tax Exemption." *New England Journal of Medicine*, Vol. 322 (1990), pp. 65–68.

SHORT, P.F., MONHEIT, A.C., AND BEAUREGARD, K. *A Profile of Uninsured Americans*. DHHS Publication No. (PHS) 89-3443. Rockville, MD: Public Health Service, 1989.

SLOAN, F.A., MORRISEY, M.A., AND VALVONA, J. "Hospital Care for the 'Self-Pay' Patient." *Journal of Health Politics, Policy, and Law*, Vol. 13 (1988), pp. 83–102.

TOWNSEND, J. "Hospitals and Their Communities: A Report on Three Case Studies." In B.H. Gray, ed., *For-Profit Enterprise in Health Care*. Washington, D.C.: National Academy Press, 1986.

WHITE, H. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *American Economic Review*, Vol. 48 (1980), pp. 817–838.

WOOLDRIDGE, J.M. "Specification Testing and Quasi-Maximum-Likelihood Estimation." *Journal of Econometrics*, Vol. 48 (1991), pp. 29–56.