EXIT FROM THE HOSPITAL INDUSTRY

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We study the exit of hospitals from the market for inpatient services. More generous hospital reimbursement significantly reduces the probability of exit throughout the 1990s. Conditional on reimbursement levels, hospital efficiency was not a significant determinant in the early 1990s but in the mid- to late 1990s, less efficient hospitals were significantly more likely to exit. Throughout the period, high-tech services increased the probability of survival, and for-profit hospitals were more likely to exit. The role of Medicare as a determinant of exit became less important in the latter half of the 1990s. (*JEL* I11, L11)

I. INTRODUCTION

The hospital industry has experienced significant changes in both reimbursement and technology over the past 20 years. Changes in both the level and type (e.g., per diem versus prospective) of reimbursement have occurred with all major payers. In addition, the demand for inpatient care has declined due to utilization management by managed care organizations and technological advances that have facilitated a shift toward treatment in outpatient settings. At the same time the industry has experienced significant exit and consolidation. Over the time period of this study (1989–97) almost 350 short-term general hospitals exited the inpatient hospital industry. In this article, we examine the characteristics of closing hospitals and study whether the factors that influence closure have changed over the decade of the 1990s.

We expect the factors behind closure to change over the time period for several reasons. First, the *relative* generosity of payment from different payers shifted over the time period. In the late 1980s and early 1990s, reimbursement by Medicaid and Medicare was relatively less generous compared to private payers. Furthermore, the hospital industry was adapting to the shift from to prospective payment to cost-based reimbursement, which began with Medicare and spread to other insurers during this time period. However, by the mid- to late 1990s, after the market adjusted to changes in the way hospitals were reimbursed, managed care pushed reimbursement of privately insured patients to historically low levels in many markets. Thus, the relative generosity of Medicaid and Medicare payments increased in the latter half of the period. Second, managed care also shifted a larger portion of risk to mainly urban hospitals in the latter half of the 1990s through capitation. Under prospective payment, hospitals are reimbursed at a fixed rate based on a patient's diagnosis. In contrast, hospitals are reimbursed based on the number of enrollees in the managed care plan under capitation. Capitation shifts more risk onto hospitals, and those that are most effective at managing the risk are more likely to be successful. Finally, the technological substitutability between inpatient and outpatient care increased throughout the period. Thus the economic climate for hospitals that performed inpatient and outpatient surgeries was more favorable at the end of the period.

Several previous empirical studies of exit have tested Ghemawat and Nalebuff's (1985,

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ABBREVIATIONS

AHA: American Hospital Association
MSA: Metropolitan Statistical Area

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1990) prediction that in an oligopolistic market for a homogenous good whose demand is declining, survival is inversely related to size.[1] Deily (1991) found no evidence of a simple inverse relationship between a plant's size and exit. Rather, proxies of a plant's profitability were important in determining which plants survived the contraction of the steel industry, thus supporting the neoclassical theory that long-run expected profit determine whether a plant will exit. Gibson and Harris (1996) also find that larger, lower cost, and older plants are less likely to exit an industry.[2]

The focus of previous empirical studies of hospital exit, however, has not been on testing competing theories of exit but describing the characteristics of hospital that close. Most likely this is because hospitals, with their many unique features, are ill-suited to testing general theories of exit. For example, the hospital industry is populated by government, nonprofit, and for-profit firms. We expect for-profit hospitals to be more likely to exit because not only do they compare uses of capital across several industries but they are also unable to credibly commit to remaining in a market with excess capacity, as shown in Wedig et al. (1989). In contrast, non–federal government and many nonprofit hospitals have alternative sources of funding that can sustain them through a marketwide shakeout.

In their study of small hospitals between 1985 and 1988, Williams and colleagues (1992) found that financial variables (total margin, costs, and revenues) are significant determinants of hospital closure and that public hospitals are less likely to close than other hospitals. Williams and colleagues also find that rural hospitals providing fewer services and surgeries are more likely to close. Using a sample of all hospitals between 1986 and 1991, Deily and colleagues (2000) study whether the hospitals that exit the market are the least efficient and find that the effect of their measure of inefficiency differed systematically among different ownership types. Less efficient for-profit and private not-for-profit hospitals were shown to be more likely to exit than their efficient counterparts. Deily and colleagues (2000) is the first study that relates a measure of the technical efficiency to closure, though they measure efficiency using a stochastic frontier cost function. Finally, Lindrooth and colleagues (2003) measure the effect of hospital closure on the costs of the remaining hospitals in the local market and find that closing hospitals had higher costs and that the reduction in capacity in the market led to a further reduction in market cost. They tie this latter result to the cost of an empty bed.

Our analysis is different from previous studies on exit in several ways. First, we use panel rather than cross-sectional data, so we are able to control for unobserved heterogeneity and state dependence using a random effect logit specification. Second, we use direct measures of total costs, revenues, outputs, and capacity, so we are able to separately identify the role of excess capacity from that of costs and revenues on the decision to exit. Third, we identify the regression equations through differences within the same industry across local markets, rather than using differences across industries, as in Gibson and Harris (1996).

Our analysis shows that efficiency and reimbursement are critical determinants of exit—hospitals that are less efficient and provide services with lower reimbursement are more likely to exit. This finding supports the neoclassical theory that efficiency determines the order of exit of plants in a declining industry. We also find that differentiation into outpatient and high-tech services decreased the likelihood of exit throughout the time period. Hospitals that adapt to the changing demand for their services are more likely to survive. Third, we find that not-for-profit hospitals are less likely to exit than for-profit hospitals. This supports the notion that the exit threshold of for-profit hospitals is higher than that of nonprofit hospitals. This is likely because for-profit hospitals compare uses of capital across industries, whereas nonprofit hospitals may be strongly committed to inpatient care. Fourth, we find that the role of Medicare and

1. Ghemawat and Nalebuff assume that capacities and production costs are common knowledge, unit costs are constant, and fixed costs are proportional to capacity. The basic insight for their result is that firms play a game of attrition. As the demand continues to decline, the larger plant cannot credibly commit to stay in the market for a longer time than the smaller plant. By backward induction, the larger firm will exit as soon as the demand cannot support more than one firm in the industry.

2. Gibson and Harris find that firms owning many plants made plant-closing decisions that did not seem to rely on relative production costs. This last piece of evidence supports Whinston's (1988) theory that multiplant firms are able to internalize the benefits of a plant's exit. We will return on this point in our discussion of the results.

Medicaid share of patients as determinants of exit has changed over the 1990s. Early in the 1990s, higher Medicare and Medicaid penetration led to an increased probability of exit, but by the late 1990s this relationship had disappeared.

II. METHODS

Hospital h decides whether to exit or remain in the market for inpatient services based on whether expected profits exceed some threshold, T:

$$(1) \qquad E(\pi_{ht}) \geq T(M_{ht}, E_s),$$

where π denotes profit, the subscript t denotes time, and M_{ht} reflects the objective, or mission, of the hospital and is proxied by ownership. For example, $T(M_{ht}, E_{st})$ for a for-profit hospital would reflect the opportunity cost of capital across a wide range of industries, whereas $T(M_{ht}, E_{st})$ at a nonprofit hospital may reflect a mission to provide inpatient care. E_{st} is the "external" long-run benefit to the other hospitals owned by system s from shutting down the inpatient operations of hospital h. It only accrues to systems with multiple hospitals in the same market, as in Whinston (1988).

Profit is modeled as a function of revenue, R, and total operating costs, C:

$$(2) \qquad \pi_{ht} = f(C_{ht}, R_{ht},),$$

where C_{ht} is the long-run cost of providing care as measured by the American Hospital Association. R_{ht} is a function of the reimbursement levels of the hospital, reflecting, for example, payer mix. We parameterize Equation (1) as follows:

$$(3) \qquad \begin{aligned} &Close_{ht} = 1 \\ &\quad \text{if } E(\pi_{ht}) - T(M_{ht}, E_s) \\ &\quad\quad = \alpha + \beta_R R_{ht} + \beta_M M_{ht} + \beta_C C_{ht} \\ &\quad\quad\quad + \beta_E E_{ht} + \tau_h + \varepsilon_{ht} < 0 \\ &Close_{ht} = 0 \\ &\quad \text{if } E(\pi_{ht}) - T(M_{ht}, E_s) \\ &\quad\quad = \alpha + \beta_R R_{ht} + \beta_M M_{ht} + \beta_C C_{ht} \\ &\quad\quad\quad + \beta_E E_{ht} + \tau_h + \varepsilon_{ht} \geq 0, \end{aligned}$$

where τ_h is a hospital-specific error component that reflects fixed hospital characteristics, such as age of plant and cost of capital and R_{ht}, M_{ht}, C_{ht} and E_{ht} are as already defined. Note $u_{ht} = \tau_h + \varepsilon_{ht}$ is a combination of a hospital-specific component and a temporally independently identically distributed component, which are by construction independent of each other. ε_{ht} is assumed to have a Weibull distribution, $F(\varepsilon_{ht}) = \exp(\exp(-\varepsilon_{ht}))$, while $\tau_h \sim N(0,\sigma^{2t})$ and $\sigma_U^2 = 1$, and furthermore we assume that there is no structural state dependence once heterogeneity across hospitals has been taken into account as shown in Heckman (1981a). Under these conditions Equation 3 can be modeled as:

$$(4) \qquad \begin{aligned} &P(d_{ht} = 1 | X_{ht}, \tau_h) \\ &\quad = \Lambda(X_{ht}\beta + \tau_h) \\ &\quad = e^{X_{ht}\beta + \tau_h} / (1 + e^{X_{ht}\beta + \tau_h}), \end{aligned}$$

where X includes all explanatory variables in Equation (3). If we define $\theta = e^{X_{ht}\beta + \tau_h} / (1 + e^{X_{ht}\beta + \tau_h})$ then the distributional assumption of τ implies that we can integrate out the individual hospital random effect, yielding:

$$(5) \qquad \begin{aligned} &P(d_{ht} = 1 | X_{ht}) \\ &\quad = \int_{-\infty}^{+\infty} (\theta) e^{-\tau_h^2 / 2\sigma_\tau^2} / \sqrt{2\pi}\sigma_\tau d\tau. \end{aligned}$$

The log likelihood function is then:

$$(6) \qquad \begin{aligned} L = \sum_{h=1}^{N} \log \Bigg\{ \int_{-\infty}^{+\infty} & e^{-\tau_h^2 / 2\sigma_\tau^2} / \sqrt{2}\pi\sigma_\tau \\ & \times \prod_{y = Y_h^{start}}^{Y_h^{end}} (\theta)^{d_h} (1 - \theta)^{1 - d_h} d\tau \Bigg\}. \end{aligned}$$

Here Y_h^{start} is the first year the hospital h appears in the data set. Y_h^{end} is the last year the hospital appears in the data set. Hospitals turn up in the data set at different times as entry occurs, thus $Y_h^{start} \neq 0$ differs across hospitals. This introduces the problem of nonexogenous initial conditions. If the process has been in operation prior to the time it is sampled, and if the disturbances are serially dependent, the initial conditions are not exogenous variables and the exit/stay decision and the entry decision are stochastically dependent on τ_h. However, if no structural state dependence is present once heterogeneity is properly accounted for, and if the stochastic process that drives the discrete choice random variable is stationary, then maximizing the log likelihood returns consistent estimates of the parameters β.[3]

Note that the probability of exit at the mean value of the control variables is extremely low in our sample (approximately 0.6%). Thus, the marginal effect of a change in one of the independent variables on the probability of closure is also very small. It is more interesting to study the percentage change in the probability of closure conditional on a marginal change in the independent variable, $[(\partial P(d_{ht} = 0|X_{ht}, \tau_h))/P(d_{ht} = 0|X_{ht}, \tau_h)]/\partial X^k_{ht}$, which in this context is approximately equal to the coefficient estimates. To see this note that $[\partial P(d = 0)/P(d = 0)]/\partial X^k = \beta_k/[1 + \exp(X\beta)]$ and because the probability of exit is small, $\exp(X\beta)$ is very close to zero (i.e., the realizations of exit are far on the left-hand side of the distribution). Thus $\partial P(d=0)/P(d=0) \approx \beta^k \partial X^k$. For independent variables in logged units the parameter estimates are very close to elasticities. For other variables measured in percentages we report the effect of an X percentage *point* change on the percentage change in the probability of exit. We estimate Equation (6) using the entire sample and separately for the 1989–93 and 1994–97 periods. We also estimate Equation (6) using only urban hospitals, which are defined based on a location within a metropolitan statistical area (MSA).

The standard errors of Equation (6) are estimated using a bootstrap with clustering at the hospital level. Thus in each draw the hospitals are sampled accounting the fact that hospitals appear in multiple years. This technique was suggested by Bertrand et al. (2004), who show it yields more accurate standard errors in a time-series context. We report standard errors based on 100 repetitions in the tables. We performed a bootstrap with 500 repetitions on the urban subsample and found that there were trivial differences in the standard errors if 100 versus 500 repetitions were used. Thus we perform 100 repetitions for all of the estimates.

3. To avoid the assumption of stationarity, Heckman (1981b) proposes to use a fixed-effect model. In this context, such a solution would not work because the only hospitals in the restricted sample would be the hospitals that exit the industry. Hospitals are present in the industry only once—they do not re-enter the industry after exit.

TABLE 1
Closures over Time

Year	Open	Closed
1989	5052	63
1990	4988	54
1991	4918	48
1992	4879	44
1993	4818	25
1994	4684	34
1995	4649	27
1996	4463	31
1997	4387	21
Total		347

III. DATA

The data set includes all nonfederal short-term urban and rural general hospitals in the American Hospital Association's *Annual Survey of Hospitals* operating between 1989 and 1997. We identified closures using data from American Hospital Association (AHA). We followed up on the closures reported by the AHA to confirm that the hospital did in fact remain closed. There were several instances where the AHA reported name changes as closures. In addition, we identified one case where a hospital was reported as closed when in fact it was only temporarily closed for remodeling. We treated these hospitals as survivors in our analysis. Overall, we identified 347 closures of general short-term hospitals. A closure is defined as a permanent elimination of general inpatient bed capacity. Thus, for example, a permanent conversion to a specialty hospital is treated as a closure. Table 1 shows the total number of closures over the time period. The number of closures in the whole nation has been declining over time, and closures were more frequent prior to 1993. The closure rates were close to 1% in 1989 and 1990 but decline to 0.5%–0.7% in the latter half of the period.

IV. VARIABLE CONSTRUCTION

We derive a measure, which we call the *revenue premium*, to represent the revenue each hospital gets relative to it competitors within the market. The revenue premium, denoted $\hat{Q}^{dev}_h$, is a proxy for quality and case-mix in the analysis. We derive the revenue premium as follows. First, we calculate net patient revenue per adjusted admission using net patient

TABLE 2
Summary Statistics

Variable	All (n = 43,185) Mean	All SD	Exiting Hospitals[a] (n = 1,395) Mean	Exiting SD	Surviving Hospitals[b] (n = 41,790) Mean	Surviving SD
Revenue premium ($\hat{Q}_h^{dev}$)	0.000	0.456	−0.459	0.546	0.015	0.444
Efficiency ($\hat{F}_h^{dev}$)	0.000	0.461	0.415	0.500	−0.014	0.453
Ln(*Cost*)	16.880	1.383	15.903	1.301	16.913	1.374
Ln(*Revenues*)	16.851	1.425	15.757	1.397	16.888	1.412
System Membership	0.414	0.492	0.430	0.495	0.413	0.492
Number of Additional Sites	0.816	1.545	1.032	1.884	0.809	1.532
Log Beds	4.732	0.943	4.231	0.877	4.749	0.940
Capacity Utilization	0.552	0.191	0.465	0.221	0.555	0.189
% Medicare	0.398	0.149	0.423	0.198	0.398	0.147
% Medicaid	0.131	0.099	0.125	0.130	0.131	0.098
% ER	0.342	0.192	0.365	0.243	0.341	0.190
Have SNF	0.267	0.442	0.184	0.388	0.269	0.444
% LTC	0.015	0.042	0.020	0.064	0.015	0.041
% Outpatient	0.892	0.082	0.854	0.149	0.893	0.078
HMO Penetration	0.119	0.135	0.121	0.121	0.119	0.135
Profit	0.131	0.338	0.293	0.455	0.126	0.332
Nonfederal government	0.276	0.447	0.267	0.443	0.276	0.447
Teach	0.169	0.375	0.068	0.252	0.172	0.378
Urban	0.545	0.498	0.628	0.484	0.542	0.498
Medicare case mix	1.236	0.225	1.125	0.189	1.239	0.225
# High-tech services	3.304	2.427	1.786	1.871	3.355	2.427
Ln(*income*)	9.829	0.252	9.797	0.253	9.830	0.252
Ln(*Population Density*)	4.806	1.770	5.069	1.894	4.797	1.765
Post	0.536	0.499	0.277	0.447	0.544	0.498

[a]All observations for hospitals that will exit the industry at some point in time.
[b]All observations for hospitals that remain in the industry over the period of study.

revenue data from the Medicare Cost Report.[4] Second, we regress this variable on a hospital fixed effect, hospital patient mix, case mix, and hospital characteristics defined in Table 2 (with the exception of system membership, number of sites, ownership, and location variables) using our full data set. Prior to running the regression, we transformed the variables into deviations from the market mean for each year to control for market-level fixed effects. The revenue premium is the hospital fixed effect estimated in this regression. A large fixed effect implies that the hospital is being reimbursed at a higher rate per admission, controlling for a variety of hospital characteristics, including patient mix and case mix. The most likely reasons for the relatively generous reimbursement are unobserved case mix and quality (clinical or nonclinical). Capps et al. (2003) show that a hospital with attributes that are attractive to patients will be reimbursed by insurers at a higher rate than other hospitals because patients demand the hospital to be included in the insurance network. Among the attributes that are attractive to patients are clinical quality (e.g., favorable outcomes) and nonclinical quality (e.g., nonclinical amenities, such as private rooms or waterfalls in the lobby). Location of the hospital will also affect the attractiveness of the hospital to a group of patients, as shown in Tay (2003). This variable was previously used to control for unmeasured differences in case mix/payment generosity in Lindrooth et al. (2003).

C_{ht} includes a measure of efficiency, denoted $\hat{F}_h^{dev}$. This measure of efficiency is the hospital fixed effect from the same specification used to

4. Net patient revenue is total patient revenue net of discounts and allowances for bad debt.

calculate the revenue premium, except we replace net patient revenue with operating costs from the Medicare Cost Report and include system membership and the number of sites as independent variables. This approach to measuring efficiency was suggested by Skinner (1994), and its attractiveness is due to less restrictive assumptions than data envelopment analysis and stochastic frontier functions. In particular, the validity of the stochastic frontier model is based on zero skewness of the random component of the cost residual because all of the skewness will be attributed to inefficiency. However, the distribution of unmeasured case mix is likely to be skewed to the right, leading to potentially misleading estimates that are exacerbated by the stringent distribution assumptions.

We estimate the efficiency measure and the revenue premium separately for the 1989–93 period and the 1994–97 period, and thus we allow the measures to vary between the two periods. Overall, nonprofit hospitals have the highest revenue premium but are also the least efficient. The lower efficiency score may be due to unmeasured quality or case mix that is not captured in our crude case mix measure. Thus, alone the measure is an imperfect measure of case mix, but because we also include the revenue premium, which includes variation in unmeasured case mix and quality (insofar it is reimbursed by payers), the coefficient estimate on efficiency will be unbiased. For-profit hospitals have the highest efficiency score, and non–federal government hospitals have the lowest revenue premium. The former result is not surprising, and the latter result may be due in part to fewer amenities and more charity care at public hospitals.

M_{ht} contains a dummy variable indicating the hospital is for-profit, and another dummy that indicates the hospital is a non–federal government hospital. The excluded category is nonprofit. In addition, we created a dummy variable, *Teach*, which indicates whether the hospital was a member of the Council of Teaching Hospitals. All these variables are from the AHA annual survey. Other hospital-level variables that explain long-term costs and measure hospital heterogeneity include percent skilled nursing care admissions (%SNC); percent emergency room visits out of the total outpatient visits (%ER); percent outpatient visits out of the sum of outpatient visits and inpatient admissions (% Outpatient); total staffed beds (logged); Medicaid discharges/inpatient admissions; Medicare discharges/inpatient admissions and capacity utilization (inpatient days/[beds $\times$ 365]), all of which are calculated from the AHA data set. In addition we use the Medicare case mix index computed by the Health Care Financing Administration (currently called Centers for Medicare and Medicaid Services) and a measure of the availability and breadth of high-tech services, which is a count of the following services: extracorporeal shock-wave lithotripter; computed tomography scans; magnetic resonance imaging; positron emission tomography; diagnostic radioisotope; single photon emission computerized tomography; radiation therapy; and ultrasound.

Recall that E_{ht} is the benefit of closure that a system derives from closing one of its hospitals measured by a categorical variable, *System Membership*, which is equal to one if the hospital is part of multihospital health care system in a given market. E_{ht} also includes a count variable, *Number of Sites*, which measures the number of hospitals in the local market that are part of the system to which the hospital belongs. The variable *Number of Sites* is equal to zero if the hospital is not part of a system.

Our market-level variables include HMO penetration rates, which were calculated by allocating managed care enrollment to counties based on the managed care service area, using an approach developed by Wholey and colleagues (1997).[5] HMO market penetration rate is the number of HMO enrollees divided by the resident population in the market. In addition, we include market-level variables, such as population density and per capita income, calculated annually at the MSA level for urban hospitals and at the county level for rural hospitals from the Area Resource File.

Finally, we construct a dummy variable *Post* that divides the period 1989–97 in two equal parts. The first part is 1989–93, and the second is 1994–97. The unit of observation in the regressions that follow is the short-term general hospital. We used regression imputation of total admissions (8.21% of the observations), births (9.15%), outpatient visits (11.35%), Medicare discharges (16.68%), Medicaid discharges (17.96%), long-term admissions (8.21%), and case mix (2.06%). We

5. We thank Douglas Wholey for providing these data.

TABLE 3
Selected Characteristics of Closures and Survivors

Type	% of Closures ($n = 347$)	% of Survivors ($n = 5{,}081$)
For Profit	28.24	14.84
Government	28.53	25.15
NFP	43.23	60.01
Teaching	5.76	18.42
1 Site	64.55	53.16
2 Sites	17.87	24.76
3 Sites	6.34	8.03
4 Sites	3.75	4.17
5 Sites	2.88	3.48
>5 Sites	3.46	6.4
Urban	59.65	55.95

performed the analysis on a reduced sample of hospitals with complete data, and the results were very similar. Hence we only present the results using the imputed values. After imputation, we have 43,185 hospital-year observations for which there are complete information on all dependent variables.

V. UNIVARIATE ANALYSIS

Table 3 shows the selected characteristics of closed hospitals and survivors. Most of the hospitals that closed were not-for-profit (43.23%), but the percentage of not-for-profit hospitals that did not close is higher (60.01%). In contrast, the percentage of for-profit hospitals that closed (28.24%) is double the percentage of those that did not close (14.84%). We do not find any substantial difference with regard to the government- and church-owned hospitals. Furthermore, closures mostly occurred at not-for-profit hospitals that were not teaching hospitals. Only a few teaching hospitals closed, with the percentage that closed (5.76%) being one-third of the percentage of teaching hospitals that remained open (18.42%). About 65% of the hospitals that closed were independent hospitals (denoted "1 Site" in Table 3), and 53.16% of the survivors were independent. Hospitals that had multiple sites (i.e., system hospitals) generally comprised a larger percentage of survivors than closures.

The summary statistics for all of the variables used in the analysis are in Table 2. The first column presents the means and standard deviations for all the hospital-year observations in the sample. The second column presents the same statistics for the hospitals that close and uses each hospital-year observation for the 347 closing hospitals. The third column presents means and standard deviations for the hospital that does not close. Ln(*Costs*), Ln(*Revenues*), and Ln(*Beds*) are smaller for closing hospitals than for those that survive. In addition hospitals that survive are more likely to provide skilled nursing care, offer more high-tech services, and treat more complex cases. Less than half of the hospital-year observations are for hospitals that are not part of a system over the time period we study. The average number of additional sites is close to one for exiting (1.032) and surviving hospitals (0.809) if we consider all hospital-year observations. If we restrict the attention to the hospitals that are part of a system we find that *Number of Sites* is on average equal to 2.398 for exiting hospitals and 1.959 for surviving hospitals.

We find that closures are more likely to occur in urban areas with high population density. We also observe that the generated regressors of quality and efficiency are negative for the exiting hospitals, suggesting that competitive pressure may push less efficient and lower quality hospitals out of the market.

VI. RESULTS

The first column in Table 4 contains the results of the random effect logit regression using the entire sample. The second and third columns show the results for all hospitals in the pre- and post-1994 periods, respectively. Columns 4 and 5 display the results in the pre- and post-1994 periods for the urban hospital sample. We find that more generously reimbursed hospitals, as measured by *Revenue Premium*, were less likely to exit throughout the time period. More efficient hospitals were also less likely to exit, though this result is only significant in the entire sample and the post-1994 samples. There is a similar trend for hospitals with large percentages of skilled nursing facility (SNF) patients. Larger percentages of SNF patient had a large effect in the post-1994 sample, but were insignificant in the pre-1994 sample. In contrast, hospitals with high Medicare shares were more likely to exit in the pre-1994 sample, but the coefficient is much smaller and statistically insignificant in the post 1994 sample.

TABLE 4
Results of Analysis of Closure

	All Hospitals			Urban Hospitals	
Variable	**1988–97**	**1989–93**	**1994–97**	**1989–93**	**1994–97**
Efficiency	−1.925**	−2.015	−2.233***	−1.124	−2.421***
	(0.831)	(1.783)	(0.727)	(1.701)	(0.778)
Revenue Premium	−3.099***	−3.407**	−2.915***	−2.782*	−2.870***
	(0.791)	(1.614)	(0.724)	(1.602)	(0.699)
System	−0.292	−0.065	−0.585*	0.175	−0.600
	(0.207)	(0.258)	(0.312)	(0.423)	(0.364)
Number of Hospitals	0.119**	0.144	0.093*	0.102	0.073
	(0.057)	(0.097)	(0.055)	(0.122)	(0.072)
Total Beds	−0.369**	−0.214	−0.494**	−0.030	−0.561**
	(0.146)	(0.259)	(0.206)	(0.257)	(0.258)
Occupancy Rate	−0.585	−0.883	0.122	−1.477	−0.760
	(0.523)	(0.705)	(0.728)	(1.029)	(0.984)
Percent Medicare	1.124***	1.415***	0.467	0.916	0.147
	(0.421)	(0.521)	(0.764)	(0.823)	(0.995)
Percent Medicaid	0.917	1.194	0.166	1.602	−0.061
	(0.744)	(0.889)	(1.017)	(1.003)	(1.185)
Percent ED	0.058	0.464	−0.673	0.856	−0.920
	(0.332)	(0.408)	(0.494)	(0.668)	(0.703)
Have SNF	−0.238	−0.080	−0.406	0.308	−0.033
	(0.261)	(0.345)	(0.325)	(0.453)	(0.366)
Percent SNF	3.681***	0.020	4.930***	−1.192	4.230**
	(1.098)	(2.993)	(1.020)	(5.853)	(2.105)
Percent Outpatient	−1.461***	−1.565**	−1.274**	−1.579	−1.426
	(0.526)	(0.695)	(0.631)	(0.966)	(0.913)
HMO Penetration	0.403	−0.330	0.010	−0.881	−0.381
	(0.815)	(1.365)	(1.007)	(1.720)	(0.981)
For-profit	0.707***	0.496**	1.038***	0.381	0.882**
	(0.218)	(0.245)	(0.305)	(0.325)	(0.363)
Public	−0.184	−0.234	−0.114	−0.505	−0.452
	(0.166)	(0.229)	(0.243)	(0.378)	(0.412)
Teach	0.563*	0.141	0.566	0.172	0.570
	(0.296)	(2.116)	(0.409)	(3.567)	(0.449)
Case Mix	−0.569	−0.573	−0.877	−0.312	−0.729
	(0.576)	(0.998)	(0.729)	(1.126)	(0.740)
Tech Services	−0.349***	−0.464***	−0.241***	−0.314***	−0.232***
	(0.049)	(0.080)	(0.064)	(0.104)	(0.075)
Per Capita Income	0.571	0.454	0.923	0.714	0.800
	(0.419)	(0.468)	(0.638)	(1.036)	(0.838)
Population Density	0.265***	0.303***	0.186	0.216	0.313*
	(0.090)	(0.115)	(0.138)	(0.173)	(0.183)
Urban	−0.258	−0.744**	0.634*	N/A	N/A
	(0.268)	(0.299)	(0.372)		
Post	−0.578***	N/A	N/A	N/A	N/A
	(0.158)				
Constant	−7.640*	−6.723	−11.064*	−10.221	−8.620
	(4.113)	(4.522)	(6.439)	(9.420)	(8.637)
N	43,185	20,046	23,139	12,524	10,995

Notes: Bootstrapped SEs in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$ based on a two-sided test. All the regressions include region dummies.

Hospitals in a large system, as measured by the *Number of Hospitals* variable, were more likely to exit, and the effect is consistent across time periods, though it is marginally insignificant in the pre-1994 sample of all hospitals. Large hospitals were less likely to exit throughout the period, though the parameter estimate is only significant in the post-1994 sample. Finally, hospitals that had higher shares of outpatient visits and more high-tech services were less likely to exit throughout the time period, although the outpatient coefficients are marginally insignificant in the urban only sample.

If we consider a 10% change from the average value of efficiency and the revenue premium we find that an increase in *Efficiency* of 10% decreases the probability of exit of the hospital by approximately 19.25% and that a 10% increase in *Revenue Premium* decreases the probability of exit (at the mean values) of the hospital by about 30.99%.[6] The magnitude of the effect of *Efficiency* increases from 11.24% to 24.21% in the latter half of the period for urban hospitals. In comparison, the effect of the *Revenue Premium* is relative constant over the time period.

Note that the actual percentage of observations of closed hospitals is very small, thus the model is a much better at predicting hospitals that do not exit than those that exit. A closer analysis of the correlation between predicted and actual outcomes confirms this conjecture.[7] To further analyze whether there is serial correlation in the sample, we estimate $\rho = \sigma_\tau^2/(\sigma_\tau^2 + 1)$, the proportion of total variance contributed by the panel-level variance component. We find that ρ is significantly different from zero, in all specifications, which is evidence that there is serial correlation in the sample and lends support to the random effects logit specification.

VI. SENSITIVITY ANALYSIS

We also separately estimated an ordinary logit model and a random-effects logit model where we created the *Efficiency* and *Revenue Premium* so that they are constant over the entire time period, rather than allowing them to vary between the pre- and post-1994 periods. The results are remarkably consistent with column 1 of Table 4. In addition, we ran the following regressions with logged costs and revenues as deviations from the local market averages replacing the generated regressors of revenue premium and efficiency: a random-effects logit; a between-effect logit regression; and a conditional fixed-effects logit.

The between-effect logit regression studies the probability that a hospital closes conditional on the long-term values of the regressors. The conditional logit regression restricts the analysis to those hospitals that eventually closed over the time period. The conditional logit regression estimates the probability that a hospital will close at time $t + 1$ conditional on the hospital being open at time t, conditional on the fact that the hospital will close at some point in time, and conditional on the particular values of the regressors. The conditional logit specification uses within hospital variation for the closing hospitals and thus helps determine which variables determine the time of exit. We use the measures of revenues and costs rather than $\hat{Q}_h^{dev}$ and $\hat{F}_h^{dev}$ because they vary over time.

If the sample is truly random, then the three regressions should give the same results. If the results differ across regressions, then we should be concerned with the possibility that our baseline specification is biased. Overall the results suggest that the main results in Table 4 are robust to these changes. In particular, the coefficients on *Revenue*, *Costs*, *System*, *Number of Hospitals*, *Total Beds*, *% Medicare*; *% SNF*; *% Outpatient*; *For-profit*; and *Tech Services* are of the same sign as Table 4, and generally significant. However, if the coefficient is not close statistical significance in Table 4, the qualitative conclusions vary across specifications. Thus in our discussion we focus on the effects that are at or near statistical significance. In summary, the qualitative conclusions drawn from the main previous results are not affected by bias, though we are unable to determine to what extent the magnitude of the coefficients may be affected by bias. The results of these specifications are available from the authors on request.

VIII. DISCUSSION

In every specification we find that low–revenue premium hospitals are more likely to exit. Although this result is unsurprising,

6. $\hat{F}_h^{dev}$ measures the percentage deviation in terms of efficiency of the hospital from the *local market* efficiency mean. In particular, in our fixed-effects regression, $\hat{F}_h^{dev}$ is the percentage deviation of the hospital's costs from the constant term that is not explained by the control variables because the dependent variable is the natural logarithm of costs.

7. The results of the correlation analysis are available from the authors.

it is important to consider that variation in the revenue premium is from attributes of the hospital that are difficult for managers to change in the short run: location, amenities, and reputation. Managers are likely to be better able to influence efficiency and the effect of efficiency is largely concentrated in the latter half of the period. Private insurers increased the incentives to hospitals to lower costs through managed care, during the mid- to late 1990s. Our analysis suggests that this shift rewarded efficient hospitals at the expense of inefficient hospitals. This conclusion is strengthened by the fact that when we include a variable in the post-1994 analysis that indicates whether a hospital's efficiency increased between pre- and post-1994, the coefficient was statistically significant and positive, indicating that hospitals with improved efficiency were more likely to survive. Thus, improving efficiency is correlated with better survival prospects conditional on the level.

These results lend credence to the notion that exit from the hospital industry is orderly in that the less efficient hospitals exit first, and that payment incentives were consistent with this in the latter half of the 1990s. Conditional on efficiency, we also consistently find that for-profit hospitals are more likely to exit. Whereas others have also identified this relationship, we are the first to do so controlling for efficiency and the revenue premium. Although this result is not surprising, it lends further evidence that for-profit hospitals compare the uses of capital across industries and reallocate the capital as economic conditions warrant.

The results also reveal the value of diversification into outpatient and high-tech services. Hospitals with a relatively large share of outpatient visits and more high-tech services were less likely to exit. However, higher shares of SNF patients dramatically increased the probability of exit in the latter half of the period, though for the vast majority of hospitals the percentage of SNF patients was not large enough to overwhelm the *Have SNF* coefficient. Thus the existence of a SNF alone is not a predictor of exit. The Balanced Budget Act of 1997 included a provision to shift Medicare reimbursement of skilled nursing care from cost-based to prospective reimbursement. This provision was expected to hurt hospitals with large SNF populations, in particular. It is beyond the scope of our analysis to test whether the anticipation of SNF provision in the act led to the larger exit probabilities of hospitals with large SNF population that we observe in the latter half of the 1990s.

The percent of Medicare patients increases the probability of exit in the pre-1994 period but is significantly lower and insignificant in the post period. This result is likely due to two reasons. First, it could be a residual effect of the shift from cost-based to prospective payment. All of the hospitals that did not adapt to prospective payment exited the market by 1993. By 1994, only the hospitals that could manage prospective payment stayed in business. Second, the relative generosity of Medicare payment increased during the time period. As already mentioned, private payers were ratcheting down payment throughout the 1990s, whereas Medicare stayed relatively constant. In contrast, Medicaid share is insignificant in all specification and switches sign in the pre- and post-1994 urban specification.

In summary, our results suggest that exit from the hospital industry is orderly. Hospitals that are in a position to attract more generous reimbursement (whether it is due to location, amenities, or quality) are more likely to survive. Smaller, undiversified, inefficient hospitals are likely to be the first to leave the market when conditions become unfavorable.

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