EFFICIENCY, GROWTH, AND CONCENTRATION: AN EMPIRICAL ANALYSIS OF HOSPITAL MARKETS

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Taking an evolutionary view, Harold Demsetz hypothesized that firms differ persistently in efficiency and that industry concentration results from growth of efficient firms at the expense of inefficient ones. We test this idea with microdata from the hospital industry. Initial hospital efficiency and subsequent growth (and profitability) are significantly and positively related. Also, greater initial variation in hospital efficiency within local markets is positively related to subsequent growth in market concentration. Our findings support the evolutionary efficiency hypothesis, though they cannot confirm the stronger idea that variation in efficiency is the dominant explanation for changes in concentration. (*JEL* L11, L84, I11, L31, L20)

I. INTRODUCTION

In 1973, Harold Demsetz provided aggregate, cross-industry statistical support for his hypothesis that industry concentration is endogenous, largely the result of growth of relatively efficient firms. In this article, we provide the first known test of this hypothesis using microdata from a single industry: the hospital industry. The hospital industry is a good industry to study for both scientific and policy reasons.

Recently, hospital mergers have received much attention, and efficiencies have been claimed for them. But the courts have remained skeptical, perhaps due to contradictory findings regarding hospital scale economies (Frech and Mobley [1995]; Lynk [1995]). The Demsetz hypothesis does seem to explain cross-sectional results from older studies—that costs are lower in more concentrated hospital markets.[1] We apply the hypothesis to the hospital industry, using California data, 1983/84–1990/91. The first part of the article places the Demsetz hypothesis in context; the second part is an empirical test. Using this excellent data, we estimate firm-specific efficiency early in the sample period and relate it to subsequent growth, the persistence of profits, and change in market concentration.

We use several kinds of statistical analysis, including cross-tabulations (closely following Demsetz), and two different methods

*Earlier versions of this paper were presented at a Health Economics Research Organization session at the Allied Social Sciences Association meetings in San Francisco, January, 1996, and at the Federal Trade Commission in May, 1997. We received helpful comments in those settings, especially from Will White and Pauline Ippolito, and also from a referee. Thanks are also due to the California Office of Statewide Health Planning and Development (OSHPD) for generous provision of data, the School of Business Administration at Oakland University, Rochester, Michigan, and the Academic Senate of the University of California at Santa Barbara for research support.

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ABBREVIATIONS

ALOS: Average length of stay
CORI: Community and Organization Research Institute
DRG: Diagnosis-Related Group
FTE: Full-time-equivalent
HCFA: Health Care Financing Administration
HFPA: Health facility planning area
HHI: Herfindahl index
HMD: Health Maintenance Organization
MIA: Medically indigent adult
OSHPD: Office of Statewide Health Planning and Development
PPO: Preferred Provider Organization

1. This result has been reversed in studies using later data. See, e.g., Zwanziger and Melnick [1988].

Economic Inquiry
(ISSN 0095-2583)
Vol. 38, No. 3, July 2000, 369–384

of efficiency assessment. One method uses a deterministic frontier, while the second uses a newer stochastic frontier technique. We employ different output measures and geographic market definitions as sensitivity tests.

II. DEMSETZ'S EFFICIENCY HYPOTHESIS IN CONTEXT

The structure-conduct-performance paradigm dominated industrial organization in the early 1970s and was the subject of many empirical investigations (Weiss [1974]). It largely ignored efficiency explanations for concentration, perhaps because existing theoretical literature assumed homogeneous firms and the existing empirical literature concluded that minimum efficient scale is generally small (McGee [1988]).

Influential dissenters began to be heard in the mid-1960s (Bork and Bowman [1965]; Bork [1967]; McGee [1971]). Among them was Demsetz [1973], who argued that concentration is largely endogenous, and results from more efficient firms growing faster. Contrary to the older tradition, Demsetz stressed persistent heterogeneity among firms. His analysis is similar in spirit to the survival analysis of Stigler [1958] and to the evolutionary models of Nelson and Winter [1982].

Demsetz [1973] conducted an indirect, cross-industry test to distinguish efficiency from market power effects. He reasoned that if tacit or explicit collusion caused high rates of return in concentrated industries, it would benefit all firms therein—implying a positive correlation between the rate of return and industry concentration across all size groups. In a 1963 sample of firms from 95 industries, no such correlation was found for small firms, while the largest firms exhibited higher rates of return, more so in the most concentrated industries. He concluded that the overall correlation between concentration and profits must be caused by superior efficiency in larger firms.

Peltzman [1977] conducted a major statistical study across industries and over time to directly test the idea. From 1947 to 1967, he allocated the total effect of concentration on price between a market power effect and an efficiency (cost) effect using a panel of 165 industries. The estimated efficiency effect dominated the market power effect. Peltzman concluded that the observed increase in profits with concentration is due to prices falling less than costs do. Although some scholars disagree with Peltzman's conclusions (Scherer [1979]; McGee [1988]), this study raises further questions.

III. HOSPITAL MARKETS AS A TESTING GROUND

We provide the first known tests of the efficiency hypothesis using microdata from a single industry. Our approach has many advantages over Demsetz's (and Peltzman's). It is not clear that different industries represent different observations from a common distribution, as is the implicit assumption in cross-industry analyses. The alternative is to analyze a single industry. The hospital industry is ideal for this. By looking at many local hospital markets, we exploit the considerable variation that exists in efficiency, firm size, rate of return, and local market structure. But we avoid the large differences in technology and consumer information that are inherent in cross-industry studies.

There is no consensus on geographic market definitions for hospitals.[2] Not taking a stand, we use two geographic areas. The smaller areas are health facility planning areas (HFPAs) designated by the state, and used in setting Medicaid rates. The larger areas are counties, which are typically large in the West.[3] Happily, the findings herein are robust to the alternatives.

2. Most of the empirical approaches to defining hospital geographic markets have used a shipments (Elzinga-Hogarty [1973]) approach applied to patient origin data (Morrisey Sloan, and Valvona [1988]; Baker [1988]; Garnick, Luft, Robinson, and Tetreault [1987]). But large cross-flows may overstate markets, especially where urban hospitals are perceived to be of higher quality or offer a wider range of services than the rural ones (Werden [1989]). In the general literature, price tests (Horowitz [1981]; Stigler and Sherwin [1985]) and residual demand elasticity (Scheffman and Spiller [1987]) have been suggested. These latter methods depend on price data, which are often unreliable and noisy for hospitals.

3. There are 58 counties and 139 HFPAs in California. HFPAs are defined for the state of California by the Office of Statewide Planning and Development, based on resource flows and needs, and updated periodically to reflect population changes. HFPAs are generally much smaller than counties, except in some rural areas (the average square miles in a county are 2,742, while there are only 1,123 in the average HFPA). HFPAs often cross county borders.

The relatively short temporal span of our data has both advantages and disadvantages. As noted by Peltzman [1977], the ideal panel of data must be short enough to roughly hold constant technological change, while long enough to allow for sufficient change in market structure.

Our cost data are from 1983/84, the year in which two major policy reforms were implemented. The reforms were: Medicare's Prospective Payment System, which changed hospital reimbursement from retrospectively determined (based on costs) to prospectively determined (based on diagnoses), and the California Medicaid Reform Act of 1982 (implemented in 1983), which gave insurers legal sanction to contract selectively with health care providers. The former mimics competition by making price exogenous, and the latter increases competition. Both reforms appear to have increased hospital efficiency in California's urban markets (Zwanziger and Melnick [1988]).

The annual data are for individual California short-term general hospitals, 1983/84–1990/91, taken from annual financial and discharge data tapes, provided by the California Office of Statewide Health Planning and Development (OSHPD).[4] Kaiser hospitals are excluded, due to incomplete reporting.[5] The only other exclusions are federal and long-term hospitals, specialty hospitals, and hospitals with missing data, leaving a sample of 378 short-term general hospitals in 1983/84 (from a universe of 423 hospitals). In the computation of changes in market concentration over time (1983/84–1990/91), all short-term general hospitals that report utilization data in any period are included.

4. Reporting periods range from the years ending from July 1983 through June 1984 (fiscal year 9) and from July 1990 through 1991 (fiscal year 17).

IV. CROSS-TABULATIONS

Table I presents rate of return by firm size, following Demsetz's approach. The rate of return is net income before taxes divided by total assets.[6] The measure of market structure is the Herfindahl index (HHI) defined over market shares in net patient revenue, presumably the best measure of output.[7] County and the HFPA market def-

5. The market share of HMOs was initially included as a control variable in the cost equation, along with other payor shares, but these were insignificant as a block and dropped from the final specification.

6. Net income is defined the same whether the firms are legally organized as profit-seeking or as nonprofit. In the nonprofit case, the net income cannot be distributed to stockholders, but must be invested or used in the firm in some way.

7. Other traditional output measures are: inpatient discharges, inpatient days, or inpatient days and outpatient visits combined.

TABLE I
Hospital Rate of Return by Market Structure and Size

	1983 / 84 ($N = 454$)					
	HHI: HFPA			**HHI: COUNTY**		
SIZE	**< .28**	**.28–.47**	**> .47**	**< .06**	**.06–.20**	**> .20**
< 50	−.051	.009	−.079	−.212	−.085	.014
50–99	.091	.056	−.012	.046	.045	.029
100–199	.037	.072	.101	.067	.052	.067
200–299	.043	.065	.038	.012	.065	.145
300–399	.075	.099	.065	.100	.075	.059
400 +	.033	.103	.085	.044	.066	.094
	1990 / 91 ($N = 393$)					
	HHI: HFPA			**HHI: COUNTY**		
SIZE	**< .28**	**.28–.47**	**> .47**	**< .06**	**.06–.20**	**> .20**
< 50	−.376	.061	−.064	−.312	−.107	−.006
50–99	.003	.040	.024	.005	.020	.038
100–199	−.020	.009	.034	−.043	.020	.061
200–299	.011	.025	.020	−.039	.049	.057
300–399	.024	.054	.040	.015	.049	.097
400 +	.025	.085	.032	.015	.047	.087

initions are used. Size is measured by setup beds (those actually set up and available for use, which is a smaller number than licensed beds). Hospitals were classified into three roughly equal-sized groups, based on HHI. The results are shown in Table I.

According to the structuralist model, collusion would generate a positive correlation between the rate of return and concentration among small firms. (Read across table rows to check this.) In our data, no clear correlation is found for small firms, except in 1990/91 at the county level. This is supportive of Demsetz's earlier findings across industries. We also find that the rate of return (ROR) generally increases with firm size. (Read down table columns to check this.) But, within the most concentrated markets, the ROR is generally *not* the highest for the largest firms. We also ran regressions with the firm level data, regressing the ROR on size, the HHI, and an interaction term. The results were generally weak, but the interaction term was always positive and significant at better than the 5% level in most cases. Taken together, this indirect evidence is generally consistent with Demsetz's views. Here, we want to go beyond these simple measures to track the effect of differences in inefficiency on growth and then on market concentration.

V. MEASURING FIRM-SPECIFIC INEFFICIENCY

We take some care in measuring firm-specific inefficiency, so that our later results will not be interpreted as artifacts of poor measurement. Particularly important is the measurement of various dimensions of output, such as quality and the type of cases treated (casemix). In subsequent sections, the firm-specific inefficiency measures are related to growth, the persistence of profits, and change in market concentration.

We use two econometric approaches to measure firm inefficiency. The first approach is deterministic, as the entire error term in the cost function is assumed to represent inefficiency, analogous to corrected ordinary least squares (Greene, [1993]; Lovell and Schmidt, [1988]). The second approach employs the stochastic frontier estimator of Aigner, Lovell, and Schmidt [1977], which allows costs to deviate from the minimum due to both systematic and stochastic perturbations. While the first method has been criticized as including too much in the estimate of firm inefficiency, the second has been criticized for the strong assumptions needed in separating the stochastic from the systematic inefficiency components in the error. Although both approaches are imperfect and controversial, the results are robust. The firm-specific inefficiency measures are highly correlated and perform essentially the same in subsequent analyses.

Cost Function

The cost function is a generalized flexible-form as described in Breyer [1987] and used by, e.g., Grannemann, Brown, and Pauly [1986]. Starting with a traditional translog cost function, more variables are added to capture the heterogeneous nature of hospital products and markets, while maintaining linear homogeneity in factor prices.

We use a short-run, multiproduct variable-cost function. Following Cowing and Holtman [1983], we include fixed capital and fixed admitting physician stock as inputs.[8] Inclusion of fixed capital and physician stock allows us, in principle, to test whether hospitals are in long-run equilibrium. In long-run equilibrium, the coefficient on capital should be equal to (minus) the cost of capital. A smaller negative coefficient implies overinvestment. We find that both the capital and physician stock coefficients are actually positive (see *Estimates of Firm-Specific Efficiency* in section III). This finding, taken literally, implies overinvestment to the point where the marginal productivity of capital is negative. Instead, we believe that the capital and physician stock variables are correlated with quality of output and severity of illness.

8. This overstates the full-time-equivalent (FTE) physician stock, because physicians work in multiple hospitals, especially in larger markets. To check for sensitivity to this, we reestimated weighting physician stock by the hospital's market share. This reduced the coefficient by about 50% but it remained highly statistically significant (p-values below 0.001). The rest of the equation was essentially unchanged.

The translog function makes economic sense and it controls for heteroskedasticity, but it creates a problem for zero outputs.[9] We address this problem in two ways: (1) replacing zero outputs with a very small number (10^{-15}) and then taking logs; and (2) adopting a Box-Cox metric for variables with zero outputs, while retaining the log metric for strictly positive output variables. This hybrid translog cost function is in common use (Grannemann, Brown, and Pauly, [1986]).

The objective is to obtain robust firm-specific measures of overall inefficiency, not traditional cost function estimates of partial effects of particular variables. Thus, we eliminate second-order and cross-product terms to reduce multicollinearity and avoid convergence problems in estimation. Testing for nonlinearity showed the second-order terms to be unimportant.

Factors which might affect the shape of the cost frontier are included in the cost function. Initially, we included income per capita, market-level payor mix, and hospital ownership.[10] On a priori grounds, income is particularly important. It is probably a proxy for both the level of demand and quality (Braeutigam and Pauly [1986]; Grannemann, Brown, and Pauly [1986]). The measurement of quality and other product dimensions is an important issue, because it may bias the estimates of firm inefficiency.

A related issue is that of endogenous outputs. It has been argued that insurance coverage weakens the relationship between prices and quantity demanded, so that endogeneity of hospital outputs is not a serious concern (Grannemann, Brown, and Pauly [1986]). This is probably becoming less true over time, because of the increase in managed care (Health Maintenance Organizations [HMOs] and Preferred Provider Organizations [PPOs]).

Output endogeneity can bias estimates from both methods. In this regard, Breyer [1987] reasons that the number of individuals treated cannot be as readily influenced by the hospital as by the length of a stay. Accordingly, we measure output using discharges.[11] The cost function is:

$$\ln C_i = \ln A + \Sigma\alpha_i \ln P_i + f(Y_i, CM_i, Q_i, X_i, Z_i) + \varepsilon,$$

where

C_i = total operating expense,
P_i = input prices,
Y_i = output: inpatient discharges by 6 payor types, outpatient visits, and teaching output,
CM_i = casemix and other complexity variables,
Q_i = hospital quality,
X_i = factors which affect the level of costs, like ownership and market factors,
Z_i = fixed inputs: capital stock and stock of admitting physicians.

Efficiency and Scale Economies. The efficiency hypothesis refers to the lowest cost firms, without specifying whether the lower cost is due to efficiency (contingent on scale) or to large size in the presence of scale economies. However, on a priori grounds, the efficiency differences that are not scale-dependent seem to be the persistent ones. In the evolutionary view, an organization can change its scale easier than it can change its efficiency. (As in computers and genetics, the software is more persistent than the hardware.) Indeed, the relatively efficient firms are expected to change their scale by growing at the expense of the less efficient firms. Therefore, in our cost function analysis, we hold scale constant, so that our resulting inefficiency measure reflects only the non-scale aspects of cost.

9. Heteroskedasticity can systematically affect stochastic frontier estimates, overstating inefficiency for small firms and understating inefficiency for large ones (Caudill, Ford, and Gropper [1995]). In our data, the zero-output problem is pervasive only for TDIS5, the number of indigent patient discharges.

10. Market-level payor mix and hospital ownership were found to be statistically insignificant individually and as a block. For simplicity, we exclude them. The simple correlation of the *OLS* measure, between restricted and unrestricted models, is .940.

11. This is equivalent to defining the output as a case treated of a particular diagnosis, regardless of length of stay. The Medicare program has adopted this view of hospital output in its Diagnosis-Related Group (DRG) Prospective Payment System system, adopted in 1982. It pays a fixed amount per hospital admission (regardless of length of stay) for each DRG. However, some insurers pay per patient day. Following the latter view, one might like to control for average length of stay (ALOS). As a sensitivity test, the regressions were also run including ALOS by payor. Differences were slight, and resulting inefficiency measures correlated at better than 90%.

As a sensitivity test to determine whether this judgment is correct, we also estimated a cost function that imposes constant returns ex-ante on the output elasticities, thus impounding the effects of scale in the measures of firm-specific inefficiency. These measures of inefficiency were only about 75% correlated with the unconstrained measures. In explaining growth, the constrained measures performed similarly, but with substantially less explanatory power.[12]

The Variables. As an input price variable, we include the Health Care Financing Administration's county-wide wage index for hospital workers.[13] We use multiple output measures, payor-specific measures of casemix complexity, and other variables to control for output heterogeneity. See Table II for descriptions and Table III for sample statistics.

There are many hospital outputs, including discharges by six payor groups: Medicare, Medicaid, private insurance, self-pay, medically indigent adults (MIAs), and various other government programs (aggregated).[14] Other outputs are number of outpatient visits and teaching output.

Casemix indices are used for the payor groups: Medicare, Medicaid, private insurance, self-pay, and an aggregate over all patients (a proxy where payor-specific indices

12. Because the exact concept of scale to hold constant is not so clear, we estimated four versions as a robustness check: with/without *LOSS* defined as an output; with/without scale variables *NPPEQ*, *DOCS* (see Table II for variable definitions). The constrained inefficiency measures from these four models are highly correlated with each other (over 95%) but only 73–78% correlated with the unconstrained inefficiency measures used in the article.

13. This avoids the endogenity problem of using actual wages from the individual firm.

14. MIAs are medically indigent adults who do not qualify for Medicaid but are eligible for county assistance.

TABLE II
Variable Names and Descriptions

Dependent Variable
TOPEX: total annual operating expenditures, net of interest and depreciation

Fixed Inputs
NPPEQ: net (of depreciation and amortization) plant property and equipment at the beginning of the period, a proxy for fixed capital stock
DOCS: number of licensed physicians with admitting privileges (fixed physician stock)

Outputs
TDIS1–TDIS6: total inpatient discharges in each of 6 payor categories:
(1) Medicare, (2) Medicaid, (3) Private Insurance (Blue Cross/Blue Shield, HMO, PPO, etc.)
(4) Self-Pay and No Charge, (5) Medically Indigent Adults, (6) Everyone Else (several government programs like SSI)
LOUT: number of outpatient visits
TERNBED: number of FTE interns and residents per staffed bed (teaching output)

Casemix
MCRCASE: OSHPD's Medicare casemix index for 1983
CALCASE: OSHPD's Medicaid casemix index for 1983
PVTCASE: OSHPD's private payor casemix index for 1983
SELFCASE: OSHPD's self/no charge payor casemix index for 1983
ALL: OSHPD's all payors casemix index for 1983
OUT: proportion of outpatient visits that are nonsurgical
PBIRTH: proportion of discharges that are newborns
PSUBACT: proportion of discharges that are subacute care
PMEDSUR: proportion of discharges that are medical-surgical acute care
PINTENSE: proportion of discharges that are from intensive care units
LOSS: dollar amount of expenditures on charity care, net of any gifts or funds designated for charity

Output Heterogeneity and Quality
INFMORT: infant mortality index, larger meaning more deaths, adjusted for risk and chance (sample size)
SCOPE: scope of services index
HOSWAGE: HCFA's 1984 county-specific hospital-worker wage index (used in setting PPS rates)
PCI: income per capita in the city in which the hospital is located
MDPC: medical doctors per capita in the county
RUR: binary variable indicating that a hospital is located in a rural county

were unavailable).[15] The casemix variables are used to scale discharges: each discharge variable was multiplied by the appropriate casemix index.[16]

Another control variable is *LOSS*: dollar amount of expenditures on charity care, net of any gifts designated for charity. *LOSS* may be especially important, because we do not have a separate casemix index for MIAs or those in other government programs, who have usually been found to be more costly (Thorpe [1988]; Campbell [1990]; Epstein, Stern, and Weissman [1990]).[17] Inadequate controls for the extra costs of treating the poor may cause an artificial finding that public hospitals are inefficient. Other output heterogeneity controls include: the proportion of discharges that are newborns, subacute care, acute medical/surgical care, or intensive care.

Quality of care is proxied by several variables, including a hospital-specific infant mortality index,[18] income per capita in the city, and physicians (MDs) per capita in the county. More physicians per capita enables more specialization. We also include a scope of services index, *SCOPE*. It is a weighted

15. Casemix indices by payor were reported by California OSHPD, following the method used by HCFA for the national Medicare Casemix Index, using resource-weighted Diagnostic-Related Groups. See *Case-Mix Indices for California Hospitals*, December 31, 1985, California OSHPD. Comprehensive data were only collected for 1983/84. The data are not sufficient to derive the separate casemix indices for the MIAs or other government programs.

16. Other specifications were used to test for robustness. These included entering payor-specific casemix separately (rather than scaling outputs), and also entering both casemix and, as mentioned earlier, average length of stay (ALOS) by payor. There were no statistically significant differences.

17. Contradictory evidence exists. See Dor and Farley [1996].

18. The index is defined using data on all hospital births in the state and adjusts actual reported mortality for both risk and chance (sample size) factors, as described in Williams [1979] and Blumberg [1986].

TABLE III
Sample Statistics for Cost Functions

Variable	Natural Logs* Mean	Natural Logs* Std. Dev.	Levels (Box-Cox Models)** Mean	Levels (Box-Cox Models)** Std. Dev.
TOPEX	16.635	1.071		
TDIS1	7.311	1.056	2328.5	2094.6
TDIS2	5.577	3.963	1099.6	2940.1
TDIS3	7.515	1.142	3227.6	3796.5
TDIS4	5.259	3.165	505.63	1126.8
TDIS5	−16.270	19.036	139.15	950.73
TDIS6	3.959	2.372	132.56	248.81
TERNBED	−10.364	3.065		
NPPEQ	15.636	1.429		
DOCS	4.425	1.250		
PBIRTH	.087	.072		
PINTENS	.041	.066		
PSUBACT	.005	.026		
PMEDSUR	.682	.184		
LOUT	9.577	1.626		
OUT	.978	.108		
LOSS	13.108	2.023		
SCOPE	7.022	3.922		
INFMORT	1.001	.077		
PCI	9.204	.237		
HOSWAGE	1.214	.113		
MDPC	.223	.093		
RUR	.132	.339		

*0 discharges replaced with 10^{-15}, then discharges are logged.

**discharges (X) replaced with the expression: $(X^{\lambda} - 1)/\lambda$, where λ is the Box-Cox parameter estimate: .12276.

sum of 33 services provided.[19] The index increases over time as new technologies are introduced. Many variables already mentioned also control for quality differences: hospital-specific casemix and payor mix, hospital size, capital stock and physician stock.[20]

Statistical Methods

Least squares are used to estimate the deterministic frontier cost function. The stochastic frontier cost function is estimated using an algorithm based on the model developed by Aigner, Lovell, and Schmidt [1977] and applied to cost functions by Jondrow et al. [1982]. The method assumes that the error term is composed of a half-normal distribution (distance from the frontier) and a random shock. For both methods, we express inefficiency as a percentage of total cost.

To derive inefficiency measures from the deterministic frontier, we use the approach described by Greene [1993] and Lovell and Schmidt [1988]. The most efficient firm is assumed to exhibit the largest (in absolute value) negative residual, "min e_i." To find the cost frontier, the fitted equation is shifted down by this min e_i. Firm-specific inefficiency ε is calculated by adding the absolute value of min e_i to each firm's residual. For the most efficient firm, the calculated inefficiency is thus zero by construction, and the other estimated inefficiencies are all positive.

Estimates of Firm-Specific Efficiency

Table IV contains the results from estimation of the four empirical cost function

19. The weights are: 0 if service not provided, .5 if available through arrangement with a nearby hospital or as part of a broader hospital unit, and 1 if offered in a separate unit. The 33 services include: computed tomography, magnetic resonance imaging, diagnostic and therapeutic radioisotope, positive emission tomography, ultrasonography, megavoltage radiation therapy, histocompatibility lab, neonatal intensive care, and trauma services.

20. The coefficients on ownership are small and statistically insignificant, and these variables are dropped. Recent evidence suggests that hospitals of different ownership type located in the same markets behave very much alike (Mobley and Bradford [1995]; Banks [1993]; Norton and Staiger [1994]; Hultman [1991]). Because we control for market characteristics, the partial effect of ownership on costs is expected to be small.

TABLE IV
Hospital Cost Function Estimates 1983/84 ($n = 378$)

Variable	***OLS*** Coefficient	*P*-value	***OLS / BOXCOX*** Coefficient	*P*-value	***FRONT*** Coefficient	*P*-value	***FRONT / BOXCOX*** Coefficient	*P*-value
Constant	8.915	.000	9.711	.000	8.728	.000	9.617	.000
TDIS1	.283	.000	.122	.000	.338	.000	.125	.000
TDIS2	.003	.268	.015	.000	.005	.187	.014	.008
TDIS3	.270	.000	.093	.000	.284	.000	.097	.000
TDIS4	.004	.285	.021	.002	.002	.740	.015	.024
TDIS5	.001	.057	.005	.030	.001	.109	.003	.077
TDIS6	.004	.394	.022	.007	.007	.108	.025	.000
LOUT	.037	.005	.043	.000	.040	.001	.040	.000
OUT	.103	.475	.233	.108	.015	.896	.137	.417
TERNBED	.034	.000	.024	.000	.023	.000	.018	.000
NPPEQ	.087	.000	.074	.000	.073	.000	.086	.000
DOCS	.029	.018	.026	.020	.033	.000	.035	.000
PBIRTH	−.105	.760	−.126	.696	.107	.772	−.070	.838
PINTENSE	.418	.060	.399	.051	.566	.047	.524	.102
PSUBACT	.461	.351	.012	.978	.635	.251	.304	.744
PMEDSUR	−.190	.174	−.170	.186	−.120	.399	−.157	.251
LOSS	.027	.000	.018	.008	.034	.000	.023	.000
SCOPE	.031	.000	.021	.000	.026	.000	.019	.001
INFMORT	.047	.769	.025	.863	−.038	.797	−.026	.873
PCI	.121	.047	.141	.017	.064	.245	.110	.067
HOSWAGE	.218	.251	.379	.037	.212	.218	.313	.095
MDPC	.832	.000	.834	.000	.792	.000	.824	.000
RUR	−.076	.123	−.084	.072	−.014	.768	−.047	.341
LAMBDA BOXCOX			.123	.000				
LAMBDA FRONTIER					3.886	.000	2.137	.000
Adjusted R-Square	.951		.959		.959		.956	
Diagnostic Log-Likelihood			40.36		51.45		40.26	

models. The models labeled *OLS* and *FRONT* are estimated by replacing zero realizations of output variables with the number 10^{-15} and then taking logs. In the models labeled *BOXCOX* and *FRONT/BOXCOX*, output variables containing zero realizations (like X) are replaced with the expression: $(X^{\lambda} - 1)/\lambda$, where λ is the Box-Cox parameter estimate from maximum likelihood estimation of the model (the estimate of λ is .12276, labeled *LAMBDA BOXCOX* in Table IV).[21] The variable *LAMBDA FRONTIER* in the *FRONT* and *FRONT/BOXCOX* models is a stochastic frontier parameter, from which relative inefficiency is derived.

The estimates of firm-level inefficiency are quite reasonable. For the frontier approaches, the means are about 0.20 (20%), indicating that the average firm incurs costs about 20% above the most efficient. Chirikos [1998–99] obtained a mean inefficiency estimate of about 15% using a similar technique on a sample of Florida hospitals. (If these estimates seem high, bear in mind that this is the hospital industry and the measure includes both technical and allocative inefficiency.) The range goes from zero or near zero for the most efficient firms to about 80% for the least efficient firms. Inefficiency is higher for the OLS method because it attributes the entire error term to inefficiency, while the frontier method attributes only the nonstochastic part of it to inefficiency.

21. The *MLE* estimate of *LAMBDA BOXCOX* taken from the *OLS*-based *BOX* model is used as the estimate for the *FRONT/BOX* model as well. Full information estimation of the *LAMBDA BOXCOX* and *LAMBDA FRONTIER* variables was not possible.

Most important, firm-level inefficiency is quite robust. The simple (Pearson) correlation matrix (Table V) shows that cardinal ranking of a firm's inefficiency is robust to model specification. Not surprisingly, the effect of inefficiency in subsequent modeling is also robust. Henceforth, we report only the results from the frontier method. The other results can be found in Frech and Mobley [1997].

VI. EFFICIENCY AND GROWTH

Growth in output is calculated between 1983/84 and 1990/91, in both levels and market share (county and HFPA markets). All short-term general hospitals who report output data are included in the calculations of market share in each year. Growth is a hospital-specific measure of internal growth only; growth by multihospital chain affiliation or merger is excluded.[22]

We measure output by two methods that account for outpatient services: net patient revenue (net of contractual adjustments) and the more physical measure of inpatient days adjusted for outpatient care.[23] The former

22. In the Herfindahl index, market shares do reflect multihospital chain affiliation; hospitals owned by the same chain in the same market are considered a single firm.

23. The adjustment follows the American Hospital Association's suggestion in *Hospital Statistics*. Revenue per outpatient visit is divided by revenue per inpatient day. This result is multiplied by the number of outpatient visits, and then added to the number of inpatient days.

As a check for robustness, we also used two different measures of output that excluded outpatient services entirely: inpatient days and inpatient discharges. The results were quantitatively similar, though less precise (Frech and Mobley [1997]).

TABLE V
The Inefficiency Measures Are Similar

A. Simple Pearson Correlations among the Four Inefficiency Measures

	OLS	*BOXCOX*	*FRONT*
BOXCOX	.937		
FRONT	.896	.843	
FRONT / BOXCOX	.873	.889	.948

B. Sample Statistics for Four Inefficiency Measures

	OLS	*BOXCOX*	*FRONT*	*FRONT / BOXCOX*
Minimum	.000	.000	.030	.027
Maximum	.875	.867	.805	.678
Mean	.506	.612	.222	.194
Standard deviation	.108	.084	.133	.104

measure best reflects market valuation of services provided, while the latter measure is confounded by variation in case complexity and intensity of care. The growth model is very simple, using only firm-specific inefficiency and population growth as determinants of growth in output, because most of the firm-specific and market-specific variables have already been used to estimate firm-specific inefficiency.[24]

Alternative Monopoly Interpretation

There is an alternative interpretation of a negative correlation between inefficiency and growth that doesn't rely on a true relation between them. Consider the possibility that an apparently inefficient hospital is actually efficient, but it has a local monopoly and is effectively controlled by its doctors. The hospital spends its monopoly rents on perquisites and amenities that the physicians value. If so, the accounting data overstate costs. Since, empirically, monopoly hospitals tend to be located in slower growing regions, the data will exhibit a spurious negative relationship between inefficiency and growth. To check for this possibility and to control for possible direct effects, we included population growth in the initial model.

The empirical model is of the form:

$$\begin{aligned} Growth_{83/84-90/91} &= \alpha + \beta\ \textit{Inefficiency Measure}_{83-84} \\ &\quad + \delta\,\textit{Population Growth}_{80-90} + \varepsilon. \end{aligned}$$

We found that population growth added nothing to the explanatory power and didn't alter the other coefficients by a noticeable amount. The data seem to reject the alternative monopoly interpretation. Therefore, for ease of interpretation, Table VI presents the estimated coefficients (and *p*-values) from a simple regression of growth 1983/84–1990/91 on inefficiency measured in 1983/84. The results show a clear negative relation between inefficiency in 1983/84 and subsequent growth, which supports Demsetz's hypothesis. The relation is not sensitive to the different measures of output, market level, or inefficiency, though the effects are slightly larger and more precisely estimated using net patient revenue.

The R squared measures are low (about 5% using the net patient revenue measure), because of idiosyncratic growth at the micro level. Also, as mentioned above, variables used in generating the measures of inefficiency are excluded. But the large sample size allows detection of the effect of efficiency on growth, in spite of the idiosyncratic noise. The regressions were checked using the White statistic and associated nonlinearity test statistic, and no significant evidence of heteroskedasticity or nonlinearity was found.[25]

Quantitatively, inefficiency is an important predictor of growth. For example, doubling the mean of the frontier/Box-Cox inefficiency measure (from 19.4% to 38.8%) reduces growth in net patient revenue by about 20% and reduces growth in market share by about 6%. The effect on shares is naturally smaller than the effect on levels because share is compressed by construction (allowing for entry, growth in market shares is constrained in sum to less than one).

Overall, the result is supportive of the efficiency hypothesis. More efficient firms grow and gain share. And the magnitude of the effect is economically meaningful. But the results have another interesting, and nonconflicting, interpretation as well.

The Inefficiency Measures Appear to Be Valid

Some observers have been skeptical of hospital cost functions, believing that unobserved quality and product differences are hopelessly confounded with inefficiency. The results here show that the skepticism can be overdone. If, contrary to our view, apparent inefficiency primarily captured unmeasured high quality, we would not expect it to be

24. As a sensitivity check, we also ran a version that included the other variables that had not already been used to construct the inefficiency measures whether the hospital was acquired by a chain subsequent to the efficiency measurement (separately for profit-seeking and nonprofit chains) and the growth of the share of HMO/prepaid plans in health insurance markets. These variables were generally insignificant and made virtually no difference in the coefficients of interest.

25. The White statistic (White [1980]) is not sensitive to departures from normality, and it does not require specification of the form of heteroskedasticity (Kmenta [1986]). The nonlinearity statistic tests the joint hypothesis that all possible interactions, including squared regressors, have zero coefficients (Engle [1984]).

TABLE VI
The Effect of Firm-Specific Inefficiency on Growth 1983/84–1990/91

Model:

$$Growth_{83/84-90/91} = \alpha + \beta\ InefficiencyMeasure_{80-90} + \epsilon$$

A. Growth in Output

Measure of Growth		**Measure of Inefficiency**	
		FRONT	***FRONT / BOXCOX***
	N	**coeff (pval)**	**coeff (pval)**
GROWPR	344	−.713 (.000)	−1.056 (.000)
GROWADI	344	−.301 (.187)	−.422 (.124)

GROWPR is growth in net patient revenue.
GROWADJ is growth in adjusted inpatient days (adjusted for outpatient visits).

B. Growth in Market Share, HFPA

Measure of Growth		**Measure of Inefficiency**	
HFPA (Smaller Markets)		***FRONT***	***FRONT / BOXCOX***
	N	**coeff (pval)**	**coeff (pval)**
SGROWPR	359	−.203 (.092)	−.289 (.079)
SGROWADI	359	−.121 (.407)	−.167 (.383)

SGROWPR is growth in HFPA market share of net patient revenue.
SGROWADJ is growth in HPFA market share of adjusted inpatient days.

C. Growth in Market Share, County

Measure of Growth		**Measure of Inefficiency**	
County (Larger Markets)		***FRONT***	***FRONT / BOXCOX***
	N	**coeff (pval)**	**coeff (pval)**
SGROWPR	359	−.252 (.043)	−.341 (.043)
SGROWADJ	359	−.279 (.062)	−.349 (.074)

SGROWPR is growth in county market share of net patient revenue.
SGROWADJ is growth in county market share of adjusted inpatient days.

associated with slower growth. The rapid decline in the share of technically limited smaller hospitals suggests that hospital consumers appear to be demanding higher quality over time, not lower quality (Frech and Mobley [1995]).

VII. EFFICIENCY AND THE PERSISTENCE OF PROFITS

Firms that were relatively efficient in 1983/84 subsequently grew faster. This is consistent with the evolutionary view of persistent heterogeneity among firms. Another way to examine persistence is to look at profit rates over time.

To do so, we compare the profitability on sales (net income divided by total revenue) over time for the most efficient and least efficient quarter of the firms. Not surprisingly, the more efficient firms were more profitable in the year of measurement 1983/84 (see Table VII). The difference is large, 5.6 versus 1.2% or 6.4 versus 2.5%. The differences are statistically significant at high levels for most years. Over time, the profitability of the hospital industry has declined. But the difference in profitability among the most efficient and the least efficient firms in 1983/84 persisted. The evidence on profitability supports the belief that superior performance persists. Also, it fur-

TABLE VII
Firm-Specific Inefficiency in 1983/84 and the Persistence of Profits, 1983/84−1990/91

	Measure of Inefficiency					
	FRONT			*FRONT / BOXCOX*		
Year	Quartile 1 (Least Inefficient) Mean Profit	Quartile 4 (Most Inefficient) Mean Profit	Mean Difference *p*-value (*t*-test)	Quartile 1 (Least Inefficient) Mean Profit	Quartile 4 (Most Inefficient) Mean Profit	Mean Difference *t*-test (*t*-test)
1983/84	.056	.012	(.028)	.064	.025	(.001)
1984/85	.055	.009	(.007)	.058	.020	(.004)
1985/86	.053	.016	(.054)	.047	.018	(.145)
1986/87	.018	−.009	(.076)	.016	−.001	(.136)
1987/88	.019	−.045	(.000)	.020	−.042	(.001)
1988/89	.019	−.028	(.002)	.024	−.025	(.001)
1989/90	.013	−.045	(.044)	.035	−.039	(.002)
1990/91	.013	−.036	(.018)	.016	−.022	(.060)

Note: Profit on sales is net income divided by total revenue (operating and nonoperating sources).

ther supports the validity of the inefficiency measures themselves. Next we turn to the relationship between efficiency and concentration.

VIII. EFFICIENCY AND MARKET CONCENTRATION

In this section, we calculate the standard deviation of inefficiency within each local market in 1983/84. This standard deviation is then used to explain the subsequent change in market concentration, 1983/84−1990/91. Demsetz's hypothesis suggests that a greater initial variance in inefficiency will lead to unequal growth, thus to increased concentration.

The standard deviation of inefficiency in the market is calculated from firm-specific inefficiency measures for firms within the market. The standard deviation is weighted for firm size; weights are market shares in the output measures. Growth in concentration of output in the market (measured by the Herfindahl index, ranging from 0 to 1) is also calculated for the two output measures.[26] The growth of concentration is then regressed on the marketwide weighted standard deviation in 1983/84 inefficiency.

Population growth might also affect concentration, so we investigate this as well. The initial empirical model, using market-level data (HFPA and county), is of the form:

$$\begin{aligned}&\textit{Growth in Concentration}_{83/84-90/91}\\&= \alpha + \beta\ \textit{Standard Deviation in Inefficiency}_{83}\\&\quad + \delta\ \textit{Population Growth}_{80-90} + \varepsilon.\end{aligned}$$

In this analysis, population growth added nothing and altered no other coefficients. For ease of interpretation, therefore, we report the results from two simple regressions instead: the first on the standard deviation of inefficiency and the second on population growth as simple regressors.

Variation of inefficiency is much more important than population growth in explaining changes in concentration. Compare the R squared values of up to 5.3% for the former versus only up to 0.1% for the latter (Table VIII). Even so, R squared values are fairly low. The results are robust to both market and output definition (including measures not shown here, but reported in Frech and Mobley [1997]). Even with some smoothing at the market level, idiosyncratic factors are evidently still very important.

Quantitatively, the effect of variation in inefficiency is important. For net patient revenue, doubling the standard deviation of inefficiency (the independent variable) from its mean increases the change in concentration (the dependent variable) about 4.2% to 6.7% in the HFPA and about 5.6% to 8.2% in the county market. This almost doubles the dependent variable. (See Table IX for the sample statistics used in this calculation.)

26. Weighting by market share changes the definition from hospital to output units. Similar results were found using unweighted measures.

TABLE VIII

Effect of Standard Deviation* of Inefficiency (1983/84) and Population Growth (1980–1990) on Growth in Concentration (1983/84–1990/91). *p*-Values in Parentheses

Inefficiency Model:

$$\textit{Growth in Concentration}_{83/84-90/91} = \alpha + \beta\ \textit{Standard Deviationin Inefficiency}_{83-84} + \epsilon$$

A. HFPA (Smaller Markets)

Output Measure	**Measure of Inefficiency**	
	FRONT	***FRONT / BOXCOX***
Net patient revenue	1.120(.012)	1.092(.050)
R squared	.043	.022
Adj. inpatient days	.592 (.190)	.558 (.340)
R squared	.005	.000

B. County (Larger Markets)

Output Measure	**Measure of Inefficiency**	
	FRONT	***FRONT / BOXCOX***
Net patient revenue	1.209(.051)	1.280(.120)
R squared	.053	.028
Adj. inpatient days	.301 (.644)	.263 (.842)
R squared	.000	.000

Population Growth Model:

$$\text{Growth in Concentration}_{83/84-90/91} = \alpha + \delta\ \text{Population Growth Rate}_{80-90} + \epsilon$$

Output Measure	**Market Definition**	
	HFPA	**County**
Net patient revenue	−.125 (.403)	−.062 (.786)
R squared	.006	.001
Adj. inpatient days	−.024 (.876)	.031 (.895)
R squared	.000	.000

*Using market-share weighted standard deviation of the inefficiency measure.

Variation in efficiency is a systematic determinant of changes in concentration. The Demsetz efficiency hypothesis, following the chain of causation all the way to changes in concentration, is verified. However, the effect of variation in inefficiency cannot be said to dominate. While the basic hypothesis has been verified in our microdata, the study does not verify what might be called the strong version of the hypothesis: that concentration is mostly determined by variation in inefficiency.

IX. SUMMARY AND CONCLUSIONS

In the first study using single-industry microdata, the Demsetz efficiency-growth hypothesis has done well. We used four different statistical models to derive firm-specific inefficiency in 1983/84, and found that these four measures were highly correlated. We found that relatively efficient firms subsequently grew faster. Also, more efficient firms were persistently more profitable. This supports the fundamental evolutionary idea that efficient firms grow faster, and that the return to superior performance persists.

Because we carefully controled for product heterogeneity and quality, we believe that our efficiency measures were not simply indicators of unmeasured low quality. If our measures were indicating low quality, we would not expect that they would predict subsequent growth unless the market exhibited increasing preference for low quality. We believe that this is unlikely to have been the case.

Next, we analyzed two aspects of the relationship between efficiency and concentration. Demsetz's view suggests that a greater initial variation in inefficiency would lead to

TABLE IX
Sample Statistics for Standard Deviation* of Inefficiency (1983/84), and Growth in Concentration (1983/84–1990/91), Standard Deviations in Parentheses

A. Standard Deviation of Inefficiency across HFPAs (Smaller Markets)

Output Measure	Inefficiency Measure	
Weight	***FRONT***	***FRONT / BOX***
Net pt rev	.051(.056)	.038(.044)
Adj. indays	.051(.056)	.039(.043)

B. Standard Deviation of Inefficiency across Countries (Larger Markets)

Output Measure	Inefficiency Measure	
Weight	***FRONT***	***FRONT / BOX***
Net pt rev	.067(.055)	.050(.042)
Adj. indays	.069(.055)	.051(.042)

C. Growth Rate in Herfindahl Indexes and Population Growth

	HFPA Markets		Country Markets	
	Mean	**Std. dev.**	**Mean**	**Std. dev.**
POP GROWTH	.296	(.166)	.279	(.153)
%ΔHHI (net pt rev)	.099	(.278)	.093	(.247)
%ΔHHI (adj indays)	.040	(.287)	.013	(.251)

*Using market-share weighted standard deviation of the inefficiency measure.

unequal growth of firms in the market and, therefore, to increased concentration. We found robust statistical support for this hypothesis.

Our findings using firm-level data for the hospital industry are generally supportive of the efficiency hypothesis. Industry structure is endogenous and can be explained, in part, by differential growth of heterogeneous firms. While the logic of the hypothesis is confirmed, the analysis cannot support a strong version of the hypothesis: the idea that variation in concentration is dominated by efficiency factors. Further research would be very useful. While our results are not conclusive for the ultimate policy issues (perhaps no results will be), they do provide an economic rationale for the cautious antitrust policy toward hospital mergers that has been adopted by the enforcement agencies and the courts.

APPENDIX : DATA SOURCES

Casemix indices by payor for 1983 are provided by the OSHPD in *Case-Mix Indices for California Hospitals*, December 31, 1985 (California Health Facilities Commission). Data on infant mortality used as a quality index are from the Maternal and Child Health Data Base, Community and Organization Research Institute (CORI), UC Santa Barbara. The hospital chain data are compiled from the AHA's annual series: *Directory of Multihospital Systems* and *Hospital Guide*. County level demographic data are from the *Area Resource File*, March 1988, the 1990 U.S. *Census of Populations* and the *City and County Data Book*, *1992*. Market level payor mix data are from the annual individual hospital discharge data for California, available from the OSHPD. The hospital wage index used by HCFA in adjusting Medicare Prospective Payment System rates is available for 1984 as reported in the *Federal Register*, September 1, 1987, pp. 33095–100.

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