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Resolving the impasse on hospital scale economies: a new approach

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The existence of scale economies in hospitals is important for both public and managerial policy, yet production and cost function studies have found conflicting evidence. More recently, more sophisticated studies have typically found scale diseconomies, which is inconsistent with the views of industry participants and observers. In the early 1980s, California deregulated both private and public health insurance (MediCal), which provides a natural laboratory for examining hospital efficiency. Using Stigler's original and multivariate survivor analysis, we resolve the conflict in favour of scale economies, and reconcile the controversy. The survivorship methodology is simple to apply, and a useful tool in conjunction with statistical cost and production studies.

I. INTRODUCTION

The existence of scale economies in the hospital industry has long been both a policy and a scientific concern. Empirical cost and production function estimates conflict: some find economies of scale and some, especially newer, more sophisticated ones, do not. This paper uses survivor analysis to resolve the quandary (in favour of scale economies) and suggests an explanation for why many statistical studies go awry. Also, the multivariate extension of the technique, following Keeler (1989) enables us to address one of the problems associated with classical, univariate survivor analysis, described by Shepherd (1967). Because the technique captures the effects of all factors in addition to efficiency which enhance growth, it is important to control for these other factors statistically. We examine the effect of chain affiliation, adverse selection, and local market conditions on survivorship, and we test the robustness of the basic results on scale economies. We use California data for 1983–89 because the state substantially deregulated health insurance in 1982 and because more detailed data are available for these hospitals.

California data

California hospital markets in the 1980s provide an excellent setting for a survivor analysis because competition has recently increased due to policy changes. Important changes in insurance and insurance markets were enhanced, and Preferred Provider Organizations (PPOs) and Health Maintenance Organizations (HMOs), which had achieved modest market shares by 1980, grew phenomenally with the favourable legislation.[1]

The survivor principle states that as competition increases, the firms which survive in an industry will be at least of minimum efficient scale. As a result of the increased competition noted above, California hospitals appear to be moving towards a new, more efficient size distribution. This parallels the trucking industry's response to deregulation, studied by Keeler (1989).

II. CONFLICTING LITERATURE

The topic of hospital scale economies has long been of concern to policy makers, as larger hospitals were seen as

[1]The 1982 California Medicaid Reform Bill allows selective contracting between MediCal or private insurers and hospitals. The MediCal contracts are for fixed daily rates, regardless of diagnosis, while the private ones may be on any basis. Individual hospitals offer low rates in exchange for higher volume of patients (Bergthold, 1984).

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a means for controlling escalating healthcare costs. Also, scale economies have been used to justify mergers in small markets.[2]

Many older studies found that scale economies exist (Pauly, 1978; Evans, 1971; Carr and Feldstein, 1967; Cohen, 1967). Other studies found that moderate and large hospitals are characterized by constant returns to scale (Lave, Lave and Silverman, 1972; Francisco, 1970). On the other hand, Bays (1980) and Martin Feldstein (1968) find no evidence of scale economies when physician input costs are included in total cost. More recent studies also yield contradictory results. Evidence of scale economies was found by Feldman *et al.* (1986), Granneman, Brown and Pauly (1986), Vitaliano (1987) and Wilson and Jadlow (1982). Many other recent studies find evidence of diseconomies of scale (Jenkins, 1980; Friedman and Pauly, 1981; Becker and Sloan, 1985; Robinson, 1985; Robinson and Phibbs, 1990). Conflicting evidence in the literature is a result of many factors, but probably mainly due to differences in the success with which quality and complexity of output was measured and controlled for statistically (Cowing, Holtmann and Powers, 1983). Given data limitations, it is inconceivable that these factors can be adequately controlled for in statistical cost and production studies.

Industry experts and managers believes that scale economies exist for small hospitals. Charles Rule, during his tenure as Assistant Attorney General for Antitrust at the Department of Justice, stated that the range of most efficient hospital size was between 300 and 600 beds (Rule, 1988, p. 15). Also, bond rating companies refuse to rate hospitals with less than 100 beds (Frech, 1988). This may reflect scale economies in hospitals recognized by bond rating firms or it may simply be a scale economy in bond rating itself.[3] If there are scale economies, then the survivor principle predicts that disproportionately many small hospitals should fail. This has indeed been the case in California. Between 1983 and 1989, 46 short-term (general and special) hospitals shut down or converted to a different level of care. Of these, 96% were fewer than 200 beds, and 78% were fewer than 100 beds. For reference, hospitals with fewer than 100 beds in size account for less than 40% of all short-term California hospitals in 1989.

This trend also holds for the USA as a whole. Bays (1986) found that hospitals with fewer than 100 beds consistently lost market share in 1971–77 in a national study. Frech (1988) found that between 1970 and 1985, in both the USA as a whole and in the state of Oregon, this size group lost market share.

III. SURVIVORSHIP IN CALIFORNIA: BASIC ANALYSIS

The tables below illustrate the changes in market share and total output by hospital size group for California short-term general hospitals between 1983 and 1989, using the same eight size groupings used in earlier survivor studies (Bays, 1986; Frech, 1988). The size groups are based on beds, while total output and market share are in bed-days (Tables 1 and 2).[4] These tables suggest that scale economies exist for hospitals with up to about 400 beds, since small hospitals are disappearing in the size distribution of firms. According to this, scale economies now extend further up the size distribution than they did in the earlier studies using earlier data, noted above.[5]

Table 1. *Total short-term general hospital bed-days by hospital size: California 1983–89*

Size	1983	1989	Change	Rate of change
6–24	96	65	− 30	− 0.322
25–49	794	480	− 313	− 0.395
50–99	4652	3431	− 1221	− 0.262
100–199	10797	8854	− 1942	− 0.180
200–299	11689	10632	− 1056	− 0.090
300–399	10144	9179	− 964	− 0.095
400–499	6670	7802	1132	0.170
500 +	11609	12669	1059	0.091

Table 2. *Market share of short-term general hospital bed-days by hospital size: California 1983–89*

Size	1983	1989	Change	Rate of change
6–24	0.002	0.001	− 0.000	− 0.279
25–49	0.014	0.009	− 0.005	− 0.357
50–99	0.082	0.065	− 0.018	− 0.216
100–199	0.191	0.167	− 0.025	− 0.128
200–299	0.207	0.200	− 0.007	− 0.033
300–399	0.180	0.173	− 0.007	− 0.038
400–499	0.118	0.147	0.029	0.243
500 +	0.206	0.239	0.033	0.160

[2]Frech (1988); USA v. Carilion Health Systems and Community Hospital of Roanoke Valley, in which the Roanoke merger was approved by the district court (707 F. Supp. 840, 844, 848 (W.D. VA 1989) appeal filed No. 89-2625, 4th Cir 1989); appeal of the USA v. Rockford Memorial Corporation and Swedish American Corporation case, where merger was denied by the district court (appeal No. 88-C-20186 (N.D. ILL Feb 23, 1989)).

[3]The transaction costs of a bond issue will be spread over a smaller equity yield for small hospitals relative to large ones.

[4]Bed-days are average daily census, computed by dividing total annual in-patient days by 365. In Table 1, the body contains bed-days aggregated over all hospitals in each bed-size group. For example, the group composed of 6–24 beds in size together filled an average of 96 beds per day in 1983. Similar tables based on measuring output by beds show a similar pattern.

[5]Using a Chi-squared test, the null hypothesis of no change was strongly rejected, at better than the 0.1% statistical significance, in both Tables.

IV. LIMITATIONS OF BASIC SURVIVOR ANALYSIS

The changes in output and market shares reflect economies relating to all types of commercial success, including such subtleties as economies inherent in unique situations (Shepherd, 1967), differences in optimal management techniques (Marder and Zuckerman, 1985), and differences in quality and cost savings for customers and suppliers (Frech and Ginsburg, 1974). Thus, the technique includes factor which often cannot be measured and used in statistical studies of cost or production. This is an advantage of survivor analysis.

On the other hand, survivorship reflects private, not necessarily social, efficiency (Shepherd, 1967; Weiss, 1964). For example, one factor which may contribute to commercial success is the ability to deal with regulators, and (in particular) to obtain favourable MediCal contracts. Also, market share growth may not necessarily indicate success, to the extent that unprofitable charity cases and purveyors of bad debt are dumped on hospitals which for institutional reasons are willing to accept them. Growth in public and teaching hospitals may result from such adverse selection, and these hospitals may be quite large. Also, as noted by Shepherd (1967), multiplant ownership may be a source of comparative advantage. We control for adverse selection, multihospital ownership, and regulatory contractual advantage in the regression analysis, to better isolate the efficiency effects which contribute to growth in market share.

Stigler (1958) pioneered survivor analysis, in effect estimating a binary growth rate equation with size as the only regressor. He noted a weakness in his methodology, the inability to isolate the independent effects of different factors in addition to efficiency which determine survival. This weakness was noted by Shepherd (1967, p. 115) in this criticism of the classical survivor technique:

> Survival trends do usually reflect more than costs internal to the plant; this extra sensitivity to influences outside the plant may be a decided advantage. But for other purposes, including policy judgements, this inclusiveness (reflecting everything affecting plant size) will not be warranted. ... Analysis of why size patterns have changed must go entirely beyond the survivor technique itself.

The limitations of classical survivor analysis can be ameliorated by taking explicit account of these 'other factors' in an expanded, multivariate survivor analysis. Keeler (1989) improved the technique by including other determinants of growth, in an analysis of the US trucking industry. Even so, only a few other determinants can be measured or used. Thus survivor analysis is most useful in conjunction with statistical cost or production studies and informed industry opinion. It is not a perfect substitute for these other approaches.

Stigler was unwilling to use growth rates, rather than a binary growth measure (did or did not grow). His binary approach may be justified as a statistically robust method in a world where the sole determinant of growth is firm size. However, in models where it is possible to control for other factors, there is no reason to throw away information in the data by converting the continuous growth measure into a binary one. Following Keeler, we estimate a binary model, but stress a continuous growth version.

V. MULTIVARIATE HOSPITAL SURVIVOR ANALYSIS

In the analysis below, the localized nature of hospital market competition forces us to depart somewhat from Keeler's approach. The dependent variable in this study, as in Keeler's, is change in the 'market share' by size group, where the share is with respect to all firms in the industry (California short-term general care hospitals). This is *not* a market share out of the relevant *local* hospital market. In fact, it is simply a weighted change in output, weighted by total output, which is constant. We follow this methodology to be consistent with earlier applications of the technique. However, localized competition is very important for hospitals, and we allow for this with two explanatory variables: intensity of insurance market competition, and concentration in the local market.

Defining appropriate hospital market areas

There is no consensus in the literature regarding appropriate market definitions for hospitals. From an antitrust viewpoint, a market is the smallest geographic area and therefore a group of producers that can, in concert, achieve monopoly power.[6] Recent merger opinions have used the Elzinga–Hogarty (1973) approach, based on shipments of the product.[7] Two problems arise when applying this technique to hospital patient origin data. Potential competitors will not be identified by the patient flows. More importantly, patient flows suggest a much larger area than makes sense for

[6]US Department of Justice Guidelines, June 14, 1984.

[7]Most of the empirical approaches to defining geographic markets have used either a shipments approach applied to patient origin data (Morrisey, Sloan and Valvona, 1988; Garnick *et al.*, 1987; Phibbs and Robinson, 1993) or price tests (Horowitz, 1981; Stigler and Sherwin, 1985). Scheffman and Spiller (1987) use residual demand elasticity to determine market power of the cartel, in attempting to define antitrust markets. The latter two methods depend on product price data, which are often unreliable for hospitals.

antitrust: the smallest region in which hospitals can profitably collude. Recent court cases have (we believe sensibly) found that the geographic markets for most hospital services are small, more closely approximated by counties than by Metropolitan Statistical Areas (Baker, 1988).

Morrisey, Sloan and Valvona (1988) using patient origin data argue that markets include rural areas adjacent to cities, thus may be much larger.[8] Baker (1988) disagrees because the rural patients who migrate to an urban hospital are likely to exhibit inelastic firm level demand.[9] We estimate models using three geographic areas, but stress the results using the smallest of these areas (Table 3). The models using the two broader areas show similar results (see Table 7).

Empirical model and variables

The continuous version of the model takes the following (linear) form:

$$GROWSHR = B_0 + B_1 ADC + B_2 SYSS + B_3 HERF + B_4 PCONTRACT \quad (1)$$

These variables are defined below. The explanatory variables are preceded by the expected sign of their estimated effects on growth in market share, discussed next:

GROWSHR	= change in (statewide) market share, 1983–89
(+)*ADC*	= output (average daily census)
(+)*SYSS*	= whether affiliated (owned or leased) with a chain at the end of the period (1989).
(−)*HERF*	= Herfindahl index, 1983
(−)*PCONTRACT*	= change in local market-level proportion of hospital revenues under discount contracts, 1983–89
(+)*GROWLOSS*	= change in the proportion of losses to gross revenue 1983–89, where losses are bed debt plus charity care less gifts designated for charity care
(+)*GROWMCARE*	= change in the proportion of gross revenue accounted for by Medicare charges 1983–89
(+)*GROWMCAL*	= change in the proportion of gross revenue accounted for by Medi-Cal charges 1983–89.

Sample statistics are contained in the Appendix.

Table 3. *OLS and weighted LS regression results for growth in market share of in-patient days, by size group*

Parameter	Estimate	*t*-statistic	Corrected *t*
OLS: Dependent variable *GROWSHR*			
Mean: 0.00000000, Standard deviation: 0.004393, N = 105			
CONSTANT	0.001638	0.6327	0.7655
ADC	0.000013	3.9595	3.6371
SYSS	− 0.000762	− 0.4773	− 0.4372
HERF	− 0.000109	− 0.0352	− 0.0351
PCONTRACT	− 0.026583	− 1.5510	− 1.4649
Adjusted R^2: 0.136430			
F statistics: 5.107570			P-value 0.000871
White statistic: 38.127794			P-value 0.000497
Nonlin statistic: 22.99699			P-value 0.010758
WLS: Dependent variable *WGROWSHR*			
Mean − 0.000045, Standard deviation: 0.000338, N = 105			
CONSTANT	− 0.000189	− 0.7755	− 1.2351
WINT	0.006370	1.2294	2.7069
WADC	0.000018	1.5834	2.2978
WSYSS	− 0.000316	− 0.2585	− 0.3216
WHERF	− 0.001404	− 1.0241	− 1.4530
WPCONTRACT	0.000984	0.0998	0.1485
Adjusted R^2: 0.064265			
F statistics: 2.428507			P-value 0.040311
White statistic: 22.6817			P-value 0.304695
Nonlin statistic: 14.2411			P-value 0.507328

The sample used in this analysis consists of 506 short-term general hospitals in California, which existed in either 1983 or 1989, or both years. Both entering and closing short-term general hospitals are included in the sample.[10] Explanatory variables are hospital-specific measures which are averaged over 105 size groupings. Thus, each size group is one of 105 observations in the sample. Traditional survivor analysis uses individual data grouped by size; grouped data is used here in an application of the traditional methodology. Two different grouping methodologies were tried, and a variety of groupings, to assess robustness of the results (see Appendix). The variables used in the analysis are discussed next, followed by a section on the methodology for constructing the size groupings.

The dependent variable *GROWSHR* was constructed as follows. Hospitals were size-ranked (discussed further below) and then grouped in both 1983 and 1989. In-patient days were aggregated for each group in each of the two years. This resulted in 105 observations on aggregate in-patient days by group, in each year. A 'market share' for

[8]Morrisey, Sloan and Valvona (1988) and Wennberg and Gittelson (1982) find that rural markets are typically smaller than 50 miles in radius.

[9]This may happen if the urban hospitals are perceived to be of higher quality or offer more services than the rural ones. For a formal theoretical demonstration, see Werden (1989).

[10]In all, 506 short-term general hospitals reported in-patient days (including most Kaiser hospitals) and these were used to construct statewide totals of in-patient days. There were 486 short-term general hospitals in 1983, 452 in 1989, and 506 in either year.

each group was determined by dividing the group's aggregate in-patient days by all in-patient days in California hospitals in that year. Finally, the difference in this output share between 1989 and 1983 was taken for each of the 105 groups, yielding the dependent variable *GROWSHR*. For the probit analysis, the dependent variable *BINARY* was assigned a value of one if a group grew or maintained its share, and zero if it shrank.

The variable for chain affiliation, *SYSS*, originates from a hospital specific binary variable, taking on a value of one for members of a chain at the end of the period. The binary variable is aggregated over each group, and becomes *SYSS*: the proportion of hospitals in a group that are affiliated with chains. Although no convincing evidence of economic advantages from chain affiliation have been found in the literature to date, studies have not examined strategic dimensions of performance such as marketing and negotiation with insurers. It is possible that real, undocumented advantages exist in chain affiliation, in which case *SYSS* would be positively related to *GROWSHR*.

The localized nature of competition is captured by two explanatory variables: concentration in the local market (*HERF*), and intensity of insurance market competition (*PCONTRACT*).

The variable *HERF* is constructed as follows. The Herfindahl index of market concentration is computed for each hospital in its local market.[11] The local market is narrowly defined, the Health Facilities Planning Area (HFPA), which is generally smaller than both the Metropolitan Statistical Area and the county in urban areas (see Appendix for comparisons). The Herfindahl statistic for each size group (*HERF*) is the average of the local market Herfindahl statistics for all hospitals in the group. Groups with high average concentration in their local markets are expected to grow more slowly if both lower quality and lower price competition causes outmigration of patients to more competitive markets nearby (Frech and Woolley, 1991). We realize that changes in outmigration would be impossible if we had totally separated market areas. However, this is not the case for any actual data. Small changes in outmigration do not necessarily tie the price and quality decisions of hospitals in distinct, but neighbouring, areas so closely that the market areas should be expanded.

Recent changes in insurance and in legislation have increased growth of pro-competitive insurers.[12] These HMOs and PPOs have gained market share, with the greatest gains occurring in highly urbanized areas with dense populations. HMOs and PPOs have been aggressive in contracting with hospitals directly for price discounts and utilization controls. *PCONTRACT* is the change (1983–89) in the proportion of contracted discounts relative to gross revenues at the local market level, averaged over hospitals within a size group. Groups with more growth in contracting are in areas with growing insurance contracting competition. We expect them to grow slower as a result of the demand-constraining influence of this competition.

A third proxy for local competition was also considered for inclusion in the analysis, the extent of the local market (measured either by population growth or growth in income per capita). However, holding concentration constant, higher size (*ADC*) is only possible in larger markets. Due to the near-perfect linear relationship between these variables, it was not possible to include the extent measure. Thus the variable *HERF* may pick up the omitted effect of market extent, yielding an unexpected sign on the estimated coefficient. Also, it is possible that size may be more important to survival in a large market than a small one. We included an interaction term between size and concentration, but the estimated effect was very weak statistically, and the interaction was dropped from the model. If individual, rather than grouped, data had been used, the interaction might have been more significant.

To control for factors besides efficiency which may contribute to growth, we initially included three variables: *GROWLOSS*, *GROWMCARE*, and *GROWMCAL*, as defined above. *GROWLOSS* is a proxy for the adverse selection of unprofitable patients into the hospital over time, while *GROWMCARE* and *GROWMCAL* are proxies for success in obtaining contracts and increased patient volume in the new policy environment. These variables are expected to enhance growth, and were included in the model so that the independent effect of scale economies could be estimated. However, their inclusion had no effect on the numerical value of the estimated coefficient of the size variable, and weakened the regression as a whole (in terms of the F-statistic or the adjusted R^2). These variables are included in the results reported in Table 6. We focus next on a simpler model without these three regressors (Table 3).

Once the possibly confounding effects of localized competition are controlled, the relationship between size and survival can be re-examined. Those size groups which are relatively more efficient should grow in share of total output. The variable *ADC* is our output size variable (*ADC* is the average over bed-days in the size group), which is expected to be positively associated with growth in total output if scale economies exist in this industry.

[11]The Herfindahl statistic is the sum of squared market shares of all firms in the market, $S_1^2 + S_2^2 + \cdots + S_n^2$. The index thus accounts for both the number and the size distribution of firms in the market. The index varies from zero in an atomistic market to one in a monopoly. For four, three, or two equally sized firms the index is 0.25, 0.33, 0.50.

[12]In mid-1983, HMO enrolment was 4.8 million, and rose to an estimated 7.5 million by January 1988. From mid-1983 to June 1988, PPO enrolment grew from 250 000 to an estimated 10 million (California Hospital Association, *Insight*, 1986 and the American Medical Care and Review Association, *Directory of PPOs and Industry Report on PPO Development*, June 1988 update).

Constructing size groups

Shepherd (1967) noted the importance of the appropriate choice of output in survivor analysis. In industry studies, using employment size rather than actual output introduces the possibility of bias caused by innovation (rising output/employee over time). In the hospital industry, cost-containment pressure has led to innovation in service delivery, resulting in a shift in sub-acute care service delivery, resulting in a shift in sub-acute care service delivery from in-patient to out-patient care. This has resulted in declining occupancy rates, increased case complexity and illness severity, and longer lengths of stay for in-patient services. In our analysis, we are concerned with determining whether scale economies exist in the provision of in-patient care services, in short-term general care facilities (the traditional acute care hospital). In times of declining occupancy industry-wide, output is best measured in bed-days (average daily census), because many beds may be empty.[13] Also, beds may be adjusted in a lumpy manner, injecting noise into the output measure.

On the other hand, the number of beds appears to be superior for *defining* the size groups. When occupancy is falling, as it is here, bed-days for medium sized, low-occupancy hospitals and for small, high occupancy hospitals will be similar. Careless grouping by size in terms of *bed-days* combines empty medium-sized hospitals with full small ones. With this classification system, as industry occupancy rates fall, the smaller size groupings will swell, and appear to grow over time. This is problematic because high occupancy is indicative of success, while low occupancy is just the opposite. The swelling small size groups then send a false signal that small size hospitals are more efficient. When hospitals are grouped by size in beds (not bed-days), as in Tables 1 and 2 and earlier survivor studies, we see that the smaller size groups are not gaining market share. For this reason, the classification of hospitals into size groups here is based on bed size in each year, rather than bed-days.[14] The growth rate in output of these classes, our dependent variable, is measured in bed-days.

Regression and probit results

We estimate both a continuous growth and a binary growth model, in Tables 3 and 4. As expected in our model with grouped data by size of firm, heteroscedasticity is a serious problem. Naturally, the error term will be much larger for larger size groups. The complete disappearance of a smaller size group could not cause a large error. Since the groups are constructed to have about the same number of firms, the average size of the firm, *ADC*, is the determinant of the larger errors. If we view the heteroscedasticity as analogous to the use of grouped data, a weighting of $ADC^{-0.5}$ is natural. Adding a constant (*WINT*) to allow for bias in the constant term of the transformed equation (Kennedy, 1985, pp. 90–92) leads to the following equivalent estimating equations:

$$\begin{aligned} GROWSHR/(ADC)^{0.5} &= B_C + B_0/(ADC)^{0.5} + B_1 ADC/(ADC)^{0.5} \\ &\quad + B_2 SYSS/(ADC)^{0.5} + B_3 HERF/(ADC)^{0.5} \\ &\quad + B_4\, PCONTRACT/(ADC)^{0.5} \qquad (2) \end{aligned}$$

$$\begin{aligned} WGROWSHR &= B_C + B_0\, WINT + B_1 WADC \\ &\quad + B_2 WSYSS + B_3 WHERF \\ &\quad + B_4 WPCONTRACT \qquad (2a) \end{aligned}$$

The regression results include the White statistic and a nonlinearity statistic, whose null hypotheses are of homoscedasticity and linearity.[15] Also, the White correction for heteroscedasticity is employed in calculating the corrected standard errors and *t*-statistics for both the unweighted and the weighted models.[16]

The second model estimated employs the probit procedure to explain a binary growth measure. Valuable information is lost in converting the continuous growth variable

Table 4. *Probit regression results for growth in market share of in-patient days, by size group*

Parameter	Estimate	*t*-statistic
Probit: Dependent variable *BINARY*		
# *BINARY* = 1: 41 # *BINARY* = 0: 64;		
Likelihood ratio test (chi-squared (4)): 10.206		
CONSTANT	0.216749	− 0.2653
ADC	0.002319	1.9030
SYSS	− 0.237840	− 0.4724
HERF	− 1.29353	− 1.2829
PCONTRACT	− 2.13003	− 0.3964

[13] Average daily census (bed-days) is total in-patient days per annum divided by number of days in the year. Occupancy is bed-days divided by beds. When occupancy is low, beds overstate the output of the hospital.

[14] The results were quite sensitive to this choice. When bed-days were used rather than physical beds, both very small and large size classes appeared to grow, while the central part of the size distribution declined. Using beds to classify groups, only the large size classes appear to grow. Further details about the construction of size groups are in the Appendix.

[15] The White statistic (White, 1980) is not sensitive to departures from normality, and is quite general in that it does not require specification of the form of heteroscedasticity (Kmenta, 1986, pp. 295–96).

[16] Although heteroscedasticity does not induce bias in the estimated coefficients under ordinary least squares (OLS), it may induce biased estimates of their standard errors. To account for this, we use a non-parametric, two stage correction that uses information in the residuals from the first stage (White, 1980). Because the weighting is not a perfect solution for the heteroscedasticity, we include the corrected standard errors in the weighted model as well. As one can see, the correction is typically small.

into a binary variable. When explaining binary growth in the probit model, the model passes the joint significance test of the regressors at the 5% (but not the 2.5%) level. The continuous growth model is a bit more powerful. In it, the regressors are jointly significant at both the 5% and 2.5% levels.

Discussion of multivariate results

We focus on the results of the Weighted Least Squares. The results for variables other than scale are disappointingly imprecise. We will discuss these briefly before returning to the central issue of scale economies.

Non-scale variables

The effect of chain affiliation, *SYSS*, is of direct policy and scientific interest. Unfortunately, its estimated effect is too imprecisely measured for an assessment of its economic importance. We hope that ongoing research using individual hospital data will be more definitive.

The effect of concentration in the local market, *HERF*, is negatively associated with growth in total output, though statistically weak, with a P-value of about 15%. The 95% confidence interval for this estimate is (−0.003336 to 0.000528). Effects of this magnitude are economically significant. According to the point estimate, increasing *HERF* from zero to one would cause a decline in market share of about 14.74% for the average group.

The results are not sensitive to different local market definitions. The Weighted Least Squares results from three regressions using the Herfindahl measures from three different size market areas are presented in Table 7. The effect of local market concentration is measured more precisely for the smallest market area, the *HFPA*. The signs are consistent. Though far from definitive, the results suggest that in less competitive local markets, there is increasing outmigration to more competitive areas.

The estimated effect of the extent of insurance market competition, *PCONTRACT*, is not of the expected sign, and is statistically weak with a P-value exceeding 50%. The result is not consistent with recent research on California market incentives (Robinson and Luft, 1988; Melnick and Zwanziger, 1988). Perhaps contracting has more effect on price than on quantity. We hope that further research will shed more light on this.

Scale economies

The multivariate results are consistent with the basic survivor analysis. The effect of output measure, *ADC*, is positive and statistically significant at a P-value of less than 5% in the three weighted regressions. The nonlinearity statistic has a large P-value, suggesting that no quadratic term is needed in *ADC*. This was verified with a supplementary regression that was quadratic in *ADC*.

Table 5. *Univariate regression results for growth in market share of in-patient days, by size class*

Parameter	Estimate	*t*-statistic	Corrected *t*
OLS: Dependent variable *GROWSHR*			
Mean 0.000000, Standard deviation: 0.004393, N = 105			
CONSTANT	−0.001537	2.6039	3.7524
ADC	0.000012	3.5878	2.8750
Adjusted R^2: 0.1025			
F statistic: 12.8786			P-value 0.00051
White statistic: 26.963			P-value 0.00000
Nonlin statistics: 0.1575			P-value 0.69143
WLS: Dependent variable *WGROWSHR*			
Mean −0.000045, Standard deviation: 0.000338, N = 105			
CONSTANT	−0.000283	3.3171	4.0511
WINT	0.001638	0.9103	2.0903
WADC	0.000022	3.0852	3.2629
Adjusted R^2: 0.0687			
F statistic: 4.8359			P-value 0.009851
White statistic: 10.01			P-value 0.074985
Nonlin statistic: 0.4748			P-value 0.924381

The partial effect of size on growth is unaffected by the three different local market definitions, though this is not apparent because of the nonlinearity of the weighted regressions. It can be found by solving the equations for *GROWSHR* and then partially differentiating the equations with respect of *ADC*, giving

$$dGROWSHR/dADC = (0.5^* B_C)/ADC^{0.5} + B_1$$

where B_C is the constant and B_1 is the coefficient on *WADC*. At the sample mean, *ADC* = 127.549, and the partial effects of *ADC* from the three regressions are 0.0000097, 0.0000096, and 0.0000096. These are quite close to the estimated effects from the unweighted equations: 0.0000140, 0.0000130, and 0.0000130.

The multivariate approach is intrinsically interesting but it is not important for estimating scale economies in this data. Simple regressions of growth in share on *ADC* are shown in Table 5. These equations are similar in spirit to the basic Stigler-type survivor analysis presented above. The results are very close to those of the three multivariate equations. Focusing on the unweighted versions for simplicity, the predicted scale economies are identical. Predicted growth of zero in either multivariate or simple regression occurs at an average daily census of 142, which corresponds to 199 beds, on average. The 95% confidence interval of the simple regression extends to an average daily census of about 220 (370 beds). Given the robustness of our findings regarding the relationship between size and growth, we can be quite sure of scale economies for smaller hospitals.[17]

[17] In addition to the preceding discussion, the probit results are similar in sign to the continuous growth results. Predicted growth of zero occurs at an average daily census of about 180 (300 beds).

Table 6. *OLS and weighted LS regression results for growth in market share of in-patient days, by size class*

Parameter	Estimate	*t*-statistic	Corrected *t*
OLS: Dependent variable *GROWSHR*			
Mean: 0.00000000, Standard deviation: 0.004393, N = 105			
CONSTANT	− 0.001373	− 0.4218	− 0.5731
ADC	0.000013	3.3033	2.5573
SYSS	− 0.001181	− 0.6952	− 0.5950
HERF	0.000744	0.2206	0.2217
PCONTRACT	0.000722	0.0412	0.0546
GROWLOSS	− 0.000622	− 0.6377	− 0.6209
GROWMCARE	0.001476	0.5249	0.6009
GROWMCAL	− 0.000893	− 0.6346	− 0.6393
Adjusted R^2: 0.062846			
F statistics: 1.986748			P-value 0.064675
White statistic: 53.4182			P-value 0.023884
Nonlin statistic: 44.1125			P-value 0.027080
WLS: Dependent variable *WGROWSHR*			
Mean − 0.000045, Standard deviation: 0.000338, N = 105			
CONSTANT	− 0.000485	− 1.8544	− 2.4468
WINT	0.002926	1.4687	2.2587
WADC	0.000030	2.3358	2.7470
WSYSS	− 0.000884	− 0.6689	− 0.8264
WHERF	− 0.002365	− 1.3992	− 2.0194
WPCONTRACT	− 0.002446	− 0.2441	− 0.3699
WGROWLOSS	− 0.000574	− 1.1605	− 1.3486
WGROWMCARE	0.000896	0.8053	1.3512
WGROWMCAL	0.000088	0.1431	0.2252
Adjusted R^2: 0.049453			
F statistic: 1.669827			P-value 0.115829
White statistic: 34.7035			P-value 0.812318
Nonlin statistic: 32.0012			P-value 0.613647

However, the confidence intervals around our estimates are fairly large, so that we are less sure of precisely how large a hospital must be to exhaust them.

Reconciliation with cost and production function estimates

Many of the most sophisticated cost and production studies show costs rising with the size of hospital, yet both industry observers and the survivor analysis clearly indicate economies of scale. These divergent observations can be reconciled by consideration of the type and quality of services rendered by hospitals. Hospitals of different sizes are not identical. As valued by consumers and physicians, larger hospitals supply higher quality services than smaller ones. The differences are subtle and cannot be entirely captured in observable accounting or physical data. Thus, they cannot be fully accounted for in statistical cost and production studies. Consumers and doctors increasingly prefer the larger hospitals, even if their accounting costs and prices are higher.

Also, the demand for higher quality services offered by larger hospitals is greater for patients who are relatively sicker. Thus, in both measurable and unmeasurable ways, larger hospitals are more likely to handle sicker patients who are intrinsically more costly to treat.

In terms of the precise type of services demanded by the market, there are scale economies. This type of scale economy is masked in statistical data, but it is naturally picked up by a survivor analysis.

A study by James Robinson (1985) supports the patient selection part of the analysis. Some of the hospitals in his

Table 7. *Weighted LS regression results for growth in market share of in-patient days, by size class: three different Herfindahl measures*

Market area:	HSA (largest)	HFPA (smallest)	County
WLS: Dependent variable *WGROWSHR*			
Mean: −0.000045, Standard deviation: 0.000338, N = 105			
CONSTANT	− 0.000164	− 0.000189	− 0.000190
	(− 1.0274)	(− 1.2351)	(− 1.2059)
WINT	0.005406	0.006370	0.005097
	(2.7858)	(2.7069)	(2.3351)
WADC	0.000017	0.000018	0.000018
	(2.1057)	(2.2978)	(2.2352)
WSYSS	− 0.000208	− 0.000316	− 0.000268
	(− 0.2103)	(− 0.3216)	(− 0.2705)
WHERF	− 0.015645	− 0.001404	− 0.001862
	(− 1.2457)	(− 1.4529)	(− 1.2968)
WPCONTRACT	0.003009	0.000984	− 0.000693
	(0.3651)	(0.1485)	(− 0.1144)
Adjusted R^2	0.06404	0.06427	0.06205
F statistic	2.42319	2.42851	2.37590
P-value	0.04069	0.04031	0.04423
White statistic P-value	0.28410	0.30470	0.33882
Nonlin statistic P-value	0.38493	0.50733	0.66540

data could be linked to good data on casemix. When the better casemix data was entered into his regressions, the apparent cost disadvantage of the larger hospitals was substantially reduced (though it did not disappear). As for the quality differences, there is substantial evidence that consumers directly value the availability of a wide range of services (Feldman and Dowd, 1986; Lucas-Roberts 1986, p. 5; Frech and Woolley, 1991; Luft *et al.*, 1990).

Because of scale economies at the level of the individual hospital services, only larger hospitals can offer a large menu of these services. In our data, we found that the simple correlation between census days (size) and a simple measure of the range and complexity of services offered in hospitals was greater than 70%.

Further, higher volumes of surgery are associated with lower mortality and fewer complications. Consumers seek out hospitals with better outcomes (Luft, Garnick, Mark and McPhee, 1990, p. 108; Luft *et al.*, 1990). Of course, larger hospitals can more easily attain high surgical volumes.

Interestingly, Keeler (1989) found an analogous result for trucking. Cost and production function studies showed diseconomies of scale, but his survivor study showed economies of scale. Keeler attributes this to higher quality service, especially faster delivery on larger truck lines with denser networks. This has made the larger truck lines increasingly attractive, in spite of higher accounting costs and higher market prices.

VI. CONCLUSION

For the hospital services valued by consumers, several types of survivor analysis indicate scale economies possibly up to a size as large as 220 bed-days (370 beds), even though measured accounting costs rise with scale. Subtle changes in the service correlated to scale cause the apparent conflict. Further, chain affiliation and market competition variables also matter, but are not well estimated in this data. Surprisingly, these other variables do not appear to much affect the relation between scale and survivorship.

Just as policy makers and industry observers have thought, there is indeed a policy trade-off in this industry. Local mergers among smaller hospitals permit the achievement of scale economies, but may reduce competition, at least in smaller markets. Antitrust enforcement agencies and courts should consider scale economies as well as competitiveness in their deliberations.

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APPENDIX

Sample statistics

Name	Mean	SD	Max	Min
ADC	127.549	122	798	3.22
HERF	0.345	0.161	0.808	0.0981
INITIALSHR	0.009524	0.009	0.045	0.0002
GROWSHR	0.000000	0.004	0.015	– 0.0125
SYSS	0.465	0.298	1.00	0.0000
PCONTRACT	0.14656	0.027	0.209	0.0657
GROWLOSS	0.371996	0.452	– 1.194	1.6832
GROWMCARE	– 0.043637	0.160	– 0.660	0.6959
GROWMCAL	– 0.148509	0.326	– 1.203	0.9105

Sensitivity checks

To assess sensitivity to grouping, the model was re-estimated with different size groups. Different groupings of the data, using different rules (cardinal and ordinal) yielded samples with a variety of heteroscedastic structures. Cardinal groupings indexed size just enough to get a minimal group. Ordinal groups fixed size differences (e.g. 11–20, 21–30 beds, etc.) and allowed the number of hospitals in groups to vary widely.

In transforming the models to eliminate heteroscedasticity, we found the parameter estimates for localized market competition effects to be fairly stable, but imprecise. The effect of the scale variable, *ADC*, was stable and statistically significant.

To make sure our results were not dependent on particular dates, the model was re-estimated using data from 1980 to 1986. The size of the coefficient on the output scale, *ADC*, was virtually unchanged over time or in models which included or excluded various other explanatory variables, and it remained statistically significant. Also, the inclusion of a quadratic term in output and an interaction term between the Herfindahl measure and output added nothing to the explanatory power of the model.

Data sources

The Office of Statewide Health Planning and Development, California Health Facilities Commission, individual hospital financial data for fiscal years ending 1982/83 and 1988/89; the Office of Management and Budget Area Resource File, March 1988; the American Hospital Association Directory of Multihospital Systems, 1980–90.

Comparison of HSAs, Counties, and HFPAs in California

Health Facilities Planning Areas (HFPAs) are designated by the California Health Facilities Commission as self-contained health markets through analysis of resource flows and needs. There are 139 HFPAs and 58 counties in California, an average of 2.4 HFPAs per county. The 139 HFPAs average 5 hospitals each, while counties average 11.7 hospitals each. The maximum number of hospitals in any HFPA is 23; the maximum in any county is 209. The minimum in either is one.

The Health Service Area (HSA) is much larger than the county. There are only 14 HSAs in California, an average of 4.14 counties per HSA. But three densely populated counties coincide with their HSAs (Santa Clara, Orange, and Los Angeles). The progression of increasing size is HFPA, county, HSA. The maximum number of counties contained in an HSA is 14, the Northern California HSA. The minimum number is one, where counties coincide with HSAs.

Data grouping methodology

The 506 short-term general hospitals were sorted by bed size in 1983. Then they were grouped so that at least two were in each cell in 1983, and under the constraint that none of the corresponding size-group cells in 1989 were empty. There is also a constraint because beds occur in integers only. Thus, some cells had to include more than two hospitals at both dates.

For example, in 1983, the first cell contains hospitals with up to and including 13 beds, while the second contains those with 14 up to and including 16 beds. Cell one has 4 members, and cell two has 4 in 1983. In 1989, these cells contain 3 and 6 members. The same hospitals are not necessarily in the same cells in both periods. Also, some hospitals fail over the period, and others enter.

This method maximizes the number of cells (resulting in 105 observations) while ensuring that no cells are empty in either period.