

The University of Chicago
Graduate School of Business
Center for Health Administration Studies (CHAS)
1101 East 58th Street, Walker 111
Chicago, Illinois 60637
(312) 702-7104

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DAVID DRANOVE, PH.D.* AND WILLIAM D. WHITE, PH.D.**
Associate Professor
The University of Chicago*
The University of Illinois at Chicago**

"An Analysis of Admissions Patterns in Local Hospital Markets"

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An Analysis of Admissions Patterns in Local Hospital Markets

by

David Dranove, William D. White and Lawrence Wu^{*}

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* - The authors are respectively Associate Professor, Graduate School of Business, University of Chicago, Associate Professor, University of Illinois at Chicago and Doctoral Student, Graduate School of Business, University of Chicago. This research was partly supported by a grant from the Fishman-Davidson Center for the Study of the Service Sector at the University of Pennsylvania.

I. Introduction

There has been a growing concern about the nature of competition in local hospital markets. It is frequently asserted that perfect competition is not an appropriate model of behavior (e. g. Dranove, et. al., 1986, Robinson, 1988 and Noether, 1988). The assumed absence of perfect competition has had broad policy implications. For example, it has been an important factor in increased anti-trust activity. It has also led third party payers to introduce new payment rules, such as prospective payment and selective contracting, intended to reduce the perceived difference between price and marginal cost. In spite of the important role of assumptions regarding the structure of local hospital markets in shaping reimbursement policies, there has been surprisingly little analysis of the character of competition in these markets.¹

The recent availability of large patient level data sets has created opportunities for detailed analyses of local market behavior. This paper uses California data to investigate the structure of local hospital markets with two central goals. The first goal is to determine which, if any, demographic and medical factors distinguish choices by local patients among local hospitals. The second goal is to explore the extent to which patterns that we observe are consistent with economic models of consumer choice and search theory. In addition, we evaluate the extent to which patterns are consistent with commonly held beliefs regarding differences in hospital behavior with respect to ownership and function (e.g., teaching status).

¹ Robinson (1988) and Noether (1988) find differences in hospital behavior across markets that are consistent with oligopolistic models. But their results are also consistent with competitive local markets, mobility of capital across markets, and varying demand conditions across markets.

Our results suggest that hospitals produce differentiated products, with market segmentation occurring across both demographic and, to a lesser extent, medical dimensions. An important, if not surprising finding, is that government-owned hospitals are strongly differentiated from private hospitals; the former admit disproportionately more Medicaid patients and disproportionately fewer whites. Our results also suggest that consumers behave in a manner consistent with the economic theory of search. Together, these results suggest that hospitals possess an element of monopoly power. Moreover, we find that the nature of market segmentation differs in predictable ways across markets. An interesting implication of this finding is that so-called "pro-competitive" cost containment initiatives may be predicted to have differential success across markets.

II. Models of Patient Behavior

Standard economic models of consumer choice within markets for heterogeneous goods focus on the nature of the heterogeneity (e.g., location of the providers) as well as price and demographic variables as predictors of behavior. Search and location models point out that, *ceteris paribus*, consumers will disproportionately purchase from nearby sellers. The incentives to consume close to home increases if the consumer faces high transportation costs, perhaps because the purchase of the service involves multiple visits to the service provider. The propensity to shop around for alternative sellers will increase, however, the greater the perceived variation in seller price and quality. Further, if some consumers have lower search costs (perhaps because they have more time to conduct the search), they again will display a propensity to shop around for alternatives.

Several factors complicate the analysis of consumer choice in hospital markets. First, more than one type of service is offered and quality may vary in ways that are systematic, but unobservable to researchers. Second, while the prices which hospitals charge for services may be known, the net price faced by consumers is often difficult to calculate because of insurance arrangements. We omit quality and price from our analyses.² Third, patients' choices regarding hospitalization may be largely determined by their physicians' preferences (cf. Garnick, et.al., 1987). Unfortunately, no data are available in our sample on patients' physicians, although this may not be a serious problem for our analysis, as we will show. Finally, any observed differentiation of patient choice of hospitals may be a result of differential efforts by hospitals to attract different types of patients. We develop a model of patient choice that accounts for hospital strategies.

III. Characterization of Local Markets

If we are to be sure that we are capturing the full extent of consumer behavior within local markets, we must necessarily address the issue of what constitutes a market area as a first step. One approach to defining local markets is to use geographic units, such as states, counties, or SMSAs. Though this spatial approach is easy to apply, it is inherently arbitrary and does not make use of potentially valuable information about either purchase patterns or prices.

² Garnick, et.al. (1988) offer an analysis in which one observable dimension of quality is included as a predictor of hospital choice. They find that lower mortality is associated with higher volume, but it is impossible to determine the direction of causality.

Elzinga and Hogarty (1978) suggest utilizing information on geographic flows to determine the extent of the market. The underlying notion is that a "market" is self-contained if producers in the market "export" relatively few goods to consumers living outside the market, and at the same time, consumers in the market "import" relatively few goods from producers outside the market. If imports and exports both are less than 25% (or, more conservatively, 10%), then external supply and demand forces have only a limited effect on the local market, thereby identifying a geographically distinct market.³

A third approach to analyzing hospital markets, suggested by Stigler and Sherwin (1986), is to examine serial correlations in price movements in different geographic regions. If the regions belong in the same market, then the factors affecting supply and demand in the two markets will be similar, and we should observe price movements that are positively correlated.

In comparing these alternative approaches, it is apparent that there is no single appropriate criterion for identifying markets (see Dranove, et. al. 1989 for further discussion). In the present analysis, our goal was to identify clearly defined markets using a combination of criteria. We initially selected six "urbanized areas" (as defined by the Bureau of the Census) in central California. We then checked the plausibility of these geographically defined market areas using the Elzinga/Hogarty and Stigler/Sherwin criteria. Five of the areas considered, Bakersfield, Fresno,

³ Morrisey, et. al. (1988), using the stringent 90% Elzinga/Hogarty import/export criteria, find that rural hospital markets tend to be geographically very disperse, whereas the SMSA may over or understate the size of urban markets, depending on the city.

Modesto, Sacramento, and Stockton, appear to constitute distinct markets. Based on patient flow and price analysis we concluded that the sixth urbanized area, Riverside, really consisted of two submarkets, Riverside/Corona and San Bernardino/Loma Linda.

Table 1 provides import/export data for the seven market areas we study, where "imports" and "exports" are defined in terms of inflows and outflows of patients instead of the more customary flows of goods. Only Sacramento and Stockton satisfy both the 25% import and 25% export limits of the Elzinga/Hogarty test.⁴ In most of these markets, exports of patients to outside hospitals are uncommon, suggesting that our market definitions are not too small. On the other hand, there appears to be no way to subdivide the markets without substantially increasing imports and/or exports. Thus, our market definitions do not appear to be too big, either.⁵

IV. Data

This paper utilizes patient level data from the California Health Facilities Commission (CHFC) data file for 1985, the most recent year available. This file contains data on all patient admissions in California by hospital.⁶ It is thus a complete sample of admissions in the state and

⁴ We analyzed imports and exports separately for deliveries, electives, and high "severity" DRGs, with comparable results.

⁵ We also performed a modified Stigler/Sherwin analysis of the growth in prices for routine bed days in each community. Analysis of variance showed borderline significant within-market correlations but weaker correlations across markets. This suggests that hospitals compete within local markets, but not across markets.

⁶ To avoid double counting of patients we omit all newborn admissions.

patients seeking care outside of their own communities can be readily identified. For each patient, the data set provides the residence zip code, type of payer, age, sex, race, DRG, nature of the admission, as well as more detailed diagnostic information. Data on hospital characteristics are drawn from the American Hospital Association Hospital Guide for 1985 and from the CHFC hospital financial data file for that year.

A list of variables used in our analyses appears in Table 2. Several of the variable definitions require discussion. First, over 90% of the sample is white or hispanic, so we do not consider other races. Second, the three PAYER classes are Medicare, Medicaid and all forms of private insurance; because of sample size limitations, we exclude all uninsured and self-paying patients. Third, we employed two alternative definitions of location. The first, DISTANCE, is a categorical measure of distance from the centroid of the residence zip code to the hospital. The second defines two categorical "ZIP" parameters for each hospital X. These parameters indicate whether a patient lived in the same zip code as hospital X (SAMEZIPX) or in a zip code contiguous to hospital X (NEARZIPX). For each SAMEZIPX and NEARZIPX parameter the regression reports one coefficient for each hospital. We were mostly interested in the coefficient on hospital X, which we expect to be positive. As the DISTANCE and SAMEZIP/NEARZIP specifications each enable us to test a different set of hypotheses, we report the results for both.

We chose several variables to attempt to capture different aspects of patients' illnesses. Certain narrowly defined illness and treatment characteristics, such as open heart surgery surely predict hospital choice. We elected, however, to aggregate illness types into broad categories for three reasons. First, our analysis suggests that identification of

appropriate narrow illness categories may only be done with the benefit of hindsight. Second, as we discuss in the conclusions, the policy implications of market segmentation based on narrowly defined illness categories are unclear. Finally, econometric considerations forced us to classify illness types so that there were large numbers of patients in each category. The illness characteristics that we examined in some detail are DELIVERY, ELECTIVE, and SEVERITY, where our SEVERITY measure is based on Medicare case-weights, and therefore subdivides the sample into low cost and high cost illnesses.

We explored several other categorizations of illness type, including medical versus surgical admission, cancer versus non-cancer admission, DRG mortality rates⁷ and Major Diagnostic Category (MDC).⁸ However, not only is an economic interpretation of these categorizations generally ambiguous, but they had limited predictive power, so we do not report the results here.

V. Methods

Based on our earlier discussion, we can characterize the individual patient's choice problem as follows. An individual patient develops an illness that requires hospitalization. The patient's problem is to choose the hospital at which he or she wants to be treated. We assume that the

⁷ A DRG was classified as risky if the frequency of death among patients with that DRG exceeded 10% (and was less than 100%).

⁸ The DRGs are grouped into 25 MDCs, according to the affected organs or parts of the body. We subdivided the sample into five groups, representing the four most common MDCs (approximately 55% of the sample) and all other MDCs.

patient only considers hospitals in the local market.⁹ The patient calculates the expected utility that he or she will receive from each hospital in the local market. In particular, patient i calculates that if he visits hospital j , he will receive expected utility equal to:

$$U_{ij} = \alpha_j + \beta_j L_{ij} + \gamma_j M_i + \psi_j D_i + \epsilon_{ij} \quad (1)$$

where α_j is a hospital specific utility shifter, L_{ij} indicates the patient's residence location relative to the location of the hospital, M_i indicates the nature of the illness, D_i indicates patient demographic characteristics and ϵ_{ij} is an unobserved, randomly distributed, idiosyncratic component of utility. The patient chooses the hospital that offers the highest expected utility.

Several features of our model as expressed in equation (1) deserve special comment. First, while we describe the model as one of consumer choice, hospitals are by no means passive. One can think of the choice process as encompassing two stages. In the first stage, the hospitals set policies which, when combined with certain exogenous hospital characteristics, effectively determine the utility weights α , β , γ and ψ . In the second stage, patients observe the utility weights and choose a hospital.

A second noteworthy feature of the model as expressed in equation (1) is that it provides no role for the physician. It turns out that our patient specific parameters predict hospital choice fairly well. Moreover, as we later argue, physician "preferences" may be endogenous to patient preferences. Thus, excluding physician characteristics from the model is not especially worrisome. One can extend the model to include physicians as

⁹ The multinomial logit analysis estimates relative preferences for local hospitals, so is unaffected by excluding the patients who choose outside hospitals.

follows:

$$U_{ij} = \alpha_j + \beta_j L_{ij} + \gamma_j M_i + \psi_j D_i + \delta_j \text{DOC}_i + \epsilon_{ij} \quad (2)$$

where DOC_i is a vector of characteristics of patient i 's doctor. As long as the elements of DOC_i are uncorrelated with patient characteristics, then omitting DOC_i from the model poses no problems; it is simply an additional component of the error term. If DOC_i is correlated, then our estimates of β , γ and ψ are biased; our interpretation of the results must be guided by this possibility.

A third notable feature is that the model is consistent with theoretical models of hospital markets, such as the search-theoretic models of Satterthwaite (1979) and Dranove and Satterthwaite (1988). In these models patients gather information about one or more hospitals from friends, relatives and physicians. Patients combine this information with their own idiosyncratic preferences to determine which hospital maximizes expected utility. The error term ϵ_{ij} may be thought of as incorporating both the idiosyncratic differences in each individual's search process as well as idiosyncratic differences in consumer preferences.

The choice problem that is described by equation (1) is a standard multi-response model which, given further assumptions, is straightforward to estimate using multinomial logit techniques (Amemiya, 1981). Given that our independent variables are all categorical in nature, the logit model can be estimated using weighted least squares. Garnick, et. al. (1988) point out that such a weighted least squares analysis can be confounded if most of the non-empty cells have few observations. Our choice of predictors minimized this problem; fewer than 7% of the cells contained five or fewer

observations.¹⁰ We tested the weighted least squares results for robustness by re-estimating the model by maximum likelihood (ML) methods using the Newton-Raphson algorithm. As the log-likelihood functions from the best fitting ML model were typically less than .5% smaller than those from the weighted least squares model and a few ML parameter estimates did not converge, we only report the weighted least squares estimates.

Given the large number of predictors and the many potentially interesting interactions, combined with the fact that some predictors are significant in some markets and not in others, we chose our predictive model according to two criteria: 1) the theoretical interest of the predictors; and 2) the significance of the predictors. After some experimentation, we settled on the following model, which we applied in all markets:

$$\begin{aligned} \text{HOSPITAL} = & \text{INTERCEPT} + B_1 \text{SAMEZIP} + B_2 \text{NEARZIP} + B_3 \text{MEDICAID} + B_4 \text{MEDICARE} \\ & + B_5 \text{RACE} + B_6 \text{DELIVERY} + B_7 \text{ELECTIVE} + B_8 \text{SEX} + B_9 (\text{RACE} * \text{MEDICAID}) \\ & + B_{10} (\text{RACE} * \text{MEDICARE}) + B_{11} (\text{SAMEZIP} * \text{DELIVERY}) + B_{12} (\text{SAMEZIP} * \text{ELECTIVE}) \end{aligned} \quad (3)$$

The results from this regression model, along with the results when we replace SAMEZIP and NEARZIP with DISTANCE are discussed in section VI.

One notable omission in the final predictive model is SEVERITY. Chi-square tests indicated that SEVERITY was often insignificant in predicting hospital choice. Moreover, SEVERITY added very little to the predictive power of the model, as we will soon discuss. (The same was true for the alternative measures of illness type that we tried, including MDC.) For reasons of parsimony, we chose to omit SEVERITY from our final specification. We will, however, occasionally note some of the results that we obtained when

¹⁰ To further minimize this problem we eliminated hospitals with less than 1% market share, as well as Children's and Veteran's hospitals.

SEVERITY was included in the full model.

VI. Results

Our initial interest is in how well the individual parameters predict admission choice. At one extreme in predicting admission choice is the case where no information is known about individual patients and the best "blind" prediction that we can make is to choose the hospital with the largest market share. The "success" rate is the largest hospital's market share. Given patient-specific data, we can do substantially better. To improve our prediction we refer to the individual cells that represent unique combinations of predictors. Within each cell (i.e., for each unique combination of predictors) we choose the hospital with the largest market share. That market share is the success rate for that cell. Our overall success rate is the sum of the success rates in each cell, weighted by the number of individuals in each cell.¹¹

Table 3 summarizes the comparative predictive success rates of various models. The blind success rates tend to be fairly low, exceeding 40% in just two markets. We used a stepwise approach to determine which predictive variables to add to the model. We found that by adding LOCATION and PAYER we could substantially improve predictive performance in all markets. No other

¹¹ This procedure does not automatically improve predictive ability. If the hospital with the largest overall market share also has the largest market share within each cell, then the predictive ability based on the subdivided sample exactly equals the "blind" predictive ability.

pair of predictors performed this well.¹² The order in which other predictors should be added varied by market; we report prediction success when RACE and SEX are added before ELECTIVE and DELIVERY. It was clear from our analysis that SEVERITY was the least powerful predictor of admissions. Other diagnosis related predictors, such as MDC, mortality risk, and cancer/non-cancer, likewise did not improve predictive ability very much.

The multinomial logit estimates of equation (3) are broadly consistent with the above results. Before discussing the individual parameter estimates we should briefly mention the analyses of variance in each market. By and large, all of the main effects and interactions in equation (3) were significant at $p < .01$ in each market, based on chi-square tests. The payer and location variables explained substantially more of the variation in admission patterns than did the other predictors.

The logit regressions estimate hundreds of parameters (one for each hospital for each predictor). Rather than present the full regression results for every market, we will instead summarize the results by predictor. Some of these results are highlighted in Table 4.

LOCATION: SAMEZIP and NEARZIP

Virtually all the location parameters were significant in every market. The means of the relevant SAMEZIP and NEARZIP parameters were significantly different from zero at $p < .01$. On average, patients were 31.8% more likely than average to visit the hospital(s) in their zip code. The effect for

¹² This is not an artifact of the number of subcategories defined by LOCATION and PAYER. Dichotomous classifications of location and payer (e.g., east/west, Medicaid/other) also had substantial predictive power. Moreover, the variable MDC, which had five categories, was a consistently poorer predictor than any of the demographic variables.

NEARZIP was almost as strong. Overall, patients were 22.1% more likely than average to visit the hospital(s) contiguous to their zip code. These preferences were even stronger in markets in which the hospitals are geographically disperse, such as Corona/Riverside, San Bernardino/Loma Linda, and Stockton. In these markets, patients were 48% more likely to visit a nearby hospital than an "average" hospital. On the other hand, in markets in which the hospitals are close together, such as Fresno and Modesto, patients were only about 10% more likely to visit the hospital in their own zip code.

LOCATION: ORDINAL MEASURES OF DISTANCE

We defined DISTANCE so that an increase of one in the ordinal score corresponded to roughly a doubling of the distance to the relevant hospital. The results using this ordinal measure of distance are broadly consistent with those using NEARZIP and SAMEZIP. For example, the correlation between the relevant NEARZIP and DISTANCE coefficients was $-.53$; hospitals that are attractive to nearby residents tend to be less attractive to distant residents. The average DISTANCE coefficient of $-.16$ is significant at $p < .01$. This coefficient implies an elasticity of demand with respect to distance of $-.15$, a figure that strikes us as being rather small in magnitude. We conclude that although patients may prefer local hospitals, ceteris paribus, the utility loss associated with traveling to a more distant hospital is probably not that great.

This result has numerous policy implications. For example, insurers can selectively contract with hospitals that are geographically disperse without dramatically reducing the utility of enrollees whose neighborhood hospitals

are excluded. As another example, if an urban hospital closes then the average utility loss to community residents who must travel a few extra miles to the nearest open hospital is small. (Of course in few cases, such as trauma, the utility loss may be great.)

MEDICARE and MEDICAID

The importance of insurance status as a predictor is corroborated by the logit analysis. The standard deviation (SD) of the individual hospital coefficients is a useful measure of the degree to which the predictor affects admissions probabilities; the larger is the SD, the more patients tend to sort by that predictor. The SDs for Medicare and Medicaid are .27 and .79 respectively. By way of interpretation, if one were to select two hospitals in a given market at random, Medicaid patients would on average be $\exp(.79) = 2.20$ times as likely to go to one hospital versus the other, *ceteris paribus*. Medicare patients, on the other hand, would choose one hospital over the other only $\exp(.27) = 1.31$ times as often.

In regressions in which we included SEVERITY there was an occasionally significant MEDICAID*SEVERITY interaction. In general, the interactions suggest that the segmentation of Medicaid patients is greater among the more severely ill. This could reflect differential search, differential physician preferences, or differential hospital responses to financial incentives.

RACE

Race is a significant predictor in all markets. The SD of the RACE coefficients is .27, suggesting that race is a less important predictor of admissions than payer. The importance of race as a source of segmentation is

by no means the same across markets. The SD of the RACE coefficient ranges from .145 in SB/LL to .485 in Riverside/Corona. These areas have, respectively, the highest and lowest concentrations of hispanics (relative to whites) of the seven markets. This trend shows up throughout the sample. For example, the Spearman rank coefficient for the variables "SD of the RACE coefficient" and "concentration of hispanics" is $-.75$. This implies that hospitals are more likely to segment on race when there are relatively few hispanics in the market. This suggests that there may be some scale economies associated with serving hispanics.

It is interesting to note that the correlation between the MEDICAID and RACE coefficients for each hospital is $-.44$; hospitals that admit disproportionately many Medicaid patients also admit disproportionately many hispanics. This may again reflect scale economies. Hospitals that admit Medicaid patients will have disproportionately many hispanic patients for that reason alone; in taking steps to serve them better they may make themselves more attractive to other hispanics.

SEX

Sex is a relatively unimportant predictor; the sex coefficients have a SD of only .09. Of note is the .29 correlation between the coefficients for SEX and DELIVERY; hospitals that performed disproportionately many deliveries admitted disproportionately many women with other diagnoses as well. We obtained the same result when we excluded sex-specific diagnoses other than deliveries (such as hysterectomies), so this result is not an artifact of the preferences of gynecologists. One possible explanation of this finding may be that there are some economies associated with organizing medical care

services for women in general. Alternatively, there may be some reputation effect where women who deliver their child at a given hospital are favorably disposed to choose that hospital for future services.

DELIVERY, ELECTIVE

There is a substantial amount of sorting for deliveries and electives. The SD of the coefficients for these two predictors are .54 and .47 respectively. The sorting on DELIVERY is not too surprising, because several hospitals in the sample have no bassinets, and so have large negative coefficients for DELIVERY. The interpretation of the ELECTIVE coefficients is more problematic, since individual hospitals may code their admissions on this dimension differently.

RACE*PAYER

Hospitals that have positive coefficients for RACE and negative coefficients for MEDICAID tended to have negative coefficients for the interaction. In other words, the degree to which certain hospitals admitted disproportionately many hispanics on Medicaid is understated by the magnitudes of the RACE and MEDICAID coefficients alone.

SAMEZIP*DELIVERY, SAMEZIP*ELECTIVE

We examine the signs of these coefficients to see if they are consistent with hypotheses regarding consumer search. The relevant coefficients for both interactions were consistently negative. The average coefficients of $-.082$ for SAMEZIP*DELIVERY and $-.064$ for SAMEZIP*ELECTIVE are both significant at $p < .01$. A possible interpretation is that transportation

costs are lower for deliveries and elective admissions. One might instead consider these results in the context of search theory. Patients anticipating either type of admission have time to gather information about alternative hospitals. This enables them to broaden their search.

In regressions in which we included SEVERITY we also included a SEVERITY*SAMEZIP interaction. The relevant coefficients on the interaction were generally negative. Perhaps patients with severe illnesses, which generally require longer hospital stays, prefer to be close to home to minimize the travel costs for themselves and their immediate families.

VII. Admissions Patterns and Hospital Characteristics

According to the model expressed by equation (1), the coefficients of the multinomial logit model reflect patient choices. But these choices are conditioned, to an important degree, on choices made by individual hospitals. For example, a large positive MEDICARE coefficient indicates that the hospital has made choices that make it attractive to Medicare patients. These choices may include specializing in geriatrics, providing nurses who are especially sensitive to the needs of the elderly, or granting admissions privileges to physicians who treat Medicare patients. We have determined that within each market there is segmentation according to payer, location, race, etc. This segmentation indicates that different hospitals have made choices that make them attractive to different market segments.

We have run some simple regressions to investigate whether the same types of hospitals attract the same types of patients across market areas. The unit of observation in each regression is the hospital. The dependent variables are various coefficients from our logistic regression models. The

independent predictors are as follows:

GOVT - an indicator that equals one if the hospital is government-owned.

TEACHING - an indicator that equals one if the hospital reported a medical school affiliation to the American Medical Association in 1987.

There is at least one teaching hospital and at least one government-owned hospital in each market.¹³

HISPANIC - the percentage of residents living in the hospital's zip code who are hispanic;

INCOME - the 1985 median family income of residents living in the hospital's zip code; and

NONMOVER - the percentage of the population in the hospital's zip code that did not change residence since 1975. This variable was included in the SAMEZIP regression to measure the stability of the hospital's neighborhood.

The regression results, reported in Table 5, enable us to better describe how ownership and teaching function relate to admissions patterns. First, the results suggest that hospital ownership and function do not affect the degree to which hospitals serve their local communities. Second, government hospitals appear to serve different market segments than do private hospitals, admitting disproportionately many Medicaid patients and hispanic patients. This suggests that studies of market competitiveness that include government hospitals as potential competitors to private hospitals probably overstate the degree of competition in the market. Third, teaching hospitals seem to admit disproportionately many privately insured patients. Given the authors' own anecdotal experiences in Illinois, we are

¹³ One can also define defining teaching status according membership in the relatively exclusive Council of Teaching Hospitals. This indicator did less well at predicting admissions patterns.

not sure whether this result generalizes out of the sample.

In unreported regressions, we also estimated the INTERCEPT terms, which, according to equation (1), correspond to the general attractiveness (or "quality") of each hospital. Neither ownership status nor teaching status was a significant predictor. Following Garnick et. al. (1987) who suggest that physicians prefer to admit patients to hospitals near their practices, we added a predictor indicating the number of physicians who practice nearby each hospital. Using data from the American Medical Association, we ranked each hospital's zip code as having a high, medium or low density of physicians per capita, and primary care physicians per capita, relative to other hospitals in its market.¹⁴ The rankings using all physicians and primary care physicians were identical. This measure of physician density was a significant predictor of INTERCEPT (the coefficient of .39 is significant at $p = .05$).

The observed correlation between physician location and hospital attractiveness is not very informative, since the direction of causality is unclear. As the data available to establish causality in a two-stage model is limited, the following results should not be taken too seriously. We first estimated physician location as a function of the INCOME, HISPANIC, and NON-MOVER variables described above. The overall predictive model was significant (F -test at $p < .01$). We then estimated INTERCEPT, using "predicted location" as well as GOVT and TEACHING. The coefficient on "predicted location" had the expected positive sign but was small in magnitude (.18) and insignificant. If anything, our results suggest that

¹⁴ The results using numbers of physicians, rather than physicians per capita, are nearly identical.

physicians locate near popular hospitals, rather than hospitals are popular because physicians are located near them. Neither GOVT nor TEACHING was a significant predictor.

VIII. Conclusions

In this paper we have analyzed admission patterns for local patients in seven medium-sized California communities. While further study is needed to generalize our results, our findings are strikingly consistent across these communities. In all of them it is evident that demographic variables such as payer, location and race are significant predictors of patient admission patterns. To a lesser extent, so too are the patients' medical conditions as measured by our delivery and elective variables. On the other hand, while there is undoubtedly some segmentation based on narrowly defined illnesses (e.g., open heart surgery), this segmentation does not appear to aggregate up to broader illness categories (e.g., SEVERITY or MDC).

These results are of interest to third party payers entering into selective contracts with hospitals. If payers attempt to contract on the basis of relatively specific services, for example the treatment of lung cancer, they may find some hospitals have considerable market power. However, if as seems more likely, they attempt to select hospitals that have broad patient appeal our analysis suggests that no hospital is likely to dominate, for instance in the general provision of cancer services.

Upon closer inspection, we found that much of the differentiation on demographic dimensions can be attributed to the unique admission patterns of government-owned hospitals. Government-owned hospitals appear to be so differentiated on payer as to not be in direct competition with private

hospitals. It would be interesting to see if a similar kind of differentiation occurs in other markets, such as housing, education, and legal services, where government and private sellers exist side by side.

Our observations of patient preferences are generally consistent with theories of consumer choice and location theory. The evidence about market segmentation and consumer search, for example, is broadly consistent with the fundamental assumptions underlying the economic theory of monopolistic competition. Interestingly, the causes of market segmentation appear to differ across markets, and in predictable ways. Thus, location is a more important predictor of patient choice in markets in which hospitals are well distributed spatially. This has important implications for third party cost containment efforts; policies such as selective contracting that rely on patient switching to achieve efficiencies will be predicted to have greater success in markets that are less segmented.

Finally, our results may be at odds with some commonly held hypotheses about hospital behavior with respect to ownership and function. It has often been suggested that the missions of government and teaching hospitals differ from those of local community hospitals, where the latter seek mainly to serve local residents. (Cf. Feldstein, 1983). Our results suggest that ownership and teaching status do not predict attractiveness to local markets. It is also our impression that teaching hospitals are thought of as important sources of care for the Medicaid population. This is not the case in the markets that we study; if anything, the teaching hospitals in our markets admit disproportionately fewer Medicaid patients.

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Table 1
Imports and Exports as percentages of total patients

<u>Market</u>	<u>Imports</u> ^a	<u>Exports</u> ^b
Bakerfield	27.1%	7.8%
Fresno	38.9	9.6
Modesto	33.0	9.5
Riverside/Corona	28.7	28.1
Sacramento	14.9	11.5
San Bernardino/Loma Linda	45.8	13.3
Stockton	17.5	13.1

^a Percentage of patients in area hospitals who reside outside area.

^b Percentage of hospitalized area residents who are admitted to hospitals outside area.

Table 2

Variables used for analysis

- DISTANCE = An ordinal measure of the distance from the geographic centroid zip code to each hospital. Values of distance are as follows:
0 - 1.5 miles: DISTANCE = 1; 1.5 - 3 miles: DISTANCE = 2;
3.1 - 6 miles: DISTANCE = 3; over 6.1 miles: DISTANCE = 4.
- SAMEZIPX = Indicates whether the patient lives in the same zip code as hospital X.
- NEARZIPX = Indicates whether the patient lives near hospital X; in particular, whether the patient's zip code is contiguous to the zip code containing hospital X.
- MEDICARE = Indicates if the payer is Medicare.
- MEDICAID = Indicates if the payer is Medicaid.
- The omitted payer category is PRIVATE. This includes Blue Cross, Blue Shield, other private insurers, HMOs, PPOs, and worker's compensation. (Note that self-pay and uninsured were excluded from the analysis because of insufficient sample size.)
- RACE = Indicates if patient is white (versus hispanic). In all markets considered, whites and hispanics account for over 90% of patients.
- SEX = Indicates if patient is female.
- DELIVERY = Indicates if reason for admission was a delivery.
- SEVERITY = Indicates severity of DRG. Severity is measured by Medicare DRG case-weights, which reflect the nationwide average cost of treatment. DRG is considered severe if DRG case-weight exceeds 2.
- ELECTIVE = Indicates if admission was classified as elective (as opposed to emergency, urgent, or delivery.)

Table 3
 Predictive Success of Categorical Models

Urban Area	<u>Markets</u>		"Blind"	Payer Location	<u>Models</u>		
	No. of Hosps.	No. of Patients			Payer Location Race, Sex	Payer Location Race, Sex Elective Delivery	Payer Location Race, Sex Elective Delivery Severity
Bakers.	5	24468	29.1%	48.1%	49.9%	53.9%	55.3%
Fresno	4	25822	43.8	52.6	55.0	56.2	56.7
Modesto	5	17180	34.8	40.9	43.3	50.0	50.8
Riv/Cor	5	21052	32.9	55.8	57.2	62.1	62.3
Sacramento	8	66205	22.8	33.9	34.9	36.5	37.0
SB/LL	7	34915	24.9	44.1	44.9	46.7	46.9
Stockton	3	17843	55.8	59.7	60.6	61.7	62.6

Table 4
Summary Statistics for Predictors of Admissions Patterns

Location Parameters^a

	Mean	Std. Dev.
SAMEZIP	.28	.32
NEARZIP	.20	.28
DISTANCE	-.16	.23

Other Parameters

	Std. Dev. ^b
MEDICARE	.27
MEDICAID	.79
RACE	.27
SEX	.09
DELIVERY	.54
ELECTIVE	.47
SEVERITY ^c	.17

^a These are for the relevant hospitals only. Thus, if the parameter is SAMEZIPX, we only consider the score for hospital X.

^b By construction, the mean of each of these parameters is zero.

^c SEVERITY was not included in the final model. This estimate is included for exposition only.

Table 5

Results of Regression Analyses:

Do hospital characteristics affect admission patterns?

Dependent Variables ^a	Independent Variables						Adj R ²
	CONSTANT	GOVT	TEACHING	HISPANIC	INCOME	NONMOVER	
SAMEZIP	-.03	-.18 (.21)	.034 (.16)	.012* (.006)	.026* (.014)	-.008 (.006)	.026
MEDICAID	-.09	1.73** (.38)	-.44 (.30)	-.003 (.009)	-.003 (.022)		.457
PRIVATE	-.05	-1.35** (.28)	.53** (.22)	.004 (.007)	.011 (.017)		.434
RACE	-.11	-.25* (.14)	-.12 (.11)	-.004 (.003)	.002 (.008)		.356

* - Significant at $p < .10$ ** - Significant at $p < .05$

^a Values are the appropriate regression coefficients from the admission patterns logistic regressions.