Managed Care, Distance Traveled, and Hospital Market Definition

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ABSTRACT

Most scholars and antitrust cases have defined hospital service markets as primarily local. But, two recent decisions have greatly expanded geographic markets, incorporating hospitals as far as 100 miles apart. Managed care plans, now important in most markets, were believed to shift patients to distant hospitals to capture lower prices. We examine distance traveled and its connection to managed care penetration. In contrast to earlier literature, we examine both direct and indirect effects. We find that increases in managed care have impacted distances traveled, but these effects are too small to justify much change in geographical markets for research or antitrust law.

I. Introduction

Two recent court cases have allowed mergers between hospitals based on the argument that managed care penetration has significantly increased the distances that patients travel, bringing quite distant hospitals (as far as 100 miles away) into competition with hospitals who were allowed to merge.[1] This study will examine whether travel distances are consistent with these expansive markets, and what effect managed care penetration has had on travel distances.

We carefully chose a 14 county region within California for study, containing regions of varied urban intensity and managed care penetration. The data on patient patients discharged from short-term acute-care hospitals in these counties yielded about 1.4 million patient observations. Over the 1984-1993 period studied, the number of inpatient discharges going to hospitals in these 14 counties increased by about 4%, while the number of zipcode regions they originated from increased 12% and the number of available hospitals decreased from 101 to 89. The distance that the *average* patient traveled increased (from 6.6 miles to 7.1 miles).

The main purpose of this paper is to establish whether or not areas with greater managed care penetration saw larger increases in market *extent* (the geographic span of

[1] In the Dubuque case, U.S. v Mercy Health Services DC N. Iowa, October 27, 1996, the court determined that the proposed merger between the only two acute care hospitals in Dubuque, Iowa did not violate the antitrust laws. In the Joplin case, FTC v Freeman Hospital , the FTC's request for an injunction against the proposed merger of two out of three acute care hospitals in Joplin, Missouri was denied by the U.S. Court of Appeals for the 8th Circuit on November 1, 1996.

patient origins) than regions with lower penetration. We call this the indirect market-wide effect of managed care, which would occur if managed care changed general consumer information or the distribution of available services across hospitals. One way the services might change is through improved search, which could lead to increased specialization within the hospital industry and emerging centers of excellence for highly technical services. Travel would increase across the board for all patients seeking these specialized services, irrespective of their insurer. On the other hand, managed care insurers prefer one-stop-shopping. So, competition for their contracts might lead to less specialization, hence travel would decrease, irrespective of the insurer.

To examine the indirect effect of managed care penetration on market extent, other factors which impact distance must be controlled for. Using data on the zip codes of residence, we hold constant urban intensity, availability of alternative providers, demographic differences, market concentration and size, hospital casemix complexity, technology and physician staffing levels, and the passage of time.[2]

II. Legal and Scholarly Background

Geographic market definition is a fundamental necessity for both research on competition and for antitrust policy. The antitrust question is this: Which sellers can

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[2] Over time, and independent of managed care, there may be changes in the norms of practice which affect travel, such as closure and consolidation of hospitals, changes in the geographic population distribution, changes in technology, and increased or decreased heterogeneity among hospitals.

constrain the higher prices or lower quality of a hospital or colluding group of hospitals? From this viewpoint, a market includes the sellers from the smallest geographic area who can, in concert, exert market power. In its merger guidelines, the U.S. Department of Justice (1992) has suggested using a 5 percent price increase for one or two years as the standard for exerting market power. This makes sense for most purposes, at least as a conceptual starting point. Actual empirical studies use a variety of market definitions. But, most studies use small, local areas, as do most antitrust cases.

Use of Market Definitions in Scholarly Literature

Many studies define a market area as either the Standard Metropolitan Statistical Area (MSA) or the county. Within California, smaller areas, the Health Facilities Planning Areas, have been used recently (Vistnes 1994, Frech and Mobley 1997). This mimics small MSAs (where the MSA seems a reasonable market area), and often mimics counties, but breaks up the larger MSAs. For example, San Francisco and the four surrounding counties contain 11 Health Facilities Planning Areas (HFPAs).[3]

Many studies use a purely distance-oriented market definition. E.g. Hal Luft and Susan Maerki (1984-1985) begin with each hospital's location and calculate the number of hospitals within a fifteen mile radius. These distances typically fall in the 10-

[3] HFPAs are defined for the state of California by the Office of Statewide Planning and Development, based on resource flows and needs. They are smaller than counties (the average square miles in a county is 2,742, while it is only 1,123 in the average HFPA). HFPAs often cross county borders.

20 mile range. Pure distance measures overcome the problem of the large MSA, but they still have shortcomings. They ignore geographic factors: barriers (mountains, lakes), transport corridors (freeways, mass transit), and employment and shopping patterns. These factors enter into MSA and HFPA definitions.

These various approaches are sometimes justified by appeal to patient origin or patient flow studies showing that local market areas are self-contained. That is, there is little export or import of hospital services from the defined local market area. Further, several studies explicitly define market areas based on patient flow statistics (Morrisey, Sloan and Valvona 1988; Robinson and Phibbs 1990; Phibbs and Carson 1989; Dranove, Shanley and Simon 1992). Markets for antitrust cases are defined partly by patient flows.

Patient flow patterns lead some observers, such as Morrisey, Sloan and Valvona (1988) to suggest that small town hospitals ought to be included in the market with the sophisticated hospitals in the larger cities. But, others have argued that this would be a mistake because the long distance flows are not very price sensitive (Frech 1987; Baker 1988; Werden 1989). In any case, patient flows are an important piece of evidence for the extent of hospital markets.

Earlier Antitrust Cases and Local Markets

Earlier antitrust cases have generally found that hospital markets are quite local. In one case, the market was defined as the San Luis Obispo, California area, explicitly excluding hospitals located 25 miles away. In two other important cases, markets were defined as the Chattanooga, Tennessee urban area and the New Orleans area (Baker 1988, pp. 146-147). In the most recent and oft-cited of these cases, the 7th Circuit appellate Judge Richard Posner affirmed the district court decision, stating, "for the most part, hospital services are local. People want to be hospitalized near their families and homes, in hospitals in which their own--local--doctors have hospital privileges." (Rockford 1990). Judge Posner affirmed a market including three counties, with a radius of about 30 miles. He explicitly rejected a larger 10-county area.

Break with Tradition: Recent Cases with Expansive Markets

Two recent cases have gone against the legal and scholarly mainstream of market definition, using much larger definitions. The first was FTC v. Freeman Hospital (1995), when hospitals are far as 54 miles from Joplin, Missouri were included in the market. This was unusually large, but there was also a burden of proof issue; the FTC was trying to get a preliminary injunction to stop a merger. Thus, the FTC's burden was somewhat higher than in a usual antitrust case and, there was only a short hearing, not a full-blown trial. The decision by a panel of the 8th Circuit Court of Appeals was fairly brief, but it did include a reference to large purchasers of health care, such as managed care organizations, steering consumers to out-of-town hospitals in response to price differentials. This is but a small expansion, compared to the Court's decision in U.S. v. Mercy Health Services (1995).

In Mercy, district court Judge Melloy expanded the market area around Dubuque, Iowa to include other major hospitals from 70 to 100 miles away. This is a massive break with past decisions. Judge Melloy justified this by arguing that the new managed care plans had the ability to shift patients and that managed care enrollees are increasingly willing to travel for financial savings.

If the increased willingness of consumers to travel such large distances in response to small price changes has actually occurred, one would expect to observe some evidence in actual travel patterns. Travel distance should be increasing over time and a non-trivial proportion of consumers should be observed to travel far enough to pull hospitals that are 50-100 miles apart into the same market. Further, if the growth of managed care systems that can steer or shift patients is the cause of the change, one should observed substantially longer travel distances for managed care enrollees and perhaps also longer travel for everyone in markets with greater managed care penetration. These topics are investigated here.

The judges in the recent cases with expansive markets are certainly right on one point. Managed care has greatly increased in market share over the past few years. The proportion of privately insured individuals with HMO or PPO insurance has risen from 27.1% in 1988, to 65.4% in 1993 (EBRI, 1995).

III. Previous Literature on Distance Traveled

Most of the literature which examines distance traveled to hospitals does so in the context of hospital choice. In that literature, distance is one of several exogenous determinants of the patient's choice of hospital. Although our purpose is quite different, we discuss the choice literature here to provide a theoretical and empirical background for our work.

Early choice models used variations of the gravity model, to examine the unconditional or simple relationship between distance and hospital utilization (see McGuirk and Porell, 1984, for a review). Conditional choice models have been used more recently, which explicitly incorporate other influences besides distance on the probability that a particular hospital is chosen (see McGuirk and Porell, 1984 for an early example and Burns and Wholey, 1992, for a review). These spatial interaction models describe the flows of patients, as determined by propulsion variables (demand), attraction variables (supply) and spatial separation factors (distance, intervening opportunities, agglomeration effects, and other constraints) (Fotheringham and O'Kelly, 1989).

McGuirk and Porell (1984) find huge time and distance elasticities, greater than unity. Burns and Wholey (1992) find that distance explains almost 90% of the variation in choice, which is consistent with earlier work by Lee and Cohen (1985), while quality is a relatively weak determinant, consistent with Luft et. al. (1990, p. 2905). All of these models treat distance an independent variable explaining hospital choice. Instead, we try to explain distance.

We posit here that the market health care *system* - which includes the spatial distribution of people, hospital services, physicians, and systematic constraints– determines the distance traveled for hospital care. That is, distance (or time) traveled is endogenous to the health care system.

The literature contains only a couple of attempts to explain distance itself. Zwanziger and Melnick (1993) examined travel distance in California hospital markets from 1983 to 1987. They used an unconditional, tabular analysis of patient discharges grouped by hospital market concentration levels, and examined trends over time.[4] With the stimulus to selective contracting following the Medicaid Reform Act of 1982, they expected to find that, regardless of type of insurer, patients in competitive markets would travel farther as a result of selective contracting by managed care plans. They found no significant increases in travel distance over time, even in the most competitive markets. They concluded that managed care plans appeared to be cautious in restricting their provider networks, and that selective contracting, by 1988, had not caused a significant change in patient travel.

White and Morrisey (1998) also examined California hospital discharges, but over a slightly longer horizon (1985 to 1991), using a multivariate regression model based on the theory of consumer search. They expected to find a greater impact from managed care on distance by using a longer horizon than did Zwanziger and Melnick (1993). For one part of their analysis, they chose a random sample of 156,215 inpatient discharges (about 2.4% of the total) from the universe of all hospital discharges in all regions of California. They defined payor-specific variables for four payor groups: all private payors combined (including the HMO/prepaid plans), Medicare, Medicaid and self-pay/uninsured. The private group was assumed to have experienced the greatest impact

[4] Hospital market concentration was defined as the Herfindahl-Hirshman Index (HHI), for hospitals serving the patient's zipcode of origin.

from managed care.

Because Medicare managed care is still relatively rare, Medicare patients were presumed to be the least susceptible to steering to preferred providers, hence they provide a useful control group. The dependent variable is the distance between the patient and the chosen hospital. Explanatory variables included categorical controls for market size in the patient's neighborhood, distance from patient to closest hospital and to closest large hospital, payor and time-specific dummies, and their interactions. They found that all payor groups traveled statistically significantly further than Medicare in 1985 (but by less than five miles), but that the *increase* in distance for private payors relative to Medicare over time was not significant. Thus they concluded that managed care penetration had little impact on relative travel distance over this period.

In another part of their study, White and Morrisey (1998) used the universe of patients discharged from particular Diagnostic Related Groups (DRGs). The DRGs were selected to exhibit substantial differences in choices for managed care versus non-managed care groups. For example, elective care (hernia repair, joint/neck/back surgery, vascular repair) was expected to exhibit more steering under managed care than emergency procedures (appendectomy, heart failure and shock). Also, to the extent that managed care increases search and improves information regarding outcomes, they expected to find evidence of steering under managed care for very complex procedures (open heart surgery, kidney transplant). The results from this analysis were mixed, with no consistent managed care impact on distance. They state that the mixed results may be due in part to the endogeneity of service offerings to managed care penetration. Because

DRGs classify patients partly based on the procedures done, and managed care can influence which services are available where, similar patients could end up in different DRGs based on what services the hospital offers.[5] Thus, the DRG-level analysis may exhibit selectivity bias driven by managed care penetration, which would confound the results. This possibility is an argument for aggregating across DRGs.

White and Morrisey (1998) employ an empirical model which has some similarities with ours. But they use a very different theoretical approach, and model distance based on a standard model of consumer search. In their approach, choices regarding travel depend on travel and information cost, and anticipated gains from search in terms of better quality and lower cost. Because their orientation is toward consumer search, they focus primarily on factors which would impact search. These factors are characterized in the spatial modeling literature as origin-specific/propulsion characteristics and spatial separation factors. Among the latter category are controls for alternative choices available to the consumer, which they model using distance to closest hospital and distance to closest large hospital (whether or not this was the chosen

[5] For example, consider DRGs for cardiac care. Suppose two treatments are available for the same disease: S (surgery) and M (medical treatment). Service S and M assign different DRG codes to patients with the same illness. Suppose managed care affects the availability of service S; prior to managed care, hospitals A and B both offer both S and M, and some patients get service S, some at hospital A, and some at hospital B, while the other half get service M. Suppose that as a result of managed care, service S is dropped at hospital A, and only offered at hospital B, and M continues to be offered at both. Those patients living near A who received S at A could now travel to B for it, or stay at A and receive M. If they stay at A and receive M, they end up in the M-DRG, which now appears to have lower average travel, while the S-DRG now appears to have higher average travel. But if you combined the two DRGs, there would be no change in travel; patients are still using the same hospitals as before. The mix of services received has changed, but not the location of service (our thanks to Will White for this example).

hospital).

Our model includes spatial separation and origin-specific factors, and an additional vector of destination-specific factors. Thus we explicitly control for hospital-specific characteristics and hospital market size, while they do not. We take a different approach to sampling and data aggregation, avoiding some selection issues.

Perhaps most importrantly, we include a measure of market-level managed care penetration. Managed care can affect distance by either changing information or by changing which hospitals offer which services. The market-wide impact of managed care on information or on service availability affects all payor groups, and is picked up by including a measure of market-level managed care penetration. Failure to include this variable could confound the interpretation of relative differences among payors (for example, if managed care increases travel for both Medicare and HMO patients, this would obfuscate the estimated effects of relative travel). A second issue raised by White and Morrisey (1998) is that of patient selection of plan based on locational preferences. If such matching of patients and plans occurs, then there may be large differences in relative travel by payor, with no effect on overall market extent. In order to disentangle payor-specific effects from market-wide ones, it is important to include both a payor-specific dummy and a measure of local market penetration by managed care plans.

There is still another argument that can be made regarding endogeneity. Hospitals vary in their service mix and complexity of care given, and the more sophisticated ones attract patients from farther away. Payors with sicker patients will exhibit relatively higher travel (e.g. Medicare). Ideally, we would control for patient-specific diagnosis and severity of illness, but this is not possible. Instead, we control at the hospital level for hospital size, physician staffing, casemix, and service scope. We can then examine relative differences in distance by payor for travels to hospitals with similar levels of care. Failure to include these variables could impart omitted variables bias (e.g., if Medicare patients are sicker than HMO patients, the relative difference in travel would be biased upwards by failure to control for diagnosis or hospital sophistication). This group of variables reflect destination/attraction characteristics of the hospital, which can draw consumers from greater distances.[6]

IV. Data and Sample Selection

In this study, we use a larger number of inpatients than did White and Morrisey (1998), but from a smaller group of California hospitals within a contiguous 14-county geographical region. We include counties with considerable variation in urban intensity and managed care penetration. The study area includes counties with enough competing hospitals to engage in selective contracting with Medicaid. The data are limited to short-term general hospitals, with 101 hospitals in 1984 dwindling to 89 in 1993 through closure and consolidation (and some new entry as well). All patients from all origins

[6] The physician staffing variable - number of physicians with practicing privileges in the hospital – is also positively associated with choice of hospital (Burns and Wholey, 1992).

(urban, suburban, and rural) who utilized these hospitals are considered.[7, 8] We control for all payor groups separately (rather than aggregating other private payors with the HMO/prepaid plans) and we include the county MIA payor group, which was severely impacted by Medicaid Reform Act of 1982 (Mobley, 1998).[9] The study uses a longer horizon than White and Morrisey (1998), spanning 1984-1993. We also employ a more precise distance measure, resulting in fewer measured zero distances.[10]

Many new explanatory variables are used, including market concentration of hospitals in the patient's neighborhood, hospital market size, demographic variation in the patient's neighborhood, the number of physicians, and hospital characteristics. Also included are individual payor dummies for HMO constituents and managed care market share in the patient's neighborhood .

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[7] In contrast, White and Morrisey (1998) exclude patients originating in rural areas.

[8] If substantial numbers of patients migrated to counties outside the region for care, it might cause selection bias in our results. For example, if many patients were steered to hospitals outside our sample, the estimated impact of managed care on steering would be affected. In the 14-county region, such out-migration was small, less than 2 percent (detailed tables of leakages are available from the authors).

[9] The county MIAs are medically indigent adults who qualify for county assistance for healthcare. The hospitals primarily responsible for them are the county hospitals, which have declined in numbers since the Medicaid Reform Act of 1982 (Mobley, 1998).

[10] White and Morrisey used origin and destination zipcode centroids, which resulted in many observed zero distances in cases where the patient went to a hospital in his/her zipcode of residence. They dealt with their skewed distance distribution and zero pile-up using a Tobit estimator. We use actual hospital address in geocoding hospital locations to the map, and patient zipcode centroids. In only a few cases does the hospital address coincide with the zipcode centroid, so we do not get the zero pile-up at the left tail. Still, there is a measurement problem at low distances that causes statistical problems because the log transformation is sensitive to understated values near zero. See the Appendix for sensitivity analyses of the left-tail treatment.

V. Theoretical and Empirical Model

Our model of the determinants of distance traveled has its origins in the general formulation of a 'spatial interaction model' (Fotheringham and O'Kelly , 1989, p. 44). The traditional theoretical model determines specific flows between regions within a market system:

$$F_{ij} = g(v_i,\ w_j,\ C_{ij}\,), \qquad (1)$$

where:

F_{ij} = flows (discharges) from region i to hospital j,

v_i = demand factors/propulsion characteristics of region/discharge i,

w_j = supply factors/attraction characteristics of hospital j,

C_{ij} = spatial separation factors (distance, intervening opportunities, agglomeration)

Distances are fixed: the distance from a particular zipcode to a particular hospital can only change if the hospital moves. This is fine for looking at the flows from a zipcode to a hospital. But, this analysis doesn't give much insight into the extent of the market and how it might vary. For this, we need to aggregate and look a total flows from all residential areas to all hospitals and consider the average or expected distance. Total flows, then, are just the sum of all trips, F, where

$$F = \Sigma_i \Sigma_j F_{ij} = \Sigma_i \Sigma_j g(v_i, w_j, C_{ij}) \tag{2}$$

We can rewrite the right hand side as simply a different function of the same variables, $G(.)$, so total flows are

$$F = G(v_i, w_j, C_{ij}). \tag{3}$$

It is useful to decompose C_{ij} into two parts: d_{ij} and m_{ij}, giving equation (3'),

$$F = G(v_i, w_j, d_{ij}, m_{ij}), \tag{3'}$$

where,

$d_{ij} =$ distance from patient i to hospital j ,

$m_{ij} =$ alternative opportunities and agglomeration effects near the chosen hospital.

The specific distances, d_{ij}, here are still exogenous, but the average or expected distances are not. They depend on which hospital is actually chosen by consumers from each zipcode, which is endogeneous and subject to influence by managed care and all the other market and spatial variables.

We are interested in explaining the distance traveled by any randomly selected patient, not by a patient of a predetermined zipcode and hospital, which we indicate by d

without the subscripts. To do so, we model distance actually traveled as a function of the same underlying explanatory variables

$$d = H(v_i,\ w_j,\ m_{ij}). \tag{4}$$

Empirical Model Used in Estimation

We follow tradition in writing down a multiplicative functional form for equation (4), adding a disturbance term, ε_d.

$$d = k\, v_i^{\beta 1}\, w_j^{\beta 2}\, m_{ij}^{\beta 3}\, \varepsilon_d \tag{4b}$$

We estimate 4b, after taking logs of most variables because of an obvious right skew: [11]

$$lnd = ln\, k + \beta_1\ ln\, v_i + \beta_2\ ln\, w_j + \beta_3\ ln\, m_{ij} + ln\, \varepsilon_d \tag{4b''}$$

The v_i includes patient-specific propulsion variables: managed care market share and hospital market concentration in the neighborhood (HFPA) of patient origin;

[11] We do not log the categorical variables, nor those already in proportions. Thus, for those variables, the native functional form is :

$$d = k\, v_i^{\beta 1}\, w_j^{\beta 2}\, m_{ij}^{\beta 3}\, e^{\beta 4\, Ci\, +\, \beta 4\ Pi}\ \varepsilon_d\ , \tag{4b'}$$

where the C_i are categorical variables and the P_i are proportional ones.

demographic variables at the zipcode (of patient origin) level from the 1980 and 1990 US Census of Population (race, income, population density), and individual payor type. Higher income persons may be expected to travel farther, as they can afford better information and better access to transportation. Persons originating in more densely populated, highly urbanized neighborhoods are expected to travel shorter distances, as they have more local opportunities.

The Herfindahl index of market concentration is defined for the neighborhood (HFPA) in which the patient originates.[12] People from highly concentrated hospital markets with high prices are more likely to be steered past high-priced local hospitals to more distant ones, so we expect a positive association between the Herfindahl index and distance.

Our measure of managed care penetration is also patient-specific: it shows how prevalent managed care was in the patient's neighborhood of origin.[13] The impact of managed care penetration on market extent is theoretically ambiguous, therefore, an empirical issue. Managed care has two effects. First, it may cause hospitals to consolidate services into specialized centers, making them less widely available. This might be expected for extremely high tech services where volume improves outcomes.

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[12] The Herfindahl index of concentration is defined over net patient revenues for patients treated by hospitals located within HFPAs. When hospitals in an HFPA are owned by the same multihospital chain, their market shares are summed to reflect the chain's market share in the HFPA. The HFPA-specific concentration measure is then assigned to patients who originate in the corresponding HFPA.

[13] More specifically, it is the HMO/prepaid plans' market share of all discharges originating in the HFPA in which the patient lives.

Second, as hospitals compete for managed care business, they may adopt a broader range of technologies and services. Hospitals able to provide most services are more likely to win contracts. Thus, managed care leads to economic forces for both more and less specialization among hospitals.

The w_j, attraction variables, are measured at the hospital level. They include the Medicare casemix index, number of doctors practicing in the hospital, number of set-up beds in the hospital, and a scope of services index.[14] These attraction variables are expected to increase distance traveled.

The m_{ij} component of the model measures availability of alternatives to the consumer in the neighborhood of the chosen hospital and agglomeration effects. BEDCAP is hospital bed density (see Table 2 for variable definition), and is larger in regions with clusters of hospitals providing highly sophisticated services. The local market size around a hospital (POP20) is measured by total population within a 20-mile radius of the hospital. Both are expected to have a positive effect on distance, due to scale economies and better outcomes in the provision of highly technical services, and agglomeration effects (ability to easily get complementary goods and services - like outpatient services, physician office and clinical visits - at locations nearby).

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[14] The scope of services scale is a hospital-specific weighted sum of 33 services provided. The hospital-specific weights are: 0 if service not provided, 0.5 if available through arrangement with nearby hospital or as part of a broader hospital unit, and 1 if offered in a separately organized, staffed, and equipped unit in the hospital. Among the 33 services included are: computed tomography, magnetic resonance imaging, diagnostic and therapeutic radioisotope, positive emission tomography, ultrasonography, megavoltage radiation therapy, histocompatibility lab, neonatal intensive care, and trauma services. The scale is converted into an index by dividing by the maximum scale value for any hospital in the sample in each year.

The estimated model pools 1984 and 1993 observations, with time interactions on the payor dummies, the Herfindahl index, and HMO market share variables. The time interactions allow us to check for statistical significance of changes over time. But in consideration of the high multicollinearity in the time interaction terms, we report separate cross sections as a check on the robustness of our pooled model results. Estimation results are presented in Table 1; variable descriptions and definitions are given in Table 2. Sample statistics are in the Appendix.

(Table 1, Table 2 about here)

VI. An Interpretation and Discussion of the Estimation Results

A. Differences in Relative Distance Among Payors

The first model estimated in Table 1 is for the pooled 1984 and 1993 cross sections, with time interaction terms. Most time-interaction effects are economically and statistically significant, suggesting that relationships do change over time. The pooled and cross-sectional results are quite similar. We focus on the cross-sectional results for the quantitative interpretations which follow.

Evaluated at the average Medicare distance of 6.631, private payors travel about

0.78 to 1.11 miles farther than Medicare patients in 1984.[15] The HMO constituents' distance premium is comparable to other private payors in 1984, but it increases (by 5.8 percent, about 0.38 mile) while other private payor groups fall or remain constant over time. This suggests that the HMO group saw a relative increase in travel over time, but this is so small that it is of little importance. These findings are consistent with recent research regarding HMOs and open heart surgery in California. While distance itself was not measured, certain types of HMOs were found to steer their patients to high-volume centers, which would tend to increase the average distance traveled by HMO patients (Chernew, Hayward, and Scanlon, 1996).

The poor (Medicaid, self-pay (uninsured) and the county MIAs) travel farther than the average Medicare patient in 1984 (by about 1.0, 1.28 and 2.5 miles, respectively). Two of the poor groups (Medicaid and MIAs) also exhibit a statistically significant but small relative increase over time. By 1993, the Medicaid group is traveling about 1.32 miles farther than the average Medicare patient, while the county MIA group is traveling almost 2.9 miles farther. While these distances seem small, they may be important to the poor who lack good transportation, so they are a cause for concern about erosion of access to the poor.

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[15] Because the estimates are derived from a double-logarithmic specification, we must exponentiate to derive the equivalent effects in native units (miles). As an example, for the HMO group, the relative distance premium in miles is [exp(.155) –1]* 6.135 miles = 1.03 miles. We do a more exact smearing retransformation for the results in Table 3, where we examine more generally the impact of a 20% rise in HMO penetration on market extent. There, the smearing retransformation produces a noticeable, but small change in the reported effects.

B. The Impact of Managed Care on Market Extent Across All Payors

Next we turn to a discussion of the direct (payor-constituency), indirect (market-wide) and net (direct plus indirect) impacts of a 20% rise in managed care penetration. For the direct effect, this occurs through a rise in the payor's share, as exhibited as a rise in the average value of the HMO payor dummy across zipcodes. In Table 3, we report these direct effects for both 1984 and 1993. The direct, patient-steering effects of a 20% rise in HMO market share are 0.21 miles in 1984, rising to 0.31 miles in 1993. [16]

For the indirect effect, even if no steering occurred, we would expect managed care to affect market size if managed care improved information or created incentives for changes in the distribution of services among hospitals. The coefficient of the variable HMOSHR provides an estimate of this indirect, market-wide impact. We calculate the mileage-equivalents of this effect for a 20% increase in HMOSHR from its mean in each cross section, as reported in Table 3. The indirect effect is to decrease average distance traveled by 1.59 miles in 1984, which diminishes in magnitude to a 1.14 mile decrease in 1993.

To calculate net effects, we sum the direct and indirect effects of managed care penetration, again using a 20% increase from the mean (Table 3). Even when the direct positive steering effects on HMO patients are factored in, the net impact of increased HMO penetration in the market is negative, and diminishing in magnitude over time.

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[16] We calculate the direct effect for 1984 as follows: {exp(0.155*0.20) minus 1} times average distance 6.618 = 0.21 miles.

A more precise calculation of the net effect would employ Duan's smearing retransformation (Duan, 1984). We re-estimate the net distance effects using the smearing retransformation to translate the expected values (in logs) into distance in native units (miles). [17] The smeared results are reported in Table 3. The difference between using the smearing method and the less accurate, but simpler method of simply exponentiating the difference in the fitted value of the log and multiplying by the mean distance in native units is noticeable, but not large.

We conclude that the initial impact of HMO penetration on market extent seems to be negative, though small. Our findings are consistent with those from the earlier research (Zwanziger and Melnick, 1993; White and Morrisey 1998), wherein no positive overall impact on distance was found. And these results contrast sharply with the theory enunciated in the two recent court cases.

(Table 3 about here)

The negative estimated indirect and net effects suggest that hospitals have responded to managed care contracting by broadly expanding their service scope,

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[17] To do this, we take the sample average of the exponentiated residuals, which is called the smearing factor. Then, we calculate the fitted value of distance at the sample means for all variables, exponentiate it and multiply it by the smearing factor. We do this again with all variables at their sample means except HMOSHR and the HMO payor dummy – both of these we increase by 20% from their means. We then compare the differences (among the two smeared fits) in native mileage units, for our smeared estimate of the net impact of a 20% rise in HMO penetration on expected distance.

becoming less specialized. For the average consumer, distances traveled have diminished slightly, as closer hospitals have come to provide all the necessary services. This is consistent with research on hospital survival, showing that smaller, less sophisticated hospitals have disappeared over time (Mobley and Frech, 1994).

Recent empirical research supports the hypothesis that hospitals have become more homogeneous during this period of increased managed care and increased competition. For example, more California hospitals are offering open-heart surgery over time and the average volume has fallen, from 254 operations per year in 1983 to 223 in 1990 (Chernew, Scanlon, and Hayward, 1996; Grossman and Banks, 1998). Examining a longer horizon, 1976 to 1994, JoAnne Spetz computes two different measures of hospital service scope, and both rise in the eighties, suggesting a broader adoption of services among hospitals in California (Spetz, 1995). Zwanziger, and Melnick and Simonson (1996) examine whether hospitals in California became more or less specialized between 1983 and 1988. They found evidence that hospitals in more competitive (less concentrated) markets became less specialized over time. The more competitive markets are also those with greater HMO penetration, so it seems likely that the broader adoption of services was in response to managed care contracting.

C. Effects of Other Variables of Interest

The impact of the concentration index is small, but positive to distance in 1984, and increases five-fold over the period. This suggests that people who live in highly concentrated hospital markets are being steered outside of their own area for care, and increasingly so over time. Hospitals located in large markets with clusters of nearby hospitals drew patients from farther away in 1984, and this effect increased over time (BEDCAP, POP20). To the extent that clusters of hospitals in large markets can be more specialized, realizing economies of scope, scale, and agglomeration, the increase in these effects (BEDCAP, POP20) over time suggests that high-tech centers of excellence may eventually becoming important.

VII. Conclusions: Significance of the Research

The major focus of this study is on the question: Does managed care penetration warrant larger antitrust market definitions for hospitals? In assessing both direct and indirect effects from HMO penetration we conclude that the answer is a solid 'NO'. The distances that HMO patients were required to travel for care were very comparable to those traveled by other privately insured patient groups in 1984. Over time, the HMO group distances rose significantly but by only a small amount relative to other payors – about 0.38 miles.

We find that constituents of some payor groups traveled further than others, and that the relative distances have changed over time. The only groups with significant increases over time were those expected to be most affected by selective contracting - the HMO, Medicaid and county MIA groups. Although the increases were small in magnitude (from about 0.38 to 0.88 miles) they may reflect a real erosion in access to care. This may be especially problematic for the poor (Medicaid and MIAs) why by 1993 were traveling about 1.3 and 2.9 miles farther than the average Medicare patient.

At the market-wide level, we find that the indirect effect of managed care penetration is negative in both 1984 and 1993, and decreasing in absolute value over time. But again these effects are small – a decrease of 1.6 miles in 1984 diminishing to a decrease if 1.1 miles in 1993, for a 20% rise in HMO penetration in the patient's neighborhood. The net of direct and indirect effects is also negative in both years, diminishing from about 1.2 to 0.75 miles – effects which are too small quantitatively to warrant a change in market definition for research or antitrust markets.

The negative sign of the effect of HMO penetration on market extent suggests that hospitals have responded to managed care penetration by broadening their service scope, and becoming more homogeneous over time. The negative effect is inconsistent with the prediction of the search/information theory regarding the role of managed care as improving information and stimulating specialization into centers of excellence. But our finding is consistent with recent research regarding the persistent spread of high-technology services, despite recent healthcare reforms (GAO, 1992; Grossman and Banks, 1998; Chernew, Hayward, and Scanlon, 1996). We conclude that while there may be some increased specialization among some highly sophisticated service lines, the dominant effect appears to be broader adoption of technology and increased homogeneity among hospitals. Additional research in this area is needed to monitor further developments, and to examine more closely the impact of managed care on consumer information and hospital service mix.

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Table 1: The Determinants of Distance Traveled in 1984 and 1993						
Model:	pooled		1984 cross		1993 cross	
N:	1,330,059		651,449		678,610	
Adj Rsq:	.297		.290		.307	
Effect	Coeff	t	coeff	t	coeff	t
CONSTANT	-1.553	-53.5	-1.990	-45.8	-1.312	-30.3
MEDICAID	.131	41.5	.142	44.3	.178	62.6
BCBS	.124	30.5	.110	27.0	.126	20.0
OTHER	.159	55.5	.151	52.1	.132	35.1
HMO	.170	23.2	.155	21.0	.211	66.2
SELF	.177	34.7	.176	34.5	.098	15.0
MIA	.264	38.4	.317	45.5	.361	45.6
CASE	.267	50.4	.625	56.6	.190	28.2
DOCS	.266	167.2	.249	92.6	.273	135.3
BEDS	.251	102.2	.350	85.9	.193	55.6
SCOPEIND	-.250	-48.0	-.518	-57.3	-.142	-20.2
PW	-.421	-60.8	-.224	-19.5	-.557	-62.4
PB	-.954	-98.1	-.736	-50.1	-1.099	-81.5
MHHINC	.124	39.6	.113	24.9	.124	26.8
POPDEN	-.348	-574.1	-.342	-386.6	-.357	-421.3
BEDCAP	.367	134.8	.366	114.3	.446	65.2
POP20	.265	171.3	.238	112.1	.317	133.2
HERF	.027	5.4	.038	7.0	.193	40.5
HMOSHR	-1.121	-21.7	-1.337	-21.9	-.873	-49.6
TIME	-.037	-6.7				
TIME*MEDICAID	.057	13.7				
TIME*BCBS	-.003	-0.4				
TIME*OTHER	-.028	-6.0				
TIME*HMO	.035	4.3				
TIME*SELF	-.071	-8.6				
TIME*MIA	.125	12.0				
TIME*HERF	.158	24.7				
TIME*HMOSHR	. 233	4.5				
Mean distance, Medicare			6.135		6.758	
Mean distance, all payors			6.618		7.105	

Table 2: Variable Names and Definitions

Dependent variable:

DISTANCE= distance 'as the crow flies' from zipcode centroid of patient origin to hospital street address

Explanatory Variables:

Payor and time dummies:

MEDICAID = payor dummy indicating Medicaid recipient
BCBS = payor dummy indicating Blue Cross/Blue Shield plan
OTHER = payor dummy indicating other private insurance
HMO = payor dummy indicating HMO/prepaid health plan
SELF = payor dummy indicating self-insured (no insurance)
MIA = payor dummy indicating county MIA recipient
TIME = indicator variable with value=1 in 1993, value=0 in 1984.

Attraction vector w_j:

CASE = HCFA's Medicare casemix index, for 1984 or for 1993 for each hospital
DOCS= number of physicians on board in each hospital
BEDS = number of set-up beds in each hospital
SCOPEIND = index of services available in each hospital (footnote 19)

Propulsion vector v_i :

PW = proportion of zipcode population who are primarily of Caucasian descent
PB= proportion of zipcode population who are primarily of African American descent
MHHINC = median household income in the zipcode of patient origin
POPDEN= population density in the zipcode of patient origin
HMOSHR = HMO/prepaid health plan market share in each patient's neighborhood
HERF = Herfindahl index of hospital market concentration in the patient's neighborhood (footnote 14)

Separation factors m_{ij}:

BEDCAP = number of short-term hospital setup-beds in all hospitals (including self) within a 20-mile radius of each hospital , divided by POP20 (below)
POP20= total population within a 20-mile radius of the hospital

Table 3: Effects of a 20% Increase in HMO Penetration

	1984	1993
HMO dummy coeff	0.155	0.211
HMOSHR coeff	-1.337	-0.873
Average distance	6.618	7.105
Direct effect of a 20% increase in HMO dummy	0.032 * 6.618 = 0.21 mile	0.043 * 7.105 = 0.31 mile
Indirect effect of a 20% increase in HMOSHR	-0.24 * 6.618 = -1.59 mile	-0.16 * 7.105 = -1.14 mile
Net effect of a 20% increase in HMO penetration	-1.39 miles	-0.88 mile
Net effect of a 20% increase in HMO penetration, smeared[18]	-1.18 miles	-0.74 mile

[18] Duan's smearing retransformation (1983) was employed to calculate native miles from the logarithmic units. Here are the calculations:

	1984	1993
Mean distance	6.618	7.105
Mean HMO dummy	.025	.198
Mean HMOSHR	.024	.191
Smearing factor (mean exp resid)	1.486	1.478
Yhat at means, in log units	1.334	1.399
Smearing of above, in miles	5.64 mi	5.99
Yhat at 20% higher HMOs	1.098	1.267
Smearing of above, in miles	4.46	5.25
Change attrib to 20% increase	-1.18 mi	-0.74 mi

APPENDIX

Data and Data Structure

Hospital, demographic, and market data: hospital patient-discharge abstracts by zipcode of patient origin and by expected insurance payor are used for each of the years 1984 and 1993. Inpatient discharge data and other hospital-specific data were provided by the California Office of Statewide Planning and Development. The 1990 US Census is the source for zipcode-level demographic variables.

The unit of observation in the model is the patient zipcode (there are no patient-specific data in the model). There are three dimensions in the data: 1) time, 2) hospital and 3) zipcode aggregates by payor. The discharge data are aggregated by payor and by zip within each hospital. The average hospital has hundreds of observations by payor and by zip, corresponding to patients of each payor type and all contributing zipcode regions.

In the estimation, the number of discharges per zip are used as frequency weights for the sample, so that each patient discharged receives equal weight/ importance in the estimation. The number of observations in the estimation is the number of patients discharged. The distance d_{ij} 'as the crow flies' between hospital j's street address from patient's zipcode centroid i was calculated using GIS software. The great circle trigonometric formula, which calculates the shortest distance between two points along the earth's curved surface, was used with the Albers Equal-Area Conic projection. The GIS software was used to map zipcodes to HFPAs in constructing the Herfindahl index and HMO market share variables in the neighborhood of patient origin.

Specification Checks and Model Robustness

Because the distance measure and several population variables are zipcode-level averages, there is a possibility of grouped-data heteroskedasticity as described by Kmenta (1986, pp. 367-372). We see no evidence of heteroskedasticity in a visual plot of the residuals against the fitted values (the sample is too large for a statistical test). We estimated a weighted model, using the square root of flows as weights (flows are patient discharges in zip i to hospital j) to correct for this type of heteroskedasticity. But there were no meaningful changes in the slope coefficients, and we report the unweighted model here.

We are also wary of the impact of outliers on least squares estimators. Examination of outliers in the model estimated on the full sample reveals that both extremely small and extremely large distances exert undue influence. Extremely large distances (greater than 100 miles) are rare, accounting for less than 1% of our sample. We trim the upper tail at 100 miles to eliminate these extreme values. Extremely small distances (very large negative numbers in the logs) occur when the hospital's address is very close to the patient's zipcode centroid. Dealing with the extremely small distances is a more difficult problem. About 3.8% of the sample have measured distances less than ½ mile, and about 8.5% have distances less than 1 mile. We are not willing to trim off such large chunks of the sample, and instead take a reasonable replacement approach to solve the problem posed to the log metric by extremely large negative numbers. It is hard to imagine people traveling less than ½ mile to any hospital; most hospital grounds have physical dimensions greater than ½ mile. We replace all distances less than ½ mile with ½ mile distance, then take logs, and use this outlier treatment in the estimated models reported in Table 1. To check for robustness to this sample treatment, we estimate five models with different sample treatments (Table 4). The results are robust to the treatment of the left tail, unless it is completely removed (sample 5). In Samples 1-4, the net impact of a 20% HMO expansion on distance is negative in both 1984 and 1993, and increasing in magnitude over time.

Table 4 : Robustness of Results to Sample Treatments

	1984	1993
Sample 1: Trim upper tail at 100 miles and do nothing to lower tail except replace 0s with 0.2 before logging distance (0.2 % deleted)		
HMO dummy coeff	0.161	0.238
HMOSHR coeff	-2.659	-0.566
Average distance	6.608	7.094
Net effect of a 20% increase in HMO	-2.60	-0.45
Sample 2: Trim upper tail at 100 miles and replace distances< 1 mile with 1 mile (0.2 % deleted)		
HMO dummy coeff	0.149	0.198
HMOSHR coeff	-1.084	-0.948
Average distance	6.650	7.136
Net effect of a 20% increase in HMO	-1.13	-0.99
Sample 3:Trim upper tail at 100 miles and replace distances< ½ mile with ½ mile (0.2 % deleted)		
HMO dummy coeff	0.155	0.211
HMOSHR coeff	-1.337	-0.873
Average distance	6.618	7.105
Net effect of a 20% increase in HMO	-1.39 miles	-0.88 mile
Sample 4: No trimming or distance adjustments except replace 0s with 0.2 before logging distance		
HMO dummy coeff	0.155	0.236
HMOSHR coeff	-2.859	-0.650
Average distance	6.954	7.418
Net effect of a 20% increase in HMO	-2.90	-0.59
Sample 5: Trim upper tail at 100 miles and lower tail at ½ mile (4 % deleted)		
HMO dummy coeff	0.160	0.189
HMOSHR coeff	0.363	-1.594
Average distance	6.850	7.369
Net effect of a 20% increase in HMO	+0.76	-0.25

Table Sample Statistics 1984 -49*

Variable	Min	Max	Mean	St.Dev.
DISTANCE**	0.500	99.924	6.618	8.918
LDIS	-0.693	4.604	1.323	1.045
Medicare	0.000	1.000	0.302	0.459
Medicaid	0.000	1.000	0.205	0.404
Other	0.000	1.000	0.097	0.296
BC/BS	0.000	1.000	0.288	0.453
HMO/prepaid	0.000	1.000	0.025	0.156
Self Insured	0.000	1.000	0.055	0.227
County MIA	0.000	1.000	0.028	0.165
CASE	0.902	1.638	1.176	0.128
DOCS	5.000	867.0	273.6	218.9
LogDOCS	1.609	6.765	5.228	0.985
BEDS	12.000	615.0	249.7	127.0
LogBEDS	2.485	6.422	5.355	0.636
SCOPEIND	0.002	1.000	0.549	0.227
PW	0.086	1.000	0.753	0.181
PB	0.000	0.832	0.078	0.136
MHHINC	9802.	101923	34043	13033
LogMHHINC	9.190	11.532	10.368	0.366
POPDEN	0.587	66250	3159	3162
LogPOPDEN	-0.533	11.101	7.146	1.757
BEDCAP	0.001	0.037	0.004	0.005
LogBEDCAP	-6.570	-3.289	-5.628	0.473
POP20	11935	2589840	919331	754077
LogPOP20	9.387	14.767	13.311	1.005
HERF	0.112	1.000	0.368	0.241
HMOSHR	0.000	0.079	0.024	0.025

Distance 100 miles where distance mile replaced by distance mile

Table 5B Sample Statistics 1993 678,610*

Variable	Min	Max	Mean	St.Dev.
DISTANCE**	0.500	99.986	7.105	9.452
LDIS	-0.693	4.605	1.393	1.055
Medicare	0.000	1.000	0.288	0.453
Medicaid	0.000	1.000	0.318	0.466
Other	0.000	1.000	0.032	0.177
BC/BS	0.000	1.000	0.114	0.318
HMO/prepaid	0.000	1.000	0.198	0.398
Self Insured	0.000	1.000	0.030	0.170
County MIA	0.000	1.000	0.020	0.140
CASE	0.866	2.106	1.509	0.235
DOCS	2.000	1526	397.6	334.2
LogDOCS	0.693	7.330	5.592	0.979
BEDS	20	551	267.4	127.8
LogBEDS	2.996	6.312	5.440	0.602
SCOPEIND	0.002	1.000	0.520	0.216
PW	0.076	1.000	0.678	0.198
PB	0.000	0.752	0.083	0.126
MHHINC	9802	119204	34319	13186
LogMHHINC	9.190	11.689	10.376	0.364
POPDEN	0.059	49396	3580	3653
LogPOPDEN	-2.832	10.808	7.272	1.726
BEDCAP	0.001	0.006	0.003	0.001
LogBEDCAP	-6.866	-5.052	-5.986	0.260
POP20	15013	2941310	1176716	840789
LogPOP20	9.617	14.894	13.645	0.911
HERF	0.146	1.000	0.434	0.249
HMOSHR	0.002	0.426	0.191	0.073

Distance 100 miles where distance mile replaced by distance mile