RESEARCH REPORT

Where Do HMOs and PPOs Locate? Debunking an Urban Myth

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Contents

Abstract

The potential geographic distribution of preferred provider organizations (PPOs) differs greatly from that of health maintenance organizations (HMOs). We explain this theoretically by the natural ordering of insurance types according to the degree of consumer choice of provider. We examine the issue empirically, employing a unique data set based on California hospital discharges in 1998, a time when PPO and HMO insurance types were coded separately. Because HMOs are more restrictive than PPOs in the provider networks allowed, we find that they require urban areas with many physicians to form viable networks. PPOs are less restrictive in the provider networks, which we find allows PPOs to thrive outside of urban areas where HMOs cannot. We find that indemnity-type plans, also known as fee-for-service plans, can survive anywhere because they do not impose restrictions on provider choice. These findings have real-world implications for Medicare modernization efforts aimed at increasing the proportion of seniors enrolled in Medicare managed care plans. Regional PPOs established under the Medicare Modernization Act of 2003 are likely to thrive, extending the geographic coverage of managed care service options to all seniors.

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Introduction

Managed care insurance has been available in urban areas for decades and has been found to reduce costs, making it an attractive option for employers who hope to contain health care costs for their workers. The primary vehicle for cost containment has been restrictions on provider choice, with plans limiting choices to providers who demonstrate practice styles consistent with the plan's objectives. Restrictions on provider choice have made managed care plans unpopular with seniors, who have had free reign under traditional fee-for-service (FFS) Medicare.

In an effort to reduce Medicare expenditures, the Centers for Medicare & Medicaid Services (CMS) has sought to increase enrollment in managed care plans through a series of initiatives and modernization efforts. The Medicare Prescription Drug Improvement and Modernization Act (MMA) of 2003, for example, mandated that all managed care plans offer prescription drug coverage by January 1, 2006. This mandate was expected to increase seniors' interest in managed care plans. MMA also established several demonstration plans using preferred provider organizations (PPOs) (rather than health maintenance organizations [HMOs]) and evaluated whether the PPO option was more palatable to seniors (Pope et al., 2006).

CMS was especially interested in expanding managed care options to constituents who lived outside urban areas, as Medicare managed care plans by 2003 were located only in urban areas. MMA established 26 large (sometimes multistate) market areas for a new type of Medicare Advantage plan, called the "regional PPO" plan, which is designed to serve large areas with few urban components (National Health Policy Forum, 2005). In this paper, we demonstrate how adding the regional PPO option is likely to extend Medicare managed care into more remote, rural areas so that managed care plans are available to all seniors.

The more traditional HMOs and the more recent PPOs differ in fundamental ways. HMOs offer prepaid, comprehensive health insurance coverage for both hospital and physician services. Members are typically required to use providers from the managed care network and are often required to get permission from a "gatekeeper" physician to seek specialist care. HMOs also use other managed care tools, such as mandatory second surgical opinions, utilization review of providers, and creative monetary incentives for providers to control utilization. Through these restrictions on consumers and providers, managed care organizations (MCOs) are able to save on costs and offer lower prices (premiums) for comparable coverage than do other types of health insurance.

By contrast, PPOs establish preferred provider networks but typically allow customers to seek medical care outside the physician network at additional cost. In addition, premiums are often higher than those for HMOs for otherwise comparable coverage. Because PPOs are similar to HMOs in many significant ways, economists sometimes think of them as "soft" HMOs (Frech, 1988). Indemnity plans, like FFS Medicare, allow free choice of providers but are typically more expensive or offer less coverage than similarly priced managed care plans. Because freedom of provider choice to consumers directly affects plan costs, the premiums charged for these three types of insurance typically follow the same ranking as the degree of freedom to choose one's own providers, with greater freedom costing more (all else the same).

Economists have studied the determinants of HMO entry into markets and market shares (penetration), but have not studied PPO entry or market shares. In a Tobit analysis of HMO penetration between 1966 and 1976, Goldberg and Greenberg (1981) determined that HMO penetration had a weakly significant, negative relationship with per capita income. Apparently, lower income consumers are attracted to HMOs because of low costs, whereas wealthier consumers prefer greater freedom in provider choice, suggesting that provider choice is a normal good. Morrisey and Ashby (1982), looking at HMO formation and growth across 253 metropolitan statistical areas, found that lower income, larger populations between the ages of 15 and 65, and greater mobility were positively correlated with HMO formation and growth. The authors also found evidence that a higher bed-to-population ratio, perhaps representing excess provider capacity, increased HMO formation and growth. More recently, Dranove, Simon, and White (1998) also looked at determinants of managed care penetration across metropolitan areas. They found that hospital concentration and capacity limits (i.e., high occupancy rates) reduced managed care penetration. Income had a slight, sometimes statistically significant, negative effect, whereas employment in large firms had a statistically significant positive effect. The authors used one of the few data sets that include PPOs as part of managed care; however, they did not distinguish between HMOs and PPOs.

Based on this body of research, economists have described managed care insurance as an urban phenomenon, because managed care penetration is typically greater in urban areas than in rural areas (Dranove, Simon, and White, 1998). An accepted explanation is that MCOs have greater ability to build provider networks in urban areas. However, due to lack of available data, economists have not considered differences between HMO and PPO market requirements.[1] We contribute to the literature by explicitly studying the three-part choice between HMOs, PPOs, and indemnity. We also look at smaller geographical units that better reflect medical care markets and control statistically for the degree of urbanicity, physician density, hospital capital assets (net of depreciation), and hospital concentration.

Methods

We examine insurer market shares using California data. Because California had early managed care activity in both urban and rural markets, plans of all three types (HMO, PPO, and indemnity) were well established by 1998, the time period we study. We construct market shares with data on California hospital discharges by payer type, drawn from the year 1998, when HMO, PPO, and indemnity discharges were all coded separately. More recent data separating HMO and PPO discharges (or plan enrollees) in small areas are not available. Thus, these data provide a unique natural experiment for testing our theory.[2]

In descriptive mapping analysis, it is visually apparent that HMO market shares in California are larger in densely populated urban areas, whereas PPO market shares appear to be randomly distributed among urban and rural areas (Figure 1). These differences between HMO and PPO location outcomes are a puzzle, because ease of building a provider network in urban areas would be expected to aid PPOs as much as HMOs.

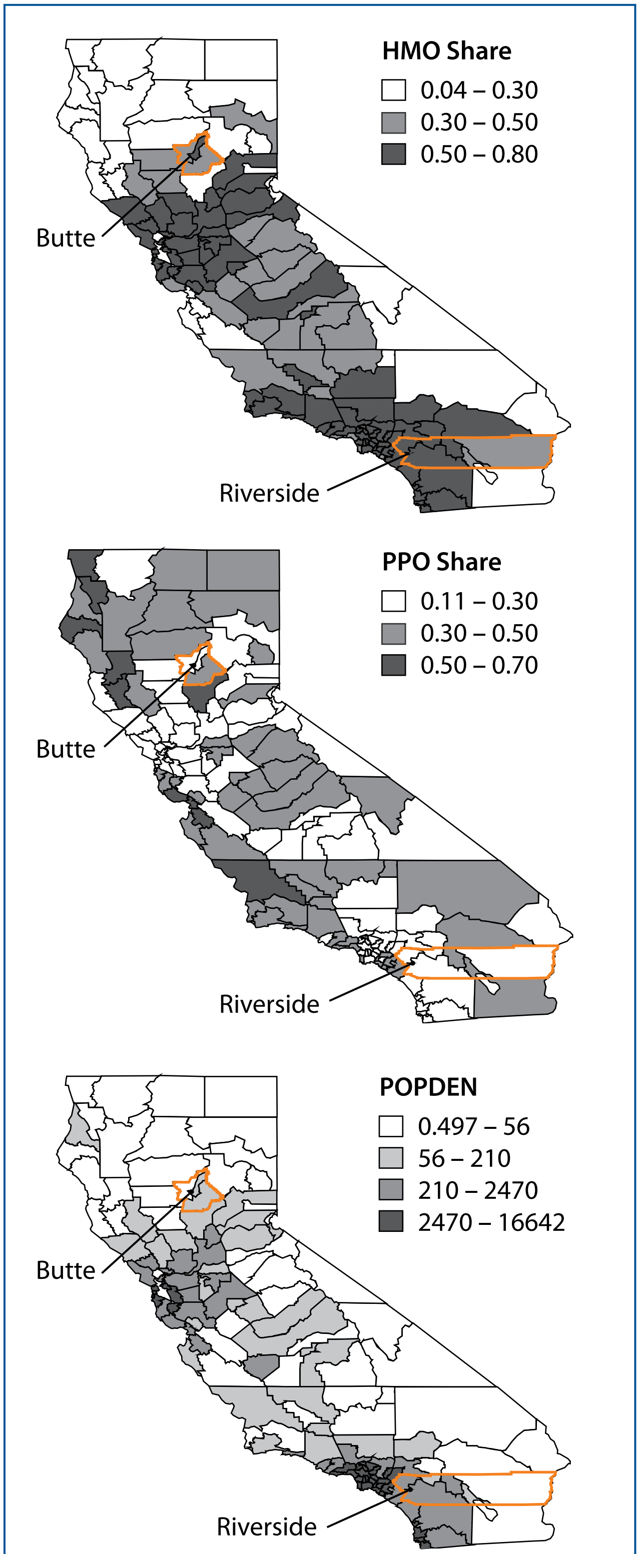
In this report, we describe the results from a theoretical model that explains the observed differences in HMO and PPO market shares in urban areas. "Increased value" is defined as better coverage at a lower price. The model postulates that larger provider networks in an urban market increase the value of HMOs relative to PPOs, so customers will be more likely to join HMOs and less likely to join PPOs. At the same time, the larger networks increase the value of PPOs relative to standard indemnity insurance, so customers will be more likely to join PPOs and less likely to carry indemnity insurance. Consequently, larger provider networks will unambiguously result in higher HMO shares and lower indemnity shares, whereas the effect on PPOs is ambiguous. Thus, if getting to larger provider networks were easier in urban areas, then we would expect to see greater HMO penetration, but not necessarily greater PPO penetration, in urban areas.

We focus on market aspects conducive to provider network formation, because plan premiums or costs are not available for study, yet premiums/costs and freedom to choose doctors can be ranked in the same order (higher price/cost, greater freedom). The reduced form market equilibrium produces a set of

1 In previous empirical studies, economists have treated HMOs as representative of the entire category, ignoring PPOs, because data on PPOs are scarce (Goldberg and Greenberg, 1981; Escarce, Polsky, Wozniak, and Kletke, 2000). The reason for this availability of data on HMOs is that the law requires HMOs to report their activities in most states. Research explicitly separating HMOs and PPOs is rare, and what does exist suggests that HMOs and PPOs should not be treated as identical (Morrisey, 2001).

2 The California Office of Statewide Health Planning and Development (OSHPD) periodically updates the report form and field requirements used by hospitals for reporting discharge data. HMOs and PPOs were not coded separately in the discharge data except for 1997 and 1998 on (http://www.oshpd.cahwnet.gov). Accessed December 15, 2008.

Figure 1. HMO and PPO market shares, and population density, in California health plan facility areas, 1998



HMO Share = health maintenance organization discharges divided by all hospital discharges in the area

PPO Share = preferred provider organization discharges divided by all hospital discharges in the area

POPDEN = total population per square mile

market shares for each insurance type, determined jointly by the consumer and physician choices. We are interested mainly in the effect of market network variables on the market shares of each health insurance choice, holding consumer characteristics constant. To find this, we perform an ordered probit empirical analysis with grouped data that flows directly from the ordered nature of market choices.

The ordered choice model is a natural fit for this problem because the dependent variables can be ranked according to the patient's ability to choose any doctors they desire: no choice outside plan (HMO), restricted choice outside plan with higher cost sharing (PPO), and free choice of any provider (indemnity). Researchers commonly use the ordered probit technique in cross-sectional analyses in which the dependent variable takes on a finite number of values with a natural ordering (Maddala, 1983). In our work, we apply ordered probit to an aggregate form of the choice data, which is not usually seen in the literature but is a straightforward extension of the empirical methodology.[3] We aggregate patient discharges based on home zip code into the health plan facility area (HPFA) market units delineated by the California Office of Statewide Health Planning and Development (OSHPD).[4]

Theoretical Model

This study builds on the results of the theoretical model that Grefer (2003) explored formally to explain insurance choices. That model postulates that providers are more likely to serve a managed care market if a higher percentage of consumers signed up for managed care organizations. Similarly, consumers are more likely to sign up with MCOs if a higher percentage of providers are in the network.[5] This is a kind of feedback effect, with the result that markets with larger provider networks will have greater managed care penetration.

3 The maximum likelihood estimator on grouped data is equivalent to the maximum likelihood estimator on individual-level data in ordered choice models, because of canceling of terms in the likelihood function (personal communication by Grefer with Dr. William Greene, LIMDEP developer, New York University, October 2001).

4 The 139 HPFAs are defined by the state, based on resource flows and needs, and are smaller than the 58 counties.

5 We use the term "providers" or "medical providers" here in the broad sense, meaning both physicians and hospitals.

To begin the feedback mechanism, urban areas attract medical providers, resulting in more professionals, more hospital resources, and lower hospital concentration. Hospitals prefer urban areas primarily because of economies of scale (Robinson and Luft, 1985; Frech and Mobley, 1995).

Physicians are attracted to urban areas for a variety of reasons. For some specialties, there are economies of scale, implying a minimum population base (Newhouse, Williams, Bennett, and Schwartz, 1982; Lankford, 1974). Perhaps more importantly, physicians are attracted to hospitals, for several reasons. First, many specialists need hospital capital inputs, such as specialized high-tech equipment, that because of economies of scale and/or scope are viable only in larger facilities, making physician office investment inefficient. Second, hospitals are a source of knowledge spillovers from colleagues (Feldman, 1979; Morrisey and Jensen, 1997). Third, physician incomes are higher with multiple hospital affiliations, which is more likely in urban areas (Rizzo and Goddeeris, 1998). Finally, when hospitals compete for doctors, costs of affiliation are smaller (Robinson and Luft, 1985; Morrisey and Jensen, 1990). Thus, the per capita number of physicians should be larger in urban areas than in rural areas, and we find this in the California data on physician locations.

Another important characteristic is provider market power. There are two distinct types of market power among providers, both of which tend to encourage network construction in urban markets. The first type results from information asymmetries and high search costs inherent in medical care. As shown by Pauly and Satterthwaite (1981), when many doctors are present (i.e., in urban markets), information asymmetries and search costs are higher, reducing the elasticity of demand for doctors' services and increasing the price of medical care. MCOs can reduce these search costs, making managed care more valuable to consumers, which encourages network building in urban areas.

The second type of market power results from concentrated medical care markets and explicit or tacit collaboration, or less intensive competition among providers. This is more common in rural markets, which have fewer providers than do urban markets. This type of market power allows providers, acting in concert, to refrain from joining the managed care network without incurring large costs. Further, a single hospital or a single specialty group may be essential to constructing an attractive managed care network. This second type of market power discourages network building and, hence, managed care growth in rural areas because of more concentrated markets. Finally, it is worth noting that in our analysis, the HMO urban phenomenon does not come from economies of scale or agglomeration. Such economies would increase the tendency for managed-care penetration to be higher in urban regions.

In summary, urban areas have characteristics that encourage medical network building. The reduced medical costs as a result of the growth of these networks encourages consumers to join managed care organizations. This model applies to both HMOs and PPOs. The fundamental difference between HMOs and PPOs is that HMOs impose a higher cost on patients for out-of-network care. Therefore, one might expect to find that PPO penetration is greater in urban areas than rural areas. However, we observe that PPO penetration appears to be about the same in urban and rural areas (see Figure 1).

One explanation is this: because of the ordered choice, larger MCO provider networks in urban areas will increase the value of HMOs relative to PPOs and attract some PPO consumers to HMOs. Larger networks increase the value of PPOs relative to indemnity insurance, and some indemnity consumers will be attracted to PPOs for the same reason. As a result, HMO shares will be unambiguously larger and indemnity shares will be unambiguously smaller in urban areas, which have larger networks than do rural areas. The effect of urban areas on PPO penetration, however, is theoretically ambiguous. In the next section, we use this theoretical background to construct the empirical model.

Empirical Model

Although researchers often use the ordered probit model with individual micro-level data, we use it here with aggregated, market-level data on market shares by insurance types. We aggregate micro-level data on hospital discharges by payer type to form market-level payer shares of individuals in HMOs, PPOs, and indemnity plans. No other data are available that separate HMO and PPO insurance choices by people. Our dependent variable is defined as the proportion of all private discharges within each of 139 medical care markets (i.e., HPFA) served by HMO, PPO, and private indemnity plans.

We have no direct data on the size of the managed care provider network (X) in each market. Further, the actual size of the managed care network and managed care density are endogenously determined. Thus, the systematic component of our empirical model is expressed as a latent choice function $Y_i^*(X_a)$ of a vector of exogenous market-level variables, one set related to the size of the provider network and another controlling for consumer characteristics that determine demand for managed care. The latent choice function has the following expression:

$$Y_i^*(X_a) = \sum_{k=1}^{K-1} X_{iak}\,\beta_k$$

where $\mathbf{X}_{iak}$ is a vector ($k = 1,\ldots,K\text{-}1$) of attributes of each market ($a = 1,\ldots,A$) and characteristics of consumers ($i = 1,\ldots,N_a$) in market a, and where β_k is a k-vector of parameters.

We estimate an ordered probit relationship for the three types of market shares using maximum likelihood. Because we have three ordered choices, we have two threshold parameters, $\mu 0$ and $\mu 1$, but (following convention in the literature) only the magnitude of the distance between $\mu 0$ and $\mu 1$ matters. Consequently, we normalize by setting $\mu 0 = 0$, and thus estimate only $\mu 1$. Using the parameter estimates, we calculate the predicted proportions of the populations that subscribe to each insurance type and find the marginal changes in probabilities that occur with small changes in each of the Xs. If we define H = 0 to represent choice of an HMO, H = 1 as choice of a PPO, and H = 2 as choice of indemnity, then the marginal changes in probabilities that occur with small changes in X are highly nonlinear terms involving the probit probability density function $\phi(\varepsilon)$ evaluated at different points along the distribution (see Figure 2). These marginal probabilities are evaluated as follows (Greene, 1990):

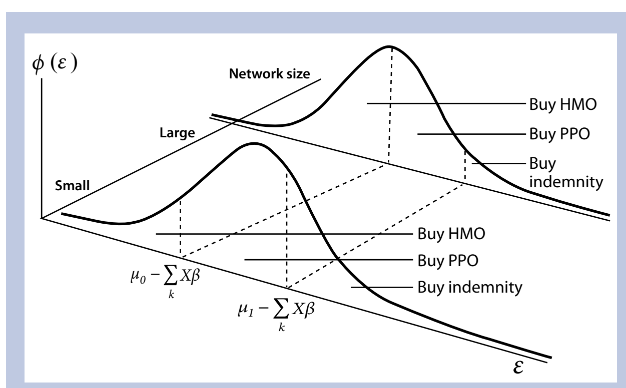
$$\frac{\partial\,\Pr(H=0)}{\partial X_k} = -\hat{\beta}_k\Big[\frac{1}{\sqrt{2\pi}}\exp(\hat{\mu}_0 - \sum_k X_k\hat{\beta}_k)\Big]$$

$$\frac{\partial\,\Pr(H=1)}{\partial X_k} = -\hat{\beta}_k\Big[\frac{1}{\sqrt{2\pi}}\exp(\hat{\mu}_1 - \sum_k X_k\hat{\beta}_k) - \Big[\frac{1}{\sqrt{2\pi}}\exp(\hat{\mu}_0 - \sum_k X_k\hat{\beta}_k)\Big]$$

$$\frac{\partial\,\Pr(H=2)}{\partial X_k} = -\hat{\beta}_k\Big[-\frac{1}{\sqrt{2\pi}}\exp(\hat{\mu}_1 - \sum_k X_k\hat{\beta}_k)\Big]$$

The sign of a probit beta coefficient (β) tells us the direction of the change in HMO and indemnity shares, given a small change in one of the independent variables. If, for example, the sign of a β is negative, we know that, upon a change in X, the probability distribution curve over Y* moves to the left, resulting in an unambiguous increase in HMO shares (Figure 2), because HMO choice is represented by the area in the left tail of the distribution, which becomes larger. Indemnity shares, in the right tail of the distribution, become unambiguously smaller. PPO shares, reflected in the central portion of the distribution, could either increase or decrease. To

Figure 2. Latent choice ordered probit distribution of consumers, by valuation of provider choice $\phi(\varepsilon)$, and by size of provider network



ε is the valuation of provider choice from the ordered probit model, and $\phi(\varepsilon)$ is the ordered probit density function for provider choice. See Greene, 1990, pp. 703-705 for more about the ordered probit specification.

infer anything about the direction of the change in PPO shares, or anything about the magnitude of the changes in (any) insurance shares, we need to know the marginal probabilities. The marginal probability at the market level is the change in its share. There is a marginal probability for each insurance type.

Explanatory variables relating to the managed care provider network include physician availability (physicians per capita), hospital market concentration (hospital Herfindahl index [HERF], measured using the Herfindahl index defined on net patient revenues), and hospital capital assets (assets per capita, measured as the dollar value of capital assets, net of depreciation). Higher values of physicians and hospital assets per capita and lower values of hospital concentration make it easier to build larger provider networks. Consequently, the effect of these variables on choices can also be interpreted as giving us information about the effect of changes in the size of provider networks on HMO, PPO, and indemnity shares, which we cannot observe.

Further, even without the size-related interpretation, the variables are independently interesting. This is especially true of hospital concentration, which is a major concern of antitrust policy. Explanatory variables relating to consumer characteristics in each market are HPFA-level variables describing per capita consumer incomes (income per capita), consumer age distribution (with seniors defined as the proportion of the population ages 60 years and older, and young defined as the proportion of the population ages 30 and younger), and a measure of urban intensity in the HPFA market (population density, defined as population per square mile).

Results

Variable names, descriptions, and sources are presented in Table 1, and sample statistics are presented in Table 2. In our table of ordered probit empirical results (Table 3), marginal probabilities are presented, rather than the beta coefficient estimates from the model.

Table 1. Variable names, descriptions, and data sources

Variable Name	Description	Source
CHOICE: H = 0 (HMO), H = 1 (PPO) and H = 2 (indemnity)	Market shares by HPFA of hospital discharges for HMO, PPO, and indemnity insurance	California OSHPD, hospital discharge data from 1998
Hospital HERF[a]	Herfindahl index by HPFA, constructed from net patient revenue for all hospitals that report revenues (excludes Kaiser hospitals)	California OSHPD, hospital financial data from 1995
Physicians per 10,000 capita	Number of practicing physicians per 10,000 capita, by county	1986 data by county from the February 2001 DHHS/HRSA Area Resource File
Assets per capita	Total capital assets (less depreciation) among hospitals in an HPFA divided by total population in the HPFA	California OSHPD, hospital financial data from 1995
Income per capita	Consumer income per capita in HPFAs, in thousands of dollars	US Bureau of the Census, 1990
Population density	Total HPFA population per square mile of land area in the HPFA	US Bureau of the Census, 1990
Young people	Proportion of the HPFA population age 30 or younger	US Bureau of the Census, 1990
Seniors	Proportion of the HPFA population age 60 or older	US Bureau of the Census, 1990

HERF = hospital Herfindahl index; HMO = health maintenance organization; HPFA = health plan facility area; OSHPD = California Office of Statewide Health Planning and Development; PPO = preferred provider organization.

[a] An alternative hospital HERF defined on patient discharges, which does include Kaiser input and was based on patient address in the same HPFA as the hospital, correlated at better than 90 percent with our measure and produced essentially the same statistical results. We use the revenue-based hospital HERF because we want the market power interpretation to be price-based.

Sources: California OSHPD, 1995, 1998; US Census Bureau, n.d.; US Department of Health and Human Services, Health Resources and Services Administration, 2001.

Table 2. Descriptive statistics of variables

Statistic	Chose HMO	Chose PPO	Chose Indemnity	Hospital HERF	Physicians per 10,000 Capita
Mean	0.480[a]	0.307[a]	0.213[a]	0.689	18.924
Median	0.529	0.293	0.139	0.704	18.236
Maximum	0.819	0.702	0.831	1.000	61.242
Minimum	0.039	0.110	0.032	0.154	3.896
Std. Dev.	0.208	0.119	0.166	0.307	7.581
N	139	139	139	139	58[b]
	Assets per Capita	**Income per Capita**	**Young People**	**Seniors**	**Population Density**
Mean	0.896	15.487	66.609	7.910	1,716.715
Median	0.708	14.411	66.389	7.400	141.447
Maximum	6.326	38.353	91.150	24.357	15,926.810
Minimum	0.000	5.422	43.558	0.800	0.497
Std. Dev.	0.816	5.421	9.572	4.303	3,082.351
N	139	139	139	139	139

HERF = hospital Herfindahl index; HMO = health maintenance organization; PPO = preferred provider organization.

[a] Three market shares sum to 1.

[b] Fifty-eight county-level measures.

Table 3. Ordered probit results, marginal probability estimates

Variable	HMO	PPO	Indemnity
Constant	0.158	−0.048	−0.110
Hospital HERF	−0.189**	0.057**	0.131**
Physicians per 10,000 capita	0.009**	−0.003**	−0.006**
Hospital assets per capita	−0.019	0.006	0.014
Income per capita	0.002	−0.001	−0.001
Young people	−0.004*	0.001	0.003*
Seniors	0.006	−0.002	−0.004
Population density	0.007*	−0.002	−0.005*

HERF = hospital Herfindahl index; HMO = health maintenance organization; Indemnity = indemnity plan; Kaiser = Kaiser HMO; PPO = preferred provider organization.

** Coefficient is statistically significant at the 95 percent level or better.

We constructed HPFA-level variables from zip code-level census data, and the zip code of hospital or patient address data, using a crosswalk between the zip code centers and HPFA boundaries. We defined the market shares using 1998 hospital discharge data and physicians per capita using much earlier (1986) data to reduce potential endogeneity bias. Physicians per capita were measured at the county area (which is larger than HPFAs) because no other data were available at the zip code level in 1986. The timing of all variables is presented in Table 1.

Discussion

Following our theoretical analysis and also following Dranove, Simon, and White (1998), we expect the Herfindahl index of hospital concentration to be negatively correlated with the size of the provider network in any market. It follows that this variable should be negatively correlated with HMO shares and positively correlated with indemnity shares. We expect a high physician/population ratio (physicians per capita) to be positively correlated with HMO shares and thus negatively correlated with indemnity shares. We lagged this variable back to 1986 to reduce potential endogeneity, which might be caused when high HMO density drives physicians from markets. This endogeneity would drive the observed effect of physicians per capita on HMO density in an opposite direction, potentially even reversing the sign. (This endogeneity was apparent in our data, as successive substitution of increasingly recent physician data resulted in smaller and smaller estimated coefficients and reduced the precision of their estimation.) The hospital capital assets variable reflects the size of hospital infrastructure relative to the immediate population.

In accordance with our theoretical analysis, and consistent with Dranove, Simon, and White (1998) and Morrisey and Ashby (1982), we expect greater levels of hospital assets per capita to be conducive to network building by HMOs because of the potential for savings in hospital costs and undermining of hospital market power. Additionally, we expect that large hospital capital infrastructure draws physicians, making HMO penetration easier.

However, another characteristic of markets complicates the effect of this variable (hospital assets per capita) on HMO shares. In some small markets, hospital excess capacity is large relative to the size of the market. These markets are too small to allow hospitals to make full use of scale economies, and yet they must be prepared for large-scale emergencies, such as earthquakes and floods. These markets may tend to have other characteristics that reduce HMO shares, such as provider market power. We attempt to control for these with other right-hand-side variables. However, to the extent that these variables are measured with error, this could mask the effect of hospital assets per capita on HMO shares.

We expected income levels, urban intensity, and the population age distribution to impact market shares. Demand for free choice of provider is expected to increase with income (income per capita). This would result in a negative correlation between income and HMO penetration and/or a positive correlation between income and indemnity shares. Population density is our measure of urban intensity; it captures characteristics of urban markets that are not caught by our provider network variables.

We expect population density to be positively correlated with HMO shares. We have no a priori expectations regarding the effect of the proportion of the market population under age 30 or younger (young people) or age 60 or older (seniors); they are included as controls. One might expect seniors to behave differently than younger people, but because Medicare did not offer PPOs during the time period of our data, and because our data include only private insurers, the impact that seniors might have on our analysis is likely to be slight.[6]

In Table 3, we present results from the ordered probit analysis on the 139 HPFA-level market shares for the three insurance types. For each variable, we report the maximum likelihood estimates of the marginal probabilities and indicate those that are statistically significant at the 10% level or better. A larger physician density (physicians per capita) is statistically significant and positively associated with greater HMO penetration, and negatively associated with PPO and indemnity private insurance shares. This is consistent with our expectation that greater competition among physicians increases the likelihood that physicians will join MCOs, increasing the size of the network and making the managed care market more attractive to consumers.

6 Starting January 2003, Medicare offered 35 PPO plans to Medicare beneficiaries in 23 states, as part of a Medicare demonstration project. Before this, no Medicare PPO plans were operating and the few private PPO plans available to seniors tended to be associated with employer-sponsored retirement plans.

The marginal probability shows the magnitude of the effect. For example, the change in probability that a particular HMO is chosen, given a one-unit change in physicians per 10,000 population, is 0.009. An increase in one physician per 10,000 people, for example, from 18 to 19, will increase HMO shares by 0.9 percent of the population. Similarly, a one-unit increase in physician density would be expected to decrease PPO and indemnity shares by 0.3 percent and 0.6 percent of the population, respectively.

In Table 3, we see that the variable "hospital assets per capita" has no statistically significant effect estimate. It is possible that the provider-networking potential is dominated by unmeasured market power and physician availability effects. Further, it might be that high hospital capacity in rural areas does not signify excess capacity, as is discussed above. Our statistically weak findings are consistent with those of Morrisey and Ashby (1982), although they employed a hospital beds-to-population ratio. Dranove, Simon, and White (1998), by contrast, did find that greater hospital capacity (lower occupancy rate) raises MCO market penetration.

Analysis of our consumer control variables reveals some interesting results. For example, the directions of the effects of consumer incomes on market shares are opposite what our theory (and prior literature, such as Goldberg and Greenberg [1981]) predicts if provider choice is a normal good, but those effects are not statistically significant. The correlation between young people and HMO shares is negative and statistically significant. Conversely, the correlation between seniors and HMO shares is not statistically significant. The correlation between young and indemnity shares is positive and statistically significant. However, the correlation between seniors and indemnity shares is not statistically significant. Finally, population density (i.e., population per square mile) is statistically significant and positively correlated with HMO shares and negatively correlated with indemnity shares.

More concentrated hospital markets (higher values of hospital HERF) have statistically significant effects that decrease the probability of penetration by HMOs but increase the probability of penetration by PPOs and indemnity private insurance. This suggests that greater hospital control over prices is not attractive to HMOs, which is consistent with our theory and with what Dranove, Simon, and White (1998) found across metropolitan areas. The marginal probability that an HMO is chosen is −0.189, suggesting that a 1-unit increase in market concentration (i.e., a change in HERF from 0 to 1) would decrease HMO penetration by almost 19 percent. The marginal probability that PPO and indemnity plans are chosen is 0.057 and 0.131, implying increases in PPO shares and indemnity shares of 5.7 percent and 13 percent, respectively, upon a 1-unit increase in HERF.

Policy Importance of Hospital Concentration

Because of the policy importance of hospital concentration, we examine this effect further. Consider a market with five hospitals, one with half the market and the rest with equal shares of the remaining 50 percent. The HERF in this market is

$$[0.5 \text{ x } 2 + 4\ (0.125 \text{ x } 2)] = 0.3125.$$

Suppose that the HMO share in this market is 48 percent (the sample mean). If the large hospital were to buy one of the four smaller hospitals and retain its patients, the new HERF would be

$$[0.623 \text{ x } 2 + 3\ (0.125 \text{ x } 2)] = 0.4375.$$

The change in the HERF would be about 0.125, and the change in HMO shares implied by the model would be [0.125 (−0.19)] = −0.02375, or a little less than a 2.5 percentage point decline in HMO share. Even this small change in concentration would reduce HMO penetration from a 48 percent share to about 45.6 percent of the market.

The marginal probability for a change in hospital HERF on PPO shares is 0.057. The inference from the above market is that a 0.125 change in hospital HERF would increase PPO shares by 0.7 percentage points—for example, from the mean market share of 30.5 percent to 31.2 percent of the market. On indemnity shares, the marginal probability is 0.131, implying that the market change described above would result in a 1.64 percentage increase in indemnity shares, from 21.3 percent to about 22.9 percent of the market.

The marginal effect of hospital market concentration on market shares of managed care insurance is both statistically and economically significant. The result is consistent with the commonly observed HMO resistance to hospital mergers. Also, our illustration posits a small change in market concentration as a result of the merger of one small hospital with one large hospital. This is a relatively common event.

However, if we use the model to compare markets across space instead of time, the differences in market concentration are often profound. For example, we can compare two California counties: Butte County, which is mostly rural, and Riverside County, which contains rural and urban areas. Butte has a hospital HERF of 0.66, which is fairly concentrated. Conversely, Riverside has a hospital HERF of 0.29, a relatively unconcentrated market. The ordered probit regression suggests that, all else equal, there should be an approximately 7 percent smaller HMO share in Butte than in Riverside. Of course, not all else is equal between the two counties. Butte has a physician density more than twice as high as that of Riverside and a population density one-fourth that of Riverside. In fact, their HMO shares are roughly 46 percent and 75 percent, respectively.

Checks for Robustness

Discharge data for enrollees in one large HMO—Kaiser Permanente—are available, but no hospital bed size or assets per capita are available for these hospitals. We included Kaiser HMO discharges among the other HMO discharges in the analysis (Table 3), although we view Kaiser plans as a different type from the other HMOs we study. Kaiser plans offer vertically integrated closed panels of physicians and hospitals, with even less choice of provider than other HMOs. To assess the robustness of our findings from lumping these Kaiser and other HMOs together, we re-estimated the model using four groups for the ordered choice: Kaiser (most restrictive choice), HMO, PPO, and indemnity. Table 4 shows that the market shares for the plan types and the estimated effects for the two market power variables—HERF and physicians per capita—are entirely consistent with the three-group model. In Table 4, Kaiser's market share overall is about 10.6 percent, and other HMOs have a share of about 37.4 percent; when summed, Kaiser and the other HMOs have about 48 percent of the market share (see Table 2, in which these two HMO types are combined). The estimated effects for the Kaiser variables are a bit smaller than those for the other HMOs, reflecting Kaiser's greater insulation from market forces as compared to newer, smaller HMO entrants. To preserve degrees of freedom in regard to our few observation points, we prefer the three-choice model in Table 3.

Table 4: Market shares and ordered probit results, marginal probability estimates

Variable (market share)	Kaiser (0.106)	HMO (0.374)	PPO (0.307)	Indemnity (0.213)
Hospital HERF	–0.089**	–0.121**	0.062**	0.148**
Physicians per 10,000 capita	0.005**	0.007**	–0.004**	–0.009**
Assets per capita	0.0001	0.0001	0.0001	0.0001

HERF = hospital Herfindahl index; HMO = health maintenance organization; Indemnity = indemnity plan; Kaiser = Kaiser HMO; PPO = preferred provider organization.

** Coefficient is statistically significant at the 95 percent level or better.

Maximum likelihood estimators from the ordered probit model can yield biased parameter estimates in the presence of heteroskedasticity (non-constant error variance) or spatial autocorrelation (correlation of errors in adjacent HFPAs). Therefore we conduct ordinary least squares (OLS) linear probability model estimation applied to separate equations for each payer share as a reasonable modeling alternative to the ordered probit.[7] The major difference between these two approaches is that OLS estimates three separate equations. Thus, it does not take into account the interdependencies and the order among the choices. Still, the interpretation of the estimated betas from the ordinary regression is comparable to the interpretation of the marginal effects calculated for the probit. The OLS residuals can also be checked for the presence of spatial autocorrelation, and if it is

7 The data are aggregated to the market level, and most of the shares are not near 1 or 0. Aggregation greatly reduces the problems of using OLS on discrete choices, especially when little of the data is actually close to 0 or 1 (Pindyck and Rubinfeld, 1981).

found, an appropriate spatial regression model can be estimated. Estimates from the OLS and spatial regression models are presented in Table 5.

The results of the OLS model are consistent with the ordered probit, especially for the two variables of most interest: physician density and hospital concentration (see the first column of Table 5). The OLS coefficient on physicians per capita in the HMO model is 0.008, with a standard error of 0.0035. Although the magnitudes of the OLS and probit coefficients are not identical, they are quite close (0.009, Table 3 versus 0.008, Table 5)—well within a standard deviation of the estimator for either method. The OLS coefficient for physicians per capita on PPO is −0.003 (Table 5), almost exactly the same as the probit marginal probability (Table 3). The OLS coefficient for physicians per capita on indemnity is −0.005, also within 1 standard deviation of the probit marginal probability (Table 3).

Turning to the hospital concentration, in the OLS model, the coefficient on the hospital HERF variable for HMO shares is −0.162, which is very close to the marginal probability from the probit model (−0.189, Table 3). For PPO shares, the coefficient of the HERF variable is not statistically significant, in contrast with the ordered probit model, where the coefficient of the HERF variable is statistically significant and positive (Table 3). Based on theoretical considerations, one would expect PPO shares to be the most difficult to predict. For indemnity shares, the OLS coefficient on

Table 5. HMO, PPO, and indemnity shares: OLS and spatial regression results

Variable	HMO		PPO		Indemnity	
	OLS	Spatial	OLS	Spatial	OLS	Spatial
			Coefficient			
Constant	0.533	0.348	0.556	0.378	−0.089	−0.262
Hospital HERF	−0.162**	−0.109**	0.019	0.019	0.143**	0.103**
Physicians per 10,000 capita	0.008**	0.004**	−0.003	−0.002	−0.005*	−0.003*
Assets per capita	−0.015	−0.008	−0.003	−0.000	0.018	0.009
Income per capita	0.001	−0.004*	0.003	0.003	−0.003	0.0001
Young	−0.003	−0.003	−0.002	−0.002	0.005**	0.005**
Seniors	0.009*	0.005	−0.010**	−0.008**	0.0001	0.002
Population density	0.0001*	0.0001	0.0001*	−0.0001*	0.0001	0.0001
Spatial term (rho)	N/A	0.133**	N/A	0.089**	N/A	0.104**
			Regression Statistics			
OLS R-squared	0.608		0.220		0.488	
Adjusted R-squared	0.420		0.107		0.386	
OLS F-statistic	15.271		3.362		13.407	
Probability (F-statistic)	0.000		0.002		0.000	

HERF = hospital Herfindahl index; HMO = health maintenance organization; OLS = ordinary least squares; PPO = preferred provider organization; rho = spatial lag estimate from the spatial lag regression.

Notes: The diagnostic results for the three models are the result of the following tests: the errors pass a normality test; the errors pass a heteroskedasticity test; the spatial term is statistically significant; no evidence of spatial autocorrelation remains in the errors of the spatial regression model.

* Coefficient is statistically significant at the 90 percent level or better.

** Coefficient is statistically significant at the 95 percent level or better.

HERF is statistically significant and 0.143, which is very close to the marginal probability on the probit model (0.131, Table 3).

OLS and probit models agree that the coefficient on assets per capita is not statistically significant. In the OLS model, the signs of the coefficients on consumer incomes are the same as in the probit model; that is, they are the opposite one would expect if provider choice were a normal good. OLS and probit results are also similar, although imprecisely estimated, for the consumer variable. Overall, the OLS results confirm our probit results.

We analyze the OLS residuals to assess evidence of heteroskedasticity and spatial autocorrelation. Some evidence of heteroskedasticity exists in the equations for HMOs and indemnity. Heteroskedastic standard errors are biased, so we present heteroskedasticity consistent standard errors in the OLS regression results. However, this approach does not change the qualitative results.

When values for the errors of the econometric equations cluster together in space, there is spatial autocorrelation in the data. Much like time series autocorrelation, spatial autocorrelation does not necessarily cause parameter estimates to be biased (except in a special case with endogenous spillovers). However, spatial autocorrelation may cause variances to be underestimated, creating problems for statistical inference (Anselin and Bera, 1998).

The spatial clustering (market segmentation) of HMOs and PPOs is visually apparent when we examine maps of California HPFAs (see Figure 1). HMOs locate in dense urban markets, whereas PPOs and indemnity insurers have larger market shares in rural and lesser urban markets. Although this phenomenon does not prove that the errors are spatially clustered, it does raise suspicions that they might be.

We can assess the effects of spatial autocorrelation by examining the residuals from the OLS linear probability model using GeoDa software (Anselin, Syabri, and Kho, 2006). We examine the OLS residuals for evidence of spatial autocorrelation, using the tests described by Anselin and Bera (1998).

We find strong evidence of spatial autocorrelation of the lag type, and we then estimate a spatial lag econometric model (see Table 5). One can see the strong evidence of spatial autocorrelation in the large significant spatial lag term estimate (rho). Its size and statistical significance dwarf all the other variables in the model (see the Spatial columns in Table 5). Because rho (the spatial lag term estimate) is positive, these results suggest that HMO, PPO, and indemnity shares are similar among neighboring HPFAs. When this similarity is ignored in the OLS specification (the OLS columns in Table 5), the OLS residuals exhibit spatial autocorrelation, suggesting that the OLS model is mis-specified. The spatial econometric model passes all diagnostic tests, suggesting that it is the correct specification.

Although we find evidence that spatial autocorrelation is present, correcting for it does not change the estimation results by much. Overall, the probit and OLS models largely agree with each other in sign, magnitude, and statistical significance. The spatial model also largely agrees, but the magnitudes of the coefficients are mostly smaller. The spatial model is perhaps the most robustly estimated mode, owing to the heteroskedasticity and autocorrelation found in the data, so the conformity of results lends credibility to our ordered probit results.

The spatial model is consistent with the other two models for physicians per capita. The coefficient is 0.004 for HMO, −0.002 for PPO, and −0.003 for indemnity. The coefficients on hospital HERF for the spatial model also confirm the results of the other two methods. The coefficients in the spatial model for HMO shares and indemnity shares are both statistically significant; the coefficient for PPO shares is positive but not statistically significant, the same as in the OLS model.

Limitations

In this work, we are limited to data from a natural experiment in California that provided hospital discharges broken out by HMO, PPO, and indemnity insurance type; this is the only source available to date for constructing payer market share by type in small areas. However, California is a large state with varied demographics along the urban-rural continuum, and it may serve as a small model of the United States. For that reason, we expect that the findings are broadly generalizeable. Other limitations of the data include unobserved prices or actual network structures, unmeasured disease severity, and unknown degree of correlation with market shares in plan enrollments by insurance type. Because of these limitations, we model a reduced form equilibrium and not the actual complex dynamics that underlie it.

Given these limitations, it is encouraging that our findings seem to have face validity; that is, they are consistent with the market dynamics observed with the roll-out of Medicare regional PPO plans and private indemnity plans in rural areas since January 1, 2006. For years, CMS had tried to extend Medicare managed care into rural areas, and the agency has finally succeeded after defining 26 market areas with sufficient rural populations to provide a viable risk pool for Medicare regional PPOs and private indemnity plans. Future research may be able to confirm our findings, if and when the data necessary to validate them become available at small geographic scales.

Summary and Policy Relevance

The implications of our theoretical model are largely confirmed by the statistical results. Most interestingly, the signs on the coefficients of physician density and hospital market concentration are as predicted and are statistically significant, indicating that more competitive provider markets are conducive to HMO penetration. Providers are more likely to join managed care networks if many consumers are enrolled in managed care. Consumers are more likely to join HMOs when the managed care networks have more providers. Larger networks increase the relative value of HMO services. Thus, positive feedback effects link provider and consumer behavior. The types of plans are naturally ordered by degree of consumer choice among providers, ranging from the least choice with HMOs, to a middle ground with PPOs, and the most choice with indemnity.

The position of PPOs in the middle ground of an ordered choice leads to the theoretical ambiguity concerning the effect of larger provider networks on PPOs. As networks become easier to assemble, the value of PPOs rises relative to indemnity insurance but falls relative to HMOs. Thus, factors that make it easier to assemble large networks will raise shares for HMOs, reduce them for indemnity, and have ambiguous effects on PPOs. It is the connection of these factors to urban areas that leads to HMOs' being a largely urban phenomenon.

The connection of these factors to provider competition has implications for health policy. PPOs can grow in areas where physician densities are lower and hospital concentration is higher, compared with HMOs, because HMOs are more adversely affected by physician and hospital market power. Thus, HMOs are an urban phenomenon, but PPOs are not.

These findings have real-world implications for Medicare modernization efforts aimed at increasing the proportion of seniors enrolled in Medicare managed care plans. Plans in remote rural areas with few physicians would have difficulty building closed provider networks of the HMO type. Only looser arrangements, available as PPOs, are likely to thrive in remote areas. The MMA of 2003 mandated, among other things, the creation of regional PPO plans for seniors. CMS divided up the country into 26 regions, each large enough in terms of population to support a regional PPO plan, with the provision that market entrants cover the entire area with plan offerings. This was an attempt to expand managed care insurance options and extend them to seniors in remote rural regions. Our findings suggest that this strategy can provide the market structures conducive to PPO or indemnity plan formation in more remote rural areas.

References

Anselin, A., & Bera, L. (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. In D. Giles & A. Ulah (Eds.), *Handbook of applied economic statistics.* New York: Marcel Dekker.

Anselin, L., Syabri, I., & Kho, Y. (2006). GeoDa: An introduction to spatial data analysis. *Geographical Analysis, 38,* 5-22.

California Office of Statewide Health Planning and Development (OSHPD). (1995). Healthcare Information Division—data products. Hospital financial data; accessed Feb. 20, 2009. Available from http://www.oshpd.ca.gov/HID/DataFlow/HospData.html

California Office of Statewide Health Planning and Development (OSHPD). (1998). Healthcare Information Division—data products. Hospital discharge data; accessed December 15, 2008. Available from http://www.oshpd.ca.gov/HID/DataFlow/HospData.html

Dranove, D., Simon, C. J., & White, W. D. (1998). Determinants of managed care penetration. *Journal of Health Economics, 17*(6), 729-745.

Escarce, J. J., Polsky, D., Wozniak, G. D., & Kletke, P. R. (2000, October). HMO growth and the geographical redistribution of generalist and specialist physicians, 1987-1997. *Health Services Research, 35*(4), 825-848.

Feldman, R. (1979). A model of physician location and pricing behavior. In R. M. Scheffler (Ed.), *Research in health economics, a research annual.* Greenwich, CT: JAI Press.

Frech III, H. E. (1988). Preferred provider organizations and health care competition. In H. E. Frech III (Ed.), *Health care in America* (pp. 358-370). San Francisco, CA: Pacific Research Institute.

Frech III, H. E., & Mobley, L. R. (1995, March). Resolving the impasse on hospital scale economies, a new approach. *Applied Economics, 27*(3), 286-296.

Goldberg, L. G, & Greenberg, W. (1981). The determinants of HMO enrollment and growth. *Health Services Research, 16*(4), 421-438.

Greene, W. H. (1990). *Econometric analysis.* New York: Macmillan Publishing Company.

Grefer, J. E. (2003). *Spatial economics of health care, health care plans and physicians.* PhD dissertation, University of California, Santa Barbara.

Lankford, P. M. (1974, July). Physician location factors and public policy. *Economic Geography, 50*(3), 244-255.

Maddala, G. S. (1983). *Limited-dependent and qualitative variables in econometrics.* London: Cambridge University Press.

Morrisey, M. (2001, April). Competition in hospital and health insurance markets, a review and research agenda. *Health Services Research, Part II, 36*(1), 191-221.

Morrisey, M. A., & Ashby, C. S. (1982, Summer). An empirical analysis of HMO market share. *Inquiry, 19*(2), 136-149.

Morrisey, M. A., & Jensen, G. A. (1990, Spring). Hospital demand for physicians. *The Quarterly Review of Economics and Business, 30*(1), 16-39.

Morrisey, M. A., & Jensen, G. A. (1997, Fall). Switching to managed-care in the small employer market. *Inquiry, 34*(3), 237-248.

National Health Policy Forum (NHPF). (2005, November). *The Basics: Medicare Advantage.* George Washington University. Retrieved December 15, 2008, from http://www.nhpf.org/pdfs_basics/Basics_MA_11-29-05.pdf

Newhouse, J. P., Williams, A. P., Bennett, B. W., & Schwartz, W. B. (1982, Autumn). Does the geographical distribution of physicians reflect market failure? *Bell Journal of Economics, 13*(2), 493-505.

Pauly, M. V., & Satterthwaite, M. A. (1981, Autumn). The pricing of primary care physicians' services, a test of the role of consumer information. *Bell Journal of Economics, 12*(2), 488-506.

Pindyck, R., & Rubinfeld, D. (1981). *Econometric models and economic forecasts* (2nd ed.). New York: McGraw-Hill, Inc.

Pope, G., Greenwalk, L. M., Kautter J., Olmstead, E. A., & Mobley, L. R. (2006). Medicare preferred provider organization demonstration: Plan offerings and beneficiary enrollment. *Health Care Financing Review, 27*(3), 96-109.

Rizzo, J. A., & Goddeeris, J. H. (1998, June). The economic returns to hospital admitting privileges. *Journal of Health Politics, Policy, and Law, 23*(3), 483-515.

Robinson, J. C., & Luft, H. S. (1985). The impact of hospital market structure on patient volume, average length of stay, and the cost of care. *Journal of Health Economics, 4*(4), 333-356.

US Census Bureau. (Last modified 2008, March 18). Census '90 gateway. Data from 1990 census; accessed Feb. 20, 2009. Retrieved from http://www.census.gov/main/www/cen1990.html

US Department of Health and Human Services, Health Resources and Services Administration. (2001, February). Accessed Feb. 20, 2009. Area Resource File, national county-level health resources information database. Available from www.arfsys.com

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