Does Competition Kill?
Hospital Quality and Competition

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Abstract

We seek to estimate the effects of competition for both Medicare and HMO patients on the quality decisions of hospitals in Southern California. We find that increases in the degree of competition for HMO patients decrease risk-adjusted hospital mortality rates. Conversely, increases in competition for Medicare enrollees are associated with increases in risk-adjusted mortality rates for hospitals. In conjunction with previous research, our estimates indicate that increasing competition for HMO patients appears to reduce price and save lives and hence appears to be welfare improving. However, increases in competition for Medicare appears to reduce quality and perhaps reduces welfare. The net effect of a given merger on hospital quality will depend on the geographic distribution of different payer groups.

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I. Introduction

Two types of insurers dominate the US health care economy: the federal and state governments, through the Medicare and Medicaid programs, and privately purchased managed care. These insurance systems reimburse healthcare providers differently, which gives providers different and potentially offsetting incentives to deliver quality care. It has been argued that in a managed care environment competition will provide the appropriate incentives for health care insurers and providers to deliver the optimum level of care at prices that approach marginal cost (Enthoven (1993)). There is substantial evidence that since the rise of managed care, increasing competition in hospital markets leads to lower prices.[1] What is less clear is the effect of competing for both Medicare and HMO patients on hospital quality.[2] In this paper we seek to estimate the effects of competition for both Medicare and HMO patients on the quality outcomes of hospitals in Southern California.

We find that increases in competition for HMO patients decrease risk-adjusted hospital mortality rates. This is true for the treatment of both acute myocardial infarction (AMI) and is likely true for pneumonia. Conversely, increases in hospital competition for Medicare enrollees increase the expected risk-adjusted mortality rate. This is true for both AMI and pneumonia diagnoses. Using data from the same geographic region and period and employing an empirical model that allows for geographic and product differentiation, Town and Vistnes (2001) find that hospital prices decrease with the ability of the HMO to turn to hospital networks that exclude the hospital. Thus, our estimates in conjunction with the previous research indicate that increasing competition for HMO patients appears to reduce price and save lives. Put differently, our findings indicate that competition for HMO patients improves welfare. These results run contrary to the popular press characterization of the effect of HMOs upon the provision of the quality of care in which the HMOs are viewed as severe cost cutters, sacrificing the quality of care in order to increase profits.[3] Importantly, the measures of hospital quality we use here have been carefully constructed to minimize the possibility that they are contaminated by severity differentials across hospitals.

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[1] For recent surveys of the relationship between hospital prices and competition see Gaynor and Vogt (2000) and Dranove and Satterthwaithe (2000).
[2] Kessler and McClellan (2000) find an unambiguous, positive association between the degree of competition for Medicare patients and hospital mortality rates starting around 1991. We discuss this paper in greater detail below.
[3] Miller and Luft (1997) also argue that the empirical evidence does not support the claim that HMOs deliver lower quality care to their enrollees relative to fee-for-service plans.

These results suggest that the effects of competition on the quality of hospital care depend on the incentive environment in which competition takes place. Hospitals have little control over the reimbursement rates they receive from Medicare.[4] If the reimbursement rates are limited, hospitals may have little reason to compete for Medicare patients on the basis of quality (Ellis and McGuire (1996)). There is evidence that the Medicare hospital margins during the period we study are low or even negative (ProPAC (1994)).[5] Also, consistent with this view, Staiger and Gaumer (1992) found a negative correlation between Medicare reimbursement and hospital mortality rates. Low or negative Medicare margins can explain our result that increased competition for Medicare patients lowers hospital quality.

Antitrust policy towards hospital mergers has focused almost exclusively upon the consequences of hospital combinations on the prices insurers pay. Kessler and McClellan (1999) note that the antitrust enforcers' solitary focus on price ignores the potentially large effects of mergers on hospital mortality rates. Under plausible circumstances, the welfare consequences of mergers on mortality rates may outstrip the anti-competitive harm caused by price increases. By ignoring the quality consequences of hospital acquisitions, antitrust authorities may be pursuing policies that are ultimately harmful to social welfare.

Our results suggest that the quality consequences of mergers may be substantial. However, the direction and magnitude of those consequences depend upon the geographic distribution of Medicare and HMO enrollees that the merged parties are serving. That is, a merger between two neighboring hospitals in an area that has a large Medicare population may increase quality, while a similar merger between hospitals in an area that has a large population of HMO enrollees may reduce quality. Thus, our results suggest that antitrust authorities should pay close attention to the underlying patient population and should be more concerned about hospital mergers in areas with large HMO populations.

In contrast to the body of work on the pricing effects of competition, the literature on the effect of hospital competition on medical outcomes is sparse. We are aware of only three papers that address this topic with any rigor: Shortell and Hughes (1988), Ho and Hamilton (2000) and Kessler and McClellan (2000) (hereafter, KM). Shortell and Hughes study the effects of competition on in-hospital mortality rates for Medicare enrollees in approximately 1,000 hospitals located in 45 different states for the 1983-1984 period. Using rather crude market definition criteria and hence a correspondingly crude measure of

[4] See McClellan (1997) for a discussion of cost sharing under prospective payment and the ability of hospitals to affect the level of reimbursement for Medicare patients.
[5] Only 21% of all hospital reported earning a positive return on treating Medicare patients.

competition, they do not find a significant relationship between their measure of competition and in-hospital mortality rates. Ho and Hamilton (2000) examine the relationship between hospital mergers and hospital quality. They find that mergers have no significant effect on hospital quality. However, most of the mergers in their data are between geographically dispersed hospitals and therefore their study comments more on the organizational effect of hospital mergers on quality rather than on the effect of changes in hospital competition on quality.

Our work is closely related to the important KM study. They examine the effects of competition on one-year mortality, one-year re-admittance rates, and expenses for Medicare patients who were diagnosed with AMI from the period 1986-1994. In the post-1990 period, they find that increases in competition decrease expected mortality and patient expenses. In the pre-1990 period, the effects of competition on mortality were ambiguous. Additionally, they find that competition unambiguously reduces mortality only in states with above median HMO penetration. Our results, in combination with the fact that the proportion of HMO patients grew at a very large rate during the late 1980s and early 1990s, may explain their findings.

Our work differs from KM's in several important respects which allow us to clarify the relationships between hospital competition and quality. First, we examine the effect of competition when there are patients with different types of insurance. Different health insurance reimbursement schemes give hospitals differing incentives to compete for patients. Thus, it is likely, and our results support the conclusion that, examining the competition for only one type of patient may lead to an incomplete picture of the overall landscape of the effects of hospital competition on patient mortality. If HMO competition affects hospital mortality differently than Medicare competition, then failure to include controls for HMO competition could lead to erroneous conclusions regarding the effects of hospital mergers on hospital mortality.

Second, we examine the effect of competition on the risk-adjusted mortality rates for two very different diagnoses where considerable care is used in formulating these risk-adjusted measures. The incentives to provide quality care may differ across diagnoses. For example, the margins for treating Medicare enrollees differ across DRGs (McClellan (1997)). Furthermore, patients likely place different weights upon the value of reduced mortality depending upon their diagnoses and age.

Third, we focus on a single geographic area. There are advantages and disadvantages to this strategy. The advantage of focusing on a given region is that regional variation in hospital concentration is correlated with other unobservable variables that likely impact health outcomes which could confound the effect of concentration on mortality. In order to reduce the impact of unobserved characteristics on mortality, KM include zip code fixed-effects in the estimation. Thus, they identify the effects of concentration through changes in hospital concentration over time eschewing the 'between' variation for identification. Changes in hospital concentration are primarily driven by hospital exits.[6] Thus, KM in essence find that hospital exits are associated with an increase in expected mortality. KM assume that the causal mechanism underlying this relationship is that exits reduce competition and that it is this reduced competition that ultimately results in increased expected mortality. Of course, in addition to the causal mechanism posited by KM, differences in hospital exit rates are likely related to many different factors including changes in population, income and health insurance rates which may independently affect hospitals quality. Focusing on a single geographic area reduces the potential biases induced by not controlling unobservable geographic variation in mortality that are unrelated to competition. Of course, the disadvantage of our approach is we are relying solely on the between hospital variation to identify the parameters of interests, and we might not be able to generalize our findings to different geographic areas.

The rest of the paper has the following structure. The next section presents a simple framework to analyze the relationships between competition and quality. Section III outlines our estimation framework. Section IV describes our data. Section V presents the results and Section VI concludes.

II. Competition and Payer Groups: A Simple Framework

In order to fix ideas regarding the relationship between price, quality and competition in hospital markets, we present a simple theoretical model that is an extension of Hodgkin and McGuire (1994). While our estimation does not directly impose the theoretical model, the theoretical model is of guidance in choosing a functional form for the estimation, understanding the forces that influence a hospital's choice of quality and interpreting the results.

Hodgkin and McGuire (1994) seek to model the effects of changing the Medicare reimbursement system on the hospital's incentive to provide quality. Here we consider the behavior of one hospital in isolation taking the behavior of the other hospitals in the market as given. We assume that hospitals can treat two types of patients: Medicare and HMO enrollees. Hospitals choose both the price for HMO

[6] Public information regarding changes hospital ownership is difficult to obtain. It is our understanding that national hospital databases such as collected by the American Hospital Association are not very accurate at tracking changes in ownership. KM

patients and quality in order to maximize profits. Our main assumption is that quality is a public good within the hospital. That is, the hospital cannot offer different quality levels for patients with different types of insurance.[7] Haile and Stein (1999) find that the quality of care within the hospital does not differ by insurance type.

We assume that Medicare patients choose hospitals on the basis of quality, while HMO patients choose hospitals on the basis of both price and quality and that the hospital takes the price for treating Medicare patients as given. The profit function for the hospital is

$$\pi = p_M x_M(q) + p_H x_H(q, p_H) - c(x_M, x_H, q), \tag{1}$$

where x_z denotes the quantity of patients in group z treated by the hospital, p_z denotes price for group z, q is the quality of care, c is the cost function and $x_M(q)$ and $x_H(q, p_H)$ are the residual demand curves faced by the hospital. The subscripts M and H denote Medicare and HMO, respectively. We assume that quality is increasingly costly to provide (e.g. $\frac{\partial c}{\partial q} > 0$ and $\frac{\partial^2 c}{\partial q^2} > 0$) and that the number of patients treated by the hospital increases in quality (e.g. $\frac{dx_M}{dq}$ and $\frac{\partial x_H}{\partial q}$ > 0). Here we are explicitly assuming that HMOs prefer to send their patients to higher quality hospitals, all else equal.[8]

From (1), the first-order conditions for the hospital are

$$\frac{\partial \pi}{\partial p_H}: \; x_H + (p_H - mc_H)\frac{\partial x_H}{\partial p_H} = 0, \tag{2}$$

$$\frac{\partial \pi}{\partial q}: \; (p_M - mc_M)\frac{dx_M}{dq} + (p_H - mc_H)\frac{\partial x_H}{\partial q} - \frac{\partial c}{\partial q} = 0, \tag{3}$$

where mc_z denotes the marginal cost of treatment for group z. Equation (2) is the standard marginal revenue equals marginal cost condition, and Equation (3) states that the marginal revenues from quality equals the marginal cost of quality.

Our goal in this paper is to examine the effects of competition on quality. Instead of modeling competition directly, we will examine competition through its impact on the sensitivity of a hospital's

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are unclear about the procedures they use, if any, capture changes in hospital ownership.

[7] See Gertler (1989) for a model in which a provider can discriminate in the quality of care they provide across patients with different types of insurance.

residual demand to price and quality levels. Define $\varepsilon_{q,M}$ to be the semi-elasticity of quality for Medicare patients, i.e. the percentage change in residual demand resulting from a unit increase in quality. Similarly, define $\varepsilon_{q,H}$ to be the semi-elasticity of quality for HMO patients. We expect that an increase in competition for a given hospital would increase its semi-elasticities of quality, $\varepsilon_{q,M}$ and $\varepsilon_{q,H}$.[9] In our estimation, we will parametrize $\varepsilon_{q,M}$ and $\varepsilon_{q,H}$ to be a function of the level of competition – see Section 3, and also allow the levels of demand x_M and x_H to directly vary with competition. Noting that

(4) $$\frac{dx_M}{dq} = x_M \frac{1}{x_M}\frac{dx_M}{dq} = x_M \varepsilon_{q,M},$$

we can rewrite (3) as:

(5) $$(p_M\text{-}mc_M)x_M(q)\varepsilon_{q,M} + (p_H - mc_H)x_H(q, p_H)\varepsilon_{q,H} - \frac{\partial c}{\partial q} = 0.$$

Equation (5) suggests that the hospital's quality decision should be a function of the levels of competition by payer type multiplied by the number of patients.

We would like to use (2) and (3) to understand the forces that determine how changes in competition, or equivalently changes in the residual demand elasticity and number of patients, influence a hospital's quality. There are two key points that we take from these first-order conditions. First, the effects of competition are different for Medicare and HMO patients. Second, there are spillover effects across insurance categories. We now detail these points.

First, since hospitals do not choose the Medicare price, it is relatively simple to understand the effects of competition for Medicare patients. One can see that for a given hospital, there is some threshold $\bar{p}$ such that an increase in $\varepsilon_{q,M}$ (or equivalently, an increase in competition for Medicare patients) will reduce quality if and only if $p_M < \bar{p}$. The intuition is straightforward. An increase in $\varepsilon_{q,M}$ will make it easier for a hospital to shed patients by reducing quality. Hospitals want to shed patients with negative margins at the given quality level and may even want to shed patients with low positive margins because

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[8] Luft (1988) discusses the incentives for HMOs to monitor and use high quality providers. Recent work by Chernew, Scanlon and Haywood (1998) and Escarce *et al.* (1999) indicates that, at least in California, HMO patients receive care at higher quality hospitals.
[9] For instance, in a simultaneous moves Nash equilibrium, the residual demand elasticity for quality will be more elastic at a given price and quality vector if another competitor is added. Even after accounting for the change in price and quality resulting from the new competitor, we would expect this to remain true.

this will reduce marginal cost.[10] During the period from which our data is drawn, Medicare margins were low or negative (ProPAC (1994)).[11] Thus, it is likely that for many hospitals, $p_M < \overline{p}$ and we would expect an increase in $\varepsilon_{q,M}$ to be associated with lower quality. Also, McClellan (1997) calculates the Medicare margins for different diagnoses and finds that generosity of pneumonia payments were higher than for AMI.

In contrast, it is more difficult to characterize the effect of $\varepsilon_{q,H}$ on quality because of the joint nature of the HMO price and quality decision. Any inference about the effects of a change in competition on quality is very sensitive to specific assumptions concerning the nature of interactions and equilibrium. For example, Moorthy (1988) shows that while a monopolist would choose the optimal quality, in the duopoly equilibrium the quality levels chosen by the firms are not socially optimal: one firm chooses a level of quality that is too high and the other chooses a quality level that is too low.[12] Spence (1975) shows that a monopolist can choose either too high, just right, or too low a level of quality.[13]

Second, there are spillovers across insurance categories that result from our assumption that hospitals are unable to meter out different care to patients by type of insurance. For instance, since the optimal choice of quality will be a function of both Medicare and HMO levels of competition $\varepsilon_{q,M}$ and $\varepsilon_{q,H}$, the threshold $\overline{p}$ will be a function of the marginal cost for Medicare patients, the marginal cost of HMO patients, and the Medicare and HMO demand-side parameters. In particular, if competition for HMO patients increases the equilibrium level of quality, this will increase Medicare costs and hence increase the threshold $\overline{p}$. Similarly, changes in competition for HMO patients will impact the quality of care Medicare patients receive and vice versa. Moreover, the level of Medicare reimbursements will affect the impact of competition for HMO patients. Because of these interactions, we must jointly model the choice of quality as a function of both Medicare and HMO competition.

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[10] Another interesting model of the effects of the PPS system is Dranove (1987). He constructs a model of quality competition under PPS where hospitals differ in their costs of production for different DRGs. In his model, the move to the PPS can increase efficiency if hospitals specialize in those DRGs for which they are more efficient. However, these effects may be mitigated if hospitals treat healthier patients within DRGs.

[11] For diagnoses other than AMI and pneumonia, researchers have also found that the level of payments also vary significantly by type of payer (Chernew, Gowrisankaran and Fendrick (1999) and Dranove and White (1998)).

[12] See, also, Shaked and Sutton (1982) and Motta (1993).

[13] A concise review of this literature can be found in Tirole (1988).

There are at least two issues that are not modeled in (1) that may have a significant bearing on the effects of competition on hospital quality. The first issue is information problems. Hospital quality may be difficult for patients and/or their physicians to observe prior to receiving treatment. If patients cannot easily observe quality and the provision of quality care is costly to provide, hospitals may under invest in quality.[14]

Second, the profit-maximizing model may not be correct for some hospitals. Most hospitals in the US are not-for-profit organizations and are prevented from distributing any monies to shareholders. Researchers have used many different functional forms to model not-for-profit behavior. For instance, Gowrisankaran and Town (1997) find that the distribution of hospital size is consistent with not-for-profit hospitals maximizing a convex combination of profits and quality. Alternatively, several researchers have modeled not-for-profit hospitals as maximizing patient welfare subject to a break-even constraint.[15] Also, the hospital industry has a reputation for inefficiency (Chirikos (1999)). Thus, some researchers have modeled hospitals as not always operating on the cost-quality frontier, with competition serving as a disciplining force. The results in KM are consistent with the view that hospitals are inefficient since increases in competition increase quality and decrease costs.

While these different objective functions would yield different comparative statics, our central point, that quality needs to be modeled as a function of the level of competition interacted with the number of patients, separately for both payer types, still holds. In the next section we outline our strategy for examining the relationship between competition for different types of patients, hospital prices and quality of care.

III. The Empirical Framework

The purpose of this paper is to estimate the relationship between competition and hospital quality. As discussed in the previous section, we need to formulate a measure of competition for each payer group, to proxy for the residual demand elasticity. Besides controlling for payer groups, we have two other broad concerns in measuring the level of competition. Traditionally, measures of competition are formulated using a two-step method. The first step defines the extent of the geographic and product market. In studying hospital competition, this is generally done by defining the geographic markets (e.g. counties) in

[14] It is also possible that improvements in information can lead to greater inefficiencies (Dranove and Satterthwaite (1992)).
[15] Hoerger (1991).

which hospitals compete. The product market usually is a set of inpatient services. The second step involves measuring market shares given the market definition.

As KM point out, both steps are may introduce significant biases to the competition measure. For example, defining the geographic market is usually based on geo-political boundaries (e.g. counties or SMSA) and may not be related to economic notions of markets and thus is often ad hoc. These ad hoc measures of market concentration could lead to substantial biases. Besides being ad hoc, it is difficult to model the fact that hospitals are geographically dispersed within a given geographic market with substitutability of hospitals varying substantially within the market.

The second problem in formulating measures of competition is one must construct measures of hospital size. Again, as KM point out, measures of competition that are based on actual patient flows will be endogenous: high quality hospitals may attract more patients from further away. Thus, an exogenous increase in a hospitals quality would cause this hospital to appear to have more market power. This problem will be exacerbated with HMO patients because HMOs typically form hospital networks – including a subset of the total population of hospitals in the network. For example, consider a region with one HMO and two hospitals. If the HMO negotiates a favorable rate with one hospital and includes it in its network, an HHI based on actual HMO patient flows will be extremely high and will underestimate the intensity of the actual hospital competition.

Following KM, we compute a measure of competition that is based upon the results of a multinomial logit model of hospital choice. Our specification for the choice model explicitly accounts for geographic and product differentiation but is not based on latent or other endogenous hospital variables. This allows us to formulate hospital specific measures of competition for the different insurance categories that satisfy both of our concerns. In the remainder of this section, we discuss our model of hospital choice, and our construction of competition and quality measures.

A. Model of Hospital Choice

We now detail our exact choice model. We posit that the indirect utility that a patient with diagnosis s receives from being admitted to hospital $j \in J$, conditional on deciding to be admitted to a hospital, is given by

(6) $$u_{ij}^{s} = \lambda_1^{s} d_{ij} + \lambda_2^{s} beds_j + \lambda_3^{s} close_{ij} + \lambda_4^{s} d_{ij} \times emerg_i + \lambda_5^{s} close_{ij} \times emerg_i + e_{ij}^{s},$$

where d_{ij} is the distance from the center of the patient's zip code to the center of the hospital's home zip code, $beds_j$ is the number of beds at hospital j, $close_{ij}$ is an indicator variable taking the value of one if the hospital is the closest one to the patient's home zip code, and $emerg_i$ is an indicator variable taking the value of one if the patient had an emergency admittance. The error term, e^s_{ij}, is iid and captures the effects of unobservable attributes on patient choice. For example, it is possible that the patient's physician plays a role in selecting the hospital and we do not have any information on the identity of a patient's physician. The error term is assumed to be distributed Type I extreme value. This is the standard conditional multinomial logit framework and the parameters from (6) are estimated via maximum likelihood.

A well-known drawback to the multinomial logit model with independent errors is that it imposes the rather restrictive assumption of independence of irrelevant alternatives (IIA). The IIA implication is particularly troublesome in combination with the assumption of a homogeneous population as it implies that substitution patterns between hospitals are proportional to market shares. Since we are using individual data and there is variation across individuals and hospitals in the explanatory variables and these variables explain a good deal of the actual hospital choices, in our case the unappealing consequences of the IIA assumption are mitigated.

We estimate the parameters of (6) using California patient discharge data. Ideally, the parameters of (6) should be estimated separately for every payer group. The discharge data, however, does not permit that approach. This is because the privately insured patients in our patient-level data are covered by different HMOs, each of which defines a different set of hospitals that its enrollees use. Without knowing the feasible choice set for each HMO patient in the data set, we cannot calculate unbiased estimates for (6). Instead, we estimate (6) using the hospital selection decisions of traditional Medicare enrollees. We use this population because, in general, the price they pay for inpatient services (essentially a small deductible) does not differ by hospital, and they are free to choose any hospital. We then assume the parameter estimates of (6) hold for the HMO population. Previous work (Town and Vistnes (2001)) has tested this assumption by assessing how well this Medicare-based choice model describes hospital choices for a very different patient population, Medicaid enrollees. While Medicaid enrollees' preferences also likely differ from those of other patients, they find the Medicare-based choice model translates quite well to the younger, Medicaid population.

B. Formulating Measures of Market Concentration and the Geographic Dispersion of Patients

We use the estimated parameters of (6) to formulate hospital specific measures of competition for each type of payer category. For a given hospital choice set J, let $\hat{P}_{ij}^{s}$ be the estimated probability that individual i with diagnosis s will be admitted to hospital j. Under the logit assumption, $\hat{P}_{ij}^{s}$ is given by

$$(7) \qquad \hat{P}_{ij}^{s} = \frac{exp(\hat{u}_{ij}^{s})}{\sum_{k \in J} exp(\hat{u}_{ik}^{s})},$$

where $\hat{u}_{ij}^{s}$ is the expected utility of being admitted to hospital j as implied by the parameter estimates of the logit model.

We proxy for residual demand elasticity for patient i of group z with diagnosis s via a Herfindahl index:

$$(8) \qquad HHI_{iz}^{s} = \sum_{j \in J} \left(\hat{P}_{ij}^{s}\right)^{2}.$$ [16]

As in (5), we can control for the effect of competition for a given payer type by multiplying the residual demand elasticity by the number of patients of that payer type. For a given patient, the 'number of patients' is just the probability of admission $\hat{P}_{ij}^{s}$. Our measure of competition for hospital j for patients z and s, which we denote as H_{jz}^{s}, is just the sum of this measure over patients:

$$(9) \qquad H_{jz}^{s} = \sum_{i \in I_{z}^{s}} \hat{P}_{ij}^{s}\left(HHI_{iz}^{s}\right).$$

Where I_{z}^{s} is the set of patients with diagnoses s with insurance z.

Thus H_{jz}^{s} is, in essence, the weighted sum of the estimated, patient-level HHI. Note that, H_{jz}^{s} will capture both the effects of competition and number of patients. As highlighted in the theory section, we need to capture both effects to properly weight different payer types, and the variable constructed in (9) in fact incorporates both of those effects.

We formulate (9) for five different payer groups for each diagnosis. The five groups are Medicare enrollees (MED), HMO enrollees (HMO), self-pay and medically indigent (IND), traditional indemnity

[16] The actual HHI that we use is somewhat different as there is cross-ownership across hospitals. We calculate (7) for each separate hospital corporation summing the probabilities across hospitals within the corporation to calculate the corporation probability. Likewise, the summation in (8) is over hospital corporations.

insurance (IDM), and enrollees in California's Medicaid program, MediCal (MCD). The effects of competition for these payer groups will depend on the generosity of the payments and the ultimate size of the population.

There are two sources of variation that identify the parameters on H^s_{jz}. First, there is significant variation across zip codes in the number of potential patients by insurance type. The coefficient of variation across zip codes on the number of AMI procedures is approximately 1.0 for all five payer groups. The across zip code correlation in the number of AMIs is 0.59 between the Medicare and HMO categories, 0.47 between the Medicare and Medicaid categories, and 0.35 between the HMO and Medicaid categories. The second source of variation is the result of hospitals facing different competitive environments. Town and Vistnes (2001) find significant differences in hospital bargaining power in the Los Angeles area.

C. Measures of Hospital Quality

Our focus in this paper is on the relationship between hospital quality and concentration. An obvious and nontrivial issue is: How do we measure hospital quality? There is a rather large literature in health services research devoted to answering that question. The literature has identified multiple measures of hospital quality that can be grouped into two categories: Process based or outcomes based. In essence, process based measures of hospital quality count the amount and the quality of inputs that are used in treating patients. Outcome based measures are what the name implies; they measure actual patient outcomes from treatment. The most common and oldest measure of hospital quality is mortality and it is the one we focus on here.[17] Throughout this paper we will use the term quality to refer to the negative of a hospital's risk-adjusted mortality rate.

Hospitals that are of the same quality may have different mortality rates because they are treating patients with different risk profiles. Thus, it is important that hospital mortality rates are adjusted to reflect the risk characteristics of the patients they treat. Again, there is a large literature on the methods one can use to adjust mortality rates for risk (see Iezzoni (1997) for an overview). Considerable care is exercised here in order to diminish the likelihood that severity differences across hospitals are contaminating our measures of hospital quality.

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[17] Florence Nightingale (1863) conducted the first study of the determinants of hospital mortality rates.

We use two different risk-adjusted hospital mortality rates: one for pneumonia and one for acute myocardial infarction (AMI). The pneumonia mortality rates come from Geweke, Gowrisankaran, and Town (2001) (hereafter, GGT). GGT estimate a Bayesian model of the 10-day in-hospital mortality that corrects for both observable and *unobservable* severity of illness of the patient. That is, if there are unobservable (to the econometrican) components of severity that influences a patients choice of hospital (e.g. sick patients seek care at better hospitals, all else equal) standard risk adjustment techniques will yield biased estimates of the quality of care provided by the hospital. GGT correct for this bias using Bayesian techniques that are analogous to the classical econometric method of instrumental variables. The methodology they develop generates precise estimates of hospital-specific component of mortality. The evidence indicates that GGT's procedure succeeds in removing both the observed and unobserved severity differentials from the risk-adjusted hospital mortality rates. In order to form our measure of hospital quality used here, we draw a random sample of patients and calculate for each patient their likelihood of death at each hospital. The hospital mortality rate is the mean estimated mortality rate across this sample of patients. They use data from for the years 1989-1992. Because of the computational complexity of the estimation procedure, GGT limit the number of hospitals they include in their sample to those hospitals located in Los Angeles County (N=114).

Our other mortality measure is the AMI mortality rates that come from Luft and Romano (1997) (hereafter, LR). They estimate the 30-day risk-adjusted mortality rates for AMI for most hospitals in California. LR link the hospital discharge records to death certificates and thus are able to accurately measure whether a patient died within the 30-day outcome window. In addition to controlling for patient demographics, LR carefully control for comorbidities by linking up the AMI discharge records with other possible past admissions to California hospitals. LR have formulated a risk-adjusted measure that is unlikely to contain systematic biases due to unobservable severity. We believe this for two reasons. First, LR's study carefully controlled for potential observed severity differences across patients. Second, AMI patients have less discretion over their choice of hospital since time until treatment is rendered is a critical determinant of mortality for heart attacks, thus the need to control for unobservable severity, which is important for pneumonia, is less acute for AMI.

As patients have less discretion in selecting their hospital when they suffer an AMI, it is reasonable to ask: What are the competitive forces at work that affect the hospitals incentives to provide quality care for AMI? We believe there are at least two forces at play. First, while hospitals may not compete directly for AMI patients, they do compete to be a part of an HMOs network and insofar as quality of care impacts the HMOs decision to include the hospital in the network it will affect the hospital's incentive to provide quality care. Second, the quality of care for AMI is likely positively correlated with quality of care for other heart procedures and diagnoses. For most of these diagnoses, patients do have discretion over the choice of hospital.

We focus our attention on the Los Angeles region. We limit ourselves to this geographic area for three reasons. First, GGT limit their study of hospital quality for pneumonia to Los Angeles County. Their econometric methods are rather computationally intensive and do not allow for wider geographic scope. Thus, our estimates of hospital quality for pneumonia are limited to Los Angeles County. Second, in previous work Town and Vistnes (2001) have analyzed the pricing behavior of hospitals in this region over this time period. They found that the price a hospital charges an HMO is decreases in the ability of the HMO to drop or replace the hospital from its network. Thus, we can link our measures of concentration and quality to the pricing behavior of these hospitals. Finally, by limiting our geographic focus, our results likely will not be driven by geographic variation in unobservable characteristics that may affect mortality but are unrelated to hospital competition.

Our empirical strategy is straightforward. Once the measures of market concentration have been formulated and the measures of hospital performance have been collected, we regress the risk-adjusted mortality rate on the relevant measure of competition for the different payer groups using OLS, controlling for hospital for-profit status, teaching status, and size.

IV. Data

Our primary data comes from the State of California Office of Statewide Health Planning and Development (OSHPD) patient discharge database. As discussed above, the risk-adjusted mortality rates were obtained from LR and GGT for AMI and pneumonia, respectively. Both LR and GGT use OSHPD data to formulate their mortality rates. The OSHPD data records information for every individual who was discharged from an acute care facility in the state. Both LR and GGT use the OSHPD data to formulate their risk-adjusted mortality figures. LR estimate the AMI rates for 1991-1993. We use the hospitals' average mortality rate over that period. GGT use data from 1989-1992 to formulate the hospital's relative contribution to patient mortality. Thus, there is substantial overlap in the time frames used by both studies in formulating their measures of hospital mortality rates.

The parameters from (6), the hospital choice problem, are also estimated using patient discharge data from OSHPD. For this purpose, the Version B data provides patient-level information on zip code of residence, DRG, race, sex, age (by classes), hospital that the patient was admitted to, source of admittance (emergency room, etc.) and disposition (normal discharge, death, etc.). From this data we kept those patients who were admitted to a hospital in Los Angeles, Orange, Riverside, San Bernardino and Santa Barbara counties and who were coded as a Medicare enrollee. We removed from the data set any patient whose source of admission was other than the emergency room or routine and those patients who had missing zip code information. All of the hospitals for which we have mortality data are located in Los Angeles County. We include patients and hospitals from the surrounding counties in this sample to avoid biases that may occur for those hospitals located near the county border.

We estimate the parameters of (6) for two different types of conditions: AMI and pneumonia. We use the recorded primary DRG as the basis for determining which patients were treated for pneumonia and which were treated for AMI.[18]

In addition to the patient level data, OSHPD is the source of our hospital-level data that includes size and for-profit status. Our measure of hospital size is number of staffed beds. We construct three dummy variables based on staffed beds (150-199, 200-299, greater than 300—the omitted category is less than 150 beds) that we use as independent variables. We use categorical variables in order to allow for nonlinear relationships between hospital size and mortality.[19] We also used a hospital's teaching status as a regressor. We define a hospital to be a teaching hospital if it is a member of the Council of Teaching Hospitals, as listed in the American Hospital Association (AHA) Annual Report of Hospitals database. Our data also includes the longitude and latitude for the center of each zip code, which we obtained from the TIGER database.[20] This longitude/latitude data allows us to calculate straight-line distances using the great circle formula between hospitals' and patients' home zip code.[21] Lastly, there is significant cross ownership of hospitals in Los Angeles and in order to perform the appropriate calculation of our measure of concentration for the different diagnoses we need to track hospital ownership. We use information from OSHPD to track hospital ownership.

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[18] The DRG codes for pneumonia are 89 and 90, while the DRG codes for AMI are 121, 122, and 123.
[19] Our results are unaffected if we include just the size of the hospital as a regressor.
[20] Center-of-zip code longitudes and latitudes can be off when zip codes are very large. By restricting our study to hospitals in the Los Angeles/Orange County metropolitan area, where most zip codes are relatively small, we largely avoid this problem.
[21] Using data from upstate New York, Phibbs and Luft (1995) show a strong correlation between travel times and straight-line distances. We assume the same correlation holds for the metropolitan Los Angeles region.

Table 1 presents summary statistics for the different data sets used in the analysis. The top half of the table presents the summary statistics for the Medicare discharge data for the AMI and pneumonia diagnoses. The typical AMI patient is younger (75 versus 76.5 years), travels slightly further to her chosen hospital (7.7 versus 7.5 km), and is more likely to be admitted via the emergency room (63% versus 20%) than her pneumonia counterpart. Over a third of both AMI and pneumonia patients are admitted to the closest hospital.

The hospital data is presented in the bottom half of Table 1. Both AMI and pneumonia carry a significant likelihood of death with the AMI mortality rate being higher than the pneumonia mortality rate (14.9% versus 9.5%). The relatively high likelihood of death for these conditions suggests that mortality is an appropriate measure of hospital quality. There is also significant variation in the mortality rates for both diagnoses across hospitals. The standard deviation is 3.9% and 2.3% for AMI and pneumonia, respectively. The average hospital has 242 staffed beds. The hospitals are roughly split between for-profit and not-for-profit hospitals (49% versus 44%) and 4% of the hospitals are members of the Council of Teaching Hospitals.

V. Results

A. Hospital Choice and Estimates of H_{jz}^{d}

Table 2 presents the results of estimating equation (6) for the Medicare population, with both AMI and the pneumonia diagnoses. The coefficient estimates are roughly as expected. The coefficient on the impact of distance on hospital choice is negative and significantly different from zero for both diagnoses. Larger hospitals are more attractive for both conditions—the coefficient on number of beds is significant and positive. AMI patients appear to be more sensitive to size than pneumonia patients. Patients are inclined to go to the closest hospitals for the treatment of both AMI and pneumonia. This coefficient is significantly different from zero. AMI patients who are admitted via the emergency room are more likely to go to hospitals that are closest to their home. The coefficient on $Emergency \times Distance$ is significantly negative in the both samples. The coefficient on $Emergency \times Distance$ is the AMI sample is larger than the one in the pneumonia sample. As time until treatment is a key determinant of AMI survival it is not surprising that patients who experience a heart attack reduce the distance they are willing to travel when they are aware that their condition needs immediate treatment. The coefficient on $Emergency \times Close$ is not significantly different from zero at traditional confidence levels for either diagnosis.

Using the coefficient estimates in Table 2, we formulate our measures of competition for the five payer groups for both medical conditions. Table 3 presents the summary statistics of the measures of competition, H, by diagnosis for each payer group. There is significant variation across hospitals in these measures. In general, the standard deviations are larger than the means and the maximum value for each measure is over ten times the mean value for each measure. The measures are highly but imperfectly correlated. OLS regressions of H for one payer group on H for *all* other payer groups for the same diagnoses yield an average R^2 of 0.90. Within diagnoses, differences in H are going to be solely due to differences in the geographic distribution of patients. This suggests that even in an urban area such as greater Los Angeles, hospitals will face differences in the patient mix and competition for patients from different payer groups.

B. Hospital Competition and Hospital Quality

Next we examine the multivariate relationship between the measures of hospital quality and hospital concentration for AMI and pneumonia diagnoses. We control for similar hospital-specific characteristics as in (6) to avoid any endogeneity of our competition measures. The results are presented in Table 4 in the form of three regressions. Two regressions examine the relationship between measures of competition and mortality for each diagnosis separately. The third regression pools the data from across the two diagnoses. In these regressions we transform all continuous variables by the natural logarithm.

The main findings of this paper are captured in these regressions results. Hospital quality is correlated with our weighted measure of competition that correlation differs across payer groups. All else equal, increased competition for Medicare enrollees decreases hospital quality. This is true for both diagnoses. The coefficient on H_{MED} is negative and significantly different from zero at traditional levels of confidence in all three regressions. Increases in H_{MED} across hospitals correspond to the hospitals facing an increase in the number of Medicare enrollees nearby and/or a decrease in competition for those enrollees. Recall that our measures of hospital quality are risk adjusted so it is unlikely that this finding is driven by differentials in risk patient profiles that may be correlated with differentials in H_{MED}. The magnitudes of the coefficients imply that a 10% increase in H_{MED} is associated with a decrease in hospital mortality of 3.5% for AMI and 3.4% for pneumonia. That is, increasing H_{MED} from the median level to the top quartile decreases expected mortality by about 22% for AMI and 17% for pneumonia.

McClellan (1997) finds that reimbursements for pneumonia are relatively more generous than for AMI. In so far as our results imply that the mortality rate for AMI is more sensitive to changes in the competitive environment for Medicare patients than pneumonia mortality, they are consistent with McClellan's estimates.

Previous research has concluded that increases in Medicare reimbursements will increase hospital quality (e.g. Staiger and Gaumer (1992), Hodgkin and McGuire (1994), and Gowrisankaran and Town (1997)). Our results are consistent with this finding. However, our results also suggest that the magnitude of the quality improvement will be a function of the competitive environment. Hospitals that operate in more competitive environments should experience larger increases in hospital quality relative to those hospitals in less competitive markets for a given increase in the Medicare payment schedule.

Increases in the degree of competition for HMO patients are correlated with increases in hospital quality. In the AMI regression the coefficient on H_{HMO} is positive and significant at the 1% level. In the pneumonia regression the coefficient is positive but insignificant at traditional levels — the p-value is 0.33. Deaths from pneumonia are a relatively rare event for patients under 65 years old compared to AMI. Pneumonia is the tenth leading cause of death for those 25 to 64 years of age, while heart disease is the second leading cause of death for those 25 to 64 years of age (National Center for Health Statistics).[22] Given that pneumonia is a relatively infrequent occurrence for the population that is likely to enroll in HMOs, it is not surprising that the relationship between HMO competition and pneumonia mortality is weaker than for AMI mortality.

Using data from the same geographic region over the same time frame, Town and Vistnes (2001) found that the bargaining power of an HMO with a hospital increases with the ability of the HMO to replace or remove a hospital from its network of hospitals. Thus, our findings in conjunction with the work of Town and Vistnes imply that from the perspective of an HMO enrollee, increased hospital competition leads to lower hospital prices paid by the HMO and to higher hospital quality. These results run contrary to the popular press characterization of the effect of HMOs upon the provision of the quality of care in which the HMOs are viewed as severe cost cutters, sacrificing the quality of care in order to increase profits.

[22] For the 65 and over population, heart disease is the leading cause of death while pneumonia is the fifth leading cause of death.

Our results refine and clarify the findings of KM. They find that competition unambiguously improved welfare for AMI patients in the post-1990 period. Importantly, increases in hospital competition significantly improved hospital quality for Medicare patients in those states with above median HMO enrollment. In states in which the HMO penetration was below the median, the effect of competition on mortality was not significant. That is, they find a HMO penetration / hospital competition interaction spillover effect for Medicare enrollees. Our results indicate the mechanism behind these spillovers. That is, an increase in the competition for HMO patients directly leads to improved hospital mortality rates. Furthermore, the effects of competition depend upon the type of payer, and the generosity of those payments.

The magnitudes of the coefficients imply that a 10% increase in H_{HMO} is associated with an increase in hospital mortality of 3.4% for AMI and 1.0% for pneumonia. That is, increasing H_{HMO} from the median level to the top quartile increases expected mortality by about 22% for AMI and 7.4% for pneumonia. This result is consistent with the work of Chernew, Scanlon, and Hayward (1998) and Escarce, *et al.* (1999). They find that HMO patients in California are more likely to be admitted to higher quality hospitals for coronary artery bypass graph surgery than non-HMO patients. The results of these papers along with our findings suggest that HMOs have preferences for higher quality hospitals, at least with respect to heart conditions. Thus, increased competition for HMO patients places more pressure on hospitals to improve their quality. Our results also hint that HMOs are less concerned about the quality of care for pneumonia, as increased competition for HMO patients does not have an estimated large or significant effect on pneumonia mortality.

The coefficients on the other payer group H's are all insignificant at traditional levels of confidence. The coefficients on the hospital characteristics are insignificant in the AMI regression. In the pneumonia regression, public hospitals (the excluded category), the parameter estimates indicate that hospitals between 150-199 beds and non-teaching hospitals have higher expected mortality. For both diagnoses, there is no significant difference in the quality of not-for-profit and for-profit hospitals.

Our results suggest that, consistent with the simple theoretical framework presented earlier, the incentives for hospitals to reduce mortality rates differ according to the method of reimbursement. This, in turn, implies that both antitrust and Medicare policies will play a role in determining hospital quality. Hospital mergers can lead to either increases or decreases in hospital mortality and the net effect will depend upon the geographic distribution of the Medicare and HMO populations about the hospitals. As in

Section 2, the finding that vigorous competition for Medicare patients is associated with high mortality rates suggests that Medicare margins are low or negative. This result may also be due to non profit-maximizing behavior on the part of hospitals. For instance, if not-for-profit hospitals are maximizing revenues subject to a break-even constraint, then even relatively generous Medicare margins may cause competition to result in a decrease in quality.

We explore the competition policy consequences of our estimates in greater detail by simulating a hypothetical hospital merger for each hospital in our dataset. We simulate a merger between each hospital and the geographically closest hospital to it. These are the mergers that will have the largest effects on expected mortality according to our estimates. We then recalculate (9) with the new market structure and calculate the percentage change in expected mortality as implied by the regression coefficients in Table 4. Figures 1 and 2 plot the histogram of the expected change in mortality due to these hypothetical mergers.

In Figure 1 we plot the expect change in mortality due to a hypothetical merger for AMI.[23] Most of the distribution is clustered around zero (the mean is –6.2% and the standard deviation is 4.5%) and the distribution is left-skewed. Thus, according to our estimates hospital mergers between close geographic substitutes can increase or decrease hospital quality, however the changes would likely be modest. The direction of the change will depend upon the geographic distribution of Medicare and HMO patients about the merging hospitals. If the hospitals likely would serve a disproportionately Medicare population the merger would, according to our estimates, increase hospital quality. The opposite would be true it the hospitals likely would serve a disproportionately managed care population. It should be noted that the left tail of the distribution is substantial implying that a significant number of hypothetical mergers (20%) would reduce expected mortality by 10% or more.

A somewhat different story emerges from Figure 2 where we display the histogram of the expected changes in mortality from these hypothetical mergers for pneumonia. Almost the entire mass of the distribution lies below zero (the mean is -22%, the standard deviation is 8%), implying that almost all hypothetical mergers would lead to an increase in quality for the treatment of pneumonia. The logic underlying this result that appears to be that, at least during the early 1990s, Medicare reimbursements for pneumonia were low and that the ability of hospitals to shed these patients creates powerful incentives to

[23] We view the magnitudes of the predicted changes in mortality due to merger with some caution as they emanate from a model in which we are using parameters that capture average effects to predict marginal changes in mortality.

reduce quality. With the increase in concentration, hospitals cannot shed themselves of these patients as easily thereby reducing the incentives to degrade quality.

Kessler and McClellan (1999) argue that the appropriate antitrust policy towards hospital mergers should take into account both the price and quality impacts of the merger. In particular, KM find that decreases in competition reduces welfare during the1990s. Thus, they contend that current antitrust analysis, with its solitary focus on price, most likely understates the harm caused by hospital mergers.

Like Kessler and McClellan (1999), our results suggest that the quality consequences of mergers may be substantial. However, the direction and magnitude of those consequences depends upon the geographic distribution of Medicare and HMO enrollees that the merged parties serve. That is, a merger between two neighboring hospitals in an area with a large Medicare population may increase quality, while a similar merger between hospitals in an area with a large population of HMO enrollees may reduce quality. Reinterpreting KM's conclusions using our results, the reason for the change in the effect of competition may be the large increase in the percent of HMO patients that occurred during the late 1980s and early 1990s. Thus, our results provide an explanation for the pattern of KM's findings and clarify when a merger is likely to have a positive impact on hospital quality.

V. Conclusions

In this paper we examine the effect of competition for HMO and Medicare patients on hospital-specific mortality rates. We also study the effect of competition and hospital quality (as measured by the morality rates) on hospital prices. Competition for HMO patients reduces the hospital mortality rates for both pneumonia and AMI. Conversely, competition for Medicare patients increases the hospital mortality rates for both pneumonia and AMI. Thus, competition for Medicare and HMO patients has the opposing effects on hospital quality.

The results, in conjunction with the work of Town and Vistnes (2001), provide empirical evidence in support of Enthoven's (1993) argument that competition between managed care providers will result in higher quality and lower prices. Competition for HMO patients saves lives. However, the results also indicate that the Medicare system does not generate incentives for hospitals to compete on quality, and competition over Medicare patients leads to more deaths. The competitive consequences of hospital mergers may be significant, and are likely to depend upon the geographic proximity of different patient types.

Table 1

Summary Statistics
Mean and Standard Deviations
(standard deviations in parentheses)

Medicare Patient Discharge Data			
	AMI sample	Pneumonia Sample	
Age (in years)	75.0 (6.9)	76.5 (6.9)	
Percent admitted to closest Hospital	37%	36%	
Distance to Chosen Hospital	7.74 km (11.9)	7.46 km (10.8)	
Percent Emergency Admit	63%	20%	
Number of Observations	4,153	6,750	
Hospital Summary Statistics			
	Mean (Standard Deviation)	Min	Max
AMI Mortality Rate	14.9% (3.91)	5.2	26.5
Pneumonia Mortality Rate	9.5% (1.6%)	5.6	15.5
Staffed Bed Size	242.0 (222.8)	14	1,879
Percent Private, Not-for-profit	43.5%	0	1
Percent For-profit	48.7%	0	1
Percent Teaching Hospital	4%	0	1

Table 2

Parameter Estimates from Multinomial Logit Hospital Choice Model
(standard errors in parenthesis)

Variable	AMI Coefficients	Pneumonia Coefficients
Distance/10	-1.96*** (0.079)	-2.09*** (0.043)
Beds/100	0.11*** (0.0045)	0.083*** (0.0036)
Closest Hospital	0.53*** (0.12)	0.55*** (0.062)
Emergency $\times$ (Distance/10)	-0.79*** (0.092)	-0.56*** (0.063)
Emergency $\times$ Closest Hospital	0.0025 (0.12)	-0.10 (0.076)
N	4,153	6,750
Log-Likelihood	-11,785	-20,202

***Significant at the 1% level.

Table 3

Summary Statistics of Concentration by Payer-Group and Condition

Variable	Means (Standard Deviations)	Min	Max
AMI Estimates			
H^{AMI}_{MED}	5.91 (6.91)	1.83	64.0
H^{AMI}_{HMO}	1.95 (3.03)	0.38	12.8
H^{AMI}_{IND}	0.63 (0.74)	0.18	6.73
H^{AMI}_{IDM}	1.31 (2.16)	0.30	20.9
H^{AMI}_{MCD}	2.18 (3.14)	0.56	24.7
Pneumonia Estimates			
H^{P}_{MED}	8.31 (8.86)	2.92	73.2
H^{P}_{HMO}	1.95 (3.16)	0.43	30.4
H^{P}_{IND}	0.96 (1.36)	0.31	11.0
H^{P}_{IDM}	1.72 (2.73)	0.37	20.4
H^{P}_{MCD}	1.92 (2.41)	0.53	16.2

Note: The superscript "P" denotes pneumonia. The subscripts "MED" denotes Medicare enrollees, "HMO" denotes HMO enrollees, "IND" denotes the indigent population, "IDM" denotes those covered by traditional indemnity insurance and "MCD" denotes Medicaid.

Table 4

OLS Regression of Hospital Mortality on Hospital Characteristics
(robust standard errors in parenthesis)

Variable		Dependent Variable	
		Log of AMI Mortality	Log of Pneumonia Mortality
Log of H_{Med}		-0.35*** (0.10)	-0.34** (0.14)
Log of H_{HMO}		0.27*** (0.11)	0.10 (0.10)
Log of H_{IND}		-0.10 (0.092)	0.073 (0.13)
Log of H_{IDM}		0.10 (0.11)	0.13 (0.11)
Log of H_{MCD}		0.021 (0.061)	-0.024 (0.13)
Not-for-profit		0.052 (0.10)	-0.46*** (0.10)
For-profit		0.0077 (0.11)	-0.48*** (0.12)
Teaching Hospital		0.070 (0.14)	-0.42*** (0.12)
Size Dummies	150 – 199 Beds	0.10 (0.10)	0.23*** (0.073)
	200 – 299 Beds	-0.047 (0.12)	0.13 (0.074)
	Greater than 299 Beds	-0.020 (0.13)	0.032 (0.090)
Log of AMI Quantity		0.025 (0.045)	—
Constant		2.88*** (0.27)	3.22*** (0.29)
R^2		0.19	0.22
N		107	114

Note: standard errors are robust standard errors. In pooled regression, the continuous independent variables are transformed by the logarithm. The measures of competition are diagnoses specific.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

Figure 1

Histogram of Estimated Distribution of the Percentage Change in Expected AMI Mortality Rates Due to Merger

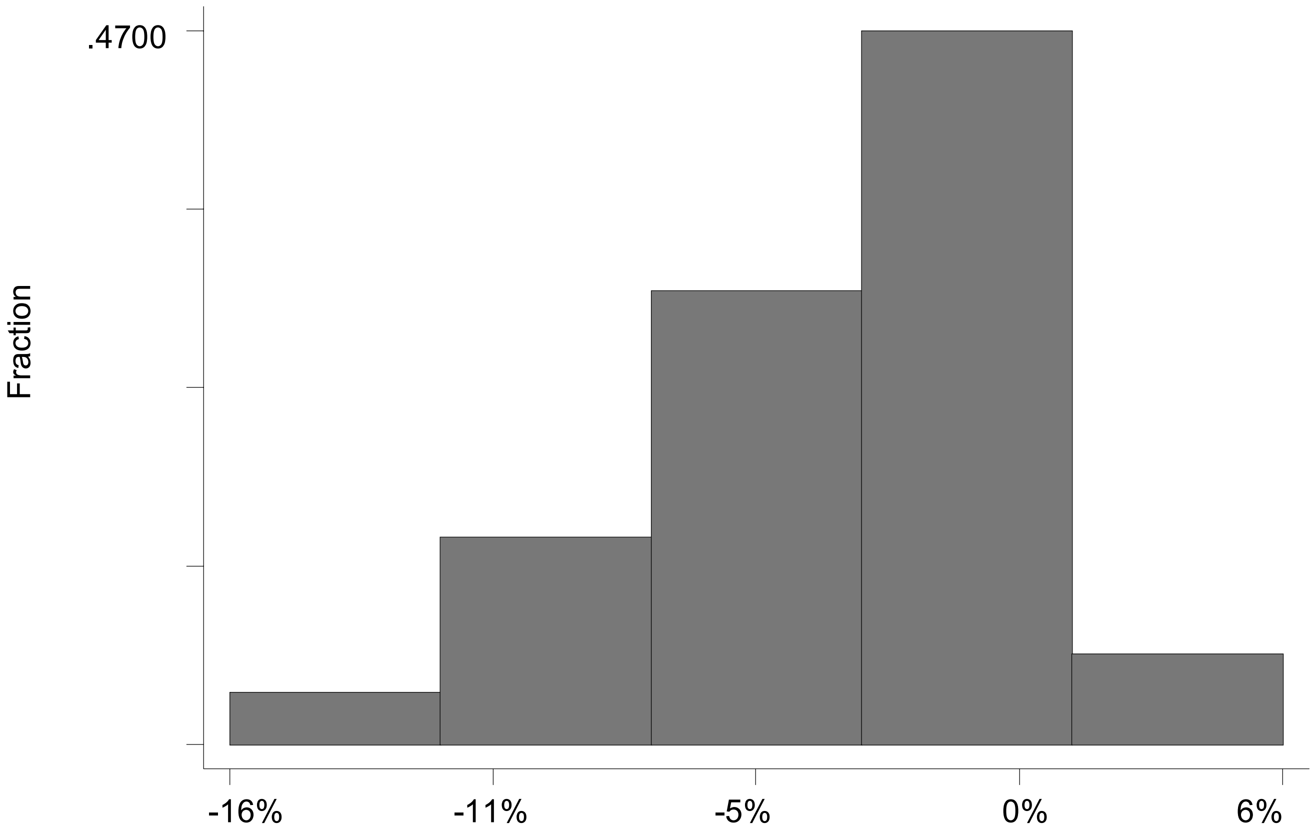
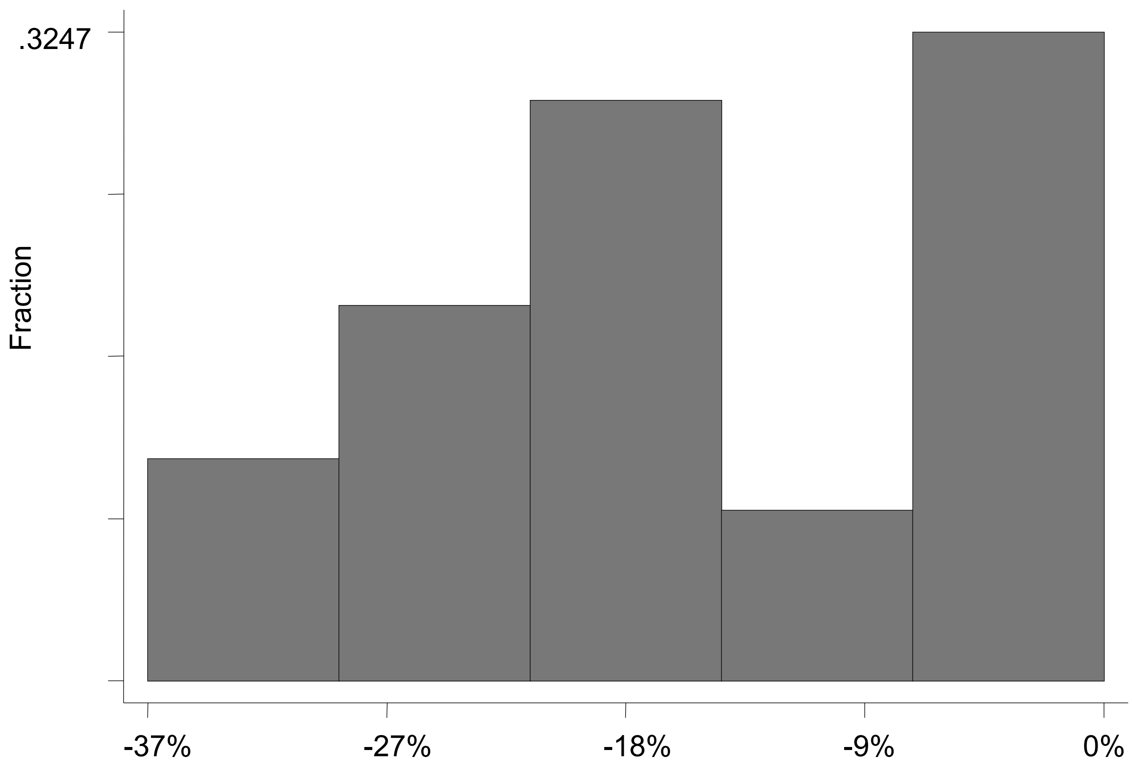


Figure 2

Histogram of the Estimated Distribution of the Percentage Change in Expected Pneumonia Mortality Rates Due to Merger



References

Chirikos, T. (1999) "Further evidence that hospital production is inefficient," *Inquiry*, Winter 1998/1999, 35(4): 408-416.

Chernew, M., G. Gowrisankaran and A.M. Fendrick (1999) "Payer type and the returns to \bypass surgery: evidence from hospital entry behavior," mimeo.

Chernew, M., D. Scanlon, and R. Hayward (1998) "Insurance type and choice of hospital for coronary artery bypass graft surgery," *Health Services Research*, 33:447-66.

Dranove, D. (1987) "Rate-Setting by diagnosis related groups and hospital specialization," *Rand Journal of Economics*, 18(3):417-427.

Dranove, D. and M. Satterthwaite (2000) "Industrial Organization," in *Handbook of Health Economics*, A. Culyer and J. Newhouse, eds., Amsterdam: North Holland.

Dranove, D. and M. Satterthwaite, (1992) "Monopolistic competition when price and quality are imperfectly observable," *Rand Journal of Economics*, 23(4):518-534.

Escarce, J., L. Van Horn., M. Pauly, S. Williams, J. Shea, W. Chen, (1999) "Health maintenance organizations and hospital quality for coronary artery bypass surgery," *Medical Care Research and Review*, 56 (3): 340-362.

Ellis, R. and T. G. McGuire (1996) "Hospital response to prospective payment: Moral hazard, selection, and practice-style effects," *Journal of Health Economics*, 15(3):257-277.

Enthoven, A. (1993) "The history and principles of managed competition," *Health Affairs*, 12, (supplement): 24-48.

Gertler, P. (1989) "Subsidies, quality, and the regulation of nursing homes," *Journal of Public Economics*, 38(1):33-52.

Gaynor, M. and W. Vogt, (2000) "Antitrust and competition in health care markets," in *Handbook of Health Economics*, A. Culyer and J. Newhouse, eds., Amsterdam: North Holland.

Geweke, J., G. Gowrisankaran and R. Town (2001) "Inferring hospital quality from patient discharge data using a Bayesian selection model," mimeo.

Gowrisankaran, G. and R. Town (1997), "Dynamic equilibrium in the hospital industry," *Journal of Economics and Management Strategy*, 6(1): 45-74.

Haile, P. and R. Stein (1999) "Managed care incentives and inpatient complications," Mimeo.

Ho, V. and B. Hamilton (2000) "Hospital mergers and acquisitions: Does market consolidation harm patients?" *Journal of Health Economics*, 19(5):767-791.

Hodgkin, D. and T. G. McGuire (1994) "Payment levels and hospital response to prospective payment," *Journal of Health Economics*, 13(1):1-29.

Hoerger, T. (1991) "'Profit' variability in for-profit and not-for-profit hospitals," *Journal of Health Economics*, 10, 259-289.

Iezzoni, L., ed., (1997) *Risk Adjustment for Measuring Healthcare Outcomes*, 2nd edition.

Kessler, D.P. and M. McClellan (2000) "Is hospital competition socially wasteful?" *Quarterly Journal of Economics*, 115(2): 577-615.

Kessler, D.P. and M. McClellan (1999) "Designing hospital antitrust policy to promote social welfare," NBER working paper 6897.

Luft, H. (1988) "HMOs and the Quality of Care," *Inquiry*, 25: 147-156.

Luft, H.S., S. Hunt, and S. Maerki, (1987) "The volume-outcome relationship: practice-makes-perfect or selective-referral patterns?" *Health Services Research,* 22:147-182.

Luft H.S. and P.S. Romano (1997) *Report on Heart Attack, 1991-1993, Volume 3: Detailed Statistical Results*. Sacramento, CA: California Office of Statewide Health Planning and Development.

McClellan, M. (1997) "Hospital reimbursement incentives: an empirical approach," *Journal of Economics and Management Strategy*," Spring, 6 (1): p. 91-128.

Miller, R. and H. Luft (1997) "Does managed care lead to better or worse quality of care?" *Health Affairs,*16(5):7-25.

Moorthy, K. S. (1988), "Product and price competition in a duopoly," *Marketing Science*, Spring 1988, 7(2):141-168.

Motta, M. (1993) "Endogenous quality choice: prices vs. quantity competition," *Journal of Industrial Economics*, 41(2): 113-131.

Nightingale, F. (1863) *Notes on Hospitals*, 3rd edition, London: Longman, Green, Longman, Roberts, and Green.

Phibbs and Luft, H. (1995) "Correlation of travel time on roads versus straight line distance," *Medical Care Research and Review* (52), 532–542.

Prospective Payment Assessment Commission (ProPAC) (1994*) Medicare Prospective Payment and the American Health Care System: Report to the Congress***,** Washington, D.C.: The Commission.

Shaked, A., and J. Sutton (1983) "Natural oligopolies," *Econometrica*, 51:1469-1484.

Shortell, S. and E. Hughes (1988) "The effects of regulation, competition, and ownership on mortality rates among hospital inpatients," *New England Journal of Medicine*, 318:1100-1107.

Spence, M. (1975) "Monopoly, quality and regulation." *Bell Journal of Economics,* 6(2): 417-29.

Staiger, D. and G. Gaumer (1992), "Quality of care in hospitals: post-admission mortality under Medicare's prospective payment system," mimeo.

Tirole, J. (1988) *The Theory of Industrial Organization*, Cambridge: MIT Press.

Town, R. and G. Vistnes (2001) “Hospital competition in HMO networks,” mimeo.