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Quality Information and Quality Competition:

Evidence from the Pennsylvania CABG Market

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1. Introduction

Public disclosure of data rating the performance of hospitals and physicians -- often referred to as report cards -- has proliferated in the 1990s. The rationale behind this effort stems from the economic belief that "even a small amount of information imperfection" can cause market failure (Stiglitz, 2002). In the context of health care, where asymmetric information is profound (Arrow 1963), providing more information may increase hospitals' incentive to provide a better quality of care, particularly when hospitals engage in quality competition. In this paper we examine the impact of online publication of Coronary Artery Bypass Graft (CABG) report cards on quality competition among hospitals in Pennsylvania.

We focus on the competition among hospitals in quality rather than on price. In the 1980s, Medicare's adoption of prospective pricing and the emergence of HMOs seemed to focus hospitals' efforts on price competition. However, since the mid-1990s several changes in market dynamics and policies have led to a re-emphasis on quality competition.[1] At the same time, concentration in hospital markets has increased substantially (Gaynor, 2006). Our goal is to examine whether the availability of quality information intensified hospitals' quality competition, and to determine whether the strength of this effect varied with market concentration.

There are well-established theoretical results demonstrating that the effect of market concentration on quality depends critically on whether firms set their own prices. If firms set both price and quality, the effect of greater competition may lead to more or less quality being provided. But if price is regulated, as is the case for Medicare patients, then firms will increase the amount of quality as market concentration falls: essentially, in more competitive environments firms that cannot compete on the basis of price will do so on the basis of quality, so long as the regulated price exceeds the marginal cost of another patient (Gaynor, 2006).

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[1]First, managed care became less stringent about selective contracting as HMOs moved to establish broader and more stable networks, as a result hospitals feel less pressure to compete on price. Second, specialized inpatient and outpatient hospital competitors began entering hospital markets following a general loosening of the regulatory environment which saw state certificate of need (CON) laws relaxed or phased out. As a result, general acute care hospitals and systems have needed to expand or enhance services to retain market share. Third, public disclosure of the performance of health care providers has been increasing since the early 1990's, allowing consumers to compare health outcomes of different providers using data from an impartial third party. Thus, Devers, Brewster and Casalino (2003) suggest that a new medical arms race has emerged.

However, these results assume that consumers know the quality of output offered by rival firms, a situation unlikely to exist for hospitals but that report cards are designed to address. Theorists have recently begun examining the impact of more precise information about quality on the level of quality provided by competing hospitals in price-regulated markets. This work, which is motivated in part by the conflicting empirical evidence on the simple relationship between concentration and quality,[2] gives only qualified support for the general supposition that better quality information will result in intensified quality competition. Rather, the results emphasize that the effect on equilibrium quality depends on how the existence of rivals causes improved information to affect a firm's marginal revenue of quality. However, Gravelle & Sivey (2009; 2010) find that when the cost of producing quality is not very different across hospitals, equilibrium quality will increase with more precise information and less concentration.

In this paper we study the relationship between better quality information, quality competition, and market concentration by examining how the online publication of CABG report cards affected health outcomes of individual Pennsylvanians living in hospital markets of differing degrees of concentration. As in other studies of the effects of market concentration, potential endogeneity poses a major challenge for our analysis because unobserved heterogeneity may determine both the health outcomes as well as the extent of market competition. For example, hospitals with distinctive services tend to locate in more competitive markets and also to treat sicker patients. Therefore, if the relative sickness of patients is not well-controlled, hospitals in less concentrated markets would appear to have worse outcomes. In Pennsylvania, another possible source of endogeneity arises from the termination of CON regulation in 1996: this termination may have affected the structure of individual markets and as well as having independent effects on hospital quality (Ho, 2006; Cutler, et al., 2009). Consequently, although we include variables to control for variation in severity of illness across patients as well as for new entry over time, we may attribute worse (or better) health outcomes to market competition that are fundamentally caused by patients' selection of hospitals or by contemporaneous changes in other health policies.

[2] A number of empirical studies of the effects of competition on quality in price-regulated health care markets show, as expected, that quality improves in more competitive hospital markets (Kessler and McClellan, 2000; Kessler and Geppert, 2005; Shen, 2003; Tay, 2003; Cooper, et al., 2010). Other studies, however, show either a negative relationship or no relationship at all (Gowrisankaran & Town, 2003; Mukamel, Zwanziger & Tomaszewski, 2001; Shortell & Hughes, 1988). See Gaynor (2006) for a recent summary of this literature.

We address this problem using the approach adopted in Kessler and McClellan (2000), Town and Vistnes (2001), and Gowrisankaran and Town (2003), which is to measure market competitiveness based on predicted market shares. First, we estimate patient-level conditional logit models of hospital choice as a function of exogenous variables (e.g. marginal travel distance) that are not correlated with unobserved patient or hospital characteristics. We can then calculate the predicted market share for each hospital using the estimates from the choice model. Finally, we calculate Herfindahl indices (HHI) based on these predicted patient flows (rather than actual patient flows), and assign them to patients based on their zip code of residence (rather than their actual hospital of admission). The competitiveness measures thus reflect the choices available to patients in their zip code of residence.

We examine the relationship between hospitals' quality decisions and market concentration in the Pennsylvanian CABG market for several reasons. First, Pennsylvania has been "grading" hospitals performing CABG procedures and disseminating report cards for some time. Report cards were first published in the early 1990s as printed documents that were available at public sites such as libraries, or by request, making them relatively difficult to access. As of the second quarter of 1998, however, the reports have been posted on the PHC4 website (www.phc4.org), making them far more accessible.

Second, in 1995 there were 37 hospitals in Pennsylvania that offered CABG because, as is the case in a number of states, Pennsylvania restricted entry with a Certificate of Need (CON) program. There was, however, pressure from hospitals without CONs to enter this lucrative market, and in December 1996 the Pennsylvania legislature failed to extend the CON regulations restricting entry of new CABG programs. Within a few years more hospitals had opened their own CABG facilities, expanding the available suppliers to 58. Thus, because of the expiration of the CON and the subsequent entry of new programs, many CABG patients in Pennsylvania faced hospital markets that experienced significant variation in concentration over time as well as across markets.

Third, CABG is a relatively common procedure for patients with coronary heart disease and many CABG patients are Medicare beneficiaries, so we have a good number of observations of the outcomes for patients who received these services at a fixed price. Further, when predicting a conditional logit model to construct the HHI, Medicare patients' choice set is less constrained by the insurance network.

Finally, the inpatient data collected by the PHC4 allows us to track individual patients over time, so we can measure longer term health impacts arising from the CABG surgery. We use data from 1994 through the second quarter of 2006 to study outcomes for Medicare patients receiving CABG surgeries during the period 1995 through the second quarter of 2005.

Our results suggest that easier access to better information about health outcomes causes hospitals in more competitive markets to employ more resources to provide better health outcomes. Specifically, after the report cards went online, hospitals in less concentrated markets had a higher total cost per patient and lower readmission rates. We consider a number of alternative interpretations for our findings, but our results are very robust.

We present evidence that, after online publication of report cards, hospitals did not engage in any patient selection based on patients' severity of illness. Hospitals in more competitive markets tend to use more resources on low-risk patients, possibly because those patients are more likely to use the quality information (Cutler, Huckman and Landrum, 2004). However, the marginal benefits of the additional resources are very limited – health outcomes are not improved for low-risk patients. On the other hand, hospitals in more competitive markets also increase treatment intensity on high-risk patients after 1998, and these additional resources lead to significantly lower readmission rates. Finally, we also find that hospitals in more competitive markets are using better surgeons to perform the CABG after online publication of the report cards.

2. Quality, Information, and Concentration

2.1 Theory

The analysis of quality competition among price-regulated firms was developed early in the 1970s by economists studying competition between such firms as airlines. A series of papers established that firms unable to compete on price would instead compete on the basis of quality, and that the incentive to compete would be greater as the number of firms increased.[3]

Gaynor (2006) sketches a representative model in which n firms face demand that is separable in market share, and choose quality, z. Each firm *i* therefore faces a demand of

$$q_i = s_i(z_i, z_{-i}) D(\bar{p}, z_i, z_{-i}),$$

[3] For examples, see White (1972) and Douglas and Miller (1974).

where s_i is firm *i's* market share, z_i is firm *i's* quality, z_{-i} is a vector of other firms' qualities, *D* is market demand, and $\overline{p}$ is the regulated price. If we assume that firms have the same technology and face the same input prices, then firm *i's* costs are a function of its own demand and the quality it provides:

$$c_i = c(q_i, z_i) + F,$$

where c(·) is variable cost, increasing in quantity and quality, and *F* is fixed cost.

Each firm maximizes profits,

$$\underset{z_i}{Max}\ \pi_i = \bar{p} \cdot s_i(z_i, z_{-i}) D(\bar{p}, z_i, z_{-i}) - c(q_i, z_i) - F,$$

and the model is closed with a zero profit entry condition. The first order condition with respect to quality is,

$$\frac{\partial \pi_i}{\partial z_i} = \left(\bar{p} - \frac{\partial c_i}{\partial q_i}\right)\left[\frac{\partial s_i}{\partial z_i} D(\cdot) + s_i \frac{\partial D(\cdot)}{\partial z_i}\right] - \frac{\partial c_i}{\partial z_i} = 0. \quad (1)$$

Equation (1) gives the familiar result that a firm finds its optimal quality level where the marginal revenue from an increase in quality just equals the marginal cost of such an increase. Assume that the regulated price is greater than the marginal cost of treating an additional patient. The expression in brackets indicates that the marginal revenue from increasing quality comes from two sources: the increase in the firm's share of overall demand caused by its increase in quality, a "business stealing" effect, and the increase in overall demand caused by the firm's increase in quality, a "public good" effect in an oligopoly. If the firm is a monopolist, then the benefit of increasing quality comes solely from shifting out the demand curve, the second effect. Therefore, the existence of a ``business stealing'' effect raises the return to improving quality for an oligopolistic competitor relative to a monopolist, and forms the basis for the prediction that more competition in a price-regulated market will increase provision of quality.

We are interested in considering how the equilibrium level of quality will be affected by consumers having better information about the quality of hospitals. Let the quality elasticity of market share and the quality elasticity of market demand be

$$\epsilon_z^s \equiv \frac{\partial s}{\partial z}\frac{z}{s} \qquad \text{and} \qquad \epsilon_z^D \equiv \frac{\partial D}{\partial z}\frac{z}{D}.$$

The first order condition for quality can then be rewritten as:

$$z_i = \frac{(\bar{p}-c_q)(\in_z^S+\in_z^D)s_i D}{c_z}, \quad (2)$$

where c_q and c_z are the first derivatives of the cost function. This expression suggests that quality will be greater if consumers are more responsive to hospital quality, which might be plausibly linked to their having better information about it.

However, drawing such a conclusion requires a comparative static analysis that incorporates the best responses of rival firms in a model where patients have imperfect information. Gravelle & Sivey (2010) study the effect of uninformed consumers getting better information about quality on hospitals' quality choices, where patients have different individual information about the hospitals. They find that in the symmetric case, where all costs are the same for both hospitals, better information increases each hospital's equilibrium quality. However, as differences between the hospitals in the cost of producing quality increase, it is more likely that equilibrium qualities of both hospitals will decrease as information improves, as in that case the marginal revenue from greater quality may be negative. Extension of their model to include horizontal as well as vertical differentiation gives similar results for oligopoly, but also suggests that in monopolized markets firms will not change their quality at all in response to better information (Gravelle & Sivey, 2009).[4]

Now consider the market for CABG procedures for Medicare patients in Pennsylvania. As price is fixed, hospitals can compete only on the basis of quality, so we expect quality to be greater in more competitive hospital markets. The procedure is not available in many hospitals; those that offer it tend to be large teaching hospitals located in more densely populated areas. Thus, we assume that the costs of quality, that is, the technology and input prices associated with producing quality, should be similar for the hospitals in the sample. We therefore expect that the improved quality information provided by online CABG report cards should increase equilibrium quality, and that quality increases will be more clearly directed at health outcomes.[5]

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[4]The latter analysis is done in a Hotelling framework. If hospitals are located far from each other, and travel is costly, then hospitals may not respond to better information about their quality because nearby patients will still choose to use the hospital, given the costs of traveling to an alternative.

[5] Mukamel, Zwanziger, and Bamezai (2002) study the possibility that competition causes hospitals to shift resources from clinical care to more easily-monitored "hotel services" (e.g., food quality). See also Held and Pauly (1983), who find that more competition is associated with increased spending on both amenities and clinical quality in dialysis facilities.

2.2 CABG Report Cards

The Pennsylvania Health Care Cost Containment Council (PHC4), a state agency, collects inpatient data from Pennsylvania hospitals and publishes various performance assessments. Since 1992, PHC4 has published a Guide to Coronary Artery Bypass Graft Surgery that grades the performance of individual hospitals and individual surgeons based on the health outcomes of their CABG patients.

Hospitals must have performed at least 30 isolated CABG procedures[6] on adults in a year to be graded.[7] Grades are reported for four different outcomes: in-hospital mortality, 30-day mortality, 7-day readmission and 30-day readmission. In the report, a hospital receives a grade of ``Same as expected'' if its risk-adjusted outcome falls within a 95% confidence interval for the state. Hospitals with adverse outcomes outside the 95% confidence interval receive either a ``Lower than expected'' grade, if their probability of having an adverse outcome falls below the 95% confidence interval (a grade referred to in this paper as good or high or superior), or a ``Higher than expected'' grade if mortality or readmission rates are above (a grade referred to in this paper as low or poor). Outcomes are all risk-adjusted to correct for the possibility that a hospital may on average treat sicker patients.[8]

Prior to 1998, the report cards were distributed to hospitals, surgeons, public libraries, business groups, legislature, the media, and any individual who requested them (Schneider and Epstein, 1998). Beginning in May 1998, however, PHC4 posted the 1994/95 and all subsequent report cards on the agency web site, making reports more easily accessible to health care consumers and their physicians.

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[6]CABG patients undergoing additional procedures such as mitral valve repair or atrial septal defect repair are not considered isolated CABG cases and are excluded from the report card assessment (Shahian et al. 2001).

[7] Some CABG operations occurred at hospitals that performed too few to be graded. From 1995 to 2001, the number of such facilities increased, and then declined sharply: many of these facilities were expanding their services following the termination of the CON program. As these growing programs finally reached the ``gradable'' threshold, the number of ungraded CABG providers plummeted (to a single facility in 2005), and the number of graded hospitals increased, from 37 in 1995 to 59 in 2005.

[8] The risk-adjustment methods currently reflect both administrative data on the patients (e.g., age, sex, gender, co-morbidities) and some clinical data, but the methods have changed over time. Details are contained in the Technical Notes to each report card report. Technical notes are posted on the PHC4 website.

3. Specification and Variables

3.1 Basic Specification

The hypothesis to be tested is that level of quality provided by hospitals in more competitive markets was higher after report card information became more easily available online. We test the hypothesis by analyzing the effect of competition and information on the outcomes of individual CABG patients. The basic specification is

$$Outcome_{ikt} = \alpha + \beta_1 C_{kt} + \gamma C_{kt} \times Post_t + \beta_2 M_{kt} + \beta_3 P_{it} + \tau_t + \varsigma_k + \epsilon_{ikt} \quad (3)$$

where $Outcome_{ikt}$ is the hospital quality consumed by Medicare patient *i* from zip code area *k* in year *t*, C_{kt} is a vector of variables measuring the level of market competition, M_{kt} is a vector of market characteristics variables, P_{it} is a vector of patient characteristics, τ_t denotes a set of year dummies, and ς_k denotes the zip code dummies. Finally, ϵ_{ikt} is a mean-zero independently distributed error term so that $E(\epsilon_{ikt} | \ldots) = 0$.

To capture the impact of online hospital CABG report cards, we interact our competition measures with an indicator variable $Post_t$, which equals one for years following the posting of report cards in the second quarter of 1998.[9] Thus, in equation (3), the coefficient γ identifies the change in the effect of competition after the introduction of online report cards.

Year fixed effects are included to control for the unobserved state-level trends in hospital service quality growth, as well as changes in Medicare reimbursements and costs experienced by all hospitals over time, that might affect patient outcomes. Patient zip code fixed effects help to capture the unobserved, time-invariant geographic variances in consumer taste, health status, and public facilities, all of which affect the consumption of hospital services.

[9] We split our sample in to pre- and post-report card sections between the second and third quarters of 1998 because the report cards were published online as of May 1998. However, if it took time for people to become aware of the report card's easier availability, the coefficient γ will be underestimated. Therefore, we also estimated a variant of the equation, redefining the 'post' period as the period following the fourth quarter of 1998. Our results were not affected by this redefinition, and so we report only one set of estimations.

3.2 Variables

3.2.1. Outcomes Measures

We use three different measures to capture different aspects of the quality of the services a patient receives. The first measure is in-hospital mortality: $Outcome_{ikt}$ equals one if the patient died in the hospital after being admitted as a CABG patient, and zero otherwise. Mortality is a commonly used measure of the overall quality of a patient's experience when death in not so rare an occurrence as to make it unusable, as is the case here. However, this measure is limited to capturing only the most extreme outcome, and only during the length of a patient's stay.

Therefore, we also estimate equation (3) using an outcome variable based on readmission conditions that are frequently associated with readmission following the patient's CABG surgery.[10] The readmission variable is equal to one if a CABG patient was readmitted (to any hospital) for problems related to ischemic heart diseases within 12 months of their CABG, and zero if they were not. Since patients that died in the hospital when originally admitted are excluded from these estimations, the sample sizes for estimations with this outcome variable are slightly smaller.

Finally, we use the log of the total cost for each patient as a measure of the amount of resources used on the patient. The PHC4 data include the "total charge" for each patient, which is the sum of the list prices of all goods and services the hospital provided a patient during their stay, not including physicians' fees. However, the actual reimbursement received by the hospital for the patient's care differs from the list price and is unknown. As a more accurate measure of resource use, we calculate the total cost for each patient's treatment by multiplying the patient's total charge by the cost-to-charge ratio for the admitting hospital using the cost-to-charge ratios published by the Centers for Medicare & Medicaid Services (CMS) for individual Medicare providers each year.

3.2.2. Measuring Hospital Market Concentration

Our market concentration measures are based on a Herfindahl-Hirschman Index (HHI), which is calculated as the sum of squares of each provider's market share. Different approaches to defining hospital markets include using the hospitals in a fixed geographic radius around each hospital, or

[10] The conditions are those covered by ICD-9 codes 410 through 414 and consist of acute myocardial infarction, other acute and sub-acute forms of ischemic heart disease, old myocardial infarction, angina pectoris, and other forms of chronic ischemic heart disease.

identifying a geographic area using data on patient flows. However, because we are interested in evaluating the impact of hospital competition on individual patients' health outcomes, a key concern in measuring market concentration is its potential endogeneity. For example, using the variable radius method to define hospital markets means that our measure of competition would be based on patient flows of the hospital where a patient was admitted rather than reflecting the competition of the hospital market in which a patient lives. This approach may thus lead to correlation between competition and unobservable factors of a patient's health (Kessler and McClellan, 2000).

Consequently, we follow Kessler and McClellan (2000), Town and Vistnes (2001), and Gowrisankaran and Town (2003) and construct our HHI measure of competition using *predicted* rather than actual market shares. The predicted market shares are based on conditional logit estimations of the probability of patients choosing each hospital within a 75 mile radius of their home zip code.[11] The coefficients of the conditional choice model are then used to predict each hospital's share of the market from the point of view of a patient's zip code. Using the predicted demand for each hospital from each zip code, we then aggregate the zip code-level predicted HHI to the hospital level. Finally, we calculate the HHI for the hospital market faced by each patient using the weighted average of hospital-level HHIs, where the weights are the predicted hospital choices in patient's zip code of residence.

Essentially, the HHIs represent the number and availability of substitute hospitals from the patient's point of view, as identified from choices made by patients from that zip code: they represent the competitiveness of the hospital market that within which a zip code is located. As we include zip code fixed effects, the HHIs will vary if there are (1) changes in the sizes of hospital markets because of consolidation, entry, or exit; (2) changes in how patients trade off travel distance against other hospital characteristics; or (3) changes in the distribution of patient populations.

Our initial estimations suggested that the impact of concentration was nonlinear. Rather than using HHI and HHI-squared, which would obscure the marginal impact of concentration, we follow Kessler & McClellan (2000) and Kessler and Geppert (2005) and group zip codes into different categories of market competitiveness, with the categories based on the distribution of HHIs over our study period.

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[11]We estimate a patient's choice of hospital H as a function of arguably exogenous characteristics -- the extra distance an individual has to travel (beyond the closest hospital) to hospital H, and interactions between characteristics of hospital H and the patient's characteristics. See the appendix for details of the conditional logit specification as well as of the construction of the predicted HHI measures.

The dummy variable 'Most Competitive' equals one if the patient lives in a zip code in the most competitive hospital markets, where most competitive means in the lowest quartile of the predicted HHI measure. The dummy 'Competitive' equals one if the HHI for the patient's zip code lies in the second or third quartile of the HHI distribution. The base group is the most concentrated quartile of predicted HHIs.

3.2.3. Market and Patient Characteristics

M_{kt} is a vector of variables that represent different market characteristics: these variables are included to control for differences in outcomes across zip codes that might be related to the characteristics of the hospitals available to the patients in the zip code. As is the case with the HHI, these characteristics are based on the conditional logit that predicts hospital choices by patients in a zip code and thus represent the predicted characteristics for the hospital market of each zip code. They include: the predicted demand (expected number of patients from the zip code each year), the predicted market size (the total number of beds in the hospitals used by patients from a zip code, weighted by the predicted patient flow from the zip code), and predicted teaching status (the expected number of teaching hospitals in the zip code's hospital market).

P_{it} is a vector of our Medicare patient characteristics that are included to control for any effects of these characteristics on a patient's health outcome, independent of the degree of competition or of the characteristics of a hospital market, and of the availability of quality information. These variables are: age (patient is younger than 44 or patient is 45 to 65 years old, with older than 65 as the base group), gender (with female as the base group), ethnicity or race (Hispanic or African-American, with non-Hispanic white as the base group), distance to the closest CABG hospital (measured in miles between the centroids of the zip code of the patient and the zip code of the hospital), admission source (physician referral, transfer from a hospital, or transfer from a skilled nursing facility, where the base group is transfer from some other source such as a clinic or an ambulatory surgical center), and whether the admission was scheduled (as opposed to emergency). We also include a dummy to indicate whether the Medicare patient was an HMO enrollee.

Finally, we include dummy variables to control for variation in patients' health status when they arrive at the hospital. We first calculated a Charlson index, a measure of the likelihood the patient will die, for each patient, based on the patient's diagnosis codes at admission and for any hospital visits in the 12 months prior to admission. Values for the Charlson index range from zero (the patient is in relatively good health) to 16 (the patient is very severely ill). We then use our calculated index to create six dummies, one for each value of the Charlson index from zero to 5, and a final dummy to identify those patients that have a Charlson index that is greater than or equal to six.

Table 1 reports the descriptive statistics for the variables in our estimation over time and by market concentration. The top panel gives this information for the dependent variables: for the entire sample, in-hospital mortality fell from 3.3% in 1995, to 2.7% in 2000, and was still 2.7% in 2005. (The data for 2005 reflects observations for the first two quarters only.) By contrast, the readmission rate fell continually over the entire period from 20.2% in 1995 to 12.2% in 2005. The total charge, not reported, rose from $52,000 to $80,000 over the period, suggesting that hospitals increased expenditures on these patients significantly. However, after these figures are adjusted by the Medicare cost-to-charge ratio, we see a slight decrease in the total cost, indicating that the actual resource use did not increase for the sample as a whole.

Table 1 also shows the percentage of patients in each competitive category over the period: the figures indicate that over time the share of patients located in the most competitive and in the most concentrated hospital markets decreased: from 52% to 31% and from 20% to 13%, respectively. Table 2 reports more detailed information about the structure of the Pennsylvania CABG market. The first row shows that the number of Medicare CABG patients fell from 5877 in 1995 to 4839 in 2004: improved access to preventive care (such as beta-blockers and test for cholesterol level) has reduced the incidence of coronary artery disease and hence the need for CABG surgery (Arciero, et al., 2004). In addition, the introduction and diffusion of percutaneous coronary intervention (PCI) and stenting procedures have further reduced the demand for CABG among those those patients who do develop coronary artery disease (Ulrich, Brock, and Ziskind, 2003).

At the same time, the number of hospitals performing CABG increased from 37 in 1995 to 58 in 2005, with the most pronounced increase occurring during the years 1996 to 1998, when CON regulation in Pennsylvania was allowed to lapse. Hospitals have an incentive to enter the CABG market because the procedure is highly profitable under the Medicare reimbursement schedule, and because offering CABG improves a hospital's technology profile and thus attracts more patients who might come to it for other services in the future. The rapid growth of HMO market share during 1990s may have reinforced this latter incentive because selective-contracting managed care plans seem to value the presence of technology in making decisions about the network providers (Baker & Phipps, 2002). The new entrants improved access to CABG hospitals: table 2 shows that the mean and median distance the patients traveled to their admitting hospitals decreased over time.

These changes would suggest that the Pennsylvania CABG market has become less concentrated over time. However, the predicted HHIs show that while the average zip code-level concentration fell slightly during 1995 to 2000, it then began to rise again. Previous research has found evidence that in health care markets, entry may result in a redistribution of consumers (Cutler, et al., 2009). The data for the predicted HHIs suggest that new entry into the CABG market did cause some initial reduction in market concentration, but that eventually more patients shifted to higher-quality hospitals, making the market more concentrated (recall that the HHIs are based on a conditional logit of patients' choices).

As a check, however, we re-calculated our predicted HHI measures using two alternative radii: 50-mile and 100-mile. We also calculated more traditional measures of hospital-based HHIs based on three fixed radii around the hospital as well as on a variable radius around the hospital based on 95% patient flow. While the fixed-radius and variable-radius methods yield, respectively, higher and lower HHI levels than the conditional logit HHIs, all concentration measures reflect similar time trends over our study period.

3.3 Effects of Contemporaneous Events

Aside from the online release of report card grades, three changes occurring during our sample period may also have affected how hospitals responded to their competitive environment, and therefore patients' outcomes. We referred above both to the expiration of CON regulations and to changes in Health Maintenance Organization (HMO) penetration; in addition, Congress passed the Balanced Budget Act of 1997, which affect Medicare reimbursement rates. As part of our robustness analysis we add additional variables to control for the effect of these changes, as opposed to the effect of report cards, on hospital quality competition.

First, as described above, the Pennsylvania Legislature allowed CON regulation to lapse in December 1996, and the result was significant entry into the CABG market. Entry rates around the state varied: many of the new programs were started by hospitals located in the more densely populated areas of southeastern Pennsylvania, where there were a number of incumbent programs (see Figure 1 and Figure 2). As hospitals in markets with more entry are under greater competitive pressure, they will tend to provide more services and quality in equilibrium. To isolate the impact of new entry from the effect of the online report cards, we add to our specification a variable that is the share of CABG procedures in each county each year performed at hospitals that entered the CABG market after 1996.

Second, HMO penetration changed during our test period. We include whether our patients are HMO enrollees among the patient characteristics and thus control for any direct effects of HMO enrollment on our patients relative to non-HMO Medicare patients. However, the CABG hospitals in Pennsylvania also serve non-Medicare patients, some of them HMO enrollees. HMOs have been successful in negotiating lower prices, forcing providers to better contain their costs. Hospitals in high HMO penetration areas are thus more likely to be under greater financial pressure, which in turn limits their ability to adopt new technologies, hire more skilled nurses, or spend money on other quality-improving resources. To the extent that these resources are shared by all patients, HMO penetration could have a spillover effect on health outcomes of all non-HMO patients, including Medicare patients. We control this possible spillover effect by including the HMO penetration each year for the county containing the patient's zip code.

Finally, passage of the Balanced Budget Act (BBA) in 1997 may also have affected patient outcomes. The BBA imposed substantial reductions in Medicare payments to hospitals, and empirical research suggests that these reductions were particularly hard on those hospitals with a greater reliance on Medicare reimbursements (Wu, 2010). We control for possible effects of the cost-containment legislation by including the fraction of the admitting hospital's patients who are Medicare patients in the year that the patient is treated there.

4. Data and Sample

Our principal data set, collected by and obtained from the Pennsylvania Health Care Cost Containment Commission (PHC4), consists of all the inpatient claims from Pennsylvania hospitals for the years 1994 through the second quarter of 2006. Our study sample includes the records for all non-rural Pennsylvania residents[12] (aged 30 and above) who were covered by Medicare and who underwent an isolated CABG procedure (CABG surgery with no other major heart surgery during the same admission) in a Pennsylvania hospital that submitted at least five claims for CABG within a year.

[12] We dropped patients living in other states from the sample; this represented about 10% of the total number of patients.

Each inpatient record in the PHC4 data includes the patient's residential zip code, age, gender, ethnicity, race, payer type, admission status, diagnosis codes, and information on whether the patient died in the hospital. Patient identifiers allow us to link records for the same patient over time, and thus construct both our readmission variable, which is based on readmissions in the 12 months following CABG surgery, and our Charlson indices, which are based on diagnosis codes at admission and on in-patient records for a patient during the 12 months before their surgery. Since our Charlson index measures require information for the 12 months preceding a patient's admission, and our readmission outcome variable requires information from the 12 months following a patient's CABG surgery, our sample covers the years 1995 through the second quarter of 2005. Our final sample consists of 57,039 patients.

We use hospitals' cost-to-charge ratios from the *Medicare Cost Report* to convert hospital charges to our total cost outcome variable. We obtained hospital zip codes, bed size, and teaching status from the American Hospital Association's *Annual Survey of Hospitals*. We used the PHC4's CABG report cards to identify hospitals receiving above average, average, and below average mortality scores in the conditional logit estimation of individual demand for hospitals: the report card grade most recent to a patient's admission enters the demand equation as a quality characteristic of hospitals. We obtained HMO penetration rates in Pennsylvania counties from the Pennsylvania Department of Health.

5. Results

5.1. Basic Results

Our key results are reported on Table 3. Robust standard errors, clustered by patient zip code, are reported in brackets.[13] Each column shows the impact of the independent variables on a different outcome: total cost of a patient's CABG surgery, whether the patient died, and whether the patient was readmitted within a year after their CABG surgery for a related problem.

[13] We use generated variables as regressors and ideally should report standard errors that have been corrected for the additional variation introduced by generated variables, or, given the complicated construction of the variables based on the conditional logits, bootstrapped standard errors. We have made some preliminary efforts at bootstrapping the main regression, block bootstrapping our standard errors by patient zip codes and thus allowing for an arbitrary variance-covariance matrix within zip code areas across time (Bertrand, et al., 2004). Our results are not affected, possibly because we use the quartile dummies rather than the individual predicted HHI measures.

The first panel of independent variables indicates the impact of the characteristics of a patient's residential zip code on his or her outcomes. Inspection of the results for the first two variables, which show the effect of competition on outcomes before the CABG information was posted online, indicate that more competitive markets were not significantly more likely to spend more or to have better outcomes in this period. In fact, the one significant coefficient shows that patients from competitive zip codes had relatively less spent on them compared to patients from the most concentrated markets.

However, the coefficients for the next two variables, the competitive and most competitive markets indicators interacted with the post dummy, suggest that the nature of the competition changed in these markets after the CABG reports were published online. The estimates indicate that, compared to patients using hospitals in the most concentrated markets, patients in the most competitive and in competitive markets had significantly lower readmission rates and, in the case of competitive markets, significantly more resources expended on their cases. This pattern of results suggests that during this period the hospitals in less concentrated markets were competing along quality dimensions that directly affected the patients' health outcomes.

Aside from the predicted concentration, the predicted hospital size and the predicted teaching status for hospitals in a patient's zip code also affected the total cost; the larger the hospitals, the higher was total cost, while the greater the expected number of teaching hospitals, the lower the cost. Outcomes in markets with greater predicted demand did not differ significantly from markets with less.

The lower panel of independent variables show the estimated coefficients for all patient characteristics included to control for patient heterogeneity. Patient characteristics variables affected both cost and health outcomes: costs were higher for the oldest patients, female patients, Hispanic and black patients, emergency admissions, more the more severely ill patients, and patients whose closest hospital was further away from their home. Costs were lower for patients referred by a physician or transferred from another facility, and for HMO enrollees.

As for the two health outcomes, the oldest and more severely ill patients, as well as those transferred from other facilities, tended to have worse outcomes, while those that were referred by a physician or who were HMO enrollees tended to have better outcomes. Finally, note that our results show that HMO enrollees had better health outcomes at a lower cost. Therefore, our results indicate that, even after controlling for the possible effect of HMO membership, online information significantly affects total cost and health outcomes in less concentrated markets.

5.2. Contemporaneous Influences

We test the robustness of our results by adding variables to control for the effects of contemporaneous changes that may otherwise be driving our results. As discussed above, HMO penetration was increasing, there was new entry into the CABG market due to the end of CON regulation, and Congress passed the Balanced Budget Act during the years of our analysis. We include three variables: the HMO penetration rate at the county level, the market share held by new entrants to the CABG market, and the share of patients covered by Medicare at the admitting hospital, to capture the effects of these changes on patients' total costs and health outcomes.

We report our results on Table 4. The HMO penetration rate is associated with lower costs but no significantly different health outcomes, suggesting that, after controlling for the direct effect of HMO enrollment on a patient's outcome, HMO penetration had a spillover effect of reducing costs for our sample of Medicare patients but did not further affect health outcomes. We also find that patients treated in hospitals where higher market shares were held by new entrants had both lower costs and lower readmission rates. This suggests that markets with greater entry competed in quality, as suggested by the theory, but were unable to pass the cost of those changes onto patients, compared to areas with fewer new entrants. Finally, we see that Medicare patients treated in hospitals that had higher shares of Medicare patients experienced both higher costs and higher readmission rates compared to those treated in hospitals that had fewer Medicare patients.

Most important, however, we find that the inclusion of these variables strengthens our results on the effect of improved quality information. We continue to find significantly lower readmission rates in less concentrated hospital markets, and, with the additional control variables are included, we find that hospital costs are significantly higher in both most competitive and competitive hospital markets after the quality information is posted online. All the additional estimations we report below include these three variables.

As an additional test of the robustness of our results, we re-estimated our three outcomes equations including variables to control for pre-existing trends or mean reversion (Finkelstein, 2007). We examine the possible effect of pre-existing trends by adding two variables, interactions of each of the competition variables with a year dummy for 1997, the year before the CABG information went online. Including these two variables, which capture the average difference in outcomes in 1997 compared to those in 1995 and 1996, ceteris paribus, insures that the outcome results we find for the

1998-2005 period are not the continuation of a pre-existing trend. Examination of columns (1), (3), and (5) on Table 5 indicates that our results are not affected by the inclusion of these variables: during the period when CABG grades were available online, costs in more competitive markets were higher and readmission rates were lower.

Finally, we test for the possible effects of mean reversion by re-estimating our specifications with a set of year dummies interacted with the mean value of the relevant dependent variable in each zip code in 1995. Mean reversion could affect our results if, for example, total cost was unusually low in competitive markets in 1995: subsequent changes in its value might merely represent reversion to its mean. However, examination of columns (2), (4), and (6) of Table 5, which include these additional 20 controls in each outcomes estimation (estimated coefficients are not reported), indicates that the effect of competition in the post period continues to suggest that hospitals in the most competitive and in competitive markets increased spending and improved health outcomes for CABG patients relative to those in concentrated markets.

5.3. Quality Competition and Patient Severity

On Table 6 we examine whether the effects we have identified vary by patient severity: Kessler and Geppert (2005), for example, found that hospital competition affected the resources used to treat different types of patients. We separate our patient sample into low, medium, and high risk based on their Charlson scores: patients with a Charlson index of 0 are in the low risk group (about 18%), the patients with a Charlson index of 1 are medium risk (about 30%), and patients with a Charlson score of 2 or more are in the high risk group (about 52%).

In panel A we report the results of estimating our model for each of these three risk groups. As before, our estimates suggest that before quality information was available hospitals in competitive markets spent significantly less on CABG cases of all severity levels, and that morality rates may have been higher in less concentrated markets for some patients. Again, publication of quality information online is associated with increased expenditure and better health outcomes, but our results show that while expenditures increased across all risk categories, improvements in health outcomes were confined to the high risk patients.

In panel B we check to see if selection is affecting our results by estimating the effect of competition before and after the CABG grades were posted on the patient's severity score. There is no evidence that the competitiveness of hospital markets is significantly associated with patient risk, suggesting either that there is no selection or more likely that predicted HHI scores do provide exogenous measures of market concentration. In either case, our results on the effect of competition on health outcomes do not appear to be caused by these hospitals choosing to operate on healthier patients.

5.4. Competition, Quality Information, and Choice of Hospital & Surgeon

Our results suggest that patients living in zip codes with more hospital competition have better health outcomes after quality information becomes available online. The estimations on Table 6 indicate that this is unlikely to be a result of hospitals selecting healthier patients. Instead, it is possible that better outcomes occur because patients in more competitive markets are selecting better quality hospitals and surgeons, one of desired goals of publishing report cards.

We investigate this possibility first by estimating the probabilities of patients selected higher quality hospitals as a function of hospital market concentration before and after the CABG grade information was released, as well as the other independent variables in our outcomes specification. As noted above, although PHC4 grades did not go online until 1998, they were published during the entire period of our sample. Therefore, we use a hospital's most recent grade as a measure of its quality: the dependent variable is 1 if the patient had their surgery at a hospital whose most recent report card grade was above average, and 0 if the patient went to a hospital with an average, below average, or no grade reported (meaning that fewer than 30 CABG surgeries occurred at the hospital).

We report our results in Panel A of Table 7. The estimated coefficients show that the availability of online information significantly increased the probability that patients were admitted to higher quality hospitals if they lived in less concentrated hospital markets. Examination of hospital choice for each risk group indicates that the result does not appear to be driven by the choices of high risk patients: patients of all risk categories were more likely to have their surgery in higher quality hospitals once the CABG grades went online.

One interpretation of this result is that patients become aware of the grades once they are published online, and use them to make better choices about which hospital to use. However, we further investigated the role of the patients in this sorting process by examining the probability that a patient would use a higher quality surgeon after the CABG grades went online. This is an interesting exercise because, although the PHC4 CABG report cards also include grades for CABG surgeons, those grades have little variation: almost all surgeons are in the average category. Therefore, instead of using the report cards to identify high quality surgeons, we used patient data from 1995 to 1998, before the report cards went online, to "grade" the surgeons ourselves,[14] and identified the surgeons with grades among the top 10% and those with grades in the top 40%. We then estimated the probability that patients would use a high quality surgeon, even though they themselves did not have the information to distinguish the top 10 or 40% surgeons.

Our results are reported in Panels B and C of Table 7, where we see that after the CABG information went online, patients living in more competitive hospital markets were more likely to use higher quality surgeons. The results are much stronger when we look at the probability of choosing a surgeon among the top 40%, and appear to be mostly the result of the choices of patients in the low and medium risk categories. Since patients did not have the information that would allow them to identify the top 10 and 40% surgeons, these results must be driven by the sensitivity of other actors, whether hospitals or the surgeons themselves, to the public availability of CABG grades.

6. Discussion

Our principal goal is to study a price-regulated market of Medicare patients to see whether online publication of report cards causes hospitals in more competitive markets to provide higher quality services and thereby generate better health outcomes. Our findings suggest that the availability of quality information online for a specific procedure, CABG, resulted in lower readmission rates in less concentrated hospital markets: in essence, the information availability encouraged quality competition in these markets. Although we cannot make an overall welfare assessment without comparing the benefits of reduced readmission rates to the increase in total costs, this type of quality competition, rather than competition on the basis of technology or amenities, seems more likely to be desirable from a taxpayer point of view. Mortality rates, on the other hand, seemed largely unaffected by market characteristics: in general we found that it is individual patient characteristics that determine the probability of a patient's death.

The average HHI for the Most Competitive zip codes was 1827, while the average HHI in the Competitive zip codes, where we consistently found our strongest results, was 4429. Since the HHI measure is sensitive to both the number and the size distribution of the firms, it is difficult to relate these numbers to a particular industry structure. However, an HHI of 1827 lies between the HHIs for

[14] We used a method similar to that which underlies the PHC4 grades, based on actual versus expected mortality.

markets with five and six equally-sized firms, and an HHI of 4429 lies between the HHIs for two and three equally-sized firms, suggesting that the number of hospitals necessary to create competition is not large, consistent with previous empirical research on manufacturing and local service markets (Kwoka, 1979; Bresnahan & Reiss, 1991). The most concentrated hospital markets, where health outcomes were worst, had an average HHI of 7744, which lies between the HHI for two equally-size hospitals and one hospital.

Virtually all of the hospitals in our sample are private not-for-profit (NFP), so there is little scope to test for any differential effects related to owner-type. Instead, our results imply that the NFPs responded to competitive pressures similarly to what would be expected of profit-maximizing firms, or at least firms with a profit goal in their objective function, as predicted in Gaynor (2006).

We restricted our sample to patients from nonrural counties, as defined by the Census Bureau, which caused us to exclude about 18,000 patients, roughly 22.5% of the sample. Excluding rural patients insured that the patients in our sample were more similar; almost all rural patients must travel greater distances to reach any hospital providing CABG (as virtually all such hospitals are located in nonrural areas). Given that the predicted HHIs depend on some initial assumption of a fixed radius, there is a degree of arbitrariness that might have affected our measures of market concentration for these zip codes. However, we did re-estimate our specification including these patients, and found that our basic result, the availability of online information increased expenditures and improved health outcomes in less concentrated markets, still held.

Finally, our results about the association of online quality information with changes in patients' selection of hospitals and surgeons suggests that better health outcomes are being achieved at least in part because patients are using better hospitals and surgeons. However, we do not think that this is the result, at least during our sample period, of patients themselves using the information. While people were increasingly likely to have online access during these years, using the web was still rather new and unusual for many people, particularly older people. Further, a quick search of Pennsylvanian newspapers for 1998 found only two stories in May that mentioned (at the end of the article) that the PHC4 report cards were available online. While people may have learned about this from other media sources such as TV or radio, the lack of newspaper coverage suggests that the story of report cards going online did not make a big impact on the general public.

However, we know that cardiologists and surgeons in Pennsylvania were aware of the report cards (Schneider and Epstein, 1996), and certainly hospitals care about this type of publicity. It seems likely that the diversion of patients toward better hospitals and better surgeons may have been the result of hospitals, particularly those in more competitive areas, acting to control or retrain lower quality surgeons,[15] of lower-quality surgeons themselves choosing to avoid higher risk patients, and/or of cardiologists using the information to make better recommendations. Since these responses by providers to the availability of report cards would serve to steer patients toward better hospitals and surgeons, the improved health outcomes that we found may be explained.

7. Conclusion

This paper investigates the effect of online availability of CABG report cards on hospital competition by examining changes in total cost and health outcomes of Medicare beneficiaries who had a CABG operation in Pennsylvania during the period 1995-2004. Our results indicate that costs were higher, readmission rates lower, and in-hospital mortality rates unaffected for non-rural Medicare patients treated in hospitals located in competitive and most competitive hospital markets after the report cards went online. These results suggest that hospitals were more likely to compete along dimensions directly related to health outcomes once information about those outcomes became available to patients.

[15] See, for example, Chassin, 2002.

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Table 1. Descriptive Statistics for CABG Medicare Beneficiaries in Pennsylvania during 1995 - 2005[a]

	By Admission Year			By Predicted HHI		
	1995	2000	2005	Low	Median	High
Patient Outcome Variables						
Death	0.033	0.027	0.027	0.031	0.025	0.029
1-Year readmission	0.202	0.184	0.122	0.182	0.153	0.241
Total costs	24359	21402	21798	28124	21980	21987
	[11199]	[11501]	[10673]	[75125]	[21562]	[10925]
Predicted HHIs						
Most Competitive (HHI in lowest quartile)	0.517	0.436	0.306	1	0	0
Competitive (HHI in second and third quartiles)	0.287	0.471	0.566	0	1	0
Concentrated (HHI in highest quartile)	0.196	0.093	0.129	0	0	1
Predicted Zip Code-Level Market Characteristics						
Predicted demand (number of patients)	21.531	20.054	12.501	19.709	17.652	17.888
	[4.564]	[4.337]	[2.93]	[3.568]	[5.157]	[5.709]
Predicted market size (number of beds)	542.787	642.578	925.557	755.803	698.536	333.81
	[189.562]	[278.631]	[536.724]	[286.776]	[372.14]	[115.794]
Predicted number of teaching hospitals	0.897	1.095	1.465	1.233	1.152	0.524
	[0.465]	[0.566]	[0.986]	[0.612]	[0.705]	[0.216]
Patient Characteristics						
Age below 44	0.003	0.002	0.003	0.003	0.002	0.002
Age between 45 and 64	0.046	0.048	0.061	0.045	0.058	0.053
Male	0.642	0.636	0.652	0.633	0.632	0.636
Hispanic	0.002	0.003	0.01	0.006	0.008	0.004
Black	0.017	0.019	0.025	0.036	0.01	0.018
Distance to the closest hospital	8.961	7.505	7.164	6.623	8.228	9.201
	[7.689]	[7.03]	[7.125]	[5.968]	[7.648]	[8.592]
Referred by a physician	0.543	0.563	0.588	0.57	0.552	0.608
Transferred from another hospital	0.244	0.152	0.113	0.218	0.134	0.113
Transferred from another nursing home	0.039	0.055	0.025	0.055	0.029	0.029
Emergency admission	0.418	0.39	0.343	0.403	0.363	0.373
HMO enrollee	0.001	0.302	0.289	0.238	0.163	0.099
Charlson index=0	0.18	0.188	0.178	0.175	0.187	0.188
Charlson index=1	0.302	0.305	0.295	0.293	0.304	0.307
Charlson index=2	0.246	0.244	0.237	0.242	0.24	0.254
Charlson index=3	0.144	0.139	0.156	0.148	0.146	0.139
Charlson index=4	0.067	0.067	0.078	0.075	0.07	0.061
Charlson index=5	0.032	0.034	0.029	0.036	0.029	0.028
Charlson index>=6	0.029	0.024	0.026	0.03	0.025	0.024
Contemporaneous Change Variables						

HMO penetration (County level)	30.586	45.805	39.494	49.661	38.4	28.299
	[10.069]	[14.716]	[9.565]	[9.592]	[12.132]	[7.127]
New entrants share (County level)	0	0.124	0.282	0.153	0.123	0.027
	[0]	[0.121]	[0.207]	[0.194]	[0.146]	[0.074]
Percent Medicare patient share (Hospital level)	0.409	0.437	0.462	0.438	0.431	0.388
	[0.078]	[0.071]	[0.077]	[0.086]	[0.075]	[0.066]
Hospital Characteristics Used in Conditional Logit						
Hospital Beds 200 to 400	0.256	0.328	0.47	0.296	0.375	0.168
Hospital Beds above 400	0.717	0.616	0.461	0.648	0.564	0.758
Teaching Hospital	0.847	0.806	0.646	0.835	0.724	0.784
Non-for-profit Hospital	1	1	0.983	0.998	0.994	1
High grade	0.15	0.117	0.067	0.087	0.101	0.084
Average grade	0.658	0.705	0.856	0.762	0.73	0.747
Low grade	0.137	0.023	0.073	0.04	0.059	0.145
Observations	5877	6078	2241	24651	28339	6978

[a] Our sample covers the years 1995 through the second quarter of 2005. The sample size is 57,039 patients. Standard deviations for continuous variables are reported in brackets.

Table 2. Measure of Pennsylvania CABG Market Concentration for Medicare Beneficiaries during 1995-2005[a]

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Number of patients	5877	6150	6237	5771	5874	6078	5935	5539	5427	4839	2241
Number of hospitals	37	38	46	47	49	51	55	57	63	61	58
Mean distance to hospitals	11.895	11.669	11.292	10.658	10.727	10.468	10.382	9.982	9.673	9.791	9.842
	[10.448]	[10.392]	[10.319]	[9.849]	[10.185]	[9.862]	[9.644]	[9.463]	[9.165]	[9.307]	[9.439]
Median distance to hospital of admission	8.394	8.502	7.677	7.274	7.212	7.206	7.261	7.107	6.743	6.844	6.891
Predicted HHI											
50-mile radius	0.369	0.369	0.382	0.369	0.362	0.344	0.351	0.36	0.375	0.364	0.404
75-mile radius	0.338	0.34	0.345	0.321	0.326	0.307	0.315	0.323	0.342	0.328	0.364
100-mile radius	0.317	0.315	0.32	0.302	0.307	0.292	0.303	0.306	0.333	0.312	0.348
Fixed radius HHI											
50-mile radius	0.568	0.565	0.57	0.572	0.572	0.546	0.568	0.578	0.573	0.587	0.62
75-mile radius	0.567	0.56	0.56	0.566	0.568	0.539	0.556	0.569	0.566	0.578	0.61
100-mile radius	0.562	0.556	0.555	0.562	0.566	0.534	0.553	0.566	0.562	0.574	0.608
Variable radius HHI											
95% patient flow	0.254	0.238	0.253	0.267	0.222	0.249	0.252	0.253	0.259	0.271	0.283

[a] Our sample covers the years 1995 through the second quarter of 2005. The sample size is 57,039 patients. Standard deviations for continuous variables are reported in brackets.

Table 3. Impact of Competition on Patient Outcomes[a]

	Log of Total Cost	Mortality	Readmission
	(1)	(2)	(3)
Zip Code Market Characteristics			
Most competitive*post	0.0262	0.0029	-0.0401**
	[0.0239]	[0.0052]	[0.0188]
Competitive*post	0.1243***	-0.0038	-0.0353*
	[0.0245]	[0.0055]	[0.0185]
Most competitive	0.0038	0.0075	0.0324
	[0.0404]	[0.0059]	[0.0227]
Competitive	-0.1330***	0.0062	0.0091
	[0.0389]	[0.0053]	[0.0185]
Predicted demand	-0.0015	-0.0004	0.0001
	[0.0025]	[0.0004]	[0.0010]
Predicted bed size	0.0005***	-0.0000	-0.0000
	[0.0001]	[0.0000]	[0.0000]
Predicted teaching status	-0.2191***	-0.0004	-0.0279
	[0.0634]	[0.0103]	[0.0253]
Patient Characteristics			
Age<44	-0.0065	0.0064	0.0384
	[0.0296]	[0.0142]	[0.0327]
Age between 45 and 64	-0.0331***	-0.0109***	0.0150**
	[0.0085]	[0.0026]	[0.0070]
Male	-0.0357***	-0.0141***	-0.0352***
	[0.0038]	[0.0015]	[0.0035]
Hispanic	0.0599**	-0.0189***	0.0020
	[0.0255]	[0.0049]	[0.0188]
Black	0.0255	-0.0030	-0.0033
	[0.0203]	[0.0059]	[0.0124]
Emergency admission	0.1083***	0.0030	-0.0435***
	[0.0070]	[0.0019]	[0.0053]
HMO enrollee	-0.0264***	-0.0006	-0.0283***
	[0.0055]	[0.0018]	[0.0044]
Distance to the closest hospital	0.0060**	-0.0002	0.0019*
	[0.0027]	[0.0004]	[0.0010]
Referred by a physician	-0.1423***	-0.0077***	-0.0162***
	[0.0082]	[0.0023]	[0.0053]
Transferred from another hospital	-0.0598***	0.0068**	0.2802***
	[0.0104]	[0.0031]	[0.0121]
Transferred from another nursing home	-0.1357***	-0.0030	0.1840***
	[0.0172]	[0.0041]	[0.0216]
Severity 1	0.0626***	0.0066***	0.0281***

	[0.0050]	[0.0016]	[0.0041]
Severity 2	0.1288***	0.0158***	0.0561***
	[0.0053]	[0.0019]	[0.0047]
Severity 3	0.1865***	0.0218***	0.0747***
	[0.0063]	[0.0025]	[0.0056]
Severity 4	0.2348***	0.0305***	0.0944***
	[0.0086]	[0.0038]	[0.0075]
Severity 5	0.2607***	0.0269***	0.1191***
	[0.0111]	[0.0055]	[0.0111]
Severity 6	0.2788***	0.0177***	0.1088***
	[0.0126]	[0.0045]	[0.0111]
Observations	57039	57039	55430

[a] T-ratios, reported in brackets, are computed from standard errors that adjust for clustering at the zip code level. All regressions include year and zip code fixed effects. *** Significant at the 1 percent level (two-tailed test). ** Significant at the 5 percent level (two-tailed test). * Significant at the 10 percent level (two-tailed test).

Table 4. Estimations add HMO Penetration Rate, Market Share of New Entrants, and Admitting Hospital's Dependence on Medicare Patients[a]

Dependent Variable:	**Log of Total Cost**				**In-hospital Mortality**				**1-Year Readmission**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Most competitive*post	0.0262	0.0298	0.0648**	0.0682***	0.0029	0.0037	0.0034	0.0034	-0.0401**	-0.0412**	-0.0347*	-0.0336*
	[0.0239]	[0.0250]	[0.0254]	[0.0252]	[0.0052]	[0.0052]	[0.0053]	[0.0053]	[0.0188]	[0.0187]	[0.0186]	[0.0185]
Competitive*post	0.1243***	0.1290***	0.1324***	0.1336***	-0.0038	-0.0028	-0.0028	-0.0028	-0.0353*	-0.0367**	-0.0361*	-0.0357*
	[0.0245]	[0.0249]	[0.0238]	[0.0238]	[0.0055]	[0.0055]	[0.0055]	[0.0055]	[0.0185]	[0.0185]	[0.0185]	[0.0184]
Most competitive	0.0038	0.0029	-0.0024	0.0006	0.0075	0.0073	0.0074	0.0074	0.0324	0.0327	0.0317	0.0328
	[0.0404]	[0.0404]	[0.0391]	[0.0390]	[0.0059]	[0.0059]	[0.0059]	[0.0059]	[0.0227]	[0.0226]	[0.0224]	[0.0221]
Competitive	-0.1330***	-0.1328***	-0.1149***	-0.1128***	0.0062	0.0063	0.0061	0.0062	0.0091	0.0091	0.0124	0.0132
	[0.0389]	[0.0387]	[0.0370]	[0.0369]	[0.0053]	[0.0053]	[0.0054]	[0.0054]	[0.0185]	[0.0185]	[0.0186]	[0.0183]
HMO Penetration rate		-0.0009	-0.0019*	-0.0019**		-0.0002	-0.0002	-0.0002		0.0003	0.0001	0.0001
		[0.0010]	[0.0010]	[0.0010]		[0.0002]	[0.0002]	[0.0002]		[0.0005]	[0.0005]	[0.0005]
Share of new entrants			-0.3145***	-0.3374***			0.0022	0.0020			-0.0581**	-0.0660**
			[0.0464]	[0.0469]			[0.0084]	[0.0084]			[0.0282]	[0.0279]
% Medicare patients				0.3637***				0.0030				0.1281***
				[0.0738]				[0.0121]				[0.0387]
Observations	57039	57039	57039	57039	57039	57039	57039	57039	55430	55430	55430	55430

[a] T-ratios, reported in brackets, are computed from standard errors that adjust for clustering at the zip code level. All regressions include variables listed in Table 3 and year and zip code fixed effects. *** Significant at the 1 percent level (two-tailed test). ** Significant at the 5 percent level (two-tailed test). * Significant at the 10 percent level (two-tailed test).

Table 5. Estimations include Controls for Pre-existing Trends or for Mean Reversion[a]

Dependent Variable:	Log of Total Cost		In-hospital Mortality		1-Year Readmission	
	Add Competition Dummies×D_{1997} (1)	Add Year Dummies×Y_{1995}[b] (2)	Add Competition Dummies×D_{1997} (3)	Add Year Dummies×Y_{1995}[b] (4)	Add Competition Dummies×D_{1997} (5)	Add Year Dummies×Y_{1995}[b] (6)
Most competitive*post	0.0565**	0.0846***	0.0002	0.0029	-0.0262	-0.0379**
	[0.0268]	[0.0240]	[0.0062]	[0.0048]	[0.0203]	[0.0151]
Competitive*post	0.0729***	0.1014***	-0.0054	-0.0025	-0.0421**	-0.0445***
	[0.0260]	[0.0212]	[0.0066]	[0.0050]	[0.0206]	[0.0155]
Most competitive	0.0103	0.0146	0.0104	0.0068	0.0259	0.0408**
	[0.0371]	[0.0297]	[0.0064]	[0.0051]	[0.0231]	[0.0176]
Competitive	-0.0546	-0.0713***	0.0084	0.0059	0.0200	0.0400***
	[0.0357]	[0.0255]	[0.0061]	[0.0049]	[0.0203]	[0.0146]
Most competitive*D_{1997}	-0.0307		-0.0092		0.0217	
	[0.0371]		[0.0076]		[0.0201]	
Competitive*D_{1997}	-0.1559***		-0.0072		-0.0146	
	[0.0352]		[0.0079]		[0.0210]	
Observations	57039	56309	57039	56309	55430	54701

[a] T-ratios, reported in brackets, are computed from standard errors that adjust for clustering at the zip code level. All regressions include variables listed in Table 3, HMO penetration rate, share of new entrants, percent of Medicare patients and year and zip code fixed effects. *** Significant at the 1 percent level (two-tailed test). ** Significant at the 5 percent level (two-tailed test). * Significant at the 10 percent level (two-tailed test).

[b] Y_{1995} represents the mean value of the relevant outcome variable, by zip code, in 1995.

Table 6. Competition and Patient Severity[a]

Panel A: The impact of competition on patient outcomes, by risk groups

	Low Risk Patients			**Median Risk Patients**			**High Risk Patients**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log of Total Cost	**Mortality**	**Readmission**	**Log of Total Cost**	**Mortality**	**Readmission**	**Log of Total Cost**	**Mortality**	**Readmission**
Most competitive*post	0.1123***	0.0058	-0.0287	0.0618**	0.0071	-0.0173	0.0503	-0.0077	-0.0898***
	[0.0382]	[0.0096]	[0.0234]	[0.0250]	[0.0074]	[0.0237]	[0.0388]	[0.0128]	[0.0307]
Competitive*post	0.1599***	-0.0042	-0.0354	0.1258***	-0.0063	-0.0196	0.1228***	-0.0017	-0.0889***
	[0.0379]	[0.0100]	[0.0226]	[0.0238]	[0.0072]	[0.0234]	[0.0372]	[0.0138]	[0.0317]
Most competitive	-0.0250	0.0056	-0.0031	0.0032	-0.0010	0.0307	-0.0195	0.0272**	0.0564
	[0.0439]	[0.0103]	[0.0356]	[0.0422]	[0.0079]	[0.0258]	[0.0528]	[0.0128]	[0.0372]
Competitive	-0.1301***	0.0168*	0.0039	-0.1112***	0.0036	0.0109	-0.1087**	0.0090	0.0408
	[0.0399]	[0.0094]	[0.0258]	[0.0388]	[0.0064]	[0.0213]	[0.0481]	[0.0122]	[0.0329]
Observations	10396	10396	10251	30935	30935	30120	15708	15708	15059

Panel B: The Impact of Competition on Patient Severity

	Patient Charlson Index
Most competitive*post	-0.0727
	[0.0488]
Competitive*post	-0.0377
	[0.0519]
Most competitive	-0.0095
	[0.0568]
Competitive	-0.0005
	[0.0443]
Observations	57039

[a] T-ratios, reported in brackets, are computed from standard errors that adjust for clustering at the zip code level. All regressions include variables listed in Table 3, HMO penetration rate, share of new entrants, percent of Medicare patients and year and zip code fixed effects. *** Significant at the 1 percent level (two-tailed test). ** Significant at the 5 percent level (two-tailed test). * Significant at the 10 percent level (two-tailed test).

Table 7. Impact of Competition on Hospital & Surgeon Choices[a]

Panel A: Dependent Variable=1 if patient goes to a high-quality hospital

	Whole Sample	**Low Risk**	**Medium Risk**	**High Risk**
Most competitive*post	0.0764**	0.0529	0.0938***	0.0556
	[0.0338]	[0.0356]	[0.0352]	[0.0373]
Competitive*post	0.1594***	0.1332***	0.1825***	0.1252***
	[0.0359]	[0.0391]	[0.0376]	[0.0386]
Most competitive	-0.0199	-0.0141	-0.0406	0.0145
	[0.0414]	[0.0478]	[0.0445]	[0.0434]
Competitive	-0.0981**	-0.0760*	-0.1141***	-0.0744*
	[0.0398]	[0.0410]	[0.0427]	[0.0416]
Observations	57039	10396	30935	15708

Panel B: Dependent Variable=1 if Patient's surgeon is among top 10% in quality

	Whole Sample	**Low Risk**	**Medium Risk**	**High Risk**
Most competitive*post	0.0227	0.0413*	0.0134	0.0266
	[0.0141]	[0.0228]	[0.0155]	[0.0209]
Competitive*post	0.0009	0.0256	-0.0035	-0.0089
	[0.0131]	[0.0232]	[0.0155]	[0.0212]
Most competitive	-0.0663***	-0.0523	-0.0573**	-0.0944***
	[0.0253]	[0.0346]	[0.0273]	[0.0290]
Competitive	-0.0121	-0.0048	-0.0032	-0.0407*
	[0.0140]	[0.0223]	[0.0151]	[0.0221]
Observations	57039	10396	30935	15708

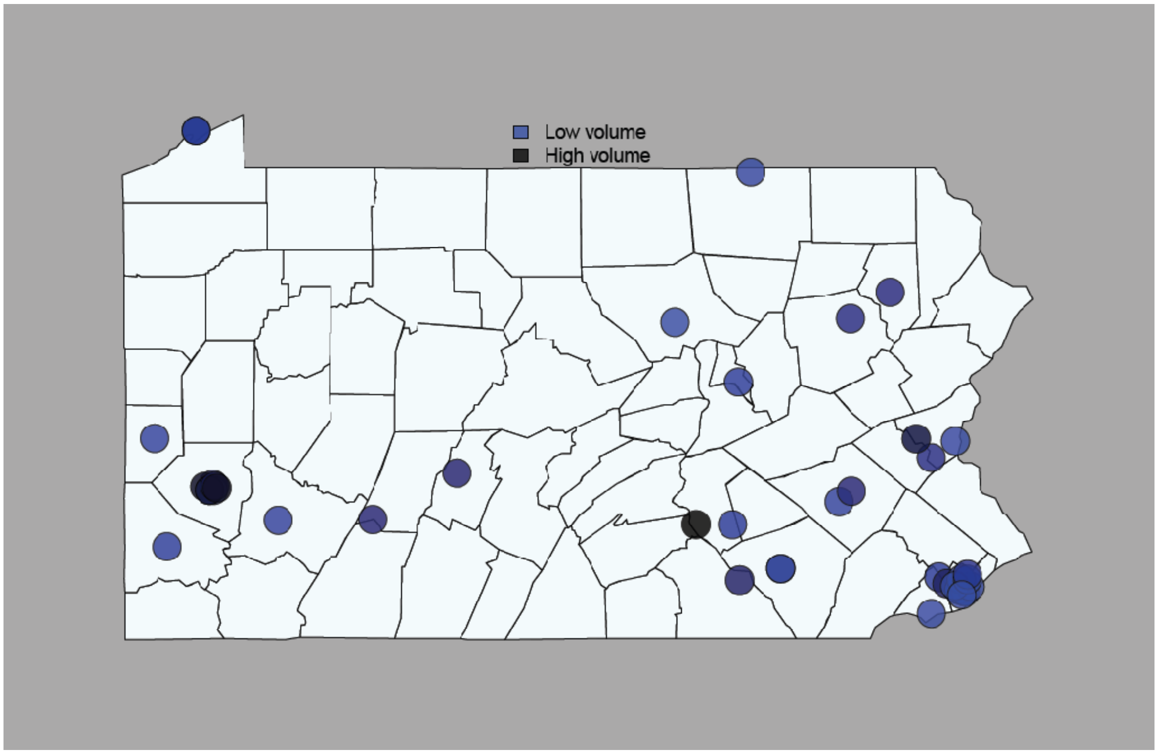
Panel C: Dependent Variable=1 if Patient's surgeon is among top 40% in quality

	Whole Sample	**Low Risk**	**Medium Risk**	**High Risk**
Most competitive*post	0.0595***	0.1019***	0.0624***	0.0259
	[0.0201]	[0.0336]	[0.0222]	[0.0290]
Competitive*post	0.0503**	0.1125***	0.0554**	0.0002
	[0.0207]	[0.0349]	[0.0239]	[0.0279]
Most competitive	-0.0763*	-0.0738	-0.0855*	-0.0519
	[0.0406]	[0.0545]	[0.0438]	[0.0504]
Competitive	-0.0048	0.0061	-0.0135	-0.0029
	[0.0266]	[0.0389]	[0.0283]	[0.0355]
Observations	57039	10396	30935	15708

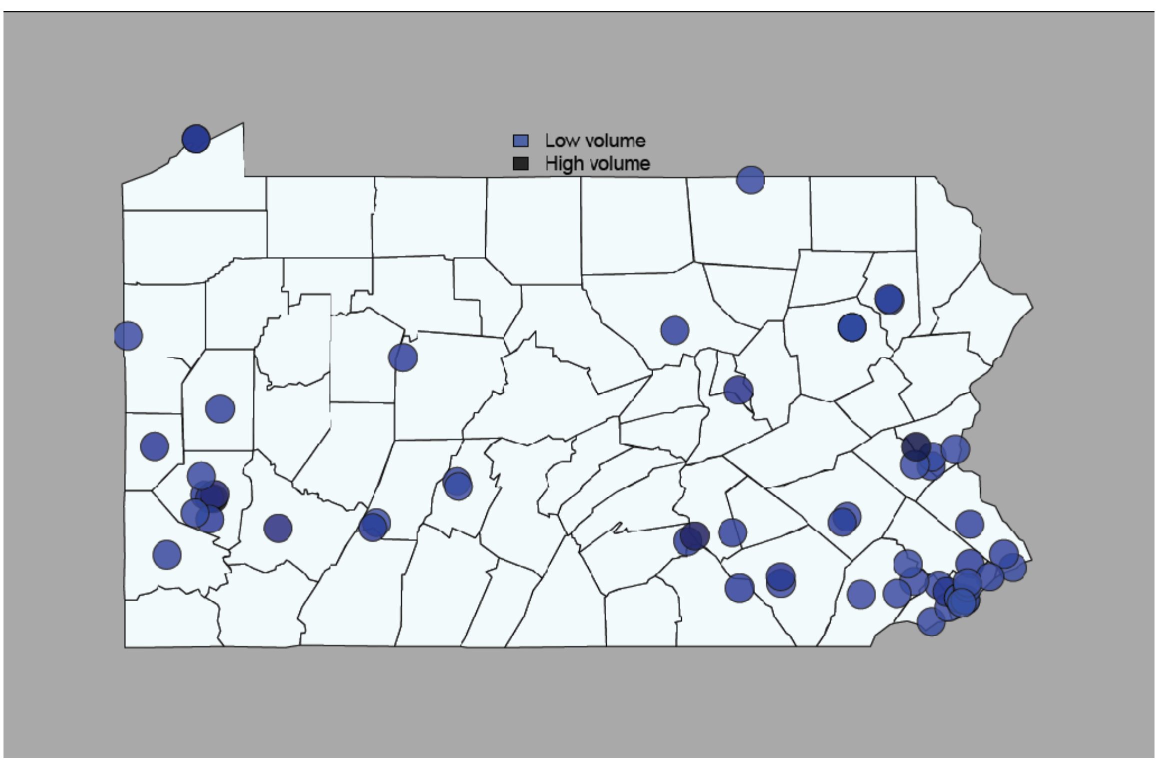
[a] T-ratios, reported in brackets, are computed from standard errors that adjust for clustering at the zip code level. All regressions include variables listed in Table 3, HMO penetration rate, share of new entrants, percent of Medicare patients and year and zip code fixed effects. *** Significant at the 1 percent level (two-tailed test). ** Significant at the 5 percent level (two-tailed test). * Significant at the 10 percent level (two-tailed test).

Figure 1 Geographic Illustration of Hospital Location in Pennsylvania in 1995 and 2004

1995



2004



Appendix: *Construction of Herfindahl-Hirschman Index using Conditional Logit Method*

There are three commonly-used approaches to defining hospital markets: basing them on a hospital's service area, using a fixed geographic radius around the hospital, or using a variable radius around the hospital. While no single measure of a hospital's market is ideal, the service area approach is most problematic, since market boundaries are defined subjectively, while the variable-radius method, which defines the market radius that contains 75% or 90% of a hospital's actual patient flows, is considered to be superior for most research questions.[16]

Nonetheless, the variable-radius method has weaknesses.[17] First, the identification of the radius is determined by actual patient choices and thus the market definition will be affected by unobservable hospital characteristics such as quality. For example, a large teaching hospital may draw patients from a very wide area because of the breadth or high quality of its services. Market measures based on the area from which the hospitals patients were drawn might suggest that the market was less concentrated that it actually is. Second, the actual patient flows used to identify a hospital's market will in fact be an outcome of the competitive process. Third, such a measure only allows for a hospital to be entirely contained in, or excluded from, a given geographic market, which eliminates different degrees of substitutability among hospitals that may be perceived by patients due to variations in location.

Finally, we are going to be interested in evaluating the impact of hospital competition on individual patients' health outcomes. Using the variable radius method to define hospital markets means that our measure of competition will be based on patient flows of the hospital where a patient was admitted, rather than reflecting the competition of the hospital market in which a patient lives. This approach may thus lead to correlation between competition and unobservable factors of a patient's health (Kessler and McClellan, 2000).

Consequently, we follow the approach found in Kessler and McClellan (2000), Town and Vistnes (2001), and Gowrisankaran and Town (2003), and construct HHIs using predicted rather than actual market shares. The predicted market shares are based on conditional logit estimations of the

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[16]See Phibbs and Robinson (1993) and Gresenz, Rogowski and Escarce (2004) for examples of papers using HHIs based on variable radii.

[17]Discussions of the advantages and disadvantages of alternative definitions of healthcare markets can be found in Dranove and White (1994), Baker (2001), and Wong, Zhan and Mutter (2005).

probability of individual patients choosing individual hospitals within a 75 mile radius of their home zip code.

A. Conditional Logit Model

We model each individual patient i choosing hospital j from J hospitals within 75 miles of their residence by maximizing an indirect utility function of the form

$$\boldsymbol{U_{ij} = V_{ij} + W_{ij} + \varepsilon_{ij}};$$

where V_{ij} and W_{ij}, the deterministic components of the utility function, are variables representing hospital and patient's characteristics. Let ε_{ij} denote patient i's unobserved preference for hospital j. We assume ε_{ij} follows the generalized extreme value distribution.

V_{ij} is a vector of variables included to measure differences among the hospitals in a patient's choice set with respect to travel distance and three other hospital characteristics: number of beds, most recent CABG report card grade, and whether it is a teaching hospital. We first identify the closest hospital j' to each patient's zip code: this is the reference hospital. Following Kessler and McClellan (2000), we then compare each other hospital j in the patient's choice set to the reference hospital. First, we calculate how much further a patient must travel to each hospital j beyond the reference hospital, as well as their difference in distance to patient i's home zipcode. ?? Second, we use dummy variables to identify whether each hospital j is the same (with respect to size, CABG grade, and teaching) or different from the reference hospital.

We then divide each hospital j's characteristic variables into two categories, same type and different type, based on whether the choice hospital j has the same characteristic as the reference hospital j', and also whether the choice hospital j has such a characteristic or not. We also group the relative distance variables, drawing boundaries at the twenty-fifth, fiftieth and seventy-fifth percentile of the distribution of the respective relative distances to create same/different-type quartile dummies. Finally we interact the same/different-type categories with same/different-type relative distance quartiles. Assuming a linear and additively separable function of such interactions between hospital characteristics and relative distance, we have

$$\boldsymbol{V_{ij} = \sum_{h=1}^{H} DD_{ij}^{h+}\left[\theta_1^h Z_{ij}^h + \theta_2^h\left(1 - Z_{ij}^h\right)\right] + DD_{ij}^{h-}\left[\theta_3^h Z_{ij}^h + \theta_4^h\left(1 - Z_{ij}^h\right)\right]};$$

where $\boldsymbol{DD_{ij}^{h+}}$ and $\boldsymbol{DD_{ij}^{h-}}$ are same/different-type relative distance quartiles, respectively, and $\boldsymbol{Z_{ij}^{h}}$ is a vector of dichotomized hospital characteristics including bed sizes (<200 beds, 200 beds to 400 beds, >400 beds), teaching status, as well as report card information (lower grade, rated the same, and higher grade). The vector [$\theta_1^h, \theta_2^h, \theta_3^h, \theta_4^h$] is the parameter of interest. A graphic description of the comparison scheme could be illustrated as follows:

Choice Hospital / Reference Hospital	j has same characteristic	j has different characteristic
Given j' has character $Z_{j\prime}^h = 1$	θ_1^h	θ_4^h
Given j' has character $Z_{j\prime}^h = 0$	θ_2^h	θ_3^h

In a conditional logit, we observe a single patient making a choice among hospitals with different characteristics: the individual patient's characteristics are obviously the same as they consider the different hospitals and cannot be entered as separate variables. However, we can include the possible effect of patients' characteristics on their choice of hospital by interacting them with different hospital characteristics. Thus, we also consider patient's average preferences on different hospital characteristics by interacting each patient's characteristics with hospital j's characteristics:

$$\boldsymbol{W_{ij}} = \sum_{\boldsymbol{h=1}}^{\boldsymbol{H}} \boldsymbol{X_i}\, \boldsymbol{Z_j^h} \boldsymbol{\beta_h}; \qquad (3)$$

X_i is a vector of patient i's characteristics (gender, ethnicity/race, admission type, admission source--referred by physicians, clinic or HMO, transferred from a different hospital, or transferred from a skilled nursing home or health care facility). Therefore, β_h controls for patients' average response or preferences to hospital j's characteristic h.

From McFadden (1978, 1981), assuming the generalized extreme value distribution implies that the conditional choice probability is given by:

$$\hat{\pi}_{ij} = \Pr\left(Y_{ij} = 1\right) = \frac{e^{\hat{V}_{ij} + \widehat{W}_{ij}}}{\sum_{j\in J} e^{\hat{V}_{ij} + \widehat{W}_{ij}}};$$

Then, we can estimate the vector θ and β by maximizing the log-likelihood function:

$$\log l = \sum_{i=1}^{N} \sum_{j=1}^{J} \log \hat{\pi}_{ij} \;\; ;$$

The patient samples are estimated year by year from 1995 to 2005 where we allow different effects of different years.

B.. Constructing HHIs

Given patients' indirect utility function maximized through the conditional logit model, we predict a patient's probability ($\hat{\pi}_{ij}$) of attending the hospitals. We construct the Herfindahl-Hirschman Index based on observable, exogenous characteristics of patients and hospitals as in Kessler and McClellan (2000). First, we calculate the market share of each hospital j in each zip code k area by summing the predicted patient flow for hospital j over all the market shares of hospitals in area k.

$$\alpha_{jk} = \frac{\sum_{i\epsilon k} \hat{\pi}_{ij}}{\sum_{j=1}^{J} \sum_{i\epsilon k} \hat{\pi}_{ij}};$$

Thus, if we assume that hospitals "are able to differentiate among patients based on their zip code of residence," then the predicted HHI for patients residing in zip code k is

$$HHI_k^{pat} = \sum_{j=1}^{J} \hat{\alpha}_{jk}^2 \, ;$$

However, it is more realistic to presume that hospitals compete over "the total demand for hospital services from all nearby areas." So we must measure the share of a hospital's predicted demand coming from a given zip code

$$HHI_j^{hosp} = \sum_{k=1}^{K} \hat{\beta}_{kj} * HHI_k^{pat};$$

where

$$\hat{\beta}_{kj} = \frac{\sum_{i\in k} \hat{\pi}_{ij}}{\sum_{i=1}^{N} \hat{\pi}_{ij}};$$

represents the share of hospital j's predicted demand coming from zip code k.

But ultimately, we use another measure as our HHI; one which is “based on the vector of average expected probabilities of hospital choice in the patient’s zip of residence.” We define it as follows

$$HHI_k^{pat^*} = \sum_{j=1}^{J} \hat{\alpha}_{jk} * HHI_j^{hosp};$$

Following this transformation of $\hat{\pi}_{ij}$, we obtain a competition metric that functions just like the more traditional HHI. $HHI_k^{pat^*}$ is bounded below by zero and above by one; additionally, $HHI_k^{pat^*}$ is decreasing in competition. Although this measure is significantly more empirically intensive than the standard fixed or variable radius indices, $HHI_k^{pat^*}$ is formulated through exogenous determinants of hospital demand, and thus not subject to the endogeneity with respect to hospital outcomes. In other words, changes in $HHI_k^{pat^*}$ originate from three sources: variations in the sizes of hospital markets – through openings, closures and mergers, changes in a potential patient’s decision to attend a hospital based off of distance, and changes in the distribution of patient populations.