The James A. Baker III Institute for Public Policy
Rice University

Vertical Integration of Hospitals:

Patient Steering or Integrated Delivery of Care?

by

Sayaka Nakamura, PhD

Sid Richardson Scholar in Health Economics
James A. Baker III Institute for Public Policy
Rice University

November 2006

Vertical Integration of Hospitals: Patient Steering or Integrated Delivery of Care?

Sayaka Nakamura*†

September 22, 2006

Abstract

When a tertiary care hospital acquires a non-tertiary care hospital, referrals from the target to the acquirer sometimes increase. This paper studies whether the increase is based on an effort to boost referrals to low quality hospitals (patient steering) or instead reflects quality improvement (integrated delivery of care). I develop a model in which reputation influences patients' preferences toward hospitals, so that a target hospital attaches greater importance to its patients' satisfaction when it faces greater competitive pressure. Based on this model, I estimate the referral choice for cardiac surgery. The results suggest that mergers of monopolistic targets and low or average quality acquirers lead to patient steering, while those of competitive targets and distinguished acquirers seem to be motivated by integrated delivery of care.

*Baker Institute for Public Policy, Rice University; Sayaka.Nakamura@rice.edu.

†This article is based on my thesis, and I am grateful to my adviser, David Dranove, and the other members of my dissertation committee, Robert Porter, William Rogerson, and Mark Satterthwaite. I also thank Vivian Ho as well as seminar participants at Aoyama Gakuin, Massey, Northwestern, Tokyo, Tsukuba, and Western Ontario for their helpful comments. I am indebted to Cory Capps who generously provided his codes for obtaining driving hours. All errors are my own.

1 Introduction

Since the 1990s, there have been many hospital merger cases in which a tertiary care hospital that provides specialized care (the acquirer) acquired a non-tertiary care hospital that does not offer such services (the target). Such mergers can be considered to be vertical rather than horizontal, similar to the integration of hospitals and physicians. Tertiary care hospitals and non-tertiary care hospitals provide complementary inputs for rural patients in need of specialized care. In addition, non-tertiary care hospitals are distribution centers of specialized care when they refer their patients to tertiary care hospitals.

Several media reports note that the acquisition of non-tertiary care hospitals could lead to increased referrals to the acquirer hospitals,[1] and two studies examine this hypothesis. Huckman (2006) reports that the acquirers experience an increase in cardiac surgery admissions from the target's primary market *on average*. On the other hand, Nakamura *et al.* (2006) find that in the majority of cases, there appears to be no change in referrals to the acquirers, although *some* acquisitions do lead to a large and significant increase in referrals.

This paper studies why some mergers are more successful in increasing referrals than others, and more importantly, whether the increase is based on an effort to boost referrals to low quality hospitals (patient steering) or instead reflects quality improvement. Increased referrals could increase the joint profit of the target and the acquirer, since a referral is always profitable as long as the payment exceeds the incremental cost of treating the patient. While the referral laws prohibit hospitals from paying physicians for the referrals, the laws exempt certain forms of payment between affiliated hospitals and between hospitals and their

[1] See, for example, Bernstein (1996) and Brown (2001).

employed physicians.[2] Thus, hospital acquisition could be used as a loophole for buying referrals. On the other hand, if the merger facilitated "integrated delivery of care" and achieved gains in quality of care and efficiency, then that would lead to an increase in referrals to the acquirers as well. Vertical merger might reduce transaction costs and make it easier for the hospitals to make joint investments in quality and cost reduction.[3] These hypotheses are related to more general questions, such as motives for hospitals to form vertical alliances and the effect of competition on the behavior of doctors and hospitals.

Analyzing referral patterns of non-tertiary care hospitals boils down to analyzing the referring physicians' behavior. Many researchers point out that physicians are imperfect agents for patients.[4] Given information asymmetry between physicians and patients, physicians behave similarly to perfect agents when they are altruistic or when the reputation mechanism works. Thus, comparing the referral patterns of physicians who are expected to be more considerate of patient welfare with those who are not, could help me identify which of the two motives is more important. If increasing referrals to the acquirers decreases patient welfare, then target hospitals that are not sensitive to reputation are more likely to do so. Conversely, if increased referrals to the acquirers result from the hospitals' effort to improve quality of care, then the increase in referrals would be larger when the target hospitals face more responsive demand.

I develop a model in which patients' preferences toward non-tertiary care hospitals are affected by the rating given by the prior users of the hospitals. The model predicts that the

[2] See Morrison *et al.* (2000), for example.

[3] Referrals might also increase if both the target and the acquirer have increased numbers of managed care contracts. Nevertheless, Nakamura *et al.* (2006) find increases in referrals for Medicare indemnity patients, which suggests there are other reasons.

[4] Folland *et al.* (2001) provides a literature review of this issue.

larger the responsiveness of demand to a rating for a non-tertiary care hospital, the greater weight the hospital places on patient welfare when choosing referral destinations. In other words, when the hospital market is more competitive and patients can avoid hospitals with a bad reputation more easily, hospitals behave more sensitively to patients' satisfaction.

Based on the model, I estimate a multinomial logit model of referral choice for cardiac surgery using hospital discharge data from Pennsylvania. I find that non-tertiary care hospitals are more likely to refer their patients to their affiliated tertiary care hospitals than to other tertiary care hospitals, but the magnitude of the effect of affiliation varies substantially depending on the characteristics of the targets and the acquirers. When the acquirers are not among the top hospitals in the region, the target hospitals facing greater competitive pressure are equally or less likely to refer patients to their acquirers, consistent with the patient steering hypothesis. On the other hand, acquirers renowned for high quality of care are more likely to attract referrals from target hospitals facing greater competitive pressure, supporting the integrated delivery of care hypothesis.

This paper proceeds as follows. Section 2 reviews previous literatures on vertical integration among the providers of health care. Section 3 presents a theoretical model of referral choice by non-tertiary care hospitals, and Section 4 explains the empirical specification used to estimate the referral choice model and discusses the identifying assumptions. In Section 5 I describe the data, and I present the estimation results in Section 6. Section 7 concludes the paper and discusses the implications of the results.

2 Literature Review

There are several hypotheses on motives for hospitals to form vertical alliances with physicians, which might also explain the motives of tertiary care hospitals for acquiring non-tertiary care hospitals. They can be categorized into two views. One is that vertical integration reduces transaction costs and facilitates quality enhancement and cost containment. To be specific, a merger could enable hospitals to eliminate duplication of treatment or medical examination by sharing medical records and developing a unified information system. Moreover, better communication between doctors at the two hospitals might lead to better coordinated care (Gillies (1993), Shortell *et al.* (1996)). The other is that the hospitals and the physicians gain financial benefits by forming vertical alliances. As Gal-Or (1999) points out, vertical integration could give collective bargaining power to hospitals and physicians when they negotiate over prices with managed care organizations. In addition, the hospitals might benefit from increasing physicians' loyalty to the hospitals. If it is difficult for patients to switch their physicians, then physicians have a strong influence over hospital choice (Barro and Cutler (2000)). Since referral laws prohibit hospitals from paying physicians for referrals, the only way for the hospitals to reward physicians for referrals is to acquire the physician practice and other hospitals.[5]

There is only weak support for quality gains due to vertical alliances of hospitals (Huckman (2006), Madison (2004b)), as well as that of hospitals and physicians (Cuellar and Gertler (2006), Madison (2004a)). Likewise, there is weak support for cost containment due to vertical alliances of hospitals (Huckman (2006), Madison (2004b)), as well as that of hos-

[5] Nakamura *et al.* (2006) provide literature review of legal issues in physician referrals.

pitals and physicians (Cuellar and Gertler (2006), Madison (2004a)). In addition, studies on the effect of hospital mergers on hospital prices suggest that merger is not highly effective in increasing prices unless the merging hospitals are geographically close and the service offerings overlap (Capps *et al.* (2003)). There are only mixed findings on the effect of vertical integration between hospitals and physicians on hospital prices (Cuellar and Gertler (2006), Ciliberto and Dranove (2006)).

On the other hand, several studies find that vertical acquisition leads to an increase in the patient volume of the acquirer. Cuellar and Gertler (2006) find hospitals that are vertically integrated with physicians tend to have larger case volume. Using hospital discharge records in the state of New York, Huckman (2006) finds that vertical integration of hospitals has similar effects for cardiac surgery. Using discharge records from New York and Florida on both cardiac surgery and a broader range of tertiary care DRGs, Nakamura *et al.* (2006) report that *some* acquisitions lead to large and statistically significant increases in admissions from the neighborhood of the target hospitals, while in a majority of cases there is no significant change in referral patterns.

While these findings suggest attracting referrals could be one of the important motives for tertiary care hospitals to acquire non-tertiary care hospitals, it remains unanswered why not all vertical mergers lead to increased referrals. It might be because some targets are more sensitive about their reputation, which prevents them from distorting referral patterns. In addition, the lack of strong evidence for quality improvement does not necessarily rule out the possibility that hospitals in vertical alliance are engaged in such efforts. In fact, increased referrals might reflect the merged hospitals' efforts for integrated delivery of care, although such efforts do not always lead to a noticeable success in a short term. In this paper, I study these possibilities by estimating hospitals' referral choice based on a theoretical model that relates hospitals' referral patterns with the competitive pressure they face. This paper differs from the prior literature especially in that it considers the effects of competition on hospitals' behavior.

3 Model of Referral Choice

In this section, I develop a theoretical model in which non-tertiary care hospitals refer patients to tertiary care hospitals for advanced treatment. In the model, patients' preferences for a non-tertiary care hospital depend on the rating given by patients who used the hospital in the previous period. Non-tertiary care hospitals are assumed to be forward looking, so in choosing referral destinations they consider the effect of patients' satisfaction on future demand and profit. I show that the non-tertiary care hospitals facing demand that are more responsive to a change in a rating by a patient place greater weights on patients' preferences in choosing referral destinations.

There are $i = 1, ..., I$ patients, $k = 1, ..., K$ non-tertiary care hospitals, and $j = 1, ..., J$ tertiary care hospitals. There are two periods, and in the beginning of each period, each patient chooses one non-tertiary care hospital, and with a certain probability, the physicians at the non-tertiary care hospital find the patient needs advanced treatment. When that is the case, the non-tertiary care hospital refers the patient to a tertiary care hospital.[6] For simplicity, assume that tertiary care hospitals do not provide non-tertiary care, and that all patients need to go to non-tertiary care hospitals first.[7] Both non-tertiary care hospitals and

[6] Strictly speaking, it is the physicians at the non-tertiary care hospitals who refer patients, but I use the words "physicians at a non-tertiary care hospital" and "a non-tertiary care hospital" interchangeably.

[7] A hospital that provides both non-tertiary care and tertiary care is treated as two separate hospitals in

tertiary care hospitals earn a fixed profit margin per admission.[8] In period 1, after referrals were made, patients rate the non-tertiary care hospitals that they chose. When patients choose non-tertiary care hospitals at the beginning of period 2, they consider the ratings by the patients in period 1.

3.1 Patients

Let V^i_{jkt} denote patient i's utility when he is referred from non-tertiary care hospital k to tertiary care hospital j at time t. Assume that

$$V^i_{jkt} = v^i_{jkt} + \varepsilon^i_{jt}, \tag{1}$$

where v^i_{jkt} is some constant, and ε^i_{kt} is a random number. v^i_{jkt} is determined by observable characteristics of patients, non-tertiary care hospitals, and tertiary care hospitals. ε^i_{jt} is determined by the factors that are unobservable to the econometrician. I assume that ε^i_{jt} is observable to patient i and the non-tertiary care hospitals when a referral is made in period t.

Similarly, let W^i_{kt} be patient i's utility when he chooses non-tertiary care hospital k in period t. I assume that

$$W^i_{kt} = \bar{w}^i_{kt} + \epsilon^i_{kt}, \tag{2}$$

where $\overline{w}^i_{kt}$ is some constant, and ϵ^i_{kt} is a random number that follows extreme value dis-

this section.

[8] In reality, prices for privately insured patients are determined in the negotiation between hospitals and insurers. Nevertheless, that would not affect the following analysis as long as physicians take the prices as given when making referrals.

tribution. $\overline{w}^i_{kt}$ is determined by observable characteristics of patients and hospitals, and ϵ^i_{kt} is determined by factors that are unobservable to the econometrician. ϵ^i_{kt} is observable to patient i at the beginning of period t, but no one knows the value of ϵ^i_{kt} before period t starts. Since ϵ^i_{kt} follows extreme value distribution, $\widehat{s}^K_{it}$, the expected probability that patient i chooses non-tertiary care hospital K in period t, is

$$\widehat{s}^i_{Kt} = exp(\bar{w}^i_{Kt})/\sum_{k=1}^{K} exp(\bar{w}^i_{kt}). \tag{3}$$

The choice of non-tertiary care hospitals by patients in the second period is affected by the average rating of each non-tertiary care hospital by the patients who chose the hospital in the first period. For simplicity, assume that the rating depends only on each patient's utility at the referral destination, and that all the patients that were referred in the previous period participate in the rating. I have

$$\bar{w}^i_{k2} = A^i_{k2} + \frac{b}{N_{k1}} \sum_{i' \in I_{k1}} \sum_{j \in C_{i'1}} \left(r^{i'}_{jk1} V^{i'}_{jk1} \right), \tag{4}$$

where A^i_{k2} is some constant, and N_{k1} is the number of patients who were referred from k in period 1. $r^{i'}_{jk1} = 1$ if patient i' was referred from non-tertiary care hospital k to tertiary care hospital j in period 1 and 0 otherwise. I_{k1} is the set of patients who were referred from k in period 1, and $C_{i'1}$ is the set of tertiary care hospitals included in the choice set of patient i' in period 1.

This specification reflects not only that there could be publicly available hospital ratings based on popular votes, but also that word of mouth could play an important role in hospital choice. An important underlying assumption is that patients do not know the actual referral patterns of the non-tertiary care hospitals. For example, suppose that a non-tertiary care hospital tends to refer its patients to its low-quality acquirer, which lowers its rating. Patients in the next period learn from the ratings by the prior users that the non-tertiary care hospital pays little attention to patients' preferences in making referrals, but patients do not know that it refers most of the patients to that tertiary care hospital. This feature of the model ensures that the choice of non-tertiary care hospitals does not depend on patients' preferences toward tertiary care hospitals.

3.2 Non-Tertiary Care Hospitals

I assume that non-tertiary care hospitals are partially benevolent, so when they refer their patients in period 1, they choose the referral destinations so as to maximize the weighted sum of the profit, convenience (or non-monetary utility) for the physicians, and the welfare of the referred patients, over the two periods. Let $\alpha_k \geq 0$ be the weight non-tertiary care hospital k places on patients' preferences. Let Z_{jk} be the referring physician's non-monetary utility when a patient is referred to tertiary care hospital j from non-tertiary care hospital k.

For simplicity, both non-tertiary care hospitals and tertiary care hospitals are assumed to earn a fixed profit margin per case. When non-tertiary care hospital k refers a patient to tertiary care hospital j, hospital j earns R^i_{jk}. Similarly, non-tertiary care hospital k earns P per patient in period 2. When the non-tertiary care hospital is vertically integrated with a tertiary care hospital, the non-tertiary care hospital is assumed to consider the joint profit of both hospitals. Let $\beta_k \geq 0$ be the weight non-tertiary care hospital k places on the profit of its acquirers and let $M^i_{jk} \equiv \beta_k \cdot R^i_{jk}$. Independent hospitals have no consideration for the income of any of the tertiary care hospitals, as the anti-kickback laws prohibit hospitals from paying physicians for referrals.

In period 1, non-tertiary care hospitals choose the referral destinations that maximize their own objective function. Formally, non-tertiary care hospital k maximizes the following objective function over $\{r^i_{jk}\}_{i=1,\ldots,I_K,\, j=1,\ldots,J}$;

$$F_k = \sum_{i \in I_k} \left[\sum_{j \in C_i} r^i_{jk} \cdot (\alpha_k \cdot V^i_{jk1} + Z_{jk}) + Aff_{jk} \cdot M^i_{jk} \cdot r^i_{jk} \right] + \rho \cdot P \cdot \sum_{i'=1}^{I} \hat{s}^{i'}_k, \tag{5}$$

subject to $r^i_{jk} \in \{0,1\}$ and $\sum_{j \in C^i} r^i_{jk} = 1$, $\forall i \in I_k$, $\forall j \in C^i$. r^i_{jk} is the indicator variable that equals 1 if patient i is referred to tertiary care hospital j from non-tertiary care hospital k in period 1, and 0 otherwise. Similarly, $s^{i'}$ is the indicator variable that is equal to 1 if patient i' chooses non-tertiary care hospital k in period 2, and 0 otherwise. Aff_{jk} is an indicator variable that is equal to 1 if non-tertiary care hospital k is affiliated with tertiary care hospital j. ρ is the discount rate for the income in the next period.

Solving the maximization problem is much easier if F_k is linear in $\{r^{i'}_{jk}\}_{i=1,\ldots,I_k,\, j=1,\ldots,J}$, so I linearize $\widehat{s}^{i'}_k$ over $\bar{w}^{i'}_{k2}$ around $\bar{w}^i_{k1}$, patient i's non-probabilistic component in utility from being treated at non-tertiary care hospital k in period 1. Taking the first order Taylor expansion of $\widehat{s}^{i'}_k$ over $\bar{w}^{i'}_{k2}$ around $\bar{w}^i_{k1}$ yields

$$\widehat{s}^{i'} \approx \widehat{s}^{i'}_0 + \widehat{s}^{i'}_0 \cdot (1 - \widehat{s}^{i'}_0) \cdot (\bar{w}^{i'}_{k2} - \bar{w}^{i'}_{k1}), \tag{6}$$

where

$$\widehat{s}_0^{i'} \equiv \widehat{s}^{i'} \Big|_{\bar{w}_{k2}^{i'}=\bar{w}_{k1}^{i'}} .$$

Note that the second term is based on the following formula for logit demand:

$$\frac{d}{d\bar{w}_k^i} \frac{\exp(\bar{w}_k^i)}{\sum_{k'=1}^{K} \exp(\bar{w}_{k't}^i)} = \frac{\exp(\bar{w}_k^i)}{\sum_{k'=1}^{K} \exp(\bar{w}_{k't}^i)} - \left(\frac{\exp(\bar{w}_k^i)}{\sum_{k'=1}^{K} \exp(\bar{w}_{k't}^i)} \right)^2 . \tag{7}$$

I have

$$\bar{w}_{k2}^{i'} - \bar{w}_{k1}^{i'} = B_k^{i'} + \frac{b}{N_{k1}} \sum_{i' \in I_{k1}} \sum_{j \in C_{i'1}} \left(r_{jk1}^{i'} V_{jk1}^{i'} \right), \tag{8}$$

where

$$B_k^{i'} \equiv A_{k2}^{i'} - A_{k1}^{i'} - \frac{b}{N_{k0}} \sum_{i' \in I_{k0}} \sum_{j \in C_{i'0}} r_{jk0}^{i'} V_{jk0}^{i'}.$$

Let me denote $\frac{1}{N_k} \sum_{i=1}^{I} \widehat{s}_0^i \cdot (1 - \widehat{s}_0^i)$ by RDR_k, Responsiveness of Demand to a Rating.

Substituting (6) and (8) into (5) yields

$$\begin{aligned} F_k \quad \approx \quad & \sum_{i \in I_k} \sum_{j \in C_i} r_{jk}^i \cdot \left[V_{jk1}^i \cdot (\alpha_k + b \cdot P \cdot \rho \cdot RDR_k) + Z_{jk} \right] \\ & + \sum_{i \in I_k} Aff_{jk} \cdot M_{jk}^i \cdot r_{jk}^i + \rho \cdot P \sum_{i'=1}^{I} \left[\widehat{s}_0^{i'} + \widehat{s}_0^{i'} \cdot (1 - \widehat{s}_0^{i'}) \cdot B_k^{i'} \right]. \end{aligned} \tag{9}$$

Note that the last term does not depend on $\{r_{jk}^{i'}\}_{j=1,\dots,J}$. Let me define F_k^i as follows:

$$F_k^i \equiv \sum_{j \in C_i} r_{jk}^i \cdot \left[V_{jk1}^i \cdot (\alpha_k + b \cdot P \cdot \rho \cdot RDR_k) + Z_{jk} + Aff_{jk} \cdot M_{jk}^i \right]. \tag{10}$$

The optimization problem above boils down to maximizing F_k^i over r_{jk}^i for each $i \in I_k$ subject to $r_{jk}^i \in \{0,1\}$ and $\sum_{j \in C_i} r_{jk}^i = 1 \; \forall j \in C^i$, taking α_k, ρ, P, $\left\{M_{jk}^i\right\}_{j \in J_k}$, $\{Z_{jk}\}_{j \in C_i}$, and $\left\{V_{jk1}^{i'}\right\}_{j \in C_i}$ as given.

3.3 Measure of the Responsiveness of Demand to a Rating

The model shows that the larger RDR_k is, the greater weight non-tertiary care hospital k places on patients' preferences. RDR_k represents the "Responsiveness of Demand to a Rating" for non-tertiary care hospital k, and is an approximation of the marginal change in demand for k given an increase in a patient's rating of k. When the hospital market is more (less) competitive, a change in reputation has a greater (smaller) effect on hospital demand, as it is easier (more difficult) for the patients to avoid hospitals with a bad reputation. Thus, RDR_k can be considered to be a measure of competitive pressure that non-tertiary care hospital k faces.

In the literature on hospital competition, the Herfindahl Hirschman Index (HHI) is commonly used as a measure of competition, where a market is defined by a geographical area. Measuring competitive pressure for individual firms by HHI requires the assumption that all firms in the same market face the same degree of competition. In the hospital market, however, this assumption is tenuous, since hospitals are vertically differentiated by quality of care and the range of service offerings, and thus even hospitals in the exactly same location could face different degrees of competition, depending on the service offerings and quality of care. RDR does not suffer from this problem.

RDR_k decreases as N_k, the number of patients the hospital treats in the current period, increases. This is because when the hospital treats a small number of patients, the weight on each of the patients in the rating is larger, so the hospital places a heavier weight on the patient's welfare in making a referral decision. RDR_k is proportional to the sum of $\widehat{s}_0^i \cdot (1-\widehat{s}_0^i)$ over all the patients. $\widehat{s}_0^i$ is the probability that the patient chooses the hospital and $(1-\widehat{s}_0^i)$ is the probability that the patient does not choose the hospital. The term $\widehat{s}_0^i \cdot (1-\widehat{s}_0^i)$ measures the patient's indifference in choosing one hospital over another. This formula results from the assumption that demand for non-tertiary care hospitals is logit, as equation (7) shows.

4 Empirical Specification

Based on the theoretical model described in the previous section, I estimate a hospital choice model for Coronary Artery Bypass Graft Surgery (CABG) and Percutaneous Transluminal Coronary Angioplasty (PTCA).[9] In this section, I explain the empirical specification of the model and discuss the identifying assumptions.

4.1 Cardiac Surgery (CABG/PTCA)

Huckman (2006) reports that vertical integration leads to increased referrals for cardiac surgery. Furthermore, Nakamura *et al.*(2006) find that the increase in referrals is larger for cardiac surgery than for other tertiary care services. Since my interest here is on why target hospitals increase referrals to their acquirers, I follow previous works and study referral choice for cardiac surgery.

Inter-hospital referrals are common for cardiac surgery cases, since only a small fraction

[9] I use the words "CABG/PTCA" and "cardiac surgery" interchangeably.

of hospitals offer CABG/PTCA. While some patients have CABG/PTCA right after having heart attacks, others have CABG/PTCA on an elective basis. The latter patients typically have initial symptoms of ischemic heart disease such as chest pain or shortness of breath, and present themselves to their local hospitals. If the hospitals do not offer cardiac surgery, the patients are referred to more technologically advanced hospitals. I study the referral choice for such patients.

There are several reasons why hospitals particularly benefit from attracting referrals for CABG/PTCA. First, cardiac surgery is known for its high profit margins.[10] This is primarily because there are large fixed costs of offering CABG/PTCA, and the payment rates to the hospitals reflect the average costs rather than the marginal costs.[11] Second, empirical works suggest that there is learning by doing in CABG/PTCA.[12] Provided that quality improves and cost decreases with the experience of the medical staff, hospitals can establish dominant positions in their local markets by performing greater numbers of surgeries. Third, hospitals rarely face capacity constraints for CABG/PTCA except for some hospitals renowned for high quality of care.[13]

[10] Huckman (2006) provides discussion on the costs and profit margins of CABG/PTCA.

[11] Medicare DRG payment rates are based on average costs. Moreover, higher fixed costs lead to more concentrated market structures and thus to higher payment rates from private insurers.

[12] There are a number of studies on volume-outcome relationship in CABG/PTCA. For recent works, see Epstein (2004) for PTCA and Hannan (2003) for CABG.

[13] Bazzoli (2003) reports that most hospitals have emergency capacity problems, but that few face capacity constraints outside of the emergency department, except for areas with high population growth and for highly renowned speciality care centers. Pittsburgh, the area I study, experienced a decline in population.

4.2 Referral Choice

Based on the model, the payoff of non-tertiary care hospital k from referring patient i to tertiary care hospital j is specified as follows;

$$\mu^i_{jk} = V^i_{jk} \cdot (\alpha_k + b \cdot P \cdot \rho \cdot RDR_k) + Z_{jk} + M^i_{jk} \cdot Aff_{jk}. \tag{11}$$

α_k could vary with the characteristics of non-tertiary care hospitals, such as ownership status. In my data set, however, all of the hospitals that offer cardiac catheterization or cardiac surgery are nonprofit, so I assume that $\alpha_k = \alpha$ for all $k = 1, ..., K$.

Let q_{jk} be quality of tertiary care hospital j as perceived by the patients referred from non-tertiary care hospital k. Let T^i_j be the driving hours from patient i's home to tertiary care hospital j. V^i_{jk}, patient i's utility when referred to tertiary care hospital j from non-tertiary care hospital k, is specified as follows:

$$V^i_{jk} = q_{jk} - \lambda_1 T^i_j - \lambda_2 (T^i_j)^2 + \varepsilon^i_j, \tag{12}$$

where λ_1 and λ_2 are parameters to be estimated, and ε^i_j is an i.i.d. random variable. Since hospital quality for cardiac surgery is hard to measure, I use hospital specific effects to account for quality differences among hospitals.[14]

Since coordination between physicians at non-tertiary care hospitals and physicians at

[14] The most common measure of hospital quality for cardiac surgeries is the mortality rate by hospitals that is adjusted for patient demographics and other clinical information. Nevertheless, the estimated hospital quality would be subject to selection bias if hospitals with superior quality attract high severity patients and the severity of illness cannot be fully captured by observable characteristics of the patients. This is especially problematic in measuring hospital quality for cardiac surgery, since most of the admissions are elective. Moreover, mortality is a noisy signal, and not all the hospitals perform large enough numbers of cardiac surgeries for the estimation.

tertiary care hospitals could influence quality of care, and organizational relationships could facilitate integrated delivery of care, I allow hospital specific effects to depend on the organizational relationships between the referring hospital and the tertiary care hospital. In other words, if patients are convinced that they can benefit from better coordination of care at the point of referral, they might wish to be referred to tertiary care hospitals that are affiliated with the referring hospitals. I also allow people's perception about the effect of the alliance on quality of care to depend on whether the acquirer is a high quality hospital. It reflects the possibility that patients might think being referred to the acquirers is good for them only when they know the acquirers are high quality hospitals. Accordingly, q_{jk} is specified as follows:

$$q_{jk} = H_j + Aff_{jk} \left(\upsilon + w \cdot High_j \right), \tag{13}$$

where $High_j$ is a dummy variable that is equal to 1 if tertiary care hospital j is regarded as one of the top hospitals in the region. H_j, υ, and w are parameters to be estimated.

To find hospitals providing exceptionally high quality of care, I use three different measures; (1) hospital rankings by US News & World Report, (2) the number of cardiac surgeries performed at each hospital, and (3) the number of cardiac surgery patients from outside of the county treated at each hospital. Assuming "practice makes perfect," the surgical volume of a hospital reflects the experience of its medical staff and thus its quality. On the other hand, provided that severely ill patients are more willing to travel for better quality care, hospitals that attract larger numbers of such patients are more likely to be superior in quality of care. Three of the tertiary care hospitals in my data set, University of Pittsburgh Medical Center (UPMC) Presbyterian, UPMC Shadyside, and Allegheny General Hospital, were far superior to the others in these criteria, so I define them as top hospitals.

I specify Z_{jk}, physicians' non-monetary utility from referring a patient from non-tertiary care hospital k to tertiary care hospital j, as follows:

$$Z_{jk} = DH_j - \kappa_1 DT_{jk} - \kappa_2 \left(DT_{jk}\right)^2 + \varsigma_{jk}, \tag{14}$$

where DH_j is the accessibility of tertiary care hospital j for the referring physicians, DT_{jk} is the driving hours from non-tertiary care hospital k to tertiary care hospital j, and ς_{jk} is an i.i.d. random variable. κ_1 and κ_2 are parameters to be estimated. Since I do not have a good measure of the (non-monetary) attractiveness of the tertiary care hospitals for the referring physicians, I use hospital specific effects.[15]

M^i_{jk}, financial gains for target hospital k from referring patient i to acquirer j, is specified as follows;

$$M^i_{jk} = \delta_1 \cdot Old^i + \delta_2 \cdot Private^i + \delta_3 \cdot FirstYr_{jk} + \delta_4 \cdot Loose_{jk} + \delta_5 \cdot High_j, \tag{15}$$

where δ_1, δ_2, ..., δ_5 are parameters to be estimated. Old^i is a dummy variable indicating whether the patient is 80 years old and above or not, and $Private^i$ is a dummy variable that is equal to 1 if the patient is covered under private fee-for-service insurance plans. δ_1 and δ_2 measure if targets selectively refer healthier and better-insured patients to the acquirers, respectively. $FirstYr_{jk}$ is a dummy variable indicating whether the referral is made within one year after the acquisition. $Loose_{jk}$ is a dummy variable that is equal to 1 if non-tertiary

[15] Teruya (2004) reports that one hospital offers physicians free meals at a special cafeteria in the hospital to attract referrals.

care hospital k has a loose organizational relationship with tertiary care hospital j but is not owned by hospital j. This specification allows the effect of vertical integration on referrals to vary with the time after acquisition and the degree of organizational integration.

If the incremental cost of treating a patient decreases with surgical volume at the hospital, the average profit margin will be higher for high quality and thus high volume hospitals. On the other hand, if the experience of the medical staff improves the quality of cardiac surgery but such effects are subject to the law of diminishing returns, high quality acquirers could have smaller incentives to attract referrals from their targets. In addition, high quality acquirers are more likely to face capacity constraints because of their own popularity (Bazzoli et al.(2003)). If the former (latter) effects dominate, δ_5 will be positive (negative).

Since I cannot observe the true value of RDR_k, I use its estimate. Let $\widehat{RDR}_k$ and φ_k be the estimated value of RDR_k and the error in the estimation, respectively. Then I have

$$\begin{aligned}
\mu^i_{jk} &= I_j + Q_j \cdot \widehat{RDR}_k + \beta_1 \cdot T^i_j + \beta_2 \cdot (T^i_j)^2 \\
&\quad + \widehat{RDR}_k \cdot \left[\beta_3 \cdot T^i_j + \beta_4 \cdot (T^i_j)^2\right] + \beta_5 \cdot DT_{jk} + \beta_6 \cdot (DT_{jk})^2 \\
&\quad + Aff_{jk} \cdot (\beta_7 + \beta_8 \cdot \widehat{RDR}_k + \beta_9 \cdot High_j + \beta_{10} \cdot \widehat{RDR}_k \cdot High_j \\
&\quad + \delta_1 \cdot Old^i + \delta_2 \cdot Private^i + \delta_3 \cdot FirstYr_{jk} + \delta_4 \cdot Loose_{jk}) + \xi^i_{jk},
\end{aligned} \tag{16}$$

where

$$I_j \equiv \alpha \cdot H_j + DH_j,$$

$$Q_j \equiv b \cdot P \cdot \rho \cdot H_j,$$

$$\beta_1 \equiv -\lambda_1 \cdot \alpha,$$

$$\beta_2 \equiv -\lambda_2 \cdot \alpha,$$

$$\beta_3 \equiv -\lambda_1 \cdot b \cdot P \cdot \rho,$$

$$\beta_4 \equiv -\lambda_2 \cdot b \cdot P \cdot \rho,$$

$$\beta_5 \equiv -\kappa_1,$$

$$\beta_6 \equiv -\kappa_2,$$

$$\beta_7 \equiv \alpha \cdot \upsilon,$$

$$\beta_8 \equiv \upsilon \cdot b \cdot P \cdot \rho,$$

$$\beta_9 \equiv \alpha \cdot w + \delta_5,$$

$$\beta_{10} \equiv w \cdot b \cdot P \cdot \rho,$$

$$\begin{aligned} \xi^i_{jk} \quad \equiv \quad & \varsigma_{jk} + \varepsilon^i_j \cdot \left[\alpha + b \cdot P \cdot \rho \cdot \left(\widehat{RDR}_k + \varphi_k\right)\right] \\ & + b \cdot P \cdot \rho \cdot \varphi_k \cdot \left[H_j - \lambda_1 \cdot T^i_j - \lambda_2 \cdot \left(T^i_j\right)^2 + \upsilon \cdot Aff_{jk} + w \cdot Aff_{jk} \cdot High_j\right]. \end{aligned}$$

Assuming ξ^i_{jk} is I.I.A. distributed according to extreme value distribution, the probability that non-tertiary care hospital k refers patient i to tertiary care hospital j' is as follows;

$$p^i_{j'k} = exp(\bar{\mu}^i_{j'k}) / \sum_{j \in C_i} exp(\bar{\mu}^i_{jk}), \tag{17}$$

where

$$\bar{\mu}^i_{jk} \equiv \mu^i_{jk} - \xi^i_{jk}.$$

4.3 Measure of the Responsiveness of Demand to a Rating

In calculating RDR, the measure of the responsiveness of the demand to a rating that each non-tertiary care hospital faces, I assume that the demand for non-tertiary care hospitals from patients who could need cardiac surgery is well represented by the choice of hospitals for AMI (heart attack) treatment. I estimate a multinomial logit model of hospital choice for AMI treatment.[16] The explanatory variables are hospital specific effects and the traveling time to the hospital from the patient's home.[17]

I allow the coefficient of traveling time from patients' residences to the hospitals to differ across the four demographic groups; young male, old male, young female, and old female, where patients at least 80 years old are defined as old. I substitute demographic specific hospital specific effects by the number of old male, young female, and old female patients treated in each hospital divided by that of young male patients treated in the hospital. This allows patients' preferences toward hospitals to vary with demographic characteristics without having too many explanatory variables. The appendix justifies this specification.

[16] Tertiary care hospitals as well as non-tertiary care hospitals are included in the choice set.

[17] Following Tay (2003), I consider only the nearest 20 hospitals to be in the choice set and assume the coefficients of driving hours to be fixed. In Tay (2003) the coefficient of squared distance from the patient's home to the hospital is statistically insignificant for all demographic groups except for patients who seem to have been away from home at the time of heart attack. Thus I do not include the square of patient's traveling hours.

4.4 Assumptions on the Referring Hospital

Since I cannot observe which hospital each patient is referred from, I try three different assumptions on the referring non-tertiary care hospital for each patient. First, there are some cases in which a patient has had cardiac catheterization for diagnostic purposes at a hospital that did not offer CABG/PTCA and then has CABG/PTCA at another hospital. I assume that these patients are referred from the former to the latter (Assumption 1). Second, I assume that a patient who had cardiac surgery at a tertiary care hospital and is highly likely to go to a non-tertiary care hospital for heart attack treatment to have been referred from that non-tertiary care hospital (Assumption 2). Based on the estimated model of hospital choice for AMI treatment, I calculate the probability of choosing each non-tertiary care hospital for each patient who has had cardiac surgery. If the probability is greater than 50%, then I assume that the patient was referred from the non-tertiary care hospital. Third, if a CABG/PTCA patient's zip code of residence is within a 5 minute drive from the zip code centroid of a non-tertiary care hospital, I assume that the patient was referred from that non-tertiary care hospital (Assumption 3).

4.5 Identifying Assumptions

The model can be estimated as a logit if I assume that φ_k, the errors in the estimation of RDR_k, are small and can be ignored and that the error term, ξ^i_{jk}, is i.i.d. distributed according to extreme value distribution. The assumption about ξ^i_{jk} implies that the error term will be uncorrelated with the regressors and the regressors are exogenous. It also implies that the multiplication of the idiosyncratic preference of the patient and the estimated responsiveness of demand to a rating, $\varepsilon_j^i \cdot RDR_k$, is small, so the variance of the error term is constant.

4.5.1 Exogeneity of Affiliation

The exogeneity assumption is violated if Aff_{jk}, the affiliation dummy, is correlated with ς_{jk}, the error term in physicians' non-monetary utility. This could be the case if physicians affiliated with a non-tertiary care hospital establish social networks with physicians affiliated with a particular tertiary care hospital, and that affects referral patterns and hospitals' merger decisions. Such a hypothesis is, however, inconsistent with the views of sociologists and physicians studying physicians' behavior and hospital mergers. Shortell et al. (1996) point out that organizational boundaries make it difficult for the providers of health care to cooperate with each other, and advocate organized health delivery systems as the means of overcoming such fragmentation. One of the reasons Shortell's works attracted the attention of people in the health care industry is that they share the recognition that it is extremely difficult for physicians and/or hospitals to cooperate with each other over organizational boundaries.

4.5.2 Potential Problems in Assumption 1

Under Assumption 1, the characteristics of the referring hospitals could be endogenous if some patients choose non-tertiary care hospitals that are close to or were acquired by the tertiary care hospitals they prefer. In other words, if patients choose the non-tertiary care hospitals based on the tertiary care hospitals to which they are likely to be referred, then the causality is reversed.

Recent surveys of pregnant women and general consumers on hospital choice help support the assumption that the choice of non-tertiary care hospital is independent of patients' idiosyncratic tastes for tertiary care hospitals. Survey results suggest that few patients have strong idiosyncratic preferences regarding tertiary care hospitals. Patients choose hospitals primarily based on their physician's recommendations, and their preferences over hospitals are largely determined by service offerings, location, and general reputation in the community (Sarel *et al.* (2005), Smithson (2003)). While these surveys also reveal that previous experience with the hospital plays an important role, this is irrelevant for the majority of CABG/PTCA patients, since few patients have cardiac surgery more than once.[18]

Assumptions 2 and 3 are free from the potential problem in Assumption 1 discussed above, provided that the location of patients is exogenous, i.e., patients do not choose where to live based on their preferences for specific hospitals. Thus, I can test the validity of the identifying assumptions described above by comparing the estimation results obtained from the three different assumptions.

5 Data

I use hospital discharge data from hospitals in Regions 1 and 3 for 1997 and 2002 obtained from the Pennsylvania Health Care Cost Containment Council (PHC4). Regions 1 and 3 cover the southwest part of Pennsylvania surrounding Pittsburgh.[19] The discharge data contains all the cases of CABG/PTCA, cardiac catheterization, and AMI patients. The

[18] These survey results also help support the assumption that the multiplication of the idiosyncratic preference of the patient and the estimated responsiveness of demand to a rating, $\varepsilon_j^i \cdot RDR_k$, is small.

[19] Region 1 includes the following counties: Allegheny, Armstrong, Beaver, Butler, Fayette, Greene, Washington, and Westmoreland. Region 3 includes Bedford, Blair, Cambria, Indiana, and Somerset.

variables include the hospital each patient is admitted to, the procedure performed, the patient's age, sex, zip code of residence, diagnoses, and pseudo-patient identifiers that link patients across records.

The information on hospital acquisition is obtained from Irvin Levin Associates and local newspaper articles. Information on the location and other characteristics of hospitals in the area is obtained from the American Hospital Association's annual survey and also from PHC4. The driving hours from the centroid of patients' zip codes of residence to those of tertiary care hospitals and those from non-tertiary care hospitals to the tertiary care hospitals are obtained by using the "driving hours calculator" on the Mapquest.com web page.

Following Nakamura *et al.* (2006), I define tertiary care hospitals as the hospitals that perform at least 20 cases of CABG and/or PTCA in that year, and non-tertiary care hospitals as the short-term general hospitals that do not satisfy this criterion. I limit my analysis to non-tertiary care hospitals that are included under Assumption 1, so that the scope of the analysis is the same across the three assumptions. Thus, non-tertiary care hospitals with few or no cardiac catheterizations are excluded from the analysis.

I limit my analysis to the patients whose hospital choice is not affected by the provider networks of the insurers. Thus, I only include patients covered under Medicare, Blue Cross, and commercial indemnity insurance plans.[20] I also exclude patients younger than 50 and those who had cardiac surgery with a primary diagnosis of AMI, since they account for a small percentage and could have different preferences toward hospitals than the others.[21]

There were six and seven health systems that included both tertiary care hospitals and

[20] I exclude patients covered under Medicare HMO and Blue Cross managed care plans.

[21] In addition, to exclude cases where patients moved and chose hospitals for catheterization and heart surgery independently before and after the move, I do not include patients recorded with more than one valid zip code of residence in the same year in the estimation under Assumption 1.

non-tertiary care hospitals in 1997 and 2002, respectively.[22] The list of health systems and their member hospitals are in Table 1, where the targets and acquirers included in the analysis are in bold letters. Some of the target hospitals are excluded, as they do not appear to have referred any patients after cardiac catheterization.

Table 2 shows the summary statistics of the characteristics of the patients and the presumptive referring hospitals under each assumption. The numbers are largely similar across assumption, and a considerable variation in affiliation status exists among the referring hospitals. Table 3 summarizes the characteristics of tertiary care hospitals included in the analysis. Acquirers have greater surgical volume and are more likely to be teaching hospitals than other tertiary care hospitals. The average surgical volume declined from 1997 to 2002 because of the increase in the number of hospitals offering CABG/PTCA.

6 Results

I estimate the models described above using maximum likelihood.[23] In order to calculate the value of RDR, the measure of competitive pressure for individual hospitals, I estimate the hospital choice model for heart attack patients separately for more than 30 different market areas.[24] The estimates are reported at the end of this paper (Table 7). To give a brief

[22] In 1997, there was a loose organization of hospitals called Pyramid Health, whose members included participants in AHERF, participants in Valley Health System, as well as St. Clair Hospital, a non-tertiary care hospital. After the bankruptcy of AHERF in 1998, Pyramid Health was resolved and former AHERF hospitals merged with Western Penn Health System and formed West Penn Allegheny Health System.

[23] I used GAUSS codes for estimating mixed logit models by Train *et al.* (1999).

[24] In estimating referral choice for cardiac surgery, I use UPMC Presbyterian as the base alternative for all demanders as it attracts referrals/patients from the entire area. On the other hand, for an AMI patient only the 20-nearest hospitals are assumed to be included in the choice set, which implies that there is no hospital that is included in the choice set of every patient in the region. Thus, I estimate hospital demand for heart attack treatment separately for each non-tertiary care hospital, normalizing the fixed effect of that hospital to be zero and using a data set of patients whose homes were within a 60 minute drive from the hospital.

summary of the results, the signs and statistical significance of the estimated coefficients are as expected. The coefficient of the patient's traveling time is negative and significant in all of the market areas, and that of the ratio of patients with certain demographic characteristics to the others is either positive and significant or insignificant, implying that patients' preferences for hospitals vary with demographic characteristic including age and gender. The summary statistics of RDR for the referring hospitals included in the analysis are in Table 4.

Table 5 shows the results of the multinomial logit estimation of referral choice for cardiac surgery.[25] The signs and statistical significance of the estimated coefficients are largely similar regardless of the assumptions on the referring hospitals, except for those of the first six variables; DT_j^i (physician's traveling time), $(DT_j^i)^2$, T_j^i (patient's traveling time), $(T_j^i)^2$, $RDR_k \cdot T_j^i$, and $RDR_k \cdot (T_j^i)^2$. This discrepancy could arise because the patient's traveling time and that of the referring physician are highly correlated under Assumptions 2 and 3, since only patients who live close to non-tertiary care hospitals are selected under these assumptions.[26] Under Assumption 1 and 2, the referring physician's traveling time clearly has negative effects on the probability of referral. This is consistent with the findings in Burns and Wholey (1992) that physicians tend to refer patients to hospitals that are close to their offices.

The coefficient on Aff_{jk} is positive and significant under any of the assumptions on the referring hospitals. The coefficient of $Aff_{jk} \times Loose_{jk}$ is negative under any of the assumptions and statistically significant under Assumption 1, while it is insignificant under

[25] Since RDRs are calculated based on estimated parameters, the standard errors reported here could be underestimated. Ideally, I would like to correct for this, but since RDRs are complicated functions of the estimated parameters, I could not apply the method proposed in Murphy and Topel (1985) in a straightforward way.

[26] Another noticeable difference is that the absolute values of the coefficients are much larger under Assumption1. It might be due to the endogeneity problem discussed earlier in this paper.

Assumptions 2 and 3. The coefficient of $Aff_{jk} \times FirstYr_{jk}$ is negative under any of the assumptions and statistically significant under Assumption 1. Results under Assumption 1 indicate that the target hospitals tend to refer patients to the tertiary care hospitals that they have organizational relationships with, but it takes time before such effects take place. This is consistent with the findings in Huckman (2006) and Nakamura *et al.* (2006). In addition, the effect of affiliation seems smaller when the acquirer does not own the target.

The coefficient of $Aff_{jk} \times Old^i$ is statistically insignificant under any of the assumptions concerning the referring hospitals. On the other hand, the coefficient of $Aff_{jk} \times Private^i$ is positive and statistically significant under Assumption 1, while it is statistically insignificant under Assumptions 2 and 3. These results are largely consistent with the findings in Nakamura *et al.* (2006) that some target hospitals selectively refer patients with more remunerative insurance to their acquirers but that they do not select patients based on severity of illness.

The coefficient of $Aff_{jk} \times High_k$ is negative and significant under any of the assumptions on the referring hospitals, implying that the highly renowned acquirer hospitals are less aggressive in attracting referrals from their target hospitals. The coefficient of $Aff_{jk} \times RDR_k$ is negative under any of the assumptions on the referring hospitals and statistically significant under Assumption 1. This indicates that when the acquirers are not one of the top hospitals, target hospitals with more responsive demand to a change in a patient's evaluation (and thus facing greater competitive pressure) are equally or less likely to refer their patients to the acquirers compared to targets with less responsive demand. On the other hand, the coefficient of $Aff_{jk} \times RDR_k \times High_k$ is positive and significant under any of the assumptions on the referring hospitals. Thus, target hospitals with more responsive demand are more likely to refer patients to their high quality acquirers compared to those with less responsive demand.

Table 6 shows how the estimated value of

$$\beta_7 + \beta_8 \cdot RDR_k + \beta_9 \cdot High_j + \beta_{10} \cdot RDR_k \cdot High_j \tag{18}$$

varies with those of RDR_k and $High_j$ under each of the assumptions on the referring hospitals. The table highlights that there are two contrasting referral patterns from non-tertiary care hospitals to their affiliated tertiary care hospitals. The increase in referrals is the largest when a non-tertiary care hospital with a low RDR value is affiliated with a tertiary care hospital that is not one of the top hospitals in the region. On the other hand, highly renowned acquirers only attract referrals from their targets with higher RDR values.

Based on my theoretical model described above, I interpret my findings as follows. When the acquirer's quality of care is not superior, increased referrals would help the acquirer increase profit and establish itself as a dominant provider in the local market. However, patients see few benefits from being referred from the target to the acquirer. The target hospitals facing highly responsive demand avoid referring patients to their acquirers when there are better alternatives for patients in terms of traveling cost and quality of care. On the other hand, targets facing unresponsive demand do not lose future customers even if they have a bad reputation, so they steer patients to their acquirers.

In contrast, extremely high quality acquirers are much less aggressive in attracting referrals from targets, probably because they face capacity constraints. At the same time, patients are more positive about quality gains from vertical integration of hospitals when the acquirer is a top hospital. Thus targets facing more responsive demand are more likely to refer patients to their acquirers, as they are more eager to attract patients by advertising themselves as having close relationships with the highly prestigious acquirers. On the other hand, targets facing less responsive demand have smaller incentives to impress patients, so they do not increase the referrals to the acquirers.

A doctor who worked at a tertiary care hospital in Philadelphia acquired by AHERF reports that although AHERF managers encouraged its affiliated doctors to refer patients to its affiliated hospitals, their strategy failed at least in Philadelphia. He points out that the doctors did not change their referral patterns, because in Philadelphia, hospitals acquired by AHERF were low quality hospitals, and doctors were afraid that referring patients to such hospitals would hurt their patients and thus their own reputation (Teruya, 2004).[27] His remarks support my findings.

7 Conclusion and Discussion

This paper examines in what circumstances the acquisition of non-tertiary care hospitals by tertiary care hospitals is more likely to lead to an increase in referrals from the former to the latter. I develop a theoretical model in which reputation affects hospital demand, and based on the model I estimate a multinomial choice model of physician referral using discharge records of CABG/PTCA patients.

I find two patterns of referrals from non-tertiary care hospitals to their affiliated tertiary care hospitals. When the acquirer is not one of the top hospitals in the region, non-tertiary care hospitals facing more responsive demand to a change in a patient's evaluation are equally

[27] Burns et al. (2000) provide detailed discussions on the rapid expansion and sudden fall of AHERF.

or less willing to refer patients to their acquirers. This is consistent with the patient steering hypothesis: The referrals to the acquirers do not benefit the patients, so only the targets without the fear of losing future customers by having a bad reputation steer patients to their acquirers. In contrast, when the acquirer is regarded as one of the top hospitals in the region, non-tertiary care hospitals that face more responsive demand are more willing to refer patients to their acquirers. This finding supports the integrated delivery of care hypothesis: Increased referrals are based on the hospitals' effort to impress patients with integrated delivery of care, and targets facing greater competitive pressure have greater incentives to make such efforts.

These findings imply that vertical mergers could reduce patient welfare if low quality (and thus low volume) tertiary care hospitals acquire non-tertiary care hospitals facing little competitive pressure. In such cases, referrals from the target to the acquirer are likely to increase, because the targets do not need to worry about the consequences of referring patients to low quality hospitals, and the acquirers desperately need to attract referrals. As a result, patients would be steered from hospitals with higher quality to hospitals with lower quality, in addition to incurring higher traveling costs.

The results also imply that patients feel vertical integration of hospitals leads to quality gains when the acquirers are highly renowned hospitals. However, whether such quality gains actually exist is a different question. So far, there are only a handful of studies on the effects of vertical mergers of hospitals on the quality of care, and the findings are mixed. Future works include studying the effects of vertical mergers of hospitals on quality of care for a wider range of diagnoses as well as finding out what aspects of integrated delivery of care actually lead to significant quality improvement.

References

[1] Barro, Jason and David Curler (2000). "Consolidation in Medical Marketplace: A Case Study from Massachusetts," in Steven Kaplan ed., *Mergers and Productivity*, Chicago: University of Chicago Press.

[2] Bazzoli, J. Gloria, Linda R. Brewster, Gigi Liu, and Sylvia Kuo (2003). "Does U.S. Hospital Capacity Need To Be Expanded?" *Health Affairs*, 22(6) 40-54.

[3] Bernstein, F. Lawton (1996). "UPMC Keeps Growing and Growing, Ignoring Long-Term Issues." *Pittsburgh Post-Gazette,* 7 October.

[4] Brown, Leslie (2001). "Hospital Merger Gets Approved; the Merger of Annie Penn Hospital into Moses Cone Health System Is Effective." *News & Record (Greensboro, NC)*, 30 June.

[5] Burns, Lawton R., and Douglas R. Wholey (1992). "The Impact of Physician Characteristics in Conditional Choice Models for Hospital Care." *Journal of Health Economics*, 11(1) 43-62.

[6] Burns, Lawton R., John Cacciamani, James Clement, and Welman Aquino (2000). "The Fall of the House of AHERF: The Allegheny System Debacle." *Health Affairs* 19(1) 7-41.

[7] Capps, Cory, David Dranove, and Mark Satterthwaite (2003). "Competition and Market Power in Option Demand Markets." *RAND Journal of Economics*, 34(4) 737-763.

[8] Ciliberto, Federico, and David Dranove (2006). "The Effect of Hospital-Physician Affiliations on Hospital Prices in California." *Journal of Health Economics* 25(1) 29-38.

[9] Cuellar, Alison Evans, and Paul J. Gertler (2006). "Strategic Integration Between Hospitals and Physicians." *Journal of Health Economics* 25(1) 1-28.

[10] Epstein, Saif S. Rathore, Kevin G. Volp, and Harlan M. Krumholz (2004). "Hospital Percutaneous Coronary Intervention Volume and Patient Mortality, 1998 to 2000: Does the Evidence Support Current Procedure Volume Minimums?" *Journal of the American College of Cardiology* 43(10) 1755-1762.

[11] Folland, Sherman, Allen C. Goodman, and Miron Stano (2001). *The Economics of Health and Health Care*. Upper Saddle River, NJ: Prentice Hall.

[12] Gal-Or, Esther (1999). "The Profitability of Vertical Mergers Between Hospitals and Physician Practices." *Journal of Health Economics* 18(5) 623-654.

[13] Gillies, Robin, Stephen M. Shortell, David A. Anderson, John B. Mitchell and Karen L. Morgan (1993). "Conceptualizing and Measuring Integration: Findings from the Health Systems Integration Study." *Hospital and Health Services Administration* 38 (4) 467-489.

[14] Gowrisankaran, Gautam, Michael Chernew, and Mark A. Fendrick (2002). "Payer Type and the Returns to Bypass Surgery: Evidence from Hospital Entry Behavior." *Journal of Health Economics* 21(3) 451-474.

[15] Hannan, Edward L., Chuntao Wu, Thomas J. Ryan, Edward Bennett, Alfred T. Culliford, Jeffrey P. Gold, Alan Hartman, O. Wayne Isom, Robert H. Jones, Barbara McNeil, Eric A. Rose, and Valavanur A. Subramanian (2003). "Do Hospitals and Surgeons with

Higher Coronary Artery Bypass Graft Surgery Volumes Still Have Lower Risk-Adjusted Mortality Rates?" *Circulation* 108(7) 795-801.

[16] Huckman, Robert S. (2006). "Hospital Integration and Vertical Consolidation: An Analysis of Acquisitions in New York State." *Journal of Health Economics* 25(1) 58-80.

[17] Madison, Kristen (2004a). "Hospital-Physician Affiliations and Patient Treatments, Expenditures, and Outcomes." *Health Services Research* 39(2) 257-278.

[18] Madison, Kristen (2004b). "Multihospital System Membership and Patient Treatments, Expenditures, and Outcomes." *Health Services Research* 39(4) 749-769.

[19] Morrison, Anne W. (2000). "An Analysis of Anti-kickback and Self-referral Law in Modern Health Care." *Journal of Legal Medicine*, 21(3) 351-394.

[20] Murphy, Kevin M., and Robert H. Topel (1985). "Estimation and Inference in Two-Step Econometric Models." *Journal of Business and Economic Statistics* 3(4) 88-97.

[21] Nakamura, Sayaka, David Dranove, and Cory Capps (2006). "Patient Admission Patterns and Acquisitions of "Feeder" Hospitals." Working Paper.

[22] Pennsylvania Health Care Cost Containment Council (1998). *Pennsylvania's Guide to Coronary Artery Bypass Graft Surgery 1994-1995.* www.phc4.org

[23] Pennsylvania Health Care Cost Containment Council (2004). *Pennsylvania's Guide to Coronary Artery Bypass Graft Surgery 2002.* www.phc4.org

[24] Sarel, Dan, Brendaly Rodriguez, Howard Marmorstein, and Paul Barach (2005). "Childbirth Choices." *Marketing Health Services* 25(1) 14-19.

[25] Shortell, Stephen M., Robin R. Gillies, David A. Anderson, Karen Morgan Erickson, and John B. Mitchell (1996). *Remaking Health Care in America*. San Francisco, CA: Jossey-Bass Inc.

[26] Smithson, Ken (2003). "VHA Study: Physician Affiliation Biggest Factor in Consumers' Choice of Hospital." *Health Care Strategic Management* 21(9) 4-5.

[27] Tay, Abigail (2003). "Assessing Competition in Hospital Care Markets: The Importance of Accounting for Quality Differentiation." *Rand Journal of Economics* 34(4) 786-814.

[28] Teruya, Jun (2004). *Daigaku Byoin ga Tosan Suru Hi: Amerika Daigaku Byoin no Tosan ni Miru Iryo Hokai no Kizashi [The Day When A Teaching Hospital Goes Bankrupt: The Signs of the Breakdown of Medicine in a Bankruptcy of an American Teaching Hospital]*. Tokyo, Japan: Haru Shobo.

[29] Train, Kenneth, David Revelt, and Paul Ruud (1999). "Mixed Logit Routine for Panel Data," GAUSS code, http://elsa.berkeley.edu/Software/abstracts/train0196.html (accessed April 11, 2005.)

[30] U.S. News & World Report with the National Opinion Research Center at the University of Chicago Ed. (1996). *America's best hospitals*. New York: J. Wiley.

A The Ratio of Patients with Certain Demographic Characteristics

Tay (2003) shows that AMI patients' preferences for hospitals vary with demographic characteristics, such as age and gender. I therefore need to allow the hospital specific effects to vary with patient demographics. If I include the interaction of dummy variables of individual hospitals and those of patient demographics, however, that will considerably increase the computational burden. Instead, I categorize the patients into groups by their demographic characteristics and use the total number of patients in a certain group treated at each hospital divided by that of patients in the base group treated at the same hospital as a measure of the hospital specific fixed effect for that group.

Suppose there are two groups of patients, group 1 and 2, and the utility of patient i in zip code z from choosing alternative j is specified as follows:

$$u_j^i \mid_{i \in I_z} = \begin{cases} w_j + y_j^z + \epsilon_j^i \text{ if } i \in I_1 \\ w_j + v_j + y_j^z + \epsilon_j^i \text{ if } i \in I_2, \end{cases}$$

where I_z, I_1, and I_2 denote the set of patients in zip code z, group 1, and group 2, respectively, and $\left\{\epsilon_j^i\right\}_{j=1,\ldots,J}$ are i.i.d. distributed according to an extreme value distribution. Then the probability that alternative j is chosen by a patient living in zip code z and belonging to group 2 is

$$P_j^z \mid_{i \in I_2} = \frac{\exp(w_j + v_j + y_j^z)}{\sum\limits_{h=1}^{J} \exp(w_h + v_h + y_h^z)}.$$

Taking the first order Taylor expansion around $v_h = 0$, $h = 1, ..., J$, yields

$$P_j^z\,|_{i\in I_2} \approx P_j^z\,|_{i\in I_1} \cdot \left[1 + v_j - \sum_{h=1}^{J} \left(v_h \cdot P_h^z\,|_{i\in I_1}\right)\right].$$

Let r^z be the number of patients in zip code z, and assume that the percentage of patients in group 2 is constant across zip codes and is equal to ρ. The expected number of patients in group 2 that choose hospital j is

$$\begin{aligned}\rho\sum_{z=1}^{Z} r^z \cdot P_j^z\,|_{i\in I_2} & \\ &\approx \rho \cdot (1 + v_j) \sum_{z=1}^{Z} \left(r^z \cdot P_j^z\,|_{i\in I_1}\right) - \rho \sum_{z=1}^{Z} \left[\left(r^z \cdot P_j^z\,|_{i\in I_1}\right) \sum_{h=1}^{J} \left(v_h \cdot P_h^z\,|_{i\in I_1}\right)\right].\end{aligned}$$

Let $\overline{N}_j^k$ be the expected number of patients in group $k \in \{1, 2\}$ who choose hospital j, and let $\overline{n}_j^{kz}$ be the expected number of patients in group k from zip code z who choose hospital j. Then I have

$$\left(\frac{\overline{N}_j^2}{\overline{N}_j^1}\right) \cdot \left(\frac{1-\rho}{\rho}\right) \approx 1 + v_j - \frac{\sum_{z=1}^{Z} \left[\overline{n}_j^{1z} \sum_{h=1}^{J} \left(v_h \cdot P_h^z\,|_{i\in I_1}\right)\right]}{\sum_{z=1}^{Z} \overline{n}_j^{1z}}.$$

The third term on the right hand side is the weighted average of the difference in expected utility between patients in group 1 and 2 across all zip codes, where the weight is the number of patients in group 1 from each zip code. This equation shows the relationship between $\frac{\overline{N}_j^2}{\overline{N}_j^1}$ and v_j.

Table 1: List of Target Hospitals and Acquirer Hospitals

1997

System	Target hospitals	Acquirer hospitals
AHERF	**Allegheny Valley** **Canonsburg General** **Forbes Regional**	**Allegheny General**
Conemaugh	Meyersdale Community Windber Hospital & Wheeling Clinic	Conemaugh Valley Memorial
Mercy	Mercy Providence	Mercy Hospital of Pittsburgh
UPMC	**Beaver Valley** Bedford Braddock **McKeesport** **South Side** **St. Margaret**	**Passavant** **Shadyside** **Presbyterian**
Valley	**Sewickley Valley**	**Medical Center, Beaver**
Western Penn	Suburban General	Western Pennsylvania

Note: In 1997, AHERF and Valley were loosely affiliated with each other through Pyramid Health. St. Clair, a community care hospital in Pittsburgh, was also a part of Pyramid Health. Pyramid Health was resolved in 1998.

2002

System	Target hospitals	Acquirer hospitals
Conemaugh	**Meyersdale Community** Miners Hospital **Windber Medical Center**	**Bon Secours Holy Family** **Conemaugh Valley Memorial**
St. Francis	Saint Francis Hospital - Cranberry	Saint Francis Medical Center
Mercy	Mercy Providence	Mercy Hospital of Pittsburgh
UPMC	Bedford Braddock **McKeesport** **South Side** **St. Margaret**	**Lee Regional** **Passavant** **Shadyside** **Presbyterian**
Valley	**Sewickley Valley**	**Medical Center, Beaver**
Westmoreland	**Frick**	**Westmoreland Regional**
West Penn Allegheny	**Alle-Kiski (former Allegheny Valley)** **Canonsburg General** **Forbes Regional** **Suburban General**	**Allegheny General** **Western Pennsylvania**

Note: Former AHERF and Western Penn hospitals formed West Penn Allegheny.

Table 2: Characteristics of Patients and Referring Hospitals

	Assumption1 (based on CATH record)		Assumption2 (based on AMI demand)		Assumption3 (based on location)	
# obs	872 (319 from 2002)		805 (309 from 2002)		1003 (346 from 2002)	
Patient characteristics	Mean	S.D.	Mean	S.D.	Mean	S.D.
Female	0.415	0.493	0.467	0.499	0.408	0.492
Age	71.9	8.0	72.5	8.4	70.8	8.1
Expired when discharged	0.000	0.000	0.020	0.140	0.015	0.121
Medicare	0.802	0.399	0.834	0.373	0.797	0.403
Blue Cross	0.155	0.362	0.147	0.354	0.176	0.381
Commercial	0.044	0.204	0.020	0.140	0.027	0.162
Hispanic	0.000	0.000	0.000	0.000	0.000	0.000
Asian	0.000	0.000	0.000	0.000	0.000	0.000
Black	0.024	0.153	0.022	0.148	0.041	0.198
Race unknown	0.010	0.101	0.084	0.278	0.072	0.258
Referring Hospitals' Characteristics	Mean	S.D.	Mean	S.D.	Mean	S.D.
Teaching	0.036	0.185	0.042	0.201	0.035	0.184
#Catheterization	3924	5535	2018	3902	1972	3446
#AMI admission	328	116	352	91	314	141
UPMC (1997 and 2002)	0.384	0.487	0.248	0.432	0.226	0.419
Westmoreland (1997 and 2002)	0.003	0.059	0.030	0.170	0.023	0.150
AHERF (1997 only)	0.119	0.324	0.103	0.304	0.164	0.370
Valley (1997 and 2002)	0.140	0.347	0.062	0.242	0.045	0.207
West Penn Allegheny (2002)	0.032	0.176	0.109	0.312	0.123	0.328
Independent	0.321	0.467	0.440	0.497	0.420	0.494
First year after acquisition	0.318	0.466	0.288	0.453	0.292	0.455

Note: All of the referring hospitals were secular non-profit.

Table 3: Characteristics of Tertiary Care Hospitals Included in the Analysis

1997	Acquirer* (n=5)		Others* (n=8)	
	Mean	S.D.	Mean	S.D.
#CABG	811	495	509	308
#PTCA	1418	1076	639	310
Teaching	0.600	0.548	0.375	0.518

2002	Acquirer* (n=10)		Others* (n=7)	
	Mean	S.D.	Mean	S.D.
#CABG	443	263	309	96
#PTCA	917	687	570	262
Teaching	0.400	0.516	0.286	0.488

Note: All of the surgery hospitals were secular non-profit.
* "Acquirers" are tertiary care hospitals whose targets are included in the analysis, so "others" include acquirers whose targets are not included in the analysis.

Table 4: Responsiveness of Demand to a Rating for Referring Hospitals Included in the Analysis

Hospital group	#hospital or #obs	Mean	S.D.	Min	Max
All referring hospitals	26	0.66	0.18	0.33	0.95
Independent hospitals	9	0.57	0.19	0.33	0.93
Target hospitals	17	0.70	0.17	0.43	0.95
Assumption 1 (based on CATH record)*	872	0.67	0.17	0.33	0.95
Assumption 2 (based on AMI demand)*	805	0.55	0.13	0.33	0.84
Assumption 3 (based on location)*	1938	0.72	0.19	0.42	0.95

*Statistics are calculated for the entire data set.

Table 5: Estimated Parameters for Referral Choice Model

	Assumption1 (based on CATH record)		Assumption2 (based on AMI demand)		Assumption3 (based on location)	
	Beta	S.D.	Beta	S.D.	Beta	S.D.
Doctor's Traveling Hrs	-0.147	0.048	-0.495	0.186	9.190	7.949
(Doctor's Traveling Hrs)^2	0.001	0.001	0.005	0.002	-0.107	0.096
Patient's Traveling Hrs	-0.146	0.152	0.324	0.307	-8.805	7.953
(Patient's Traveling Hrs)^2	-0.002	0.002	0.000	0.004	0.104	0.096
(Patient's Traveling Hrs)*RDR	0.012	0.197	0.010	0.454	-0.927	0.233
(Patient's Traveling Hrs)^2*RDR	0.004	0.003	-0.011	0.007	0.007	0.003
Affiliation	76.994	27.773	5.585	1.638	3.566	1.739
Loose Affiliation	-0.877	0.315	-0.165	0.495	0.303	0.356
First Year after Acquisition	-1.015	0.285	-0.584	0.328	-0.255	0.271
Affiliation*Old	-0.148	0.243	-0.012	0.244	0.257	0.260
Affiliation*(Privately Insured)	0.476	0.227	-0.160	0.309	0.272	0.252
Affiliation*(High Prestige)	-78.855	27.806	-8.275	1.977	-6.667	1.939
Affiliation*RDR	-102.437	38.260	-4.222	2.724	-1.320	2.695
Affiliation*RDR*(High Prestige)	107.181	38.269	9.405	3.286	6.635	2.951

Note: RDR refers to the responsiveness of demand to a rating.

Table 6: The Estimated Effect of Affiliation on the Community Care Hospital's Latent Utility

	Assumption1 (based on CATH record)		Assumption2 (based on AMI demand)		Assumption3 (based on location)	
RDR	not high	high	not high	high	not high	high
0.3	46.26	-0.44	4.32	-1.13	3.17	-1.51
0.4	36.02	0.04	3.90	-0.62	3.04	-0.97
0.5	25.78	0.51	3.47	-0.10	2.91	-0.44
0.6	15.53	0.99	3.05	0.42	2.77	0.09
0.7	5.29	1.46	2.63	0.94	2.64	0.62
0.8	-4.96	1.93	2.21	1.46	2.51	1.15
0.9	-15.20	2.41	1.79	1.97	2.38	1.68
1	-25.44	2.88	1.36	2.49	2.25	2.21

Note: RDR refers to the responsiveness of demand to a rating.

Table 7: Estimated Parameters for Hospital Choice for AMI Patients

Area	Year	Variable	Beta	S.D.
Allegheny Valley	1997	Ratio of Old Male Patient	3.042	0.610
Allegheny Valley	1997	Ratio of Young Female Patients	0.137	0.188
Allegheny Valley	1997	Ratio of Old Female Patients	1.233	0.184
Allegheny Valley	1997	Traveling Hrs*Old Male	-0.043	0.008
Allegheny Valley	1997	Traveling Hrs*Young Female	-0.020	0.005
Allegheny Valley	1997	Traveling Hrs*Old Female	-0.047	0.007
Allegheny Valley	1997	Traveling Hrs	-0.167	0.004
Alle-Kiski*	2002	Ratio of Old Male Patient	2.971	0.522
Alle-Kiski*	2002	Ratio of Young Female Patients	0.612	0.339
Alle-Kiski*	2002	Ratio of Old Female Patients	1.101	0.169
Alle-Kiski*	2002	Traveling Hrs*Old Male	-0.028	0.009
Alle-Kiski*	2002	Traveling Hrs*Young Female	-0.015	0.008
Alle-Kiski*	2002	Traveling Hrs*Old Female	-0.042	0.008
Alle-Kiski*	2002	Traveling Hrs	-0.159	0.006
Beaver Valley	1997	Ratio of Old Male Patient	2.842	0.481
Beaver Valley	1997	Ratio of Young Female Patients	0.144	0.165
Beaver Valley	1997	Ratio of Old Female Patients	1.166	0.154
Beaver Valley	1997	Traveling Hrs*Old Male	-0.036	0.007
Beaver Valley	1997	Traveling Hrs*Young Female	-0.012	0.004
Beaver Valley	1997	Traveling Hrs*Old Female	-0.047	0.006
Beaver Valley	1997	Traveling Hrs	-0.168	0.003
Aliquippa Community**	2002	Ratio of Old Male Patient	2.003	0.466
Aliquippa Community**	2002	Ratio of Young Female Patients	0.358	0.323
Aliquippa Community**	2002	Ratio of Old Female Patients	0.877	0.149
Aliquippa Community**	2002	Traveling Hrs*Old Male	-0.024	0.007
Aliquippa Community**	2002	Traveling Hrs*Young Female	-0.010	0.006
Aliquippa Community**	2002	Traveling Hrs*Old Female	-0.025	0.006
Aliquippa Community**	2002	Traveling Hrs	-0.166	0.005
Braddock	2002	Ratio of Old Male Patient	2.056	0.402
Braddock	2002	Ratio of Young Female Patients	0.067	0.262
Braddock	2002	Ratio of Old Female Patients	0.859	0.131
Braddock	2002	Traveling Hrs*Old Male	-0.024	0.005
Braddock	2002	Traveling Hrs*Young Female	-0.011	0.005
Braddock	2002	Traveling Hrs*Old Female	-0.034	0.005
Braddock	2002	Traveling Hrs	-0.146	0.003
Burler	1997	Ratio of Old Male Patient	3.070	0.617
Burler	1997	Ratio of Young Female Patients	0.144	0.208
Burler	1997	Ratio of Old Female Patients	1.180	0.192
Burler	1997	Traveling Hrs*Old Male	-0.032	0.007
Burler	1997	Traveling Hrs*Young Female	-0.016	0.004
Burler	1997	Traveling Hrs*Old Female	-0.042	0.006
Burler	1997	Traveling Hrs	-0.125	0.004

* Former Allegheny Valley
** Former Beaver Valley

Table 7 Cont.: Estimated Parameters for Hospital Choice for AMI Patients

Area	Year	Variable	Beta	S.D.
Canonsburg	1997	Ratio of Old Male Patient	2.684	0.447
Canonsburg	1997	Ratio of Young Female Patients	0.040	0.152
Canonsburg	1997	Ratio of Old Female Patients	1.168	0.145
Canonsburg	1997	Traveling Hrs*Old Male	-0.038	0.005
Canonsburg	1997	Traveling Hrs*Young Female	-0.010	0.003
Canonsburg	1997	Traveling Hrs*Old Female	-0.048	0.004
Canonsburg	1997	Traveling Hrs	-0.156	0.003
Canonsburg	2002	Ratio of Old Male Patient	2.194	0.416
Canonsburg	2002	Ratio of Young Female Patients	0.263	0.272
Canonsburg	2002	Ratio of Old Female Patients	0.989	0.134
Canonsburg	2002	Traveling Hrs*Old Male	-0.028	0.005
Canonsburg	2002	Traveling Hrs*Young Female	-0.009	0.004
Canonsburg	2002	Traveling Hrs*Old Female	-0.033	0.005
Canonsburg	2002	Traveling Hrs	-0.155	0.004
Forbes Regional	1997	Ratio of Old Male Patient	2.913	0.416
Forbes Regional	1997	Ratio of Young Female Patients	0.081	0.147
Forbes Regional	1997	Ratio of Old Female Patients	1.228	0.139
Forbes Regional	1997	Traveling Hrs*Old Male	-0.033	0.004
Forbes Regional	1997	Traveling Hrs*Young Female	-0.011	0.003
Forbes Regional	1997	Traveling Hrs*Old Female	-0.045	0.004
Forbes Regional	1997	Traveling Hrs	-0.138	0.002
Forbes Regional	2002	Ratio of Old Male Patient	2.151	0.384
Forbes Regional	2002	Ratio of Young Female Patients	0.296	0.246
Forbes Regional	2002	Ratio of Old Female Patients	0.964	0.126
Forbes Regional	2002	Traveling Hrs*Old Male	-0.026	0.005
Forbes Regional	2002	Traveling Hrs*Young Female	-0.008	0.004
Forbes Regional	2002	Traveling Hrs*Old Female	-0.033	0.004
Forbes Regional	2002	Traveling Hrs	-0.137	0.003
Frick	1997	Ratio of Old Male Patient	2.824	0.552
Frick	1997	Ratio of Young Female Patients	0.108	0.168
Frick	1997	Ratio of Old Female Patients	1.495	0.179
Frick	1997	Traveling Hrs*Old Male	-0.036	0.005
Frick	1997	Traveling Hrs*Young Female	-0.008	0.003
Frick	1997	Traveling Hrs*Old Female	-0.043	0.004
Frick	1997	Traveling Hrs	-0.130	0.003
Frick	2002	Ratio of Old Male Patient	2.333	0.441
Frick	2002	Ratio of Young Female Patients	0.072	0.269
Frick	2002	Ratio of Old Female Patients	0.983	0.149
Frick	2002	Traveling Hrs*Old Male	-0.016	0.005
Frick	2002	Traveling Hrs*Young Female	-0.004	0.004
Frick	2002	Traveling Hrs*Old Female	-0.028	0.004
Frick	2002	Traveling Hrs	-0.131	0.003

Table 7 Cont.: Estimated Parameters for Hospital Choice for AMI Patients

Area	Year	Variable	Beta	S.D.
Indiana	1997	Ratio of Old Male Patient	3.712	1.215
Indiana	1997	Ratio of Young Female Patients	-0.606	0.572
Indiana	1997	Ratio of Old Female Patients	1.031	0.589
Indiana	1997	Traveling Hrs*Old Male	-0.005	0.007
Indiana	1997	Traveling Hrs*Young Female	-0.011	0.005
Indiana	1997	Traveling Hrs*Old Female	-0.023	0.008
Indiana	1997	Traveling Hrs	-0.104	0.004
Indiana	2002	Ratio of Old Male Patient	3.919	0.969
Indiana	2002	Ratio of Young Female Patients	0.965	0.593
Indiana	2002	Ratio of Old Female Patients	0.775	0.431
Indiana	2002	Traveling Hrs*Old Male	-0.016	0.008
Indiana	2002	Traveling Hrs*Young Female	0.002	0.006
Indiana	2002	Traveling Hrs*Old Female	-0.020	0.007
Indiana	2002	Traveling Hrs	-0.099	0.005
Jefferson	1997	Ratio of Old Male Patient	2.823	0.433
Jefferson	1997	Ratio of Young Female Patients	0.058	0.151
Jefferson	1997	Ratio of Old Female Patients	1.159	0.144
Jefferson	1997	Traveling Hrs*Old Male	-0.033	0.005
Jefferson	1997	Traveling Hrs*Young Female	-0.011	0.003
Jefferson	1997	Traveling Hrs*Old Female	-0.049	0.004
Jefferson	1997	Traveling Hrs	-0.149	0.003
Latrobe	1997	Ratio of Old Male Patient	2.534	0.772
Latrobe	1997	Ratio of Young Female Patients	-0.042	0.223
Latrobe	1997	Ratio of Old Female Patients	1.560	0.256
Latrobe	1997	Traveling Hrs*Old Male	-0.025	0.006
Latrobe	1997	Traveling Hrs*Young Female	-0.008	0.004
Latrobe	1997	Traveling Hrs*Old Female	-0.030	0.005
Latrobe	1997	Traveling Hrs	-0.119	0.003
Latrobe	2002	Ratio of Old Male Patient	2.742	0.533
Latrobe	2002	Ratio of Young Female Patients	-0.102	0.319
Latrobe	2002	Ratio of Old Female Patients	0.810	0.203
Latrobe	2002	Traveling Hrs*Old Male	-0.012	0.006
Latrobe	2002	Traveling Hrs*Young Female	-0.006	0.005
Latrobe	2002	Traveling Hrs*Old Female	-0.030	0.005
Latrobe	2002	Traveling Hrs	-0.116	0.004
Lee	1997	Ratio of Old Male Patient	1.309	1.395
Lee	1997	Ratio of Young Female Patients	-0.354	0.609
Lee	1997	Ratio of Old Female Patients	0.606	0.607
Lee	1997	Traveling Hrs*Old Male	-0.010	0.010
Lee	1997	Traveling Hrs*Young Female	-0.004	0.005
Lee	1997	Traveling Hrs*Old Female	-0.018	0.009
Lee	1997	Traveling Hrs	-0.102	0.004

Table 7 Cont.: Estimated Parameters for Hospital Choice for AMI Patients

Area	Year	Variable	Beta	S.D.
McKeesport	1997	Ratio of Old Male Patient	2.399	0.590
McKeesport	1997	Ratio of Young Female Patients	0.094	0.189
McKeesport	1997	Ratio of Old Female Patients	1.245	0.181
McKeesport	1997	Traveling Hrs*Old Male	-0.040	0.009
McKeesport	1997	Traveling Hrs*Young Female	-0.009	0.006
McKeesport	1997	Traveling Hrs*Old Female	-0.045	0.007
McKeesport	1997	Traveling Hrs	-0.175	0.004
McKeesport	2002	Ratio of Old Male Patient	2.239	0.533
McKeesport	2002	Ratio of Young Female Patients	-0.030	0.349
McKeesport	2002	Ratio of Old Female Patients	0.748	0.168
McKeesport	2002	Traveling Hrs*Old Male	-0.017	0.009
McKeesport	2002	Traveling Hrs*Young Female	-0.013	0.008
McKeesport	2002	Traveling Hrs*Old Female	-0.027	0.008
McKeesport	2002	Traveling Hrs	-0.169	0.006
Meyersdale	2002	Ratio of Old Male Patient	4.985	1.595
Meyersdale	2002	Ratio of Young Female Patients	0.018	2.261
Meyersdale	2002	Ratio of Old Female Patients	-1.001	1.657
Meyersdale	2002	Traveling Hrs*Old Male	0.027	0.024
Meyersdale	2002	Traveling Hrs*Young Female	-0.029	0.027
Meyersdale	2002	Traveling Hrs*Old Female	0.013	0.035
Meyersdale	2002	Traveling Hrs	-0.077	0.010
Monongahela	1997	Ratio of Old Male Patient	2.516	0.469
Monongahela	1997	Ratio of Young Female Patients	-0.075	0.166
Monongahela	1997	Ratio of Old Female Patients	1.212	0.157
Monongahela	1997	Traveling Hrs*Old Male	-0.032	0.005
Monongahela	1997	Traveling Hrs*Young Female	-0.007	0.003
Monongahela	1997	Traveling Hrs*Old Female	-0.045	0.005
Monongahela	1997	Traveling Hrs	-0.141	0.003
Monongahela	2002	Ratio of Old Male Patient	1.969	0.455
Monongahela	2002	Ratio of Young Female Patients	-0.026	0.288
Monongahela	2002	Ratio of Old Female Patients	0.863	0.144
Monongahela	2002	Traveling Hrs*Old Male	-0.022	0.005
Monongahela	2002	Traveling Hrs*Young Female	-0.005	0.004
Monongahela	2002	Traveling Hrs*Old Female	-0.032	0.004
Monongahela	2002	Traveling Hrs	-0.133	0.003
Monsour	1997	Ratio of Old Male Patient	2.705	0.451
Monsour	1997	Ratio of Young Female Patients	-0.031	0.152
Monsour	1997	Ratio of Old Female Patients	1.264	0.148
Monsour	1997	Traveling Hrs*Old Male	-0.034	0.005
Monsour	1997	Traveling Hrs*Young Female	-0.010	0.003
Monsour	1997	Traveling Hrs*Old Female	-0.044	0.004
Monsour	1997	Traveling Hrs	-0.141	0.002

Table 7 Cont.: Estimated Parameters for Hospital Choice for AMI Patients

Area	Year	Variable	Beta	S.D.
Sewickley	1997	Ratio of Old Male Patient	2.862	0.463
Sewickley	1997	Ratio of Young Female Patients	0.122	0.158
Sewickley	1997	Ratio of Old Female Patients	1.197	0.147
Sewickley	1997	Traveling Hrs*Old Male	-0.040	0.006
Sewickley	1997	Traveling Hrs*Young Female	-0.013	0.003
Sewickley	1997	Traveling Hrs*Old Female	-0.042	0.005
Sewickley	1997	Traveling Hrs	-0.158	0.003
Sewickley	2002	Ratio of Old Male Patient	2.305	0.437
Sewickley	2002	Ratio of Young Female Patients	0.479	0.293
Sewickley	2002	Ratio of Old Female Patients	0.973	0.140
Sewickley	2002	Traveling Hrs*Old Male	-0.026	0.007
Sewickley	2002	Traveling Hrs*Young Female	-0.010	0.006
Sewickley	2002	Traveling Hrs*Old Female	-0.025	0.006
Sewickley	2002	Traveling Hrs	-0.161	0.004
Somerset	1997	Ratio of Old Male Patient	3.134	1.337
Somerset	1997	Ratio of Young Female Patients	0.405	0.472
Somerset	1997	Ratio of Old Female Patients	1.512	0.540
Somerset	1997	Traveling Hrs*Old Male	-0.013	0.007
Somerset	1997	Traveling Hrs*Young Female	-0.007	0.005
Somerset	1997	Traveling Hrs*Old Female	-0.022	0.007
Somerset	1997	Traveling Hrs	-0.099	0.004
South Side	1997	Ratio of Old Male Patient	2.839	0.420
South Side	1997	Ratio of Young Female Patients	0.074	0.149
South Side	1997	Ratio of Old Female Patients	1.228	0.141
South Side	1997	Traveling Hrs*Old Male	-0.029	0.005
South Side	1997	Traveling Hrs*Young Female	-0.011	0.003
South Side	1997	Traveling Hrs*Old Female	-0.045	0.004
South Side	1997	Traveling Hrs	-0.144	0.002
South Side	2002	Ratio of Old Male Patient	2.133	0.390
South Side	2002	Ratio of Young Female Patients	0.123	0.252
South Side	2002	Ratio of Old Female Patients	0.915	0.127
South Side	2002	Traveling Hrs*Old Male	-0.028	0.005
South Side	2002	Traveling Hrs*Young Female	-0.011	0.004
South Side	2002	Traveling Hrs*Old Female	-0.034	0.004
South Side	2002	Traveling Hrs	-0.139	0.003
St. Clair	1997	Ratio of Old Male Patient	2.910	0.439
St. Clair	1997	Ratio of Young Female Patients	0.060	0.154
St. Clair	1997	Ratio of Old Female Patients	1.215	0.145
St. Clair	1997	Traveling Hrs*Old Male	-0.030	0.005
St. Clair	1997	Traveling Hrs*Young Female	-0.011	0.003
St. Clair	1997	Traveling Hrs*Old Female	-0.044	0.004
St. Clair	1997	Traveling Hrs	-0.157	0.003

Table 7 Cont.: Estimated Parameters for Hospital Choice for AMI Patients

Area	Year	Variable	Beta	S.D.
St. Margaret	1997	Ratio of Old Male Patient	2.889	0.436
St. Margaret	1997	Ratio of Young Female Patients	0.075	0.154
St. Margaret	1997	Ratio of Old Female Patients	1.229	0.145
St. Margaret	1997	Traveling Hrs*Old Male	-0.032	0.005
St. Margaret	1997	Traveling Hrs*Young Female	-0.017	0.003
St. Margaret	1997	Traveling Hrs*Old Female	-0.051	0.005
St. Margaret	1997	Traveling Hrs	-0.150	0.003
St. Margaret	2002	Ratio of Old Male Patient	2.300	0.409
St. Margaret	2002	Ratio of Young Female Patients	0.291	0.267
St. Margaret	2002	Ratio of Old Female Patients	0.939	0.132
St. Margaret	2002	Traveling Hrs*Old Male	-0.024	0.006
St. Margaret	2002	Traveling Hrs*Young Female	-0.015	0.005
St. Margaret	2002	Traveling Hrs*Old Female	-0.029	0.005
St. Margaret	2002	Traveling Hrs	-0.152	0.004
Suburban	2002	Ratio of Old Male Patient	2.378	0.413
Suburban	2002	Ratio of Young Female Patients	0.357	0.271
Suburban	2002	Ratio of Old Female Patients	0.958	0.133
Suburban	2002	Traveling Hrs*Old Male	-0.026	0.006
Suburban	2002	Traveling Hrs*Young Female	-0.013	0.005
Suburban	2002	Traveling Hrs*Old Female	-0.026	0.005
Suburban	2002	Traveling Hrs	-0.153	0.004
Uniontown	2002	Ratio of Old Male Patient	1.323	0.887
Uniontown	2002	Ratio of Young Female Patients	-0.761	0.464
Uniontown	2002	Ratio of Old Female Patients	0.996	0.290
Uniontown	2002	Traveling Hrs*Old Male	-0.020	0.006
Uniontown	2002	Traveling Hrs*Young Female	-0.009	0.005
Uniontown	2002	Traveling Hrs*Old Female	-0.020	0.005
Uniontown	2002	Traveling Hrs	-0.115	0.004
Windber	2002	Ratio of Old Male Patient	1.962	0.639
Windber	2002	Ratio of Young Female Patients	0.667	1.059
Windber	2002	Ratio of Old Female Patients	-1.361	0.857
Windber	2002	Traveling Hrs*Old Male	-0.040	0.016
Windber	2002	Traveling Hrs*Young Female	-0.015	0.016
Windber	2002	Traveling Hrs*Old Female	0.012	0.023
Windber	2002	Traveling Hrs	-0.088	0.005