What Makes Hospitals Refer Patients to Their Affiliated Hospitals?

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February 21, 2006

Abstract

There have been many hospital merger cases in which a tertiary care hospital (the acquirer) acquired a community care hospital (the target) in the past fifteen years. Researchers found that such mergers sometimes lead to increased referrals from the target hospitals to the acquirers. This paper studies in what cases the targets are more likely to refer patients to the acquirers. I develop a theoretical model in which patients' preference toward community care hospitals is influenced by the ratings given by the prior users. It predicts that a community care hospital attaches greater weight on its patients' preference in making referrals when demand is more responsive to a change in a patient's evaluation. Based on this model, I estimate a structural model of referral choice for cardiac surgery. I find that when the acquirers are not among the top hospitals in the region, the target hospitals with more responsive demand are equally or less likely to refer their patients to the acquirers. On the other hand, the acquirers renowned for high quality of care are more likely to attract referrals from target hospitals with more responsive demand. These findings suggest patients conceive that there are quality gains from vertical integration of hospitals only when the acquirers are one of the top hospitals.

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 community care hospital that does not offer such services (the target). Such mergers can be considered to be vertical rather than horizontal, like the integration of

*I am greatly indebted to David Dranove for his invaluable advice, and to the other committee members Rob Porter, William Rogerson, and Mark Satterthwaite for great guidance. I thank Cory Capps for sharing his codes for obtaining driving hours using Mapquest.com web page. I also thank seminar participants at Northwestern University for helpful comments. All errors are mine.

hospitals and physicians. Tertiary care hospitals and community care hospitals provide complementary inputs for rural patients in need of specialized care. In addition, community care hospitals are distribution centers of specialized care when they refer their patients to tertiary care hospitals. Like the retail stores which can affect the products consumers buy, community care hospitals could affect hospital choice for the services they do not offer themselves.

Several media reports point out that the acquisition of community care hospitals could lead to increased referrals to the acquirer hospitals,[1] and two studies examine this hypothesis. Huckman (2005) reports that after the acquisition, admissions to the acquirers for cardiac surgery from the target's primary market increased. On the other hand, Nakamura *et al.* (2005) find that the acquisition of a community care hospital could lead to a significant increase in referrals to the acquirer hospital, but in the majority of cases there appears to be no change in referrals to the acquirers. Nevertheless, as far as I know, none of the existing works examine what factors account for such differences.

This paper studies in what cases the vertical alliance of a community care hospital and a tertiary care hospital leads to a significant increase in referrals from the former to the latter and examines what drives the target hospitals to increase referrals to their acquirers. There are a couple of possible motives. First, 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 anti-kickback laws prohibit the hospitals from paying the physicians for the referrals, the laws do not prohibit acquisitions of community care hospitals by tertiary care hospitals. Thus hospital acquisition could be used as a loophole for buying referrals. Second, if the merger facilitates clinical integration and achieves gains in quality of care and efficiency, then that would lead to an increase in referrals to the acquirers.[2] The first motive could hurt the patients, while the second would benefit the patients.

Analyzing referral patterns of community care hospitals boils down to analyzing the referring physicians' behavior. Many researchers point out that physicians are imperfect agents of the patients.[3] Given information asymmetry between physicians and patients, physicians would behave similarly to the perfect agents when they are more altruistic or when patients are more sensitive to their physicians' reputation. In other words, physicians care more about patients' welfare when they are more benevolent or if the market discipline makes them more careful about their reputation. Thus comparing the referral patterns of physicians who are expected to be more considerate of patients' 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 the patients' welfare,

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

[2] Another possibility is that both hospitals have increased number of managed care contracts, but it would not lead to increased referrals of patients covered under other types of insurance. Nakamura *et al.* (2005) find increases in referrals for Medicare patients, for example.

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

then the 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' preference toward community care hospitals is affected by the rating given by the prior users of the hospitals. The model predicts that the larger the marginal change in demand for a community care hospital given an increase in a patient's evaluation of the hospital, the greater weight the hospital attaches on patients' welfare in choosing the referral destinations. This model implies that if community care hospitals have different referral patterns depending on how much the demand responds to a change in a rating by a patient, then it reflects that the hospitals give different priorities to their patients' welfare.

I estimate a multinomial logit model of referral choice for open heart surgery using hospital discharge data from the southwest part of Pennsylvania surrounding Pittsburgh. I find that community care hospitals are more likely to refer their patients to their affiliated 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 with more responsive demand are equally or less likely to refer their patients to the acquirers. On the other hand, the acquirers renowned for high quality of care are more likely to attract referrals from target hospitals with more responsive demand. These findings suggest patients conceive that there are quality gains from vertical integration of hospitals only when the acquirers are one of the top hospitals. Based on my theoretical model, I interpret this to reflect patients' perception that there are quality gains from vertical integration of hospitals only when the acquirers are renowned for high quality of care.

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 community 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 possible motives for hospitals to form vertical alliances with physicians, which might also explain the motives of tertiary care hospitals for acquiring community care hospitals. They can be roughly categorized into two views. One is that vertical integration reduces transaction costs and facilitates quality enhancement and cost containment. The other is that the hospitals and the physicians gain financial benefits by forming vertical alliances. First, as Gal-Or (1999) points out, vertical integration could give the collective bargaining power to the hospitals and physicians when they negotiate over the prices with managed care organizations. Second, the hospitals might benefit from increasing the physicians' loyalty to the hospitals. If it is difficult for the patients to switch their physicians, the physicians would have strong influence over hospital choice (Barro and Cutler (2000)). Since the anti-kickback laws prohibit the hospitals from paying the physicians for the referrals, the only way for the hospitals to reward the physicians for the referrals is to acquire the physician practice.

There is only weak support for quality gains due to vertical alliances of tertiary care hospitals and community care hospitals (Huckman (2005), Madison (2004b)), as well as that of hospitals and physicians (Cuellar and Gertler (2002), Madison (2004a)). Likewise, there is weak support for cost containment due to vertical alliances of tertiary care hospitals and community care hospitals (Huckman (2005), Madison (2004b)), as well as that of hospitals and physicians (Cuellar and Gertler (2002), Madison (2004a)). In addition, studies on the effect of hospital mergers on hospital prices suggest that the merger would not be highly effective in increasing the 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 (2002), Ciliberto and Dranove (2005)).

On the other hand, several studies find that vertical acquisition leads to an increase in the patient volume of the acquirer. Cuellar and Gertler (2002) 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 (2005) finds that vertical integration of hospitals has similar effects for cardiac surgery, a typical tertiary care service which is offered by only a small fraction of hospitals and is known to have a large profit margin on average. Using discharge records from the state of New York and Florida on both cardiac surgery and broader range of tertiary care DRGs, Nakamura *et al.* (2005) report that some acquisitions lead to significant increases in admissions from the neighborhood of the target hospitals, but in a majority of cases there is no significant change in referral patterns.

Huckman (2005) points out that the "business stealing effect" due to vertical integration of hospitals might result in welfare improvement. First, patients might be steered from hospitals with less-skilled physicians to those with highly skilled physicians. Second, shifting patient volume from one hospital to another might help concentrate patient volume to the expanding hospital and thus improve quality at that hospital. Nevertheless, Huckman finds little impact of vertical integration of hospitals on average cost and quality of cardiac surgery in New York.

Nakamura *et al.* (2005) find mixed evidence that the target hospitals selectively refer patients with higher profit margins to the acquirers. They find that the increase in referrals is larger for cardiac surgery, which is known to be more profitable than most of the other tertiary DRGs. They also find that referrals from the targets to the acquirers tend to increase more for patients with more remunerative insurance. On the other hand, they do not find evidence that the target hospitals selectively refer healthier and less costly patients to their acquirers.

3 Model of Referral Choice

In this section, I develop a theoretical model of referral choice, in which patients' preference toward a community care hospital depends on the rating given by patients who used the hospital in the previous period. Community 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 community care hospitals facing demand that are more responsive to a change in a rating by a patient put greater weight on patients' preference in choosing referral destinations.

There are patients $i = 1, ..., I$, community care hospitals $k = 1, ..., K$, and tertiary care hospitals $j = 1, ..., J$. There are two periods, and in the beginning of each period, each patient chooses one community care hospital, and with a certain probability, the physicians at the community care hospital find the patient needs advanced treatment. When that is the case, the community care hospital refers the patient to a tertiary care hospital.[4] For simplicity, assume that tertiary care hospitals do not provide community care, and that all the patients need to go to community care hospitals first.[5] Both community care hospitals and tertiary care hospitals earn a fixed profit margin per admission. In period 1, after referrals were made, patients rate the community care hospitals that they chose. When patients choose community care hospitals at the beginning of period 2, they consider the ratings by the patients in period 1. Figure 1 describes the timing of the actions.

3.1 Patients

Let V^i_{jkt} denote patient i's utility when he is referred from community care hospital k to tertiary care hospital j at time t. I 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, community care hospitals, and tertiary care hospitals such as the driving hours from the patient's home to the tertiary care hospital and whether the hospitals are vertically integrated. ε^i_{jt} is determined by the factors that are unobservable to the econometrician. I assume that

[4] Strictly speaking, it is the physicians at the community care hospitals that refer patients, but I use the words "physicians at a community care hospital" and "a community care hospital" interchangeably.

[5] A hospital that provides both community care and tertiary care is treated as two separate hospitals in this section.

ε^i_{jt} is observable to patient i and the community care hospitals at the beginning of period t.

Similarly, let W^i_{kt} be patient i's utility when he chooses community 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 distribution. $\overline{w}^i_{kt}$ 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 community 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 community care hospitals by patients in the second period is affected by the average rating of each community 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 community 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 the patients do not know the actual referral patterns of the community care hospitals. For example, suppose that a community care hospital tends to refer its patients to its low-quality acquirer at a distance, which lowers its rating. Patients in the next period know that the community care hospital pays little attention to patients' preference 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 community care hospitals does not depend on the patients' preference toward tertiary care hospitals.

3.2 Community Care Hospitals

I assume that community 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 for the physicians, and the welfare of the referred patients, over the two periods. Let $\alpha_k \geq 0$ be the weight community care hospital k places on patients' preferences. By convenience for the physicians, I mean that the community care hospitals prefer to refer patients to the tertiary care hospitals that are easy to make referral arrangements and close to the hospital. Let Z_{jk} be the referring physician's non-monetary utility when a patient is referred to tertiary care hospital j from community care hospital k.

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

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

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

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 the patient i is referred to tertiary care hospital j from community 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 community care hospital k in period 2, and 0 otherwise. Aff_{jk} is an indicator variable that is equal to 1 if community 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 $\widehat{s}_k^{i'}$ over $\bar{w}_{k2}^{i'}$ around $\bar{w}_{k1}^{i}$, patient i's non-probabilistic component in utility from being treated at community care hospital k in period 1. Taking the first order Taylor expansion of $\widehat{s}_k^{i'}$ over $\bar{w}_{k2}^{i'}$ around $\bar{w}_{k1}^{i}$ yields

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

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 MCD_k. Substituting (6) and (8) to (5) yields

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

Note that the last term does not depend on $\{r_{jk}^{i'}\}_{j=1,\dots,J}$.

Let me define F_k^i as follows:

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

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. In other words, each community care hospital $k = 1, ..., K$ compares the values of

$$(\alpha_k + b \cdot P \cdot \rho \cdot MCD_k) \cdot V_{jk1}^{i} + Z_{jk} + Aff_{jk} \cdot M_{jk}^{i}$$

across tertiary care hospitals that are included in the patient's choice set, and refers the patient to the hospital which yields the highest value. If the referring hospital does not have organizational relationships with any of the tertiary care hospitals, then the last term is zero for all tertiary care hospitals.

3.3 Measure of Responsiveness of Demand

MCD_k is the marginal change in demand for community care hospital k given an increase in a patient's rating of k. The larger MCD_k is the greater weight the community care hospital places on patients' preferences. In other words, the relative importance of physicians' convenience and financial gains from referring patients to the acquirers decrease as MCD_k increases. Thus MCD_k can be considered to be a measure of competitive pressure that community care hospital k faces as well as a measure of responsiveness of demand.

MCD_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 attaches heavier weight on the patients' welfare in making referral decisions. MCD_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 community care hospitals is logit, as equation (7) shows.

This measure gives the greatest weight to a patient whose probability of choosing the hospital is 50%. In other words, the marginal effect is the largest when the choice probability is 50%. A patient whose likelihood of choosing the hospital is 25% is given the same weight as a patient whose likelihood is 75%. Accordingly, a hospital cares about its own reputation more when there are ten patients in the market and ten of them have a 50% probability of choosing the hospital rather than when five of them have a 25% probability and the other five have a 75% probability of choosing the hospital. Intuitively, this is because the effect of a patient's evaluation on the demand for the hospital depends on how indifferent patients are, rather than on how likely the patients are to choose the hospital on average.

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).[6] In this section, I explain the empirical specification of the model and discuss the identifying assumptions.

4.1 Open Heart Surgery (CABG/PTCA)

Huckman (2005) reports that vertical integration leads to increased referrals for open heart surgery. Furthermore, Nakamura *et al.*(2005) find that the increase in referrals is larger for open heart surgery than for other tertiary care services. Since my interest here is on why target hospitals increase referrals to their acquirers and not on whether the referrals increase or not, I follow previous works and study referral choice for open heart surgery. Huckman (2005) and Nakamura *et al.*(2005) provide detailed background information on open heart surgery.

Inter-hospital referrals are common for open heart surgery cases, since only a small fraction of hospitals offer CABG/PTCA. While some patients have CABG/PTCA right after having heart attacks, others have CABG/PTCA as non-emergency cases. The latter patients typically have initial symptoms of ischemic heart disease such as chest pain or short of breath, and present themselves to their local hospitals. If the hospitals do not offer open heart 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, open heart surgery is known for its high profit margins.[7] 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.[8] Second, empirical works suggest that there is learning by doing in CABG/PTCA.[9] 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.[10]

[6] I use the words "CABG/PTCA", "open heart surgery", and "cardiac surgery" interchangeably.

[7] Huckman (2005) provides detailed discussion on the costs and profit margins of CABG/PTCA.

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

[9] 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.

[10] Bazzoli (2003) reports that most hospitals have emergency capacity problems, but few face capacity constraints outside of the emergence department, except for the areas with high population growth. Pittsburgh experienced a decline in population..

4.2 Referral Choice

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

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

where Aff_{jk} is an indicator variable that is equal to 1 if referring hospital k has an organizational relationship with tertiary care hospital j when the referral is made and 0 otherwise. α_k could vary with the characteristics of community care hospitals, such as ownership status. In my data, however, all of the hospitals that offer cardiac catheterization or open heart 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 community 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 community 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 open heart surgery is hard to measure, I use hospital fixed effects to account for quality difference among hospitals.

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, provided that patients in more severe conditions are more willing to travel in search of a better quality of care, hospitals with superior quality attract high severity patients. If the severity of illness cannot be fully captured by the demographic and clinical characteristics of the patients used in the estimation, the estimated hospital quality would be subject to selection bias. This is especially problematic in measuring hospital quality for cardiac surgery, since most of the admissions are not emergent. Moreover, mortality is a noisy signal, and not all the hospitals perform large numbers of cardiac surgeries.

Another commonly used measure of quality is the patient volume of the hospital. While many researchers find high correlation between volume and quality, volume reflects other hospital characteristics as well. In particular, some hospitals might have increased numbers of heart surgery cases due to acquiring community care hospitals. If this is the case, then volume would be correlated with affiliation status and including volume as an explanatory variable could result in a multicollinearity problem.

Since coordination between physicians at community care hospitals and physicians at tertiary care hospitals could influence quality of care, and organizational relationships could facilitate clinical integration, I allow hospital fixed effects to depend on the organizational relationships between the two. In other words, if patients are convinced that they can benefit from better coordination of care at the point of referral, they could 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 themselves only when they know the acquirers are high quality hospitals.

Accordingly, q_{jk} is specified as follows:

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

where H_j is quality of tertiary care hospital j and υ is the effect of vertical integration on quality of care as perceived by the patients. $High_j$ is a dummy variable that is equal to 1 if tertiary care hospital j performs an exceptionally large number of cardiac surgeries and is regarded as one of the top hospitals in the region. w measures the effect of vertical integration on quality of care as perceived by the patients when the acquirer is a top hospital.

To measure the quality of tertiary care hospitals, I use three different measures; (1) hospital rankings by US News & World Report, (2) the number of open heart surgeries performed at each hospital, and (3) the number of open heart surgery patients from outside of the county treated at each hospital. Assuming "practice makes perfect," the surgical volume of a hospital would reflect 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 would be superior in quality of care.

Two of the acquirer hospitals in my data, UPMC Presbyterian and UPMC Shadyside, have been widely recognized as among the top hospitals in the U.S. for various tertiary care services including cardiac surgery. US News & World Report have always ranked them as among the best hospitals since the late 1990s. Another acquirer hospital in my data, Allegheny General Hospital, performed a comparable number of open heart surgeries and also accepted a comparable number of patients from outside of the county, although it has not been as highly ranked as UPMC Presbyterian and UPMC Shadyside by US News & World Report. Thus I define these three as top hospitals. The other tertiary care hospitals in my data performed much smaller numbers of cardiac surgeries and accepted much fewer patients living outside the county.

I specify Z_{jk}, physicians' non-monetary utility from referring a patient from community 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 community 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 accessibility of the hospitals for the referring physicians, I use hospital fixed effects.[11]

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

I allow the effect of vertical integration on referrals to vary with patient demographics and insurance status, the time after acquisition, the degree of organizational integration, and whether the acquirer is a top hospital. Thus M^i_{jk} is specified as follows;

$$M^i_{jk} = \delta_1 \cdot Old^i + \delta_2 \cdot Private^i + \delta_3 \cdot FirstYr_{jk} + \delta_4 \cdot Loose_{jk} + \delta_5 \cdot High_j. \quad (15)$$

Old^i is a dummy variable indicating whether the patient is 80 years old and above or not. If δ_1 is negative, then it implies that the targets selectively refer healthier and thus less costly patients to the acquirers, since it is known that the costs and mortality of heart surgery patients increase with age. $Private^i$ is a dummy variable that is equal to 1 if the patient is covered under private fee-for-service insurance plans. If δ_2 is positive, then it implies that the targets selectively refer patients with more remunerative insurance to the acquirers, since previous empirical works indicate that the average profit margin is the highest for the patients covered under private non-managed care insurance plans (Gowrisankaran *et al.* (2002)).

$FirstYr_{jk}$ 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 community care hospital k has a loose organizational relationship with tertiary care hospital j but is not owned by hospital j. $High_j$ is an indicator variable indicating whether tertiary care hospital j is renowned for high quality of care. If the incremental cost of treating a patient decreases with surgical volume at the hospital, the average profit margin would be higher for such hospitals. On the other hand, if the experience of the medical staff improves 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) report that some tertiary care hospitals occasionally face capacity problems at highly renowned heart programs, while in general few hospitals have capacity problems outside the emergency departments. If the former (latter) effects dominate, δ_5 would be positive (negative).

Since I cannot observe the true value of MCD_k, I use its estimate. Let MCD_k and φ_k be the estimated value of MCD_k and the error in the estimation, respectively. Then I have

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

where

$$\begin{aligned}
I_j &\equiv \alpha \cdot H_j + DH_j, \\
Q_j &\equiv b \cdot P \cdot \rho \cdot H_j, \\
\beta_1 &\equiv -\lambda_1 \cdot \alpha, \\
\beta_2 &\equiv -\lambda_2 \cdot \alpha, \\
\beta_3 &\equiv -\lambda_1 \cdot b \cdot P \cdot \rho, \\
\beta_4 &\equiv -\lambda_2 \cdot b \cdot P \cdot \rho, \\
\beta_5 &\equiv -\kappa_1, \\
\beta_6 &\equiv -\kappa_2, \\
\beta_7 &\equiv \alpha \cdot \upsilon + \delta_0, \\
\beta_8 &\equiv \upsilon \cdot b \cdot P \cdot \rho, \\
\beta_9 &\equiv \alpha \cdot w + \delta_5, \\
\beta_{10} &\equiv w \cdot b \cdot P \cdot \rho, \\
\xi^i_{jk} &\equiv \varsigma_{jk} + \varepsilon^i_j \cdot [\alpha + b \cdot P \cdot \rho \cdot (MCD_k + \varphi_k)] \\
&\quad + \varphi_k \cdot \left[Q_j + b \cdot P \cdot \rho \cdot (-\lambda_1 \cdot T^i_j - \lambda_2 \cdot \left(T^i_j\right)^2 + \upsilon \cdot Aff_{jk}) \right].
\end{aligned}$$

Assuming ξ^i_{jk} is I.I.A. distributed according to extreme value distribution, the probability that community 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

In calculating MCD_k, the measure of the responsiveness of the demand that each community care hospital faces, I assume that the demand for community care hospitals from patients who could need open heart 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. The explanatory variables are hospital fixed effects and the traveling time to the hospital from the patient's home. Tertiary care hospitals as well as community care hospitals are included in the choice set.

I allow the coefficient of traveling hours 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 fixed 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' preference toward hospitals to vary with demographic characteristics without having too many explanatory variables. The appendix justifies this specification.

Tay (2003) estimates a mixed logit model of hospital choice for AMI patients in urban areas, assuming that the coefficient of distance from patients' homes to the hospitals is random and has discrete distribution. She finds that about 14% of the patients incur much lower disutility from traveling. She concludes that these patients were not at home at the time of heart attack. She also finds that such heterogeneity can be excluded by limiting patients' choice sets to the 20 nearest hospitals, thus excluding outliers in which hospitals outside the assigned choice sets are chosen. Following her arguments, I consider only the nearest 20 hospitals to be in the choice set and assume the coefficients of driving hours to be fixed.[12]

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 community care hospital for each patient. First, there are some cases in which a patient has had cardiac catheterization 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 (Assumption1/Data1). A patient with symptoms of heart problems typically first consults a physician either at a hospital or physician's office. If the doctor decides that further evaluation is necessary, then the patient has cardiac catheterization in either inpatient or outpatient setting. Cardiac catheterization is essential for finding the cause of the problems and for determining whether heart surgery is necessary, so all the patients who have had CABG/PTCA must also have had diagnostic cardiac catheterization prior to the cardiac surgery (Nordlicht *et al.*, 1997).

Since the discharge data only records the quarter of the year and not the exact date on which it occurred, I do not know the order of each patient's records in most cases. As a result, Data1 might include cases where the patient had catheterization at a community care hospital only after open heart surgery and not before. In fact, the discharge data shows that some patients had cardiac catheterization in the quarters subsequent to those in which they had CABG/PTCA. Even in such cases, however, it is highly likely that the community care hospital referred the patient for CABG/PTCA, since usually the physician who is familiar with the patient's medical history is present when the patient has cardiac catheterization after CABG/PTCA.[13]

Second, I assume that a patient who has had open heart surgery at a tertiary care hospital and has highly likely gone to a certain community care hospital

[12] Tay (2003) also finds that 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 did not include the square of patient's traveling hours.

[13] This is based on my conversation with a cardiologist.

for heart attack treatment to have been referred from that community care hospital (Assumption2/Data2). Based on the estimated multinomial logit model of hospital choice for AMI treatment, I calculate the probability of choosing each community care hospital for each patient who has had open heart surgery. If the probability is greater than 50%, then I assume that the patient was referred from the community care hospital. This specification is similar to the one in Huckman (2005), in which a patient is regarded as being referred from a hospital when the hospital's share in the patient's zip code of residence is greater than 25%.

Third, if a CABG/PTCA patient's zip code of residence is within a 5 minute drive from the zip code centroid of a community care hospital, I assume that the patient was referred from that community care hospital (Assumption3/Data3). This specification is similar to the one in Nakamura *et al.* (2005).

4.5 Identifying Assumptions

The model can be estimated as a logit if I assume that φ_k, the errors in the estimation of MCD_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 patients and the estimated marginal change in demand given a change in a rating by a patient, $\varepsilon^i_j \cdot MCD_k$, is small, so the variance of the error term is constant.

The exogeneity assumption would be 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 both of the following conditions are met; (1) the referring physicians' perceptions of tertiary care hospitals in terms of quality and accessibility depend on which community care hospitals they are affiliated with, and that is unexplained by organizational relationships between the hospitals, the driving hours between the hospitals, or preferences toward hospitals all physicians have in common, and (2) that affects the hospitals' merger decisions.

The first condition could be satisfied if, for example, physicians prefer to refer their patients to physicians who graduated from the same medical school and physicians from the same medical school are more likely to be affiliated with the same hospitals.[14] Another example is that an influential person at a community care hospital convinces the physicians at the hospital to refer their patients to a tertiary care hospital that she personally prefers. Both conditions could be met in two cases. First, physicians affiliated with a community care hospital collectively have strong likes and dislikes on or establish social networks with physicians affiliated with a particular tertiary care hospital, and that affects referral patterns and hospitals' merger decisions. Second, suppose that

[14] This would have been more of a concern if I studied referrals in rural areas with a small number of medical schools and teaching hospitals nearby. In Pittsburgh area, however, there are a number of prestigious medical schools and teaching hospitals, and there are many cardiologists who were educated and/or trained outside of the state of Pennsylvania.

the first condition is met for some reason, and the effect of community care hospital specific preference on referrals is so strong that it *causes* a community care hospital to be an important source of referrals for a tertiary care hospital. Then the hospitals might want to merge in order to improve quality and efficiency through better coordination or to have increased bargaining power with managed care organizations.

Such hypotheses are, however, inconsistent with the views of sociologists and physicians studying physicians' behavior and hospital mergers. In particular, 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 why Shortell's works attracted the attention of people in health care industry would be that they share the recognition that it is extremely difficult for physicians and/or hospitals to cooperate with each other over organizational boundaries. If physicians can easily build strong networks across affiliated hospitals that do not have organizational relationships with each other, people would not have shown much interests in his advocacy.

The best way to examine endogeneity of affiliation is to estimate a model of referral choice before the merger and test if the coefficient of Aff_{jk} is positive and statistically significant. Unfortunately, however, there are few changes in hospital affiliation in my data. Instead, I use discharge data from the state of New York to examine if the patients who lived closer to the target were more likely to go to the acquirer for tertiary care service before the merger. I do not see any patterns that indicate the acquirer's share was higher in the zip codes closer to the target before the acquisition took place.

In Data1, the characteristics of the referring hospitals could be endogenous if some patients choose community care hospitals that are close to or were acquired by the tertiary care hospitals they prefer. In other words, if patients choose the community care hospitals based on the tertiary care hospitals to which they are likely to be referred, then the causality is reversed.

Ideally, I would like to estimate a dynamic model in which patients could choose community care hospitals based on their expectations of the referral pattern of each hospital. Although that would be a very complex extension, if I had a complete record of all the outpatient visits, it would have been feasible as I could then have observed the choice of hospitals at the first consultation for all the patients. Unfortunately, however, the discharge records do not include cases in which a physician is consulted and refers a patient unless the patient stays overnight or receives surgical procedures.[15]

There are several points that help support the assumption that the choice of community care hospitals is independent of patients' idiosyncratic tastes for tertiary care hospitals. First, if a patient has a strong preference for a particular tertiary care hospital, then it would be more natural for the patient to have cardiac catheterization at that hospital. Patients could have diagnostic cardiac catheterization at tertiary care hospitals. In addition, in Data1, all of the

[15] Cardiac catheterization is categorized as a surgical procedure in discharge records.

community care hospitals appear to have referred patients to various hospitals, which implies that referral patterns are not perfectly foreseeable when patients choose community care hospitals. Thus patients with strong preferences toward particular tertiary care hospitals are likely to be excluded from Data1.

Second, recent surveys of pregnant women and general consumers on hospital choice suggest that few patients have strong idiosyncratic preferences regarding tertiary care hospitals. Patients choose hospitals primarily based on their physician's recommendations, and their preference over hospitals is largely determined by service offerings, location, and general reputation in the community (Sarel *et al.* (2005) and Smithson (2003)). While these surveys also reveal that previous experience with the hospital plays an important role, this would be irrelevant for the majority of CABG/PTCA patients, since very few patients have cardiac surgery more than once. These survey results also help support the assumption that the multiplication of the idiosyncratic preference of the patients and the estimated marginal change in demand given a change in a rating by a patient, $\varepsilon_j^i \cdot MCD_k$, is small.

Another potential problem in Data1 is that some community care hospitals might refer patients to tertiary care hospitals after initial consultation without performing cardiac catheterization themselves. The volume of cardiac catheterization seems almost irrelevant to the number of other cardiac admissions, implying that this could be the case. Such behavior of a community care hospital might lead to the correlation of the error term and explanatory variables. To be specific, suppose that a community care hospital refers a patient to its acquirer without performing cardiac catheterization only if the patient has no objections; if the patient objects, the community care hospital performs cardiac catheterization itself and then refers the patient to some other tertiary care hospital. Then the effect of hospital acquisition on referrals cannot be correctly estimated, since only the latter cases are included in Data1.

Data2 and Data3 are free from such endogeneity problems, provided that the location of patients is exogenous, i.e., patients do not choose where to live based on their preference toward hospitals, and that the errors in estimating the referral sources are small and can be ignored. Thus I can test the validity of the identifying assumptions described above by comparing the estimation results obtained from the three different data sets.

5 Data

I use hospital discharge data from hospitals in Region 1 and 3 for 1997 and 2002 obtained from Pennsylvania Health Care Cost Containment Council (PHC4). The regional map and the map of Allegheny County are in Figure 2-1 and 2-2, respectively. Region 1 and 3 cover the southwest part of Pennsylvania surrounding Pittsburgh.[16] Pittsburgh is in the center of Allegheny County, and

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

Allegheny County is in the center of Region 1.

The discharge data contains all the cases of cardiac patients except for heart transplants. The 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 identifier that links 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 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 community 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.* (2005), I define tertiary care hospitals as the hospitals that perform at least 20 cases of CABG and/or PTCA in that year, and community care hospitals as the short-term general hospitals that do not satisfy this criterion. I limit my analysis to community care hospitals that are included in Data1, so that the scope of the analysis is the same across the three data sets. Thus community care hospitals with small or no volume of cardiac catheterization are excluded from the analysis.

To exclude cases where patients moved and chose hospitals for catheterization and heart surgery independently before and after the move, I exclude patients recorded with more than one valid zip code of residence in the same year. 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. I exclude patients covered under Medicare HMO and Blue Cross managed care plans. I also exclude patients younger than 50 and those who had open heart surgery with primary diagnosis of AMI, since they account for a small percentage and could have different preference toward hospitals than the others.

There were six and seven health systems that included both tertiary care hospitals and community care hospitals in 1997 and 2002.[17] The list of health systems and its member hospitals are in Table 1, where the community care hospitals included in the analysis are in bold letters. Some of the target hospitals are excluded since 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 for each data set. The numbers of patients are almost the same in Data1 and 2, while the number is larger for Data3. Data1 is different from Data2 and Data3 in several respects. The ratio of patients who died in hospitals following CABG/PTCA is about 1.5% to 2% in Data2 and Data3, respectively, while it is zero in Data1, suggesting that pa-

[17] 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 community 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.

tients in Data1 were healthier. Likewise, the ratio of white patients was higher in Data1. In addition, the presumptive referring hospitals in Data1 performed larger numbers of cardiac catheterization on average than those in Data2 and Data3. Among the patients whose presumptive referring hospitals were targets, the majority are estimated to have been referred from the hospitals affiliated with either UPMC Health System, AHERF, or AHERF's continuing organization, West Penn Allegheny Health System. Patients who were presumably referred from hospitals affiliated with the other health systems were rather rare.

Table 3 summarizes the characteristics of tertiary care hospitals. Overall, the acquirers tend to be larger and more technically sophisticated than the others. In both years, the ratio of teaching hospitals was higher among the acquirers, and the acquirers had on average higher surgical volume for both CABG and PTCA. Hospital specific mortality rates from "Pennsylvania Guide to Coronary Artery Bypass Graft Surgery" were higher among acquirers than among the others, but the mean values are not statistically different from zero for both groups. It might be simply because large teaching hospitals accept higher ratio of severely ill patients, and the case-mix adjustment in the estimation of hospital quality is not perfect.

6 Results

I estimate the models described above using GAUSS codes for estimating mixed logit models written by Kenneth Train, David Revelt, and Paul Ruud. In estimating the multinomial choice model with alternative specific fixed effects, it is crucial that there be at least one alternative which is chosen by a sufficiently large fraction of the individual demanders. For identification, the fixed effect of one of the alternatives must be normalized to zero. However, if the probability of choosing that base alternative is extremely low for some individuals, then the model is not identified. For example, patients in Pittsburgh are able to choose hospitals in Philadelphia, but very few patients actually do so because of the long traveling hours. Thus I cannot estimate the multinomial choice model with hospital fixed effects in which the base alternative is a hospital in Philadelphia, since the base hospital is virtually nonexistent in the choice sets of patients in Pittsburgh.

Even hospitals distant from Pittsburgh often referred patients to UPMC Presbyterian for CABG/PTCA. Thus in estimating referral choice for open heart surgery, I use it as the base alternative for all demanders. On the other hand, for a heart attack 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 community care hospital, normalizing the fixed effect of the hospital to be zero and using a data set of patients whose homes were within a 60 minute drive from the hospital.

I estimate the hospital choice model for AMI patients separately for more than 30 different market areas. The estimates are reported at the end of this paper (Table 7). To give a brief summary of the results, the signs and statistical significance of the estimated coefficients are as expected. The coefficient of patient traveling hours is negative and significant in all of the market areas, and that of the ratio of patients with certain demographic characteristics is either positive and significant or insignificant. The coefficients of the ratio of old male patients to young male patients and that of old female patients to young male patients are mostly positive and significant. All of the results are largely consistent with the findings in Tay (2003).

The summary statistics of MCD_k, the measure of marginal change in the demand for each community care hospital given a change in a patient's rating of the hospital, are in Table 4. MCD_k varies from 0.25 to 0.95, and the mean is 0.63. The mean value is higher among the target hospitals than among the independent hospitals. The presumptive referring hospitals included in Data2 faced less responsive demand compared to those in Data1 and Data3. The large and negative correlation (-0.88) between MCD_k and the hospital's share in its close neighborhood (zip code areas within a 10 minute drive from the hospital) explains why. Since Data2 only includes cases where the patients were highly likely to choose particular community care hospitals, the community care hospitals with small shares in the local markets tend to be excluded from Data2.

Table 5 shows the results of the multinomial logit estimation of referral choice for open heart surgery.[18] 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 hours), $(DT_j^i)^2$, T_j^i (patient's traveling hours), $(T_j^i)^2$, $MCD_k \cdot T_j^i$, and $MCD_k \cdot (T_j^i)^2$. Such discrepancy could reflect that the patient's traveling hours and that of the referring physician are highly correlated under Assumption2 and 3, since only patients who live close to community care hospitals are selected under Assumption2 and 3. In particular, under Assumption3, the difference between T_j^i and DT_j^i is less than 5 minutes for all observations, since only the patients living within a 5 minute drive from community care hospitals are included.[19]

The estimated coefficients under Assumption 2 and 3 indicate that community care hospitals facing more responsive demand are more reluctant to refer their patients to tertiary care hospitals that are far from the patients' homes. On the other hand, the estimated coefficients under Assumption1 indicate that community care hospitals are equally sensitive to patients' traveling hours regardless of the value of MCD_k. Under Assumption1 and 2, the referring physician's traveling hours clearly have 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 the hospitals that are close to their offices.

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

[19] Another noticeable difference is that the absolute values of the coefficients are much larger in Data1. It might be due to the endogeneity problem discussed earlier in this paper.

The coefficient of 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 Assumption1, while it is insignificant under Assumption 2 and 3. The coefficient of $Aff_{jk} \times FirstYr_{jk}$ is negative under any of the assumptions and statistically significant under Assumption1. Results under Assumption1 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, consistent with the findings in Huckman (2005) and Nakamura *et al.* (2005). In addition, the effect of affiliation seems smaller when the tertiary care hospital does not own the community care hospital.

The coefficient of $Aff_{jk} \times Old^i$ is statistically insignificant under any of the assumptions on the referring hospitals. On the other hand, the coefficient of $Aff_{jk} \times Private^i$ is positive and statistically significant under Assumption1, while it is statistically insignificant under Assumption 2 and 3. These results are largely consistent with the findings in Nakamura *et al.* (2005) that some target hospitals selectively refer patients with more remunerative insurance to the 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 $Aff_{jk} \times MCD_k$ is negative under any of the assumptions on the referring hospitals and statistically significant under Assumption1. 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 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 $Aff_{jk} \times MCD_k \times High_k$ 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 their patients to the high quality acquirers compared to those with less responsive demand.

Table 6 shows how the estimated value of

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

varies with those of MCD_k and $High_j$ under each of the assumptions on the referring hospitals. The table highlights that there are two contrastive referral patterns from community care hospitals to their affiliated tertiary care hospitals. The increase in referrals is the largest when a community care hospital with a low MCD 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 MCD values.

7 Conclusion and Discussion

This paper examines in what circumstances the acquisition of community care hospitals by tertiary care hospitals leads to a larger increase in referrals from the former to the latter. I develop a theoretical model in which patients' preference toward a community care hospital depends on the rating by the prior users. The model shows that community care hospitals facing demand that is more responsive to a change in a rating by a patient attach greater weight on patients' preference in choosing referral destinations. Based on this model, I estimate a multinomial choice model of physician referral using discharge records of CABG/PTCA patients who are highly likely to have been referred from community care hospitals.

The results show that hospital acquisition leads to a statistically significant increase in referrals, but the increase in referrals varies with the characteristics of the targets and the acquirers. I find two patterns of referrals from community care hospitals to their affiliated tertiary care hospitals. When the acquirer is not one of the top hospitals in the region, community care hospitals facing more responsive demand to a change in a patient's evaluation are equally or less willing to refer their patients to their acquirers. On the other hand, when the acquirer is regarded as one of the top hospitals in the region, community care hospitals that face more responsive demand are more willing to refer their patients to their acquirers.

These findings imply that both physicians and patients do not regard vertical integration of hospitals as the means of improving quality of care through clinical integration, unless the acquirers are particularly renowned for high quality of care. Increased referrals from the target to the acquirer could be a reflection of patients' preference for integrated delivery systems only when the acquirer is one of the dominant hospitals in the local market. These results support the view that with a few exceptions, the primary motive of hospitals for forming a vertical alliance is to secure the sources of referrals for the tertiary care hospitals rather than to meet patients' needs for better coordinated care.

Securing feeder hospitals could have been more important for tertiary care hospitals in Pennsylvania, where Certificate of Need (CON) regulation was abolished in the mid-1990s and a large number of entry to cardiac surgery occurred in the late 1990s. Forming vertical alliances with community care hospitals could have helped deter new entries, since potential entrants might take it as a threat that local physicians would not refer their patients to new entrants. More importantly, provided that hospital quality increases and cost decreases with its surgical volume, increasing patient volume could also be used as a means of entry deterrence, as Dafny (2005) points out. This could also explain why the increase in referrals from the targets to the acquirers is greater when the acquirers are not one of the top hospitals in the region, provided that there are diminishing returns from increasing surgical volume.

The results imply that patients believe vertical integration of hospitals lead to quality gains when the acquirers are highly renowned hospitals. Nevertheless, whether such quality gains actually exist is a different question. Given that patients appreciate vertical alliances of hospitals involving distinguished tertiary care hospitals, community care hospitals in such alliances would be motivated to advertise themselves as having close ties with top tertiary care hospitals, especially when they face demand that is highly responsive to changes in patients' evaluations. For this reason, such community care hospitals might be more likely to establish joint ventures with and increase referrals to the acquirer hospitals. In other words, increased referrals to high quality acquirers might reflect the "brand-stretching" strategy of the target hospitals.

Given that vertical integration of hospitals increases referrals to the acquirers but that the magnitude of the effects depends on the characteristics of the targets and the acquirers, the hospital characteristics discussed above could be important criteria for selecting merging partners. Thus future works include analyzing what combination of tertiary care hospitals and community care hospitals are more likely to form vertical alliances. The tertiary care hospitals looking for feeder hospitals might select merging partners based on the characteristics of demand they face. Likewise, community care hospitals that are sensitive to reputation might seek to merge with tertiary care hospitals renowned for high quality of care.

Another possible extension is to study how physicians' behavior is related to the competitive pressure for the hospitals they work at. The theoretical model in this paper shows that when a physician or a hospital makes some kind of decision independently for each patient, the physician or the hospital places greater weight on patients' welfare when a patient's evaluation of the hospital has a greater impact on the future demand for the hospital. This model could be applied to study the relationship between physicians' selection of treatment method and the competitive pressure for the hospital they practice at, for example. The measure of responsiveness of demand described above could be a better measure of competitive pressure for individual hospitals than other conventional measures such as the Herfindahl index.

8 References

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A The Ratio of Patients with Certain Demographic Characteristics

Tay (2003) shows that AMI patients' preference toward hospitals varies with their demographics such as gender and age. For example, patients older than 80 prefer hospitals with larger numbers of nurses per bed than younger patients do. I therefore need to allow the hospital fixed 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

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

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

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

Let r^z be the number of patients in zip code z, and assume that the ratio 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

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

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

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

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 that $\frac{\overline{N}_j^2}{\overline{N}_j^1}$ is correlated with v_j.

Figure 1:

Time

1	Each patient chooses one community care hospital.
2	Community care hospitals receive payment based on the number of patients who chose them in 1.
3	The state of the world is revealed, and it turns out that some patients need to go to tertiary care hospitals.
4	Each community care hospital refers the patients who chose itself and need tertiary care, based on perfect knowledge of the patient's preference over tertiary care hospitals.
5	Tertiary care hospitals receive payments based on the number of patients who chose them.
6	All the referred patients rate the community care hospitals that they chose.
7	Patients choose community care hospitals based on the patients' rating of the hospitals.
8	Community care hospitals receive payment based on the number of patients who chose them in 7.
9	The state of the world is revealed, and it turns out that some patients need to go to tertiary care hospitals.
10	Each community care hospital refers the patients who chose itself and need tertiary care, based on perfect knowledge of the patient's preference over tertiary care hospitals.
11	Tertiary care hospitals receive payments based on the number of patients who chose them.

Figure 2-1: Map of Region 1 and 3

Figure 2-2: Map of Allegheny County

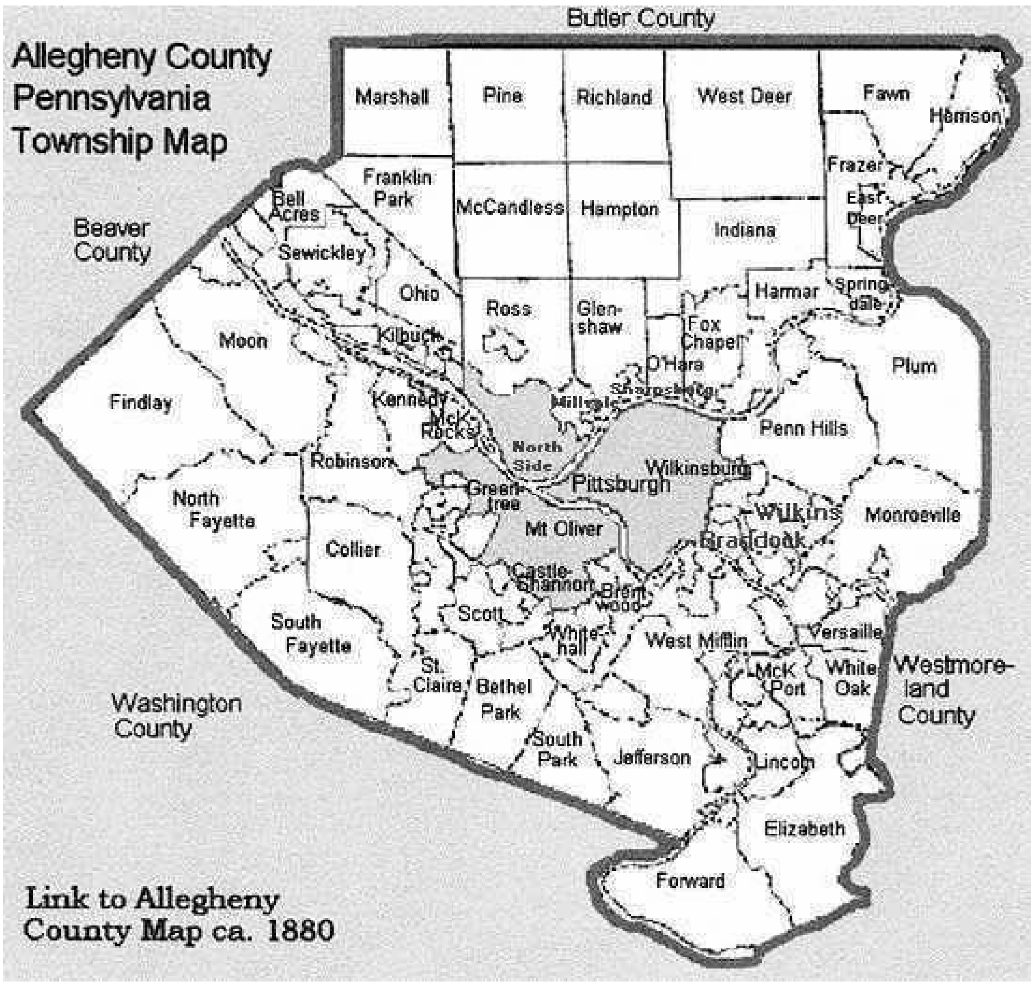

Table 1 List of target hospitals and acquirer hospitals

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 Medical Center** **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 by assumption on the referring hospital

	Assumption1 (based on CATH record)		Assumption2 (based on AMI demand)		Assumption3 (based on location)	
Patient characteristics	Mean	S.D.	Mean	S.D.	Mean	S.D.
Year2002	0.366	0.482	0.384	0.487	0.345	0.476
#obs	872		805		1003	
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

	Assumption1 (based on CATH record)		Assumption2 (based on AMI demand)		Assumption3 (based on location)	
Referring Hospitals' Characteristics	Mean	S.D.	Mean	S.D.	Mean	S.D.
Year2002	0.366	0.482	0.384	0.487	0.366	0.482
#obs	872		805		1003	
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 surgery hospitals

1997	Non-Acquirer (n=8)		Acquirer (n=5)	
	Mean	S.D.	Mean	S.D.
Hospital specific CABG mortatlity	-0.219	0.704	0.320	0.944
#CABG	509	308	811	495
#PTCA	639	310	1418	1076
Teaching	0.375	0.518	0.600	0.548

2002	Non-Acquirer (n=7)		Acquirer (n=10)	
	Mean	S.D.	Mean	S.D.
Hospital specific CABG mortatlity	-0.361	0.859	-0.009	1.321
#CABG	309	96	443	263
#PTCA	570	262	917	687
Teaching	0.286	0.488	0.400	0.516

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

Table 4 Marginal changes in demand given a change in a patient's rating for the referring hospitals

Hospital group	#hospital or #obs	Mean	Std. Dev.	Min	Max
All hospitals	37	0.63	0.20	0.25	0.95
Independent hospitals	15	0.54	0.21	0.25	0.95
Target hospitals	22	0.69	0.18	0.35	0.95
Assumption1 (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
$(\text{Doctor's Traveling Hrs})^2$	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
$(\text{Patient's Traveling Hrs})^2$	-0.002	0.002	0.000	0.004	0.104	0.096
(Patient's Traveling Hrs)*MCD	0.012	0.197	0.010	0.454	-0.927	0.233
$(\text{Patient's Traveling Hrs})^2$*MCD	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*MCD	-102.437	38.260	-4.222	2.724	-1.320	2.695
Affiliation*MCD*(High Prestige)	107.181	38.269	9.405	3.286	6.635	2.951

Table 6 The estimated effect of affiliation on the community care hospital's latent utility from referring a patient to affiliated tertiary care hospitals

	Assumption1 (based on CATH record)		Assumption2 (based on AMI demand)		Assumption3 (based on location)	
MCD	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: MCD refers to marginal change in demand given a change in a patient's rating.

Table 7 Estimated parameters for hospital choice for AMI patients

Area	Year	Variable	Beta	S.D.
Alle-Kiski	1997	Ratio of Old Male Patient	3.042	0.610
Alle-Kiski	1997	Ratio of Young Female Patients	0.137	0.188
Alle-Kiski	1997	Ratio of Old Female Patients	1.233	0.184
Alle-Kiski	1997	Traveling Hrs*Old Male	-0.043	0.008
Alle-Kiski	1997	Traveling Hrs*Young Female	-0.020	0.005
Alle-Kiski	1997	Traveling Hrs*Old Female	-0.047	0.007
Alle-Kiski	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
Beaver Valley	2002	Ratio of Old Male Patient	2.003	0.466
Beaver Valley	2002	Ratio of Young Female Patients	0.358	0.323
Beaver Valley	2002	Ratio of Old Female Patients	0.877	0.149
Beaver Valley	2002	Traveling Hrs*Old Male	-0.024	0.007
Beaver Valley	2002	Traveling Hrs*Young Female	-0.010	0.006
Beaver Valley	2002	Traveling Hrs*Old Female	-0.025	0.006
Beaver Valley	2002	Traveling Hrs	-0.166	0.005
Bedford	1997	Ratio of Old Male Patient	-0.281	2.564
Bedford	1997	Ratio of Young Female Patients	1.979	1.001
Bedford	1997	Ratio of Old Female Patients	2.706	0.879
Bedford	1997	Traveling Hrs*Old Male	-0.011	0.017
Bedford	1997	Traveling Hrs*Young Female	0.003	0.009
Bedford	1997	Traveling Hrs*Old Female	0.010	0.014
Bedford	1997	Traveling Hrs	-0.098	0.008
Bedford	2002	Ratio of Old Male Patient	2.925	1.605
Bedford	2002	Ratio of Young Female Patients	-0.207	1.406
Bedford	2002	Ratio of Old Female Patients	-0.230	0.834
Bedford	2002	Traveling Hrs*Old Male	-0.023	0.012
Bedford	2002	Traveling Hrs*Young Female	-0.013	0.010
Bedford	2002	Traveling Hrs*Old Female	-0.031	0.014
Bedford	2002	Traveling Hrs	-0.071	0.008
Braddock	1997	Ratio of Old Male Patient	2.835	0.428
Braddock	1997	Ratio of Young Female Patients	0.068	0.152
Braddock	1997	Ratio of Old Female Patients	1.217	0.143
Braddock	1997	Traveling Hrs*Old Male	-0.031	0.005
Braddock	1997	Traveling Hrs*Young Female	-0.014	0.003

Braddock	1997	Traveling Hrs*Old Female	-0.048	0.004
Braddock	1997	Traveling Hrs	-0.146	0.003
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
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
Cranberry	1997	Ratio of Old Male Patient	4.476	0.337
Cranberry	1997	Ratio of Young Female Patients	-0.418	0.302
Cranberry	1997	Ratio of Old Female Patients	1.666	0.318
Cranberry	1997	Traveling Hrs*Old Male	-0.098	0.014
Cranberry	1997	Traveling Hrs*Young Female	0.031	0.008
Cranberry	1997	Traveling Hrs*Old Female	-0.091	0.013
Cranberry	1997	Traveling Hrs	-0.157	0.003
Cranberry	2002	Ratio of Old Male Patient	2.976	0.341
Cranberry	2002	Ratio of Young Female Patients	-1.265	0.523
Cranberry	2002	Ratio of Old Female Patients	1.662	0.336
Cranberry	2002	Traveling Hrs*Old Male	-0.052	0.012
Cranberry	2002	Traveling Hrs*Young Female	0.031	0.010
Cranberry	2002	Traveling Hrs*Old Female	-0.059	0.012
Cranberry	2002	Traveling Hrs	-0.162	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
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
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
Mercy	1997	Ratio of Old Male Patient	2.837	0.425
Mercy	1997	Ratio of Young Female Patients	0.104	0.150
Mercy	1997	Ratio of Old Female Patients	1.273	0.141
Mercy	1997	Traveling Hrs*Old Male	-0.033	0.005
Mercy	1997	Traveling Hrs*Young Female	-0.013	0.003
Mercy	1997	Traveling Hrs*Old Female	-0.046	0.004
Mercy	1997	Traveling Hrs	-0.144	0.002
Mercy	2002	Ratio of Old Male Patient	2.158	0.399
Mercy	2002	Ratio of Young Female Patients	0.299	0.259
Mercy	2002	Ratio of Old Female Patients	0.953	0.130
Mercy	2002	Traveling Hrs*Old Male	-0.026	0.005
Mercy	2002	Traveling Hrs*Young Female	-0.015	0.005
Mercy	2002	Traveling Hrs*Old Female	-0.032	0.005
Mercy	2002	Traveling Hrs	-0.147	0.003
Meyersdale	1997	Ratio of Old Male Patient	4.253	5.294
Meyersdale	1997	Ratio of Young Female Patients	0.482	1.183
Meyersdale	1997	Ratio of Old Female Patients	1.286	1.241
Meyersdale	1997	Traveling Hrs*Old Male	-0.027	0.015
Meyersdale	1997	Traveling Hrs*Young Female	-0.015	0.010
Meyersdale	1997	Traveling Hrs*Old Female	-0.017	0.012
Meyersdale	1997	Traveling Hrs	-0.061	0.008
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
Miners	1997	Ratio of Old Male Patient	3.752	4.059
Miners	1997	Ratio of Young Female Patients	-0.020	1.856
Miners	1997	Ratio of Old Female Patients	-3.280	3.312
Miners	1997	Traveling Hrs*Old Male	-0.004	0.049
Miners	1997	Traveling Hrs*Young Female	0.019	0.021
Miners	1997	Traveling Hrs*Old Female	-0.093	0.068
Miners	1997	Traveling Hrs	-0.121	0.023
Miners	2002	Ratio of Old Male Patient	0.735	0.804
Miners	2002	Ratio of Young Female Patients	7.988	3.421
Miners	2002	Ratio of Old Female Patients	-8.647	3.485
Miners	2002	Traveling Hrs*Old Male	-0.069	0.030
Miners	2002	Traveling Hrs*Young Female	-0.220	0.085
Miners	2002	Traveling Hrs*Old Female	0.254	0.084
Miners	2002	Traveling Hrs	-0.114	0.017
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
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
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	1997	Ratio of Old Male Patient	2.911	0.434
Suburban	1997	Ratio of Young Female Patients	0.128	0.154
Suburban	1997	Ratio of Old Female Patients	1.240	0.144

Suburban	1997	Traveling Hrs*Old Male	-0.032	0.005
Suburban	1997	Traveling Hrs*Young Female	-0.015	0.003
Suburban	1997	Traveling Hrs*Old Female	-0.045	0.004
Suburban	1997	Traveling Hrs	-0.148	0.003
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	1997	Ratio of Old Male Patient	2.540	1.389
Windber	1997	Ratio of Young Female Patients	-0.349	0.624
Windber	1997	Ratio of Old Female Patients	0.370	0.675
Windber	1997	Traveling Hrs*Old Male	-0.004	0.011
Windber	1997	Traveling Hrs*Young Female	0.001	0.006
Windber	1997	Traveling Hrs*Old Female	-0.019	0.011
Windber	1997	Traveling Hrs	-0.107	0.005
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