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Economic Evaluation of Health Care Effectiveness: Three Essays

A Dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Economics

by

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Dedication

This work is dedicated to my parents, for making it all possible; to Gwendolyn and Theodore, for making it all worthwhile; and especially to Lolo, whose love, support, and companionship have made the journey an enjoyable one.

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VITA

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Abstract

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A basic goal of health policy is to improve the efficiency with which health care is provided. To that end, it is obviously important to understand elements of the health production function. Critically important factors that influence health range from the highly specific, such as to whom particular treatments are provided, to the expansive, such as the marginal return to different sorts of health care spending. Many of these factors are amenable to straightforward policy influence. This dissertation describes novel instruments which are used to determine the impact of policy-amenable factors on health in particular situations.

In the first chapter, the effectiveness of interventional treatment for heart attacks is assessed by using the health services received by visitors to a region to instrument for care received by locals. The visitors and locals receive similar treatments because they see the same physicians, but their unobserved characteristics are plausibly uncorrelated. The estimates suggest that such treatment may be harmful to those near the current extensive margin.

The second chapter uses a similar instrument based upon the experience of visitors to a region to estimate the impact of spending on hospital mortality for individuals with life-threatening illnesses. The estimates can easily be reinterpreted as cost-effectiveness ratios and indicate that additional spending on the illnesses considered is likely to have a measurable, albeit small, impact on hospital mortality rates.

The final chapter examines the bone marrow registry maintained by the National Marrow Donor Program and funded by the United States government. A benefit-cost analysis suggests that the registry is inefficiently small, suggesting that efforts to recruit volunteers should be expanded. Such an effort seems unlikely to be successful for all subpopulations in the United States due to biological and social factors. A strong case can be made for compensating bone marrow donors in order to expand the population of individuals willing to provide life saving donations.

Contents

Chapter 1

Visitors' Health Care as an Instrument: The Case of Heart Attacks

1.1 Introduction

A common problem encountered when assessing the effectiveness of medical procedures is that treatments are generally not randomly assigned. Physicians consider how ill a patient is when choosing a treatment plan. Ordinary least squares (OLS) estimates of the treatment effect will therefore be biased with the direction of bias depending upon the sign of the correlation between treatment status and unobserved severity of illness. This paper attempts to overcome this problem using instrumental variables (IV) analysis to estimate the causal treatment effect of medical procedures. The rate at which visitors to a region receive a particular treatment is used to instrument for whether residents of that region with the same illness receive that treatment.

Two conditions must be met in order for this approach to work. First, there

must be regional variation in medical practice patterns that is independent of the characteristics of local residents. A substantial literature suggests that this is indeed the case. The second condition is that the unobserved characteristics of individuals who live in a region be uncorrelated with those of visitors to that region after controlling for observable features of the two groups. While this exogeneity assumption can never be perfectly tested, supportive evidence is presented for a particular case study.

An estimate obtained in this manner is best interpreted as a local average treatment effect that applies to those who are considered marginal candidates for the procedure and undergo it only because they happen to reside in a high-use region. This local effect turns out to be more interesting than the average treatment effect, because it provides an estimate of the marginal effectiveness of the procedure rather than its average effectiveness. Such information is critical for determining whether to expand use of the procedure on the extensive margin by increasing the number of patients treated.

This technique is applied to the case of interventional care for acute heart attack. The treatment entails insertion of a catheter into the arteries of the heart to locate the obstruction causing the heart attack. The cardiologist attempts to relieve the blockage, thereby reducing the damage caused. Randomized controlled trials have found that interventional care reduces mortality from acute heart attack by an average of 2 to 3 percentage points relative to the primary alternative treatment. Such trials are often unable to provide much information about effectiveness at the extensive margin. The best estimates produced in this paper suggest that interventional care increases the mortality rate from heart attack by approximately 5 percentage points in marginal candidates. Another interpretation is that hospitals where interventional procedures are frequently performed are lower quality in other respects. In either case, these results suggest that these procedures are commonly

used on patients who are unlikely to benefit from them.

1.2 Background

1.2.1 Treatment of Heart Attacks

Approaches to Treatment

Heart disease is the most common cause of death among both men and women in the United States, with heart attacks being the most common fatal manifestation (National Center for Health Statistics, 2006). A heart attack occurs when there is an interruption in blood flow to part of the heart muscle. Most commonly this occurs when a clot forms in a region of partial blockage of one of the arteries supplying blood to the heart.

Two mutually exclusive treatment modalities that have the objective of limiting the scope of a heart attack are currently in use. The medical approach relies upon a class of drugs known as thrombolytics, which can dissolve the clot causing the attack. The alternative interventional approach involves attempts to reduce the size of the blockage using mechanical techniques. Various interventional techniques start with cardiac catheterization, a procedure that involves threading a narrow tube into the arteries of the heart. Cardiologists attempt to locate and to compact the blockage by inflating a balloon to reopen the artery, a procedure referred to as angioplasty. In some cases, a stent is placed in the re-opened artery with the purpose of preventing a reoccurrence of the blockage in the same area. All of these procedures have concomitant risks; while they may be beneficial for some patients, others will die as a direct result of the intervention.

Before the mid-1990s, interventional procedures for heart attack patients were used primarily for secondary prevention of heart attacks rather than for acute treat-

ment (and stents were unavailable). After an individual had recovered from the acute phase of her heart attack, the procedures were done in the hopes of preventing additional heart attacks. From the mid-1990s, interventional procedures have increasingly also been used in the acute phase of a heart attack to try to minimize the impact of the attack (Scanlon et al., 1999).

Treatment Patterns and Cost Issues

Study of heart attack care is important from a medical cost perspective, because there has been a dramatic shift in the treatment of heart attacks toward the more intensive, and more expensive, interventional approach. Between 1984 and 1998, the rate of interventional therapy among Medicare beneficiaries having heart attacks increased five-fold and the cost of treatment grew at 4.2% per year (Cutler and McClellan, 2001). This same paper suggests that this increase in spending easily met cost-effectiveness criteria because of improvement in outcomes. The improvement in survival from heart attacks over this period was such that one calculation of a medical care price index for heart attacks even suggests declining prices over the period 1983 to 1994 (Cutler, McClellan, Newhouse and Remler, 1998).

The fact that changes in heart attack care were cost-effective during this period does not necessarily mean that interventional care itself has been either effective or cost-effective. Nor does cost-effectiveness on average imply cost-effectiveness at the margin. Some research suggests that the impact of thrombolytics on mortality reduction from heart attacks is substantially higher than that achieved by interventional cardiac procedures (Cutler, McClellan and Newhouse, 1999). Other work has found that the increase in technologically intensive care was cost-effective during the period 1984 to 1991, but not between 1992 and 1994 (McClellan and Noguchi, 1998). A recent analysis updates the calculations of Cutler and McClellan (2001) and finds that the improvement in mortality after heart attack diminished after 1996 while

costs continued to grow rapidly (Skinner, Staiger and Fisher, 2006). Interestingly, this period of increasing costs without concomitant benefits corresponds to the time period where interventional therapy in the acute phase and stent insertion became more common.

Randomized Controlled Trials

There have been many randomized controlled trials published in the medical literature, most of which have found that the interventional approach is superior to use of thrombolytics in the acute phase (Keeley, Boura and Grines, 2003), with a typical mortality benefit on the order of 2 to 3 percentage points. Early results showing a mortality reduction of 5 percentage points led some to adopt the optimistic view that "it is quite feasible to reduce the mortality from acute [heart attack] to the 1 to 2 percent range from the current level of 6 to 8 percent" (Smalling and Dentkas, 2000). But this view fails to recognize that even randomized controlled trials have significant limitations, which are well described in the following passage:

> The investigators performing primary [angioplasty] studies were highly experienced interventional cardiologists, which resulted in their ability to perform [angioplasty] successfully within a short time frame (60 to 90 min) after presentation. Recent preliminary data suggest that this level of proficiency may not be duplicated in all settings for all acute [heart attack] patients. Moreover, there has been a general assumption that the results of primary [angioplasty] can be extrapolated to all patients with acute [heart attack], but these studies only included patients who were in fact eligible for thrombolytic therapy and who generally were at fairly low risk ((Scanlon et al., 1999).

In addition to the concern that the results of randomized controlled trials may not hold outside academic settings, it is often unclear from such trials what the

appropriate extensive margin of use will be because the estimates obtained are average, rather than marginal, treatment effects.

Studies Using Instrumental Variables

The limitations and expense of randomized controlled trials make it desirable to find a way to assess medical care effectiveness in the community using readily available administrative data. Because heart attack patients who are less severely ill are more likely to be treated with interventional care, OLS estimates are biased toward finding such care to be effective.[1]

In a classic study, the identification strategy used to surmount this source of bias used instruments based upon proximity to hospitals that provided interventional care (McClellan, McNeil and Newhouse, 1994). The authors found a modest benefit to interventional care, but noted that "this [benefit] was achieved during the first day of hospitalization and therefore appears attributable to treatments other than [interventional therapy]."[2] Because of this issue, it is difficult to interpret the estimates as a treatment effect, *per se*. Rather, the analysis suggests that hospitals able to provide interventional care are higher quality in other respects.

Another ground breaking approach exploited shocks caused when individual hospitals began providing interventional care (McClellan and Newhouse, 1997). This study also found small benefits to the interventional approach that were interpreted to apply to those patients near the extensive margin. One potential problem with this approach is that changes to hospital capabilities might be expected to change the mix of patients seen at each hospital. The results might therefore be corrupted

[1]The direction of bias expected in OLS regressions is discussed more thoroughly in Section 1.3.2, below.

[2]Recall that in 1994, interventional care was used primarily for secondary prevention and was rarely performed on the first day of hospitalization.

by selection effects.[3]

Two later studies (Beck, Penrod, Gyorkos, Shapiro and Pilote, 2003; Chandra and Staiger, 2007) use the same proximity instrument used in McClellan et al. (1994). The study by Beck et al. (2003) uses data from Canada and the authors expected to find a more substantial effect of interventional treatment since the Canadian medical system provides such treatment to fewer patients and thus operates on different extensive margin than the United States. They found no effect, though their point estimates showed interventional treatment to be beneficial and their standard errors were large, likely due to a small sample size. While it is not the primary objective of their study (which is discussed in more detail below), Chandra and Staiger (2007) estimate the treatment effect from interventional treatment. The estimates seem implausibly large since they are several times those found in randomized controlled trials. The results of both of these more recent studies are also hard to interpret because the time frame used in defining the treatment variable (90 days for Beck, et al. and 30 days for Chandra and Staiger) will include patients treated in the acute phase and those who are treated for secondary prevention.[4]

A recent study evaluates various approaches to overcoming treatment selection bias (Stukel, Fisher, Wennberg, Alter, Gottlieb and Vermeulen, 2007). One of the methods tested uses an instrument based on the rate at which interventional therapy is used in the region of hospitalization. The approach is similar to that employed in this paper, without the innovation of using rates among visitors to control for

[3]For example, suppose that a hospital begins offering interventional care. Knowing this, doctors and emergency medical technicians begin referring patients appropriate for such care to this hospital rather than surrounding hospitals. The patients appropriate for interventional care are healthier than those who are not so that the hospital might see an improvement in outcomes that is independent of the effectiveness of interventional treatment.

[4]This was not a problem in the original paper by McClellan, McNeil, and Newhouse because interventional treatment was rarely used in the acute phase at the time of the study.

regional differences in average severity of illness among the locals. Because the analysis uses data from the first half of the 1990s, the definition of interventional therapy is treatment within 30 days of hospitalization and the results most likely reflect the impact of secondary prevention, not treatment in the acute phase. The analysis results in a significant attenuation in the measured effectiveness of interventional care relative to OLS, suggesting that the instrument has successfully controlled for at least some of the selection bias.

In a recent working paper, methodology similar to that developed in this paper is used to address the impact of health care expenditure on heart attack outcomes (Doyle, 2008). While Doyle's paper examines a different explanatory variable, the innovation that allows identification of the desired effect is similar. In both papers the sort of health care provided to one group, locals or visitors, is used to instrument for that provided to the other group.[5]

The approach taken in this paper differs from previous approaches not only in its choice of instrument, but also in requiring interventional care to have occurred within a much shorter time after admission to the hospital. To the author's knowledge, it is the first assessment of the effect of interventional treatment in the acute phase of heart attack using instrumental variables. The analysis also complements existing randomized controlled trials by providing an estimate of the marginal effectiveness of the procedure rather than its average effectiveness and by including experience with patients who undergo the procedure at non-academic hospitals.

[5]This paper uses the care received by visitors to instrument for that received by locals while Doyle uses care provided to locals to instrument for that received by the visitors. The two approaches differ slightly in the identification assumptions required. The choice made for this paper was driven by sample size considerations. While Doyle's Florida data includes 36,000 visitors (4,500 per data year), the California data used for this paper includes only 2,100 visitors (400 per data year).

1.2.2 Geographic Variation in Medical Care

It has been widely noted, particularly in the medical literature, that medical practice patterns vary widely by region. An early observation of this sort was made by Sir Alison Glover (1938) who noted that the rate of tonsillectomy performed upon children varied widely across regions of England. Starting with the work of John Wennberg in the early 1970s (see particularly Wennberg (1973) and Wennberg, Freeman, Shelton and Bubolz (1989)), there have been hundreds of studies that explore this variation, mostly without reaching any firm conclusions about its source. The extent of variation is substantial and the source elusive; high use regions have been found to spend 60% more treating Medicare beneficiaries than low use ones, with no obvious differences in quality of care, access to care, or patient outcomes (Fisher, Wennberg, Stukel, Gottlieb, Lucas and Pinder, 2003a,b).

This phenomenon has been discussed in the economics literature, notably by Charles Phelps (see especially Phelps (2000) and Phelps and Mooney (1993)). Phelps argues that very little of the variation can be explained by income effects, price effects, substitution between competing therapies, or random noise. Some of the variation is surely due to regional differences in illness patterns and patient preferences, but this factor seems likely to explain only a small amount of the variation observed. The conclusion that Phelps reaches is that the variation is largely due not to differences among patients, but rather to disagreement among physicians about the form of the health production function. The number of combinations of treatments is sufficiently large that in many cases it is not possible to know the "best" course of action. Differences of opinion emerge that can lead to regional norms as physicians in a given area learn from one another. The eventual level of use in a region may depend upon such factors as early experience with a given treatment in that area and whether or not any physicians in the area have been subject to lawsuits due to their use of (or their failure to use) the treatment.

Consistent with Phelps's story, there is great deal of evidence that the variation in medical practice patterns correlates more with characteristics of physicians than with those of patients. A recent example is provided by Grytten and Sørensen (2003). In an examination of primary care physicians in Norway, they find that physician-specific effects explain more than 50% of the variation in expenditures for common situations while patient age explains only 1% of the variation. They also find that when physicians move to different regions, they do not change their practice style. The physicians do not seem to have adapted to any differences in the patient population in the new region. This is very suggestive that an important part of practice variation is due to physician effects rather than regional differences among patients' characteristics or preferences.

Chandra and Staiger (2007) describe a model that could lead to regional variation in medical practice patterns due to the existence of productivity spillovers. They suggest that such spillovers can lead some areas to specialize in one treatment while others specialize in a substitute for that treatment.[6] According to Chandra's and Staiger's model, a pattern of regional specialization can emerge even when there is no geographic variation in patient characteristics. This fact is consistent with the primary identifying assumption required of this paper, that some of the observed regional variation in medical practice patterns must be exogenous to patient characteristics. The interpretation of the estimates presented below will be different under Chandra's and Staiger's model, however, because the treatment effects must be allowed to vary regionally. This issue of interpretation will be discussed further below.

This paper proposes to exploit the plausibly exogenous variation in medical practice patterns to assess the effectiveness of interventional care for heart attack

[6]As noted above, Phelps concludes that this sort of substitution does not explain regional variation, at least for some particular pairs of substitutes.

patients. This approach requires that geographic variation be exhibited specifically in care provided for heart attacks. A large multi-center study in the United States (O'Connor, Quinton, Traven, Ramunno, Dodds, Marciniak and Wennberg, 1999) and a large international study (Eagle, Goodman, Avezum, Budaj, Sullivan and Lpez-Sendn, 2002) have found such variation even in the application of treatments for which there is a consensus that they are effective. It therefore seems reasonable to expect that regional variation in use of interventional care for heart attacks will be sufficient to assess the effectiveness of the treatment, provided that the variation can be isolated from concurrent regional differences in unobserved patient characteristics.

1.3 Methods

1.3.1 Analytic Framework

The goal of this analysis is to estimate the treatment effect of interventional care on mortality among individuals suffering from an acute heart attack. The primary estimation sample consists of residents of California who receive treatment for acute heart attack at hospitals near their home. We therefore wish to estimate β_1 from the following equation:

$$m_{rk} = \beta_0 + \beta_1 T_{rk} + \mathbf{X}_r' \boldsymbol{\beta_2} + \epsilon_{rk}$$

where the individuals are indexed by r to denote local ***r***esident and the county of hospitalization is indexed by k. The binary variable m_{rk} is equal to one if individual r dies after being treated at a hospital in county k, T_{rk} is equal to one if interventional therapy is provided, $\mathbf{X}_r$ is a vector of observable individual characteristics, and ϵ_{rk} reflects unobserved individual and county characteristics.

Because the proposed instrument will vary at the county level, it is particularly important to consider what components of the error term are likely to vary across counties. ϵ_{rk} is thus decomposed as follows:

$$m_{rk} = \beta_0 + \beta_1 T_{rk} + \mathbf{X}_r' \boldsymbol{\beta_2} + (q_k + s_k^{res} + \epsilon_r) \tag{1.1}$$

The county-level variables q_k and s_k^{res} are written as linearly separable merely to guide the intuition underlying the assumptions required for instrument validity. No attempt is made to separately identify these two quantities. The variable q_k captures regional differences in the health care system and is most naturally thought of as the effect on mortality due to the overall quality of health care provided in county k, aside from whether or not interventional care is provided. Note that lower values of q_k correspond to higher quality of care. Regional differences in the characteristics of patients are captured by s_k^{res}, which reflects the mean unobserved severely of illness among residents hospitalized in county k. The idiosyncratic error term ϵ_r captures any other unobserved characteristics of resident r that affect his likelihood of dying, including his deviation from the county mean severity of illness.

1.3.2 Sources of OLS Bias

Estimation of equation (1.1) by ordinary least squares will yield a biased estimate of β_1 if T_{rk} is correlated with the unobserved variables in the error term. The primary concern when measuring a treatment effect is that individuals are not randomized to treatment and control groups. Because it seems likely that physicians account for unobserved determinants of illness severity captured by s_k^{res} and ϵ_r when making treatment decisions, we expect the OLS results to suffer from bias. The direction of bias will depend upon the answer to the question: Are sicker patients more or less likely to receive interventional care?

There is some evidence that patients with more severe heart attacks are likely to derive greater benefit from interventional care (Antman et al., 2004). But it is also true that important determinants of health status *prior* to the heart attack are considered when determining who receives treatment. This issue is well illustrated by the following passages from the joint American Heart Association/American College of Cardiology guidelines for treatment of heart attacks:

> [Interventional Care] *should* be performed for patients younger than 75 years...
>
> [Interventional Care] is reasonable for *selected* patients 75 years or older... with good prior functional status who are suitable for revascularization and agree to invasive care... (both quotes Antman et al. (2004), emphasis added)

These passages suggest that patients who are younger and healthier before their heart attack are more likely to receive interventional treatment. This prediction is supported by the empirical facts (presented later in the paper) that patients who receive this treatment are younger, richer, and have fewer concurrent medical diagnoses. Other authors have also come to the conclusion that those treated interventionally tend to be healthier (for example, McClellan et al. (1994) and Stukel et al. (2007)).

The discussion above suggests that we should expect T_{rk} to be negatively correlated with s_k^{res} and ϵ_r. This fact will lead to negative bias in ordinary least squares estimates of β_1. Naïve estimates will therefore lead to the conclusion that the procedure is more beneficial than it truly is.[7] It is, of course, also possible that estimates

[7]The fact that the OLS estimates presented below suggest that interventional care is more beneficial than has been shown in randomized controlled trials is further evidence that the direction of bias is indeed toward finding the procedures to be effective.

of β_1 could be biased due to correlation between T_{rk} and q_k. The likelihood and implication of such bias are discussed below in the Section 1.4.4.

1.3.3 The Instrument

Instrumental variables analysis may be used to overcome bias that is due to the fact that severity of illness is imperfectly observed. To analyze this possibility in more detail, consider the treatment equations for local ***r***esidents of, and ***v***isitors to, a region:

$$T_{rk} = \alpha_0 + \mathbf{X}_r'\boldsymbol{\alpha_1} + (f(s_k^{res}) + d_k + \nu_r) \tag{1.2}$$

$$T_{vk} = \alpha_0 + \mathbf{X}_v'\boldsymbol{\alpha_1} + (f(s_k^{vis}) + d_k + \nu_v) \tag{1.3}$$

where $T_{(r,v)k}$ is equal to one if interventional care is performed, $\mathbf{X}_{(r,v)}$ is a vector of individual characteristics, and the terms in parentheses are unobserved. The unobserved quantities are again written in a manner that emphasizes components that are likely to vary geographically. Regionally varying characteristics of patients are captured by s_k^{res} and s_k^{vis}, which reflect the mean unobserved severity of illness among residents of, and visitors to, county k. The function $f(\cdot)$ reflects how severity of illness informs doctors' decisions whether to provide the treatment, with $f'(\cdot) < 0$ since sicker patients are less likely to be treated. The variable d_k reflects the sort of regional variation in medical practice patterns discussed in Section 1.2.2 (or characteristics of ***d***octors in county k), which is likely to be independent of patient characteristics.

I propose to use the rate at which visitors to a region receive interventional treatment to instrument for whether local residents receive such treatment. For a resident of county k, the binary treatment variable, T_{rk}, is instrumented with the rate at which visitors to county k receive interventional therapy, $\overline{T}_k^{vis}$. By taking the regression adjusted county mean of equation (1.3), the instrument for a resident

of county k is:

$$\overline{T}_k^{vis} = \hat{\alpha_0} + \overline{\mathbf{X}}^{vis'}\hat{\boldsymbol{\alpha}}_{\mathbf{1}} + \overline{\hat{e_k}} \tag{1.4}$$

where $\overline{\mathbf{X}}^{vis}$ is the mean value of $\mathbf{X}_v$ for the visitors in the sample and $\overline{\hat{e_k}}$ is the mean value of the residual for visitors to county k. The expected value of $\overline{\hat{e_k}}$ is:

$$\mathrm{E}(\overline{\hat{e_k}}) = f(s_k^{vis}) + d_k \tag{1.5}$$

so that the value of the instrument for county k should be correlated with the average severity of illness for visitors to county k and medical practice patterns particular to county k.

1.3.4 Identifying Assumptions

Instrument Relevance

For the instrument to be useful, the rate at which visitors to a region receive interventional treatment must be correlated with whether an individual local resident receives such treatment. Formally,

$$\mathrm{E}(\overline{T}_k^{vis} T_{rk}) \neq 0$$

Examination of equations (1.2), (1.4), and (1.5) reveals that one way this condition could be satisfied is if:

$$\mathrm{Var}(d_k) \neq 0$$

This simply means that there must be some regional variation in use of interventional therapy for heart attack that does not depend upon patient characteristics. In addition to the supportive evidence from the literature discussed in Section 1.2.2, empirical evidence supporting this assumption is presented in Section 1.4.2.

Instrument Validity

In order for $\overline{T}_k^{vis}$ to be a valid instrument, it must be uncorrelated with the unobserved quantities in equation (1.1). This requires the following four identifying assumptions:

1. $\mathrm{E}(f(s_k^{vis})s_k^{res}|\mathbf{X}_r) = 0$

   This is the critical identifying assumption, because it addresses the primary source of OLS bias. The assumption essentially requires that the unobserved characteristics of visitors to a region be uncorrelated with the unobserved characteristics of the residents of that region. While this cannot be perfectly tested because it deals with unobserved quantities, supportive empirical evidence is presented in the Section 1.4.2. The basic result of the paper is an instrumental variable estimate that is opposite in sign to the OLS estimate. This fact provides additional evidence that the assumption is not problematic.

2. $\mathrm{E}(d_k s_k^{res})|\mathbf{X}_r) = 0$

   This assumption states that some component of regional variation in the use of interventional therapy must be uncorrelated with regional variation in the unobserved characteristics of patients. As discussed in Section 1.2.2, this is a primary conclusion of the medical variations literature. Evidence that even observable characteristics of patients explain little of the variation is presented in the Section 1.4.2.

3. $\mathrm{E}(f(s_k^{vis})q_k)|\mathbf{X}_r) = 0$

   This assumption requires that the unobserved characteristics of visitors to a region be uncorrelated with the quality of medical care provided in that region. Because heart attacks occur without notice, the reason for travel is unlikely to be related to health status. It therefore seems unlikely that this assumption

will be violated.

4. $\mathrm{E}(d_k q_k | \mathbf{X}_r) = 0$

   This assumption states that regional variation in use of interventional therapy must not correlate with regional differences in overall quality of care. This is potentially problematic, because it may be that interventional therapy is provided as part of a "bundle" of medical services, not all of which are observed. If health care providers who tend to provide interventional care frequently also tend to do other things differently, the estimates of the treatment effect may reflect the overall effect of this correlated bundle of medical services. The potential impact on the estimates if this assumption is violated will be discussed in Section 1.4.4.

1.3.5 Interpretation

It is important to recognize that the treatment effect of interventional therapy for heart attack is quite likely to be heterogeneous. Because of this, the instrumental variables estimates reported here are best interpreted as estimates of a local average treatment effect (LATE) (Imbens and Angrist, 1994). Since the instrument used depends upon regional variation, the LATE can be interpreted as the effect of the treatment on individuals who would not receive the treatment in low use counties but who would in high use counties. This subset of patients is illustrated in Figure 1. Examination of the figure suggests that the estimated treatment effect will be that for patients just beyond the extensive margin in low use counties and just below the extensive margin in high use counties. Therefore, the LATE will approximate the effect that could be expected if use of the procedure was expanded or contracted near the current extensive margin. This quantity is useful for determining whether interventional therapy should be extended to more, or to fewer, patients.

Another interpretation of the estimated treatment effect emerges from consideration of the productivity spillover model described by Chandra and Staiger (2007). In this model, the effectiveness of both interventional care and the alternative medical approach are different in high and low use regions. The measured local effect would be the difference in mortality that results from receiving interventional treatment in a high use region rather than medical treatment in a low use region. The estimate can then be interpreted as the upper bound of the LATE in high use regions and the lower bound in low use regions.[8]

1.3.6 Data

The primary data source for this analysis is the California Office of Statewide Health Planning and Development Hospital Discharge Data (OSHPD data) for the years 1999 to 2003. For each individual patient who was seen at a California hospital during these five years, the data includes demographic information, the zip code in which the patient lives, the hospital at which the patient was seen, what general category of insurance the patient has, diagnoses received by the patient, and procedures performed upon the patient. The data was limited to those patients who had a primary diagnosis of heart attack (ICD-9 codes 410.00 to 410.91, excluding codes with a fifth digit of 2) and whose hospital admission was not planned in advance. If the patient was later transferred to another hospital, the observation was excluded to prevent double counting. The key outcome variable was defined as an indicator that equals zero if the patient was alive upon discharge from the hospital and

[8]If the Chandra and Stagier model is interpreted as a complete description of medical practice variation, then this treatment effect is uninformative about how practice should be changed. The equilibrium that exists in both high and low use regions is locally optimal. At the margin, any advantage to patients receiving one form of treatment garnered by increasing the use of that treatment is exactly offset by harm to patients receiving the other treatment.

equals one if the patient died during the hospitalization. The treatment of interest is whether or not an interventional cardiovascular procedure was performed upon the patient. An indicator variable for the treatment was defined to be equal to one if the patient underwent cardiac catheterization (ICD-9 Procedure codes 37.21 to 37.23) or a procedure that required prior cardiac catheterization (ICD-9 Procedure codes 36.01 to 36.09 except for 36.03) during the first five days of hospitalization. Other variables constructed directly from the OSHPD data include demographic indicators, county of residence fixed effects, indicators for insurance type, an indicator for whether or not the patient had a Do Not Resuscitate order in place, and the number of additional diagnoses the patient had recorded.

The OSHPD data was augmented with additional information relevant to the patient and the hospital at which the patient was seen. Zip code level data from the United States Census Bureau, including population, area, number of households, and median household income was matched to each patient. A separate dataset available from OSHPD was used to obtain information about hospital size and emergency department type. Geographic data for distance calculations was obtained from two sources. The US Census Bureau provides the latitude and longitude for the centroid of each zip code. When there was more than one hospital in a given zip code, hospitals were assigned street address level latitude and longitude values using Microsoft Streets and Trips 2000. County level data on income, population, and area was obtained from the US Census Bureau. Finally, the number of physicians and number of cardiologists working in each county of California was obtained from the web site of the American Medical Association.

1.4 Results

1.4.1 The Data

There are three subsets of the described data used in this paper. The primary data subset in which estimation was performed consists of all individuals with a home zip code located within the state of California. This group is hereafter referred to as the "full in-state" sample. Individuals who had a home zip code in California, were admitted to a hospital more than 200 miles from their home zip code, and had not been transferred from another hospital constitute the "in-state visitors" subsample. Finally, those individuals that did not reside in California at the time of hospital admission make up the "out-of-state visitors" subsample. Summary information for these three samples is presented in Table 1. Mortality is relatively uncommon at approximately 10 percent, but frequent enough that treatment effects of a reasonable size might be found. Roughly half of the sample received interventional therapy, so that adjustment of the extensive margin could readily occur in either direction. While some characteristics do differ significantly among the groups, it is important to recall that the identification strategy used in this paper does not use one group as a control for another. In fact, the primary identifying assumption is that the visitors will be different from, not similar to, the full in-state sample.

Regressions of the mortality and treatment indicator variables on a parsimonious set of patient characteristics reveal some of the basic relationships among these variables. The results, presented in Table 2, show that most of these variables do indeed appear to be correlated with severity of illness since nearly all are significant in the mortality regression. Age, the number of concurrent diagnoses, and the existence of a do not resuscitate (DNR) order all are positively correlated with mortality, as might be expected. Those from higher income zip codes are less likely to die, presumably because they are healthier or have access to better medical care.

Patients with HMO insurance have lower mortality, likely because such plans tend to attract healthier subscribers. The treatment regression supports the notion that healthier people are more likely to undergo interventional treatment. Individuals who are older, who are from lower income zip codes, who have DNR orders in place, or who have a higher number of concurrent diagnoses are all less likely to undergo interventional therapy.

1.4.2 Tests of Identifying Assumptions

There must be variation in the use of interventional therapy across the counties of California for the proposed instrument to be relevant. The data shown in Table 3 suggest that such variation exists and is substantial, even after adjusting rates for all of the variables from Table 1. Figure 2 compares the rate of interventional therapy among locals to that of the visitors. The correlation seems strong enough to avoid the weak instrument problem (Staiger and Stock, 1997), but is far from perfect. To further illustrate that the source of variation is not obvious, regressions of the raw county rates on various county-level variables are presented in Table 4. The regional variation in use of interventional treatment is not even partially explained by such obvious candidate variables as income and population. This strongly suggests that at least some part of regional variation is likely to be independent of patient characteristics.

The key identifying assumption required for instrument validity is that unobserved characteristics relevant to severity of illness do not correlate between the visitors and locals after controlling for observable characteristics. This assumption cannot be tested directly since it involves unobserved quantities. It is possible to find suggestive evidence by assessing whether some observable factors relevant to severity of illness correlate between the two groups across counties after controlling for the other observable factors. If there is correlation among the observable quan-

tities, it would be difficult to argue that the unobserved quantities were likely to be uncorrelated.

To explore this further, the adjusted county rates of four different concurrent diagnoses were calculated for each of the three samples. Correlation between the county rates of hypertension, diabetes, stroke, and cancer was then assessed for each pairing of samples. The results, presented in Table 5, support the identifying assumption. The county rates of these four conditions do not correlate between the full in-state and out-of-state visitors samples. When comparing the full in-state and in-state visitors samples, only one of the four conditions correlates significantly. Given that the significance level used is $p < 0.10$, it is hardly surprising that one of the eight comparisons with the full in-state sample should yield a significant correlation. It thus appears that the two samples of visitors do differ in some important respects from the local residents in the areas to which they travel. Two of the four conditions correlate significantly between the two groups of visitors. This simply suggests that the visitors have more in common with each other, regardless of their point of origin, than they do with the locals in the area visited. The evidence presented in this table is taken to support the notion that visitors to a region are sufficiently different from the locals to make it plausible that their treatment rate is uncorrelated with the locals' unobserved severity of illness.

1.4.3 The Estimates

Estimates of the treatment effect of interventional therapy for acute heart attack are presented in Table 6. Each entry block in the table represents the results of a different regression, with the exception that all four columns for each of the ordinary least squares regressions are identical. The results labeled "No Controls" have only the indicator for interventional treatment as an explanatory variable. The regressions labeled "Full Controls" include all of the variables listed in Table 1 as well as

indicators for the patient's county of residence.

The OLS estimates, shown in each column, are negative and suggest that interventional therapy decreases mortality from acute heart attacks. The estimate with no controls in the regression is roughly four times the magnitude of the treatment effect found in randomized controlled trials, which supports the notion that the estimate is negatively biased. Including controls improves matters, but the estimated effect of -0.063 is still much greater in magnitude than the -0.03 found in randomized studies.

The basic results of the paper are the estimates obtained using instrumental variables techniques with a full set of control variables. (The IV estimates obtained without controls will be discussed shortly.) The first stage results show the expected positive correlation between local and visitor treatment rates and the F-statistic on the excluded instrument is large enough to avoid problems with weak instruments.[9] The IV results, which are similar whether a two-stage least squares or probit approach is employed, are opposite in sign to the OLS results and statistically significant when the out-of-state visitors instrument is included. The specification in the first column is identified by geographic variation in interventional therapy rates without the innovation of looking at visitors to control for unobserved heterogeneity in mean severity of illness across counties. It is similar to the analysis by Stukel, et al (2007) discussed earlier and the results are similar as well. Rather than the substantial beneficial effect suggested by OLS, the estimated effect is essentially zero. Introducing instruments based on visitors treatment rates yields results that differ even more from the OLS results. These IV results suggest that interventional therapy may increase mortality among those near the current extensive margin. Recall

[9]The F-statistic for the specification that does not include visitors is almost "too high" in the sense that such tight correlation of the instrument with the endogenous regressor raises the concern that the instrument may be endogenous as well.

that there is a risk of death associated with the procedures, so that the estimates simply imply that any benefits to the procedure are outweighed by the risks among members of this marginal group.

1.4.4 Possible Sources of Bias and Robustness

The Role of Controls

It will not have escaped the reader's notice that the instrumental variable results obtained clearly depend upon whether controls are included: IV regressions without controls yield results similar to OLS while those with controls yield statistically significant results of opposite sign. This difference is in itself neither surprising nor alarming given that the identifying assumptions are more stringent without controls than with them. It is perfectly reasonable to suppose that the instrument could be somewhat correlated with the endogenous regressor, but that this correlation is diminished when controls are added. An "ideal" instrument would be uncorrelated with the regressor under any circumstances, however, so it is worth considering which controls are required to obtain results opposite in sign to OLS.

The only crucial control variables turn out to be the indicator variables for patient county of residence. These fixed effects are important given that it is the fact of geographic variation in patient differences that was the primary motivator for introducing an instrument based on visitors. It is worth considering this issue further, however, because the instrument is based on county of hospitalization, which is clearly correlated with county of residence. These two geographic variables are distinct because of the approximately 10 percent of the sample that crosses county lines when hospitalized. If county lines were crossed at random, county of residence would capture geographic differences among patients while county of hospitalization would captured differences among physicians. It is easy to imagine that crossing

county lines does not occur at random and perhaps possible that crossing patterns could exist that would bias the IV results.

In order to assess the possibility that the results of this paper are driven by idiosyncratic county crossing patterns, alternative geographic controls were created as follows. One hundred California zip codes represented in the data were chosen at random. Indicator variables were defined for geographic regions of radius 30 miles (zip-code centroid to zip-code centroid) for each of these randomly selected zip codes. These indicator variables were then included as controls in a two-stage least squares regression using the out-of-state visitors instrument. All other controls were also included, except for the patient zip code of residence fixed effects. This procedure was repeated ten times and the estimates obtained are presented in Table 7. While the standard errors are larger than in the original specification, all ten of the point estimates have a positive sign. It thus appears that while the instrument requires some sort of geographic controls to achieve exogeneity, the basic result is robust to the exact definition of geography used.

Alternative Sources of Bias

If the only relevant unobserved variables pertain to severity of illness, s_k^{res} and ϵ_r in equation (1.1), the omitted variables bias in the OLS estimate is expected to be downward. The positive IV estimates would then constitute lower bounds and the sign of the local average treatment effect would be established. It is therefore important to consider possible sources of positive bias.

The asymptotic bias term in the two-stage least squares regressions is equal to the covariance of the instrument with the error term divided by the covariance of the instrument with the endogenous regressor. If these two covariances are of the same sign, the asymptotic bias would in fact be positive. The first stage results establish that the instrument and endogenous regressor are positively correlated, so

this could only occur if the treatment rate among visitors is positively correlated with the unobserved severity of illness of the locals. Since higher treatment rates go with lower severity of illness, this essentially requires that the unobserved characteristics of locals and visitors be *negatively* correlated. *A priori*, it is easier to think of stories that would result in positive correlation, which would lead to a downward bias. In addition, no evidence of any correlation, positive or negative, is evident in the comparisons of locals and visitors presented in Table 5.

Another potential source of positive bias is a positive correlation between the treatment indicator, T_{rk}, and the quality of hospitals in the county of hospitalization, q_k. This would occur if interventional care was provided more often in counties with a lower quality of care (higher q_k). Recall from the discussion in Section 1.3.4 that the instrument is unlikely to protect against this sort of bias. If interventional therapy is effectively provided as part of a "bundle" of medical services, the instrument can only assess the treatment effect of the whole bundle. But consider the implications if this source of positive bias is present. We might suppose that lower quality health care providers are less likely to use the procedures appropriately. If they were in fact using them more often than high quality providers were, it would suggest that they were providing interventional therapy more often than would be optimal.

The estimates suggest that use of interventional therapy is harmful to patients near the current extensive margin. This analysis would be biased toward obtaining such a result if counties with lower use rates provide the procedure more optimally. In either case, it appears that interventional therapy for acute heart attack may currently be provided to patients unlikely to benefit from it.

Truncation by Length of Stay

The outcome measure used throughout this paper is mortality during the hospital stay. This outcome was chosen as a matter of necessity since the public version of

the OSHPD data set used here does not contain individual patient identifiers that would allow linkage to future hospitalizations or to death records. While it may be preferable to use outcomes such as 90-day mortality, one-year mortality, or repeat heart attack by one year, in-hospital mortality is meaningful and in fact is one key end point used in randomized controlled trials that have assessed interventional cardiac care.

One problem with using in-hospital mortality as an outcome measure is that it involves measurement error that could bias the results. The problem is that we observe individuals for different lengths of time. So while we may, for example, observe that patient X died on hospital day 10, patient Y may have been discharged alive on hospital day 5 and then died 3 days later. Clearly the outcome was not better for patient Y, but this fact would not be clear from the data available. This results in systematic measurement error: for any particular time period considered, some individuals are misclassified as alive. While this problem could introduce bias, it is not clear *a priori* what the sign of that bias would be. Are the individuals who are discharged and die soon afterward more or less likely than average to have received interventional care? If more likely, then the estimates would be biased negatively toward finding the procedure effective, and vice versa. Since the sign of the bias is not evident, it is clearly possible that it is positive so that the estimates presented above cannot be construed as lower bounds.

While it is not possible to entirely eliminate this problem given the current data limitations, it is possible to substantially ameliorate it by truncating the sample based upon length of stay. Consider limiting the sample to those who were in the hospital no more than five days. The only way that bias could be introduced in the manner described above is if some individuals were discharged after fewer than five days and then died by the fifth day after their heart attack. It does not seem likely that many patients would fall into this category. The very fact that the

individual was discharged in fewer than five days suggests that he or she was not expected to die imminently. The results obtained using this approach are presented in Table 8. We see that as the sample is progressively truncated to shorter lengths of stay, the IV estimates increase. This suggests that any bias introduced by the truncated observation time for some patients is negative. The results above can still be interpreted as lower bounds.

Time of Treatment Administration

The quantity I wish to estimate in this paper is the treatment effect of interventional therapy provided during the acute phase of a heart attack. Although this would generally require the procedure to have been performed on the day of admission to the hospital, the treatment variable was defined as occurring within the first five days of hospitalization. To ensure that this factor did not bias the results, the treatment effect was re-estimated after redefining the treatment variable to require the procedure to have been performed on the day of admission. The estimated treatment effect remains positive and statistically significant with this specification (results not shown).

1.4.5 Heterogeneous Treatment Effects

The estimates obtained above suggest that interventional therapy is not an effective treatment for heart attack for those patients near the current extensive margin, but this does not mean that the procedure is ineffective for everyone. Indeed, we know that this is not the case because randomized controlled trials have demonstrated effectiveness. Because the treatment effect of interventional care is clearly heterogeneous, it would be interesting to demonstrate differential effectiveness among subgroups of the population. In particular, it would be interesting to show that the treatment is effective for those deemed most appropriate for it even while it appears

to be ineffective for those on the margin.

To examine the possibility of heterogeneous treatment effects, I first calculate propensity scores for the treatment variable, using all of the control variables. (This procedure is similar to one used in Chandra and Staiger (2007).) The presumption is that those with high propensity scores are more likely to derive benefit from the procedure while those with low scores are less likely to do so. As can be seen in Table 9, even though only about half of the sample received the treatment, more than 13% of those with propensity scores in the lowest quartile and only 82% of those in the highest quartile were among the treated. It is therefore possible to assess the treatment effect by propensity score quartile. Results using the out-of-state visitors instrument are presented in the table. Although only one of the IV estimates is statistically significant, some clear patterns emerge. First, the OLS estimate remains negative and is greater than that found in randomized controlled trials for each quartile; whatever the propensity score, having the procedure is a marker for low severity of illness within the given quartile. Second, the IV estimate of the treatment effect decreases as the propensity score increases. This is consistent with the basic story told in this paper. Those who are sicker are both less likely to receive interventional therapy and are more likely to suffer net harm from it if they do. The fact that patients with higher propensity scores do better suggests that physicians are using reasonable criteria to prioritize patients. However, the point estimates here and elsewhere in this paper suggest that they are performing the procedures on too many patients in some regions.

1.5 Discussion

This paper has introduced a class of instrument that seems useful for assessing medical effectiveness and has presented interesting results for the specific case of

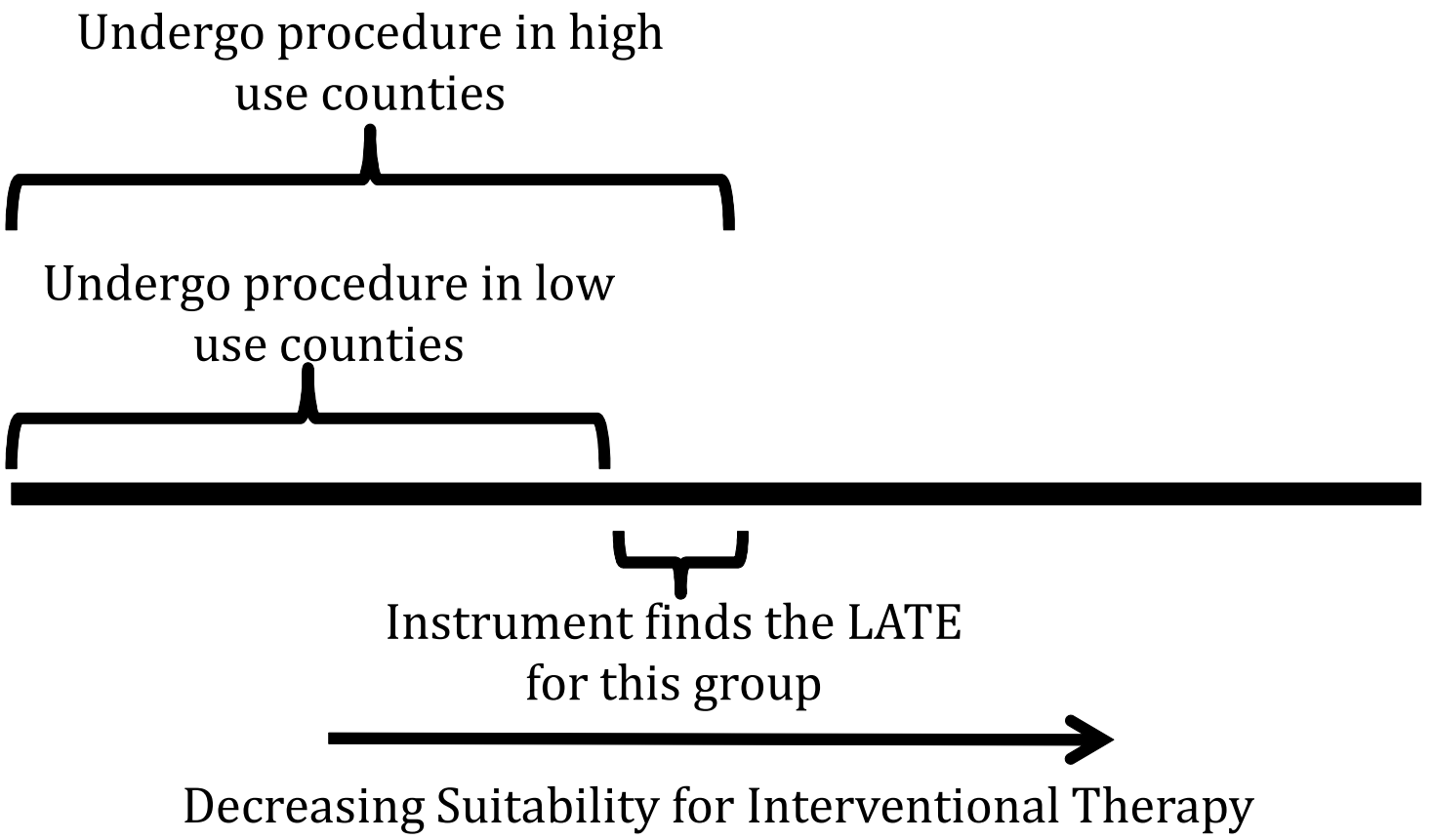
interventional therapy for the acute phase of heart attacks. The most notable finding is that the instrumental variable estimates have a sign opposite to the ordinary least squares ones. This strongly suggests that the instrument has achieved the primary objective of this work, which was to adequately account for unobserved severity of illness in an assessment of medical effectiveness. The existence of positive bias in the results cannot be ruled out, but such bias seems likely only if low quality hospitals provide the treatment more frequently than high quality ones. This supports the basic result that interventional therapy may be provided too frequently in the acute phase of heart attacks since it is more likely the low quality hospitals that have chosen the "wrong" extensive margin.

While the use of visitors' experience to instrument for the medical care received by locals can be extended to some other medical conditions and treatments, there are limitations. Heart attacks are quite common so that there were an adequate number of observations of both visitors and locals to obtain significant results. A less common condition might have yielded statistically meaningless estimates. A general issue with hospital discharge databases is the paucity of outcome variables, mortality being the primary one. While this issue is not specific to the visitors instrument, this sort of analysis can only easily be extended to other conditions with statistically meaningful short-term mortality rates. Finally, a key element of the exogeneity assumption is that heart attacks occur unexpectedly and require treatment promptly. Thus, visitors are seen in hospitals near where they were traveling for reasons unrelated to their health status. If one wished to examine cancer treatments, for example, this approach would likely fail because many individuals from out-of-state would travel to hospitals in California for the same reasons that the locals choose them.

It is important to note that the general approach developed in this paper does not require that data on "visitors" as such be available. Rather, one must simply find

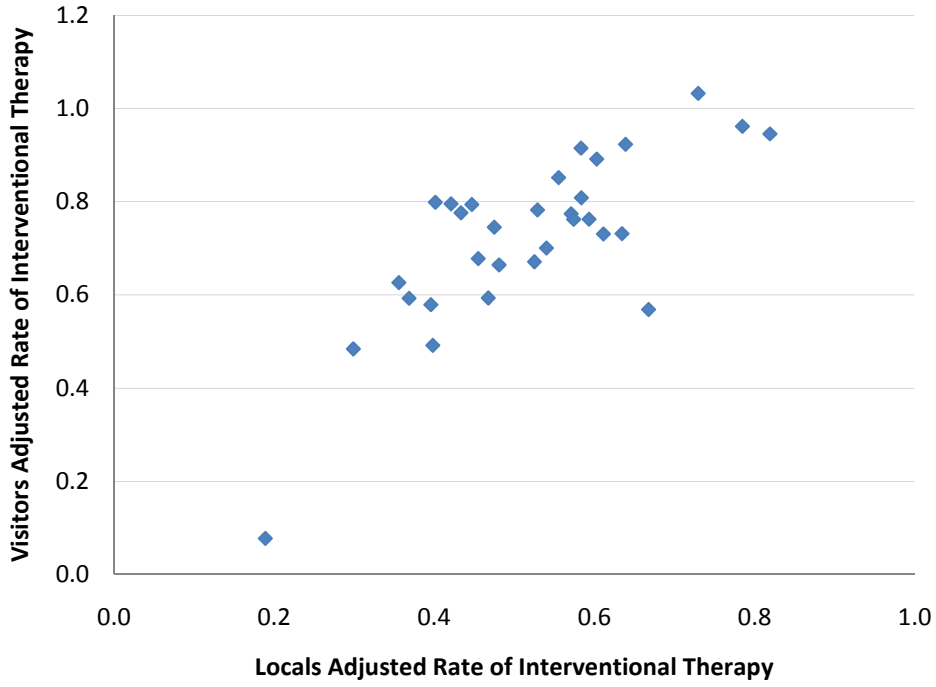
two groups of individuals who are similar in some specific respect (to ensure a valid first stage), but differ in other key ways (to avoid endogeneity). For example, it is plausible that the experience of whites from wealthy zip codes in a given county could be used to instrument for health care effectiveness among the subsample of Hispanics from poor zip codes in the same county. There would likely be substantial overlap in the hospitals in which the two groups were treated, but it is not immediately obvious that their cross-county severity of illness would be correlated. When a plausibly exogenous source of variation has been identified, it may sometimes be possible to find useful instruments simply by dividing a single data set in a systematic manner.

Figure 1. Local Average Treatment Effect



Notes: Illustration of the group for whom the instrument estimates the treatment effect. Physicians are supposed to agree on a ranking of patient appropriateness for interventional therapy, but to differ in the extensive margin employed. The LATE provides an estimate of the ATE for those individuals who fall in between: patients who would receive intensive therapy in high use counties, but not in low use ones.

Figure 2. Comparison of Visitors' and Locals' Treatment Rates



Note: The figure compares the regression-adjusted treatment rates presented in Table 3 for the full in-state and out-of-state visitors samples.

Table 1. Mean Values of Key Variables for Each Sample

Variable	Full In-State	In-State Visitors	Out-of-State Visitors	Variable	Full In-State	In-State Visitors	Out-of-State Visitors
n	196866	2780*	2106*	n	196866	2780*	2106*
Individual Characteristics				***Insurance Characteristics***			
Mortality	0.112	0.095	0.090	Medicare	0.615	0.549	0.590
	(0.315)	(0.294)	(0.286)		(0.487)	(0.498)	(0.492)
Interventional Care	0.484	0.490	0.654	Medical	0.072	0.064	0.015
	(0.500)	(0.500)	(0.476)		(0.259)	(0.244)	(0.120)
Age	69.8	68.4*	72.1*	Self Pay	0.026	0.032	0.041
	(13.2)	(13.4)	(11.3)		(0.160)	(0.177)	(0.198)
Female	0.401	0.167	0.102	HMO	0.487	0.458	0.325
	(0.490)	(0.373)	(0.303)		(0.500)	(0.498)	(0.468)
Black	0.045	0.023	0.005	***Hospital Characteristics***			
	(0.206)	(0.151)	(0.069)	Number of Beds	315	291	334
Asian	0.043	0.009	0.007		(145)	(148)	(166)
	(0.202)	(0.094)	(0.081)	Comprehensive Emergency Room	0.031	0.030	0.060
Hispanic	0.086	0.035	0.006		(0.172)	(0.170)	(0.238)
	(0.280)	(0.184)	(0.075)	Basic Emergency Room	0.948	0.927	0.897
Zip Code Characteristics					(0.222)	(0.260)	(0.304)
Population	40298	-	-	Standby Emergency Room	0.006	0.009	0.029
	(19635)				(0.076)	(0.096)	(0.169)
Area (sq mi)	46.0	-	-				
	(98.7)			***Other Characteristics***			
Population Density (/sq mi)	5510	-	-	Distance from Hospital	7.21	-	-
	(6276)				(13.64)		
Number of Households	14302	-	-	Transferred to Hospital	0.127	-	0.205
	(6165)				(0.333)		(0.404)
Mean Household Size	2.81	-	-	Do Not Resuscitate Status	0.100	0.093	0.053
	(0.75)				(0.300)	(0.290)	(0.224)
Median House. Income	51371	-	-	Number of Additional Diagnoses (max. 24)	6.53	6.09	5.95
	(33923)				(3.66)	(3.47)	(3.49)

Notes: Values are means with standard deviations in parentheses. The age variable was masked for much of the visitors' samples and was not used in constructing the instruments. The mean age reported here is from the subset of visitors for whom it was available.

Table 2. Regression of Mortality and Cardiac Catheterization Indicators on Control Variables

Variable	Mortality	Interventional Care	Variable	Mortality	Interventional Care
n	196866	196866	***Insurance Characteristics***		
			Medicare	**-0.008**	**-0.074**
Individual Characteristics				**(0.002)**	**(0.004)**
Age	**0.002**	**-0.009**	Medical	**0.008**	**-0.121**
	(0.000)	**(0.000)**		**(0.003)**	**(0.007)**
Female	**-0.006**	**-0.035**	Self Pay	**0.016**	**-0.178**
	(0.001)	**(0.002)**		**(0.004)**	**(0.009)**
Black	**-0.010**	**-0.126**	HMO	**-0.021**	**-0.057**
	(0.004)	**(0.008)**		**(0.002)**	**(0.004)**
Asian	0.002	**-0.021**	***Hospital Characteristics***		
	(0.003)	**(0.007)**	Number of Beds ($x10^{-2}$)	**-0.007**	**0.072**
Hispanic	**-0.010**	**-0.020**		**(0.001)**	**(0.003)**
	(0.003)	**(0.005)**	Comprehensive Emergency Room	**0.042**	**-0.075**
				(0.008)	**(0.032)**
Zip Code Characteristics			Basic Emergency Room	**0.022**	**-0.071**
Population ($x10^{-5}$)	**0.063**	**-0.118**		**(0.006)**	**(0.018)**
	(0.014)	**(0.062)**	Standby Emergency Room	0.006	**-0.293**
Area (sq mi) ($x10^{-4}$)	0.041	-0.460		(0.016)	**(0.023)**
	(0.088)	(0.416)	***Other Characteristics***		
Population Density (/sq mi) ($x10^{-5}$)	**0.064**	**-0.196**	Distance from Hospital	**-0.001**	**0.003**
	(0.020)	**(0.087)**		**(0.000)**	**(0.000)**
Number of Households ($x10^{-4}$)	**-0.019**	0.029	Transferred to Hospital	**-0.016**	**0.120**
	(0.004)	(0.020)		**(0.002)**	**(0.007)**
Mean Household Size	0.001	-0.002	Do Not Resuscitate Status	**0.234**	**-0.243**
	(0.001)	(0.007)		**(0.005)**	**(0.005)**
Median House. Income ($x10^{-5}$)	**-0.020**	**0.107**	Number of Additional Diagnoses (max. 24)	**0.007**	**-0.029**
	(0.006)	**(0.023)**		**(0.001)**	**(0.001)**

Notes: Values are coefficient estimates from OLS regressions with standard errors in parentheses. Standard Errors are heteroskedasticity robust and adjusted for clustering by county of hospitalization. Bold text indicates statistical significance at the p<0.10 level. County of residence fixed effects were also included in the regressions.

Table 3. Raw and Adjusted Rates of Interventional Therapy

County	Full In-State		In-State Visitors		Out-of-State Visitors	
	Raw	Adjusted	Raw	Adjusted	Raw	Adjusted
Shasta	0.818	0.583	0.731	0.771	0.894	0.915
Napa	0.806	0.785	0.871	0.913	0.818	0.962
Monterey	0.714	0.635	0.545	0.578	0.762	0.732
Ventura	0.649	0.819	0.620	0.692	0.824	0.946
Santa Barbara	0.649	0.571	0.718	0.643	0.846	0.774
Kern	0.602	0.525	0.681	0.684	0.640	0.671
Sacramento	0.580	0.421	0.453	0.364	0.851	0.795
Stanislaus	0.563	0.529	0.541	0.513	0.778	0.782
Humboldt	0.560	0.668	0.364	0.597	0.500	0.569
Santa Cruz	0.556	0.584	0.429	0.525	0.667	0.809
San Luis Obispo	0.555	0.730	0.645	0.725	1.000	1.033
Butte	0.553	0.593	0.717	0.820	0.692	0.763
Orange	0.547	0.611	0.492	0.475	0.714	0.731
Tulare	0.546	0.447	0.438	0.494	0.778	0.794
SanDiego	0.544	0.540	0.583	0.495	0.755	0.701
Yuba	0.525	0.691	0.000	0.208	-	-
Fresno	0.520	0.574	0.589	0.612	0.711	0.762
San Joaqin	0.519	0.555	0.494	0.493	0.833	0.852
Santa Clara	0.518	0.396	0.617	0.488	0.635	0.579
San Mateo	0.513	0.475	0.550	0.456	0.750	0.746
Sonoma	0.505	0.603	0.477	0.596	0.739	0.892
San Francisco	0.481	0.369	0.540	0.422	0.594	0.593
Los Angeles	0.473	0.468	0.468	0.398	0.648	0.593
Contra Costa	0.469	0.455	0.448	0.556	0.633	0.678
San Bernardino	0.466	0.356	0.500	0.413	0.500	0.627
Marin	0.464	0.433	0.526	0.540	0.789	0.776
Alameda	0.407	0.481	0.529	0.552	0.675	0.665
Riverside	0.369	0.401	0.275	0.366	0.660	0.799
Kings	0.318	0.639	0.250	0.354	0.600	0.923
Placer	0.184	0.299	0.133	0.369	0.286	0.484
Mendocino	0.159	0.398	0.000	0.213	0.000	0.492
Sutter	0.147	0.333	-	-	-	-
Nevada	0.099	0.189	0.150	0.239	0.000	0.077
Yolo	0.089	0.219	0.333	0.594	-	-
Merced	0.078	0.317	0.125	0.216	-	-
Solano	0.034	0.145	0.037	0.248	-	-
Lake	0.028	0.305	0.000	0.135	-	-

Notes: Entries are rates at which members of each sample received interventional therapy. The 37 counties in the table are those that had non-zero raw rates of interventional therapy for the full in-state sample. The table is sorted by the raw rate for the full in-state sample. Adjusted rates are regression-adjusted and evaluated for each county using the mean value of all other regressors for that sample. An entry of "-" indicates that no members of that sample were treated for a heart attack in the indicated county.

Table 4. Correlation of Interventional Therapy Rate with County-Level Variables

County Variable	Dependent Variable for All Columns: Raw County Rate of Interventional Therapy for Full In-State Sample					
Population	0.013	-	-	-	-	-0.107
(x 10^{-6})	(0.021)					(0.171)
Income (per capita)	-	0.034	-	-	-	0.039
(x 10^{-4})		(0.051)				(0.066)
Area	-	-	0.079	-	-	0.17
($x10^{-4}$)			(0.100)			(0.13)
Number of Doctors	-	-	-	0.0046	-	-0.041
($x10^{-3}$)				(0.0065)		(0.087)
Number of Cardiologists	-	-	-	-	0.196	3.13
($x10^{-3}$)					(0.268)	(3.70)

Note: The OLS regressions were limited to the 37 counties of California that had non-zero interventional therapy rates, as listed in Table 3. No estimates are statistically significant at the $p<0.10$ level.

Table 5. Correlation of County Rates of Various Illnesses Between the Samples

Full In-State vs. Out-of-State Visitors

Disorder	Correlation Coefficient	p-value
Hypertension	-0.108	0.530
Diabetes	-0.053	0.759
Stroke	-0.001	0.996
Cancer	0.153	0.373

Full In-State vs. In-State Visitors

Disorder	Correlation Coefficient	p-value
Hypertension	0.152	0.307
Diabetes	0.156	0.295
Stroke	**0.287**	**0.051**
Cancer	-0.035	0.816

Out-of-State Visitors vs. In-State Visitors

Disorder	Correlation Coefficient	p-value
Hypertension	**0.382**	**0.024**
Diabetes	**0.285**	**0.097**
Stroke	-0.062	0.722
Cancer	0.207	0.233

Notes: Numbers are correlation coefficients between the regression-adjusted rates at which the indicated diagnosis occurs in each county in the given samples. Bold text indicates significance at the $p<0.10$ level.

Table 6. Estimates of the Treatment Effect of Interventional Therapy on Mortality from Heart Attacks

		Intstrument Based Upon County Interventional Treatment Rate Among:			
		Full In-State	**In-State Visitors**	**Out-of-State Visitors**	**Both Visitors**
n		192367	192367	192367	192367
OLS- No Controls	Coefficient	**-0.126**	**-0.126**	**-0.126**	**-0.126**
	(std err)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
OLS- Full Controls	Coefficient	**-0.063**	**-0.063**	**-0.063**	**-0.063**
	(std err)	**(0.003)**	**(0.003)**	**(0.003)**	**(0.003)**
IV 2SLS- First Stage- No Controls	Coefficient	**0.581**	**0.476**	**0.462**	**-**
	(std err)	**(0.012)**	**(0.011)**	**(0.010)**	**-**
	F Statistic	2512.309	2035.366	2116.406	1382.904
IV 2SLS- Second Stage- No Controls	Coefficient	**-0.097**	**-0.076**	**-0.089**	**-0.083**
	(std err)	**(0.012)**	**(0.014)**	**(0.013)**	**(0.012)**
IV 2SLS- First Stage- Full Controls	Coefficient	**1.052**	**0.800**	**0.555**	-
	(std err)	**(0.034)**	**(0.083)**	**(0.080)**	-
	F Statistic	942.121	93.940	47.885	136.975
IV 2SLS- Second Stage- Full Controls	Coefficient	0.008	0.017	**0.081**	**0.055**
	(std err)	(0.027	(0.029)	**(0.038)**	**(0.029)**
IV Probit- Full Controls	Coefficient	0.063	0.247	**0.394**	**0.348**
	(std err)	(0.175)	(0.202)	**(0.170)**	**(0.148)**
	Partial Effect	0.010	0.041	**0.068**	**0.059**

Notes: Each coefficient is from a different regression. The unit of observation for each regression is the individual. For all but the first stage regression, the dependent variable is an indicator for mortality while the explanatory variable of interest is an indicator for whether or not interventional therapy was provided. For a given individual observation, the instrument takes the value of the rate at which interventional therapy was provided to members of the indicated sample who were hospitalized in the same county as the individual in question. Controls included (when indicated) are discussed in the text. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Bold type indicates statistical significance at the p<0.10 level. For the probit regressions, the partial effect is evaluated at the mean of the other regressors.

Table 7. Results Using Alternative Geographic Controls

Randomly Generated Geographic Controls	IV Estimate (std err)	Randomly Generated Geographic Controls	IV Estimate (std err)
Trial 1	0.006	Trial 6	0.003
	(0.031)		(0.037)
Trial 2	0.006	Trial 7	0.016
	(0.049)		(0.031)
Trial 3	0.027	Trial 8	0.071
	(0.056)		(0.067)
Trial 4	0.039	Trial 9	0.043
	(0.052)		(0.062)
Trial 5	0.043	Trial 10	0.002
	(0.042)		(0.035)

Notes: The specification is the same as that in Table 6, Column (3), labeled "IV 2SLS- Full Controls" except for the geographic contols used. In place of patient county-of-residence fixed effects, alternative geographic controls were generated as described in the text. Standard errors are in parentheses and are heteroskedasticity-robust and adjusted for clustering at the county of hospitalization level.

Table 8. Results when data is truncated by length of stay (LOS)

	No Truncation by LOS	LOS <=10 days	LOS <=5 days
n	192367	170696	123996
OLS Estimate	**-0.063**	**-0.067**	**-0.083**
	(0.003)	**(0.003)**	**(0.004)**
IV Estimate Using Instrument	0.008	0.011	0.006
Based on Full In-State Sample	0.027	0.028	0.027
IV Estimate Using Instrument	**0.081**	**0.090**	**0.100**
Based on Out-of-State Visitors	**(0.038)**	**(0.040)**	**(0.044)**

Notes: Entries are estimates from either OLS or two-stage least squares regressions using the indicated instrument. Full controls are included in each regression. Standard errors are in parentheses and are heteroskedasticity-robust and adjusted for clustering by patient county of hospitalization. Bold text indicates statistical significance at the p<0.10 level.

Table 9. IV estimates by propensity to receive interventional treatment

	Propensity Score			
	1st Quartile	**2nd Quartile**	**3rd Quartile**	**4th Quartile**
n	48091	48092	48092	48092
Fraction Reveiving Interventional Care	0.134	0.383	0.632	0.823
First Stage F-Statistic	19.844	19.844	19.844	19.844
OLS Estimate	**-0.064**	**-0.065**	**-0.063**	**-0.046**
	(0.006)	**(0.006)**	**(0.005)**	**(0.004)**
IV Estimate Using Instrument	0.294	**0.157**	0.050	0.010
Based on Out-of-State Visitors	(0.241)	**(0.047)**	(0.036)	(0.022)

Notes: The sample is divided into quartiles by propensity to receive interventional treatment. The results of OLS and 2SLS (using out-of-state visitors instrument) regressions run with full controls are presented for each quartile. Standard errors are heteroskedasticity-robust and adjusted for clustering by patient zip code. Bold text indicates statistical significance at the p<0.10 level.

Chapter 2

The Marginal Impact of Health Care Spending on Hospital Mortality

2.1 Introduction

There has been a decades-long argument among academic economists and health care researchers about the nature of the costs and benefits associated with health care. Early debate on this issue focused on the determinants of rising health care costs. Health care inflation exceeded broader growth in prices nearly every year over the second half of the 20th century, often by a substantial margin (Phelps, 2003, Table 2.6). A seminal paper by Joseph Newhouse (1992) in the early 1990s convinced many that the primary cause of increasing health care costs was the expanding capability and use of medical technologies. The increased spending was thus buying a "larger" bundle of medical services. The focus of the debate shifted to address whether the value of these new services justified their cost.

The case that health care spending has been a good value over the last few

decades has been well presented by David Cutler of Harvard University in numerous academic papers and a popular book. Cutler and his colleagues have argued that the benefits associated with increased spending in areas as diverse as cardiac care, neonatal care, and treatment of depression (Cutler, 2004) as well as in the health care system as a whole (Cutler, Rosen and Vijan, 2006) have been sufficient to satisfy standard cost-effectiveness criteria. A more skeptical view of health care spending has emerged in a large body of work performed at the Dartmouth Institute for Health Policy and Clinical Practice (until recently known as the Center for the Evaluative Clinical Sciences). This work has focused on the observation, introduced to rigorous academic study by John Wennberg, that health care practice patterns vary widely from one region to another with no obviously associated differences in patient characteristics or with health outcomes. Wennberg concludes that "systems of care serving high-cost regions are inefficient because they are wasting resources" (Wennberg, 2004). According to this view, much health care spending is of no value. It is important to note that Cutler's and Wennberg's views are not mutually exclusive; it is entirely possible that health spending is cost-effective on average but not at the margin

The medical practice variations phenomenon that forms the basis for Wennberg's position can itself be exploited to make inferences about the productivity of health care, thus informing the health care effectiveness debate. If geographic variation in the sort and amount of health care provided is uncorrelated with the characteristics of the local population, then comparisons of outcomes across regions will provide an assessment of effectiveness. There have been several studies that take this approach by examining the relationship between measures of health outcomes and aggregate health care expenditures across countries. (For recent examples, see Frech and Miller (1999) and Miller and Frech (2004).) Jack Hadley has used such an approach by examining the variation in aggregate Medicare expenditure per ben-

eficiary and health outcomes across counties in the United States (Hadley, 1982, 1988). More recent work has examined the effectiveness of treatments for particular illnesses using individual-level data (Doyle, 2008; Sheehan-Connor, 2008; Stukel, Fisher, Wennberg, Alter, Gottlieb and Vermeulen, 2007). The papers by Doyle and Sheehan-Connor have introduced a class of instruments that exploits comparisons between local residents of, and visitors to, a region. Because the visitors and locals see the same physicians for treatment of health conditions that are unexpected and acute, they receive similar treatments. If the unobserved characteristics of the two groups are sufficiently different, the treatment experience of one group can be used as an instrument to control for non-random treatment assignment in the other group.

This paper uses instruments based upon visitors' experience in the health care system to assess the impact of health care spending on outcomes for patients admitted to a California hospital with one of eight diagnoses: acute myocardial infarction (AMI, colloquially "heart attack"), acute appendicitis, cerebrovascular accident (more commonly called "stroke"), cardiac dysrhythmia, gastrointestinal bleed, acute pancreatitis, pulmonary embolism, or vertebral fracture. Individual level regressions of an indicator for in-hospital mortality on a measure of cost-adjusted charges[1] are presented for each condition and for the sample as a whole. Ordinary least squares (OLS) estimates are inadequate because it is highly unlikely that expenditure on a given patient is unrelated to her unobservable characteristics. It seems most likely that patients who are more ill will have more resources employed for their care. This will bias the OLS estimates toward finding that additional expenditure is less effective or even harmful. If they show spending to be beneficial, the estimates

[1]Because good measures of costs are scarce in health economic data, this is a commonly used proxy. The charges incurred by a patient are adjusted by the ratio of total patient-care related revenue of the treating hospital to that hospital's total charges in the year of hospitalization.

can readily be interpreted as a measure of cost-effectiveness: the expected number of lives "saved" by an additional dollar of expenditure. As discussed in Sheehan-Connor (2008), estimates obtained using instruments based on regional variation are best interpreted as local average treatment effects that apply to individuals who would receive different treatment intensities depending upon whether they happened to get ill in a low or high expenditure region. This local effect approximates the marginal effect of additional expenditure so that the estimates can be interpreted as measures of the marginal effectiveness of health care for the conditions examined.

As expected, the OLS results suggest that additional health care expenditure is harmful for patients with any of the eight conditions studied. While many of the IV results obtained are individually statistically insignificant, virtually all of the specification-disease combinations result in estimates that are opposite in sign to the OLS ones and many are significantly different from OLS according to the results of a Hausman test. The best estimates in the paper suggest that the expected cost of saving a life is approximately $270,000 for heart attack patients and an average of $890,000 for patients with one of the other seven conditions. Using crude estimates of life expectancy conditional upon survival, additional life years cost $45,000 for heart attack patients and an average of $90,000 for the other illnesses.

There are two important caveats to bear in mind in interpreting these results. First, to the extent that the instruments used are imperfect, any remaining bias is likely to cause underestimation of benefits (and thus overestimation of the cost of saving a life) since the OLS bias is toward finding expenditure to be harmful. Second, the results suggest higher expenditure is associated with better outcomes, but cannot distinguish whether this is due to the greater quantity of resources employed or due to a correlation between quantity and quality of care. Whether due to the quantity or quality of resource use, the analysis provides evidence that there is a measurable benefit, albeit a modest one, to the higher expenditure seen

in some regions, at least for the conditions studied.

2.2 Background

2.2.1 Studies of Health Care Productivity That Do Not Exploit Geographic Variation

David Cutler has done a great deal of work assessing the productivity of medical care in the United States and has concluded that "medical services and new medical technologies create value that people desire" (Chernew, Hirth and Cutler, 2003), that US spending on health care "has provided good value" over the past few decades (Cutler et al., 2006), and that we can continue to expand health care spending to purchase newly available medical care "at least for the foreseeable future" (Chernew et al., 2003). Much of Cutler's work supporting the effectiveness of medical care has exploited the fact that health spending and common measures of health, such as life expectancy, have both been trending upward over time (see, for example, Cutler et al. (2006)). For acute myocardial infarction, the disease Cutler examines most intensively, he finds evidence that: (1) health care improves life-expectancy using both time-series (Cutler and McClellan, 2001) and instrumental variables approaches (Cutler, 2007); (2) a substantial decrease in disability among the elderly is due to medical treatment of acute myocardial infarction (Cutler, Landrum and Stewart, 2008); and (3) that expensive treatments are so effective that the real price of treating myocardial infarction decreased between 1983 and 1994 (Cutler et al., 1998). These studies have not been without their critics, with some research suggesting that the high growth in the productivity of heart attack care was a transient phenomenon (Skinner et al., 2006).

Another approach to evaluating health productivity without use of geographic

variation was employed by Lichtenberg (2003). This study exploits the fact that introduction of new medications is not uniform over time to identify the impact of new pharmaceuticals on health. The results suggest that pharmaceutical research and development is very cost-effective.

2.2.2 Geographic Variation in Medical Care

It is well known that the use of medical care resources varies widely around the world with the United States spending more on heath care than all other OECD countries (see Reinhardt, Hussey and Anderson (2004) for a recent discussion). It has also long been clear that much of this variation is explained by differences in aggregate variables such as per capita GDP (Newhouse, 1977). This variation in spending has been exploited to assess the impact of health care on aggregate measures of health, as discussed further below.

There is also a considerable amount of variation in the use of medical resources within countries, an observation first made by Sir Alison Glover (1938) who noted that tonsillectomy rates varied widely around England. The phenomenon of so-called "small area" medical practice variations was first studied rigorously by John Wennberg (1973), whose initial work in the early 1970s has spawned hundreds of academic articles on the topic.[2] The most striking feature of small-area medical practice variation is that unlike international variation, it does not seem to be easily explained by obvious factors such as income (Phelps and Mooney, 1993). This fact helps make a compelling case that some of the variation might be exogenous to local patient characteristics and thus particularly useful for assessing the effectiveness of medical care.

A great deal of the work examining small-area medical practice variations has

[2]A good description of the economic issues surrounding medical practice variation is provided by Charles Phelps (2000).

been carried out under John Wennberg's auspices at the Dartmouth Institute for Health Policy and Clinical Practice. While the research in this area consistently reveals widespread variation in costs and in the use of particular types of medical care, differences in quality of care and outcomes are not typically found (see, for example, Fisher et al. (2003a,b)). As noted in the introduction, Wennberg, along with many colleagues, draws the conclusion that the high-use areas are over-providing medical care.[3]

2.2.3 Studies of Health Care Productivity Using Geographic Variation and Aggregate Data

A number of studies have used regional variation to look at the impact of total health spending on aggregate outcomes such as life-expectancy and infant mortality. H.E. Frech and Richard Miller provide a thorough review of this literature in recent studies of this sort (Frech and Miller, 1999; Miller and Frech, 2004). International studies performed before the 1990s have tended to find that while public health measures have a substantial effect on population-level outcomes, medical care as such has very little. This result is consistent with the findings of Thomas McKeown (1979) who shows that mortality rates from infectious diseases in England and Wales correlate much more strongly with the expansion of public health measures than with the introduction of effective antibiotic treatments. More recent studies, including some performed across regions of the United States and Canada rather than across countries, have found health care spending to improve aggregate outcomes (Or, 2000; Hadley, 1982, 1988), particularly when that spending is on pharmaceuticals (Miller and Frech, 2000; Cremieux, Ouellette and Pilon, 1999).

[3]For a recent example of work from this group supporting this view, see Baker, Fisher and Wennberg (2008).

2.2.4 Studies of Health Care Productivity Using Geographic Variation and Individual Level Data

A few very recent studies have exploited small-area regional variation in health care use within the United States to assess the effectiveness of medical care for acute myocardial infarction using individual level data. Two studies use such variation to assess the effectiveness of interventional care in treating AMI. The first of these (Stukel et al., 2007) uses the regional rate at which such care is provided to instrument for whether individuals in the same region receive interventional care. The second (Sheehan-Connor, 2008), presented in Chapter 1 of this dissertation, adds the innovation of using the rate of care provided to visitors to a region to instrument for care received by locals. The results of this later approach differ from those of the former, suggesting that local use rates are correlated with unobserved determinants of health outcomes. While Stukel finds essentially no impact of interventional therapy on mortality, Sheehan-Connor finds that such therapy may actually increase mortality rates. A final paper of this type (Doyle, 2008) looks at the productivity of heart attack treatment more generally by using a measure of charges to reflect overall medical resource use. The approach taken is very similar to that in Sheehan-Connor (2008) in that the identifying assumption depends upon locals and visitors differing from one another. Doyle finds that regions that provide more care have better outcomes. This does not necessarily contradict the results of the papers looking at interventional therapy, because such therapy is only one component of total resource use. In fact, the results presented below are similar to those presented in Doyle (2008), using the same data as in Sheehan-Connor (2008).

2.3 Methods

2.3.1 Econometric Specification

In order to estimate the impact of medical care spending on health outcomes, I estimate β_1 from the following mortality equation using a sample of $r$esidents with disease d hospitalized in county k:

$$m_{rdk} = \beta_0 + \beta_1 c_{rdk} + \mathbf{X}'_{rdk}\boldsymbol{\beta}_2 + \mathbf{d}_{rdk} + \epsilon_{rk} \tag{2.1}$$

where m_{rdk} is equal to one if r dies during hospitalization, c_{rdk} is equal to the cost of the care received by r, $\mathbf{X}_{rdk}$ is a vector of observable characteristics of r, $\mathbf{d}_{rdk}$ is a vector of disease fixed effects, and ϵ_{rk} captures unobserved determinants of mortality that impact r. The proposed instruments vary at the county-of-hospitalization level, making it useful to consider the following decomposition of the error term:

$$m_{rdk} = \beta_0 + \beta_1 c_{rdk} + \mathbf{X}'_{rdk}\boldsymbol{\beta}_2 + \mathbf{d}_{rdk} + (q_k + s_k^{res} + \epsilon_r) \tag{2.2}$$

as in Sheehan-Connor (2008). Writing the county effect portion of the error term as linearly separable is not meant to imply that it will be possible to identify these quantities separately. Rather, because the proposed instruments vary at the county level, it is helpful to construct a "list" of quantities that seem likely both to be in the error term and also to vary by county. Such variables include both characteristics of the health care system in county k that impact mortality, here labeled q_k (for $q$uality of care), as well as characteristics of patients hospitalized in k, labeled s_k^{res} (to indicate $s$everity of illness). The variable ϵ_r is an idiosyncratic error term that will capture the deviation of r from the county mean illness severity, s_k^{res}.

2.3.2 Interpretation of the Estimates

Estimates of β_1 can be interpreted as how many lives will be saved by spending an additional dollar. The cost of saving one expected life can easily be calculated from this figure. The coefficients can thus be interpreted as cost-effectiveness ratios that are consistent with the value of statistical life (VSL) approach to valuing interventions that change mortality risks.[4]

While the VSL approach is common in the economic literature, the standard approach for reporting health care cost-effectiveness ratios is in terms of dollars per additional life-year (sometimes quality-adjusted) gained. These ratios are then compared to some standard, typically in the range of $50,000 to $150,000, to determine whether the intervention under consideration should be considered cost-effective. For specifications that include only one diagnosis, cost-effectiveness ratios of this sort can be calculated simply by dividing the "cost of saving a life" by the expected number of years a survivor of the particular illness will live. For specifications with multiple diagnoses, an alternative dependent variable is introduced. The variable y_{rdk} is the number of life $y$ears the individual is expected to live. For patients who die ($m_{rdk} = 1$), y_{rdk} is obviously equal to zero. For those who survive until hospital discharge($m_{rdk} = 0$), y_{rdk} is the expected life expectancy conditional on surviving hospitalization for the given diagnosis. With y_{rdk} as a dependent variable, the estimated coefficient on c_{rdk} can be interpreted as the number of life-years "saved" by spending an additional dollar on health care. This figure is easily reinterpreted as a cost-effectiveness ratio specified in terms of dollars per life year.

While the manner of calculating these cost-effectiveness ratios is straightforward, additional uncertainty will be introduced by the figures used for conditional life expectancy. The manner in which the conditional life expectancies are estimated is

[4]For a comprehensive review of the VSL literature, see Viscusi and Aldy (2003).

detailed in Section 2.4.3.

2.3.3 Sources of OLS Bias

It seems likely that estimation of equation (1) by ordinary least squares will result in a biased estimate of β_1. The amount of money spent on treatment of a given patient, c_{rdk}, is almost certain to be correlated with how severely ill that patient is, s_k^{res} and ϵ_r. In particular, one would expect that patients who are more severely ill are likely to receive more care on average, and thus to incur greater cost.[5] This positive correlation between c_{rdk} and the error term would lead OLS estimates of β_1 to be positively biased. The naïve conclusion that might be drawn from such estimates is that providing more care to patients increases their chance of dying. Evidence that spending and severity of illness are indeed positively related will be presented with the results in Section 2.4.1.

2.3.4 Proposed Instrumental Variables

Results using four different instrumental variables derived from regional variation in medical practice are presented below. These are:

1. Mean cost incurred by local patients hospitalized in county k- This instrument is a single variable that, for an individual local resident r, takes on the average level of costs incurred by locals hospitalized in the same county and with the same diagnosis as r. "Locals" are defined as individuals hospitalized fewer than 200 miles from their zip code of residence.

[5]This need not be the case for every disease or for each treatment used for a particular disease. For example, Stukel et al. (2007), Sheehan-Connor (2008), and others have found that interventional care for heart attacks, which is more expensive than alternative treatments, is more likely to be provided to patients who are less severely ill.

2. Mean cost incurred by visiting patients hospitalized in county k- This instrument is similar to the previous one, except that mean costs are assessed among visitors. "Visitors" are defined as individuals from a different state or those who are hospitalized more than 200 miles from their zip code of residence.

3. Rates at which visitors undergo common procedures in county k- These instruments are designed to reflect how frequently particular treatments are provided to patients in county k. There are multiple instruments of this type calculated for each disease, one for each of the most common procedures performed on patients with that disease. For a local resident r with disease d, each instrument takes on the rate at which visitors to the area who were hospitalized with disease d underwent one of these common procedures. When equation (1) is estimated for only a single disease (and the disease fixed effects omitted), each rate is used as a separate instrument. When multiple diseases are included in the same regression, the procedure rates for each disease are summed to create a single instrumental variable.

4. Number of procedures provided to visitors in county k- For a local resident r with disease d, the instrument value is the mean number of procedures performed on visitors hospitalized for disease d in the same county.

Each of these proposed instruments must be correlated with typical expenditure in the county of hospitalization while being uncorrelated with the unobserved determinants of illness severity of patients in the county, a matter that is taken up in Section 2.3.5. The detailed manner in which the values for the instruments are calculated is discussed in Section 2.3.8.

2.3.5 Identifying Assumptions

Instrument Relevance

In order for the proposed instruments to be relevant, they must be correlated with the cost variable. The first two proposed instruments are simply mean cost levels for people with the same disease treated in the same county. As long as there is some geographic variation in costs observable at the county level, the county mean should be correlated with the costs of individuals hospitalized in that county. The first stage requirements would likely be satisfied. The other instruments are based upon the sorts of treatments received by a patient. In addition to the requirement that regional variation in treatment use be observed, it must be that treatment rates correlate with the measure of costs used. This turns out to be true in most of the specifications presented below, which also serves as a useful check that the cost variable is capturing an important part of medical resource use.

Instrument Validity

In order for the instruments to be valid, some part of the observed regional variation in costs must be uncorrelated with how severely ill people in that region are. Otherwise, the regional variation in costs that allows a valid first stage would simply reflect unobserved regional heterogeneity among patients. The extensive literature on regional cost variation strongly suggests that part of the variation will indeed be independent of locals' characteristics. But to the extent that people do vary from one region to another, some of the cost variation is likely to be due to unobserved, but important, characteristics of the hospitalized population.

Consider instrument (1) from Section 2.3.4, hereafter referred to as the "locals' cost" instrument, and suppose that substantial cross-county variation in the mean cost of treating locals for a particular disease is observed. Two factors might con-

tribute to the higher average cost observed in some counties: (1) a tendency of physicians in those counties to provide more expensive care; and (2) a higher average illness severity among the locals. Because illness severity is a component of the error term in equation (2), this second factor would lead to bias in the IV estimates in the same direction observed in the OLS ones. Of course, the correlation with the error term is likely to be less than in the OLS case, potentially mitigating the bias.

To the extent that visitors to a region differ from the locals in that region, instrument (2), hereafter referred to as the "visitors' cost" instrument, might be expected to further mitigate the bias in OLS estimates. High values of this instrument reflect higher average severity of illness among the visitors while the error term in equation (2) contains illness severity among the locals. The correlation with the error term thus seems likely to be lower than that for the locals' cost instrument and perhaps very low indeed, as suggested in Doyle (2008) and Sheehan-Connor (2008). The relationship of both the locals' and visitors' cost instruments to observable characteristics of the locals will be explored in Section 2.4.2.

Considerations for the remaining instruments, the "visitors' procedure-rate" instrument and the "visitors' procedure-number" instrument, are similar to those for the visitors' cost instrument. The use of procedures among visitors will likely capture both the tendency of physicians in the area to provide care and unobserved illness characteristics of the visitors. The former should allow for a sufficiently strong first stage while the hope is that the later are sufficiently uncorrelated with the locals' unobserved characteristics to allow consistent estimation of the desired parameter.

The focus of this discussion has been on the likelihood that measures of cost will be correlated with unobserved determinants of illness severity present in the error term of equation (2), s_k^{res} and ϵ_r. It is, of course, also possible that the cost measure and proposed instruments might be correlated with unobserved characteristics of the health care system, q_k in equation (2). Because q_k reflects the impact of the local

health care system on mortality due to factors other than cost, it seems reasonable to interpret it as a measure of the quality of care that is provided in county k. It is not clear *a priori* what the sign of the correlation between cost and quality is likely to be. Do lower quality providers tend to err by providing too much care or too little? Examples of both cases can likely be found. The issue is complicated further by the fact that the cost measure presumably reflects variations in input costs as well as true differences in resources employed in patient care. Again, the impact is not clear: Do areas with high input costs provide lower or higher quality care on average? Bias due to correlation between quality and cost, whatever the mechanism, will be considered further when discussing interpretation issues in Section 2.4.6.

2.3.6 Interpretation as a Local Average Treatment Effect

The impact of spending on mortality seems very likely to be heterogeneous. Because some medical treatments come in discrete quantities and are expensive, there may be some areas of the mortality function that are convex and some that are concave. It seems reasonable to suppose, however, that the returns to expenditure are decreasing on average. In cases where "everything possible" is not done, there is presumably some tendency to provide the treatments thought to be most cost-effective first.

Because the impact of expenditure on mortality is expected to be heterogeneous, instrumental variables estimates must be interpreted as measures of a local average treatment effect (LATE) in the sense described by Imbens and Angrist (1994). In Sheehan-Connor (2008), it is argued that the LATE is likely to approximate a marginal treatment effect when regional variation is used as the basis for an instrument, at least for the specific case of interventional care for heart attack. This argument is made in more general terms here.

The fact of medical practice variation suggests that there is disagreement among physicians about how much care it is appropriate to provide. For patients with

a given type and degree of illness, there are likely to be some sorts of care that nearly all physicians will provide, others that are provided less often, and still others that are rarely or never provided. We can imagine "lining up" all of the possible treatments, ordered so that those most often provided are to the left and those least often provided are to the right. This is done schematically in Figure 1. Based on her knowledge and experience, a physician chooses a particular "cutoff point" in the figure and provides all of the treatments to the left of that point and none of those to the right. Physicians in high-cost regions tend to use cutoff points to the right of those in low-cost regions, as depicted in the figure. Analysis based on this regional difference in cutoff points can tell us nothing about the sort of medical care that is to the left of the low-cost cutoff point; this care is provided to everyone and so there are no comparisons to be made. Similarly, we cannot learn about care to the right of the high-cost cutoff point since no-one receives these treatments. We can only learn about the effectiveness of the medical care that lies between the two cutoff points. These are treatments for which there exists disagreement among physicians about whether they are effective (or perhaps whether they are cost-effective). These sorts of treatments are reasonably interpreted as being near the "margin" of current medical care in the sense that there is no consensus regarding their usefulness. The local average treatment effect tells us, in effect, what would happen if low-cost regions started to provide care like high-use regions, or vice versa.

2.3.7 Data

The primary data set used for this analysis is the California Office of Statewide Health Planning and Development (OSHPD) Hospital Discharge Dataset for the years 1999 to 2003. For every patient hospitalized in California during this period, the dataset contains the patient's primary diagnosis, other diagnoses, procedures performed, basic demographic information, zip code of residence, type of insurance,

hospital charges, and other variables. The complete OSHPD dataset was limited to patients who had an unplanned admission to an acute care hospital with one of eight primary diagnoses. The diagnoses analyzed and ICD-9 codes used in defining them are presented in Table 1. Zip code level data on income, population, area, and number of households was merged from 2000 United States Census data. Information on hospital characteristics was obtained from the OSHPD Hospital Financial Data files for 1999-2003. The outcome variable, mortality, was defined as an indicator for whether the patient died during the hospitalization.

The charges variable included in the data reflects the hospitals' listed charges for the services provided to each patient. These list charges are nearly always greater than the actual payment received by the hospital due to confidential discounts negotiated by insurers. The "markup" of charges varies by hospital and also likely varies for different services provided by a single hospital. The cross-hospital variation in average mark-up can be corrected for by using information on total annual charges and revenues provided for each hospital in the OSHPD Hospital Financial Data files. These values were used to generate cost/charge ratios for each hospital-year combination. The variables used to generate the cost/charge ratios and their definitions are supplied in Table 2. The cost/charge ratios were used to construct a cost variable from the charges variable included in the discharge dataset. There is no way to control for the variation in the markup for different services within a hospital, but this seems likely to be fairly random. For example, the fact that one hospital has a lower markup for MRI scans than for operating room time seems unlikely to tell us about the relative markup in another hospital. This seemingly random variation may be well approximated by classical measurement error so that significant results must be interpreted as bounds due to possible attenuation bias.[6]

[6]Because the usual "solution" to measurement error is to use an instrument, it may seem tempting to say that the attenuation bias should be eliminated in the IV estimates. Unfortunately,

Finally, the dataset was divided into two samples, "Locals" and "Visitors." The Locals sample contains all individuals hospitalized within 200 miles of their home zip code. Visitors are patients from a state other than California or California residents hospitalized more than 200 miles from their home zip code. Table 3 contains summary statistics for the data used in the analyses, broken down by primary diagnosis.

2.3.8 Instrument Construction

The instruments vary at the county-of-hospitalization level and were constructed by calculating various regression-adjusted means. The regression adjustment controlled for all of the variables listed in Table 3 (other than mortality and charges) that were available for the sample being considered. The details of the construction are as follows:

1. Mean cost incurred by local patients hospitalized in county k- The mean level of regression-adjusted costs was calculated among locals of each county for each diagnosis. For a local hospitalized in county k with a given diagnosis, the instrument takes the mean adjusted cost value calculated for that diagnosis in k.

2. Mean cost incurred by visiting patients hospitalized in county k- The mean level of regression-adjusted costs was calculated among visitors to each county for each diagnosis. For a local hospitalized in county k with a given diagnosis, the instrument takes the mean adjusted cost value calculated for that diagnosis in k.

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while the instruments may not be correlated with unobserved determinants of illness severity in the error term, they probably are correlated with the measurement error. The cost variables for both locals and visitors are calculated with hospital-provided data that presumably contains the same sorts of errors.

3. Rates at which visitors undergo common procedures in county k- For each diagnosis, variables were created for each ICD-9 procedure code that was recorded for more than 5% of locals during the first 5 days of hospitalization. The regression adjusted rates at which visitors to county k had these same codes listed were used as instrument values for a local hospitalized in county k.

4. Number of procedures provided to visitors in county k- The instrument value for a local hospitalized in county k was set equal to the average number of different ICD-9 procedure codes listed for visitors to county k with the same diagnosis.

2.4 Results

2.4.1 Data Overview

The cost variable was calculated by adjusting total charges for each patient by a hospital and year specific cost-charge ratio, as described in section 2.3.7. Table 4 presents a summary of the cost variable broken down by diagnosis and county of hospitalization. The table includes mean raw costs and costs that have been regression-adjusted for all of the variables listed in Table 3 (except for mortality and charges) that were available for the given sample. The raw cost values range by more than a factor of two across counties for each of the diagnoses. Figure 1 shows plots of visitors' adjusted costs versus locals' adjusted costs using the data in Table 4 for each diagnosis. The figure includes linear trend lines which make it obvious that the correlation between locals and visitors costs is positive in each case. Figure 2 scatters the adjusted costs for locals with acute myocardial infarction against the adjusted costs for locals with each of the other seven diagnoses. Counties that spend more treating heart attacks clearly spend more treating other disorders as well. This

is consistent with the results of John Wennberg and his colleagues who find positive correlation in expenditure across different medical treatments and specialties (see for example Wennberg et al. (1989)).

The basic relationships between the variables of primary interest, mortality and cost, and the other variables used in the analysis are summarized by the OLS results presented in Table 5. For all eight illnesses, women are less likely to die than men and also incur lower costs. For seven of the diagnoses, age is positively correlated with mortality and for all eight age is negatively related to costs. This could be due to older individuals with advanced illnesses being more likely to reject expensive procedures for quality of life reasons. Zip code income is negatively related to mortality, likely due in large part to lower illness severity at the time of hospitalization, and positively related to costs. This later correlation could be due to the fact that some expensive treatments, like cardiac catheterization, are provided more often to those with lower severity of illness (see for example Stukel et al. (2007) and Sheehan-Connor (2008)), because of a tendency of physicians and hospitals to provide more care to those with better insurance coverage, or because higher income patients self-select into more expensive hospitals. Patients with MediCal insurance (California's Medicaid program) are more likely to die and incur substantially higher costs than those with private insurance. HMO type insurance is associated with lower costs, but there is no consistent correlation with mortality. Patients with Do Not Resuscitate (DNR) orders in place within 24 hours of hospitalization are more likely to die, for obvious reasons, but the impact on costs is surprisingly inconsistent given that the purpose of such orders is to avert further life-saving interventions. It may be that the orders tend not to be in place until after a great deal of expenditure has occurred and serve more as an indicator that the patient is likely to die during the hospitalization. The number of diagnoses listed for the patient tends to be positively correlated with mortality and is always positively correlated with cost. This

later relationship could be due to the patient having a higher severity of illness or the number of diagnoses could simply be an indicator that numerous tests had been done so that causality runs the other way.

2.4.2 Assessment of the Instruments

It is not possible to test directly whether an instrument is correlated with the unobserved variables that compose the error term. An examination of how an instrument correlates with observable variables may provide suggestive evidence about the likelihood that the instrument truly is exogenous. Because the instruments used here vary at the county of hospitalization level and estimation will be performed in the sample of locals, it makes sense to see whether the instruments correlate with the county means of locals' observable characteristics.

Two obvious variables that one might expect to be correlated with measures of county-level health care expenditure are income and population. The correlations of each of the four instruments with county median income and population are presented in Table 6. While county population does not correlate with any of the instruments, income does correlate in 14 of the 32 comparisons. This suggests that the instruments are not uncorrelated with locals' income, though the relationship is fairly weak. To the extent that this implies that the instruments may be correlated with unobserved variables as well, the IV estimates will not fully eliminate the bias present in OLS estimates. Table 6 also shows the correlation of the visitors' instruments with locals' mean county costs to assess the plausibility that the instruments will be sufficiently correlated with the endogenous regressor in the first stage. The correlations are often, but not nearly always, significant. Whether the first stage correlation is adequate is directly testable, however. Ultimately, the first stage F-statistics, which are reported with the results in the next section, reveal that many of the instruments are strong enough to be useful.

The key identifying assumption for the visitors' instruments is that the unobserved characteristics of locals and visitors, particularly those that relate to illness severity, are uncorrelated. The plausibility of this assumption is assessed in Table 7, which shows the correlation of the county-level means of various observed characteristics between the two groups. The characteristics compared include some that are in the regressions (age, gender, Hispanic ethnicity, number of diagnoses); the primary variables of interest (mortality, cost); and four diagnoses that may be present in addition to the primary diagnosis (hypertension, diabetes, chronic obstructive pulmonary disease (COPD), cancer). The single best indicator of illness severity, mortality, does not correlate between visitors and locals for any of the eight diagnoses considered. The cost variable is always more strongly correlated than mortality and often has among the highest correlation coefficients of the ten comparisons. The remaining eight variables do appear to have some degree of correlation, at least for some of the diagnoses, with a total of 20 of 64 comparisons statistically significant at the $p < 0.10$ level. In addition 49 of the 64 correlation coefficients are positive and only 2 of the 20 significant correlation coefficients are negative. All of this suggests that there are some important similarities between the visitors and locals, which calls into question whether the instruments will be completely exogenous. It is likely, however, that they are less correlated with the error term than is the endogenous regressor, cost incurred by the individual. The positive correlations suggest that locals and visitors are similar to one another so that any bias due to instrument endogeneity should be in the same direction as the bias in the OLS estimates. Because the sign of the IV estimates tends to be opposite that of the OLS ones, this source of bias would still establish the correct sign of the parameter. This issue will be considered further below in a discussion of possible sources of bias (Section 2.4.6).

Another way to assess the relationship of the instruments to the county-level

observable characteristics of locals is to compare the mean characteristics of counties with low instrument values to those of counties with high values. This is done for all of the variables included in Table 3, for each diagnosis, and for three of the instruments[7] with the results presented in Table 8. The entries in the table are "means of means." Counties are taken as the unit of observation and the value of each variable for a given county is the mean for the locals in that county. The table then lists the unweighted mean value of these county means for counties with instrument levels above or below the median instrument value. The first two rows of the table show the situation for the primary variables of interest: mortality and cost.[8] While the cost values are typically significantly different (suggesting a valid first stage), the mortality values do not differ significantly except in the case of acute myocardial infarction. This anticipates the finding that when diagnoses are considered separately, the most consistently significant results are for AMI. Most of the control variables used in the regressions appear to be fairly well balanced for high and low values of the instrument, but enough are significantly different to raise some concern. Table 9 summarizes the data from all the panels of Table 8 by noting how many comparisons with $p < 0.10$ were found for each diagnosis-instrument combination. The final column of Table 8 addresses the following question: What is the probability of getting the observed number of significant comparisons (or more) under the null hypothesis that none of the pairs are actually correlated? The table lists the binomial probability with parameters $n = 24$ trials, $p = 0.10$ probability of a Type I error on each trial. For 7 of the 24 diagnosis-instrument combinations,

[7]The procedures rate instrument is excluded because it consists of multiple variables, making it less obvious how to divide the counties into two groups.

[8]Note that these first two rows of the table can be used to construct "Wald estimates" (as described by Angrist (1990)) of the impact of expenditure on mortality. Such estimates are presented with the rest of the results in the next section.

the binomial probability fails to reject the null of no correlation. For the remaining 17 combinations, the null is rejected because more significant correlations occurred than would be expected by chance alone. This result could be taken to suggest that the instruments are not exogenous. On the other hand, one could argue that the assumptions of a binomial distribution are likely to be substantially violated here. Many of the variables compared are likely to correlate with one another, so that if one happens to be correlated across instrument values, the conditional probability that the other is also will be greater than 10%. In fact, this concern led to to the omission of number of households (which is likely to be correlated with population) and Medicare status (which is likely to be highly correlated with age) from the analysis because they so flagrantly violated the binomial assumption of independent trials. Various other pairs might be problematic as well, for example: income and HMO status; income and self-pay status; population and hospital beds; and population density and emergency room type. Thus, it may be that the number of significant comparisons is acceptable given that failure of the binomial assumption would bias the analysis toward finding more significant pairs. Whether or not one accepts this logic, it remains likely that the instrument will improve matters compared to OLS and in fact the IV estimates turn out to have a sign opposite to that of OLS.

2.4.3 Overview of the Results by Diagnosis

The basic results of the analysis of individual diagnoses are presented in Table 10. The ordinary least squares estimates are positive and significant for all eight of the diagnoses considered. This always seemed likely given the tendency of people who are more ill to receive more care and their greater likelihood of death. A naïve interpretation of these estimates would be to conclude that medical care increases hospital mortality rates.

The second set of estimates reported in each panel are Wald estimates. These are

easily calculable from the data in the first two rows of Table 8 and can be interpreted as causal estimates of a local average treatment effect under conditions spelled out by Angrist, Imbens and Rubin (1996). While only one of the 24 Wald estimates calculated is statistically significant, 14 have a negative sign and 19 are greater than the corresponding OLS estimate. The ones that are not greater than the OLS estimate have very large standard errors. While there is a clear lack of precision here, the general conclusion that emerges is that the instruments are attenuating the bias present in OLS. The one statistically significant result, for the locals' cost instrument and acute myocardial infarction, suggests that additional spending on heart attack care decreases mortality. The result is similar to ones obtained by two-stage least squares and its implications will be discussed in greater detail below.

Because there are no controls involved, Wald estimates make good intuitive sense in cases where the story for exogeneity of the instrument is truly compelling. A good example is the paper where the approach was developed by Angrist, who used results from the randomly generated draft lottery from the Vietnam War to instrument for service in the military during the war (Angrist, 1990). The instruments used in the current analysis clearly cannot aspire to that level of exogeneity. People who are traveling do not choose where to travel at random and it is clearly possible that some degree of match could exist between their characteristics and those of the locals. To the extent that the covariance of locals' and visitors' other characteristics is small relative to the covariance of expenditure on their care, the bias in IV estimates could be attenuated relative to that in OLS ones. Crucially, what is important here is the cumulative covariance of the instrument with variables that are not in the regression. By including control variables in the regressions, this covariance is likely to be decreased. It is for this reason that IV regressions utilizing a comprehensive set of controls are generally to be preferred to the Wald ones.

The third row of estimates in Table 10 shows the results of the first stage in a

two-stage least squares regression procedure. While the locals' cost instrument has a uniformly strong first stage with a minimum F-statistic greater than 600, many of the visitors' instruments have F-statistics less than 10 and may be susceptible to the weak instruments problem (Staiger and Stock, 1997). Because some of the instruments do not correlate with the endogenous regressor sufficiently strongly, the associated IV estimates may be biased in the same direction that OLS is. There are cases (for example, columns 2 and 3 in Table 10(a), where the first stage F-statistic is less than 10 while the IV estimate is significant and of sign opposite to the OLS one. In these cases, the sign of the estimate will be correct and any bias due to weak instruments would simply make the estimate a bound.

The two-stage least squares results for each diagnosis are also presented in Table 10. While only 6 of the 32 estimates are statistically significantly different from zero, in 27 of 32 cases, the estimates are opposite in sign to the OLS estimates. In just over half of the cases, a Hausman test for exogeneity[9] suggests that the difference between the IV estimate and the OLS one is statistically significant. These observations suggest that the instruments have at least attenuated the bias present in the ordinary least squares estimates.

The signs of most of the point estimates presented in Table 10 are negative, suggesting that increased marginal expenditure will be effective in the sense of decreasing mortality. Whether increasing expenditure will be cost-effective depends upon the magnitude of the impact on mortality. The estimates themselves tell us how many lives we could expect to save by spending an additional dollar on treatment. As discussed in Section 2.3.2, the inverse of the estimates gives a measure of how many dollars would have to be spent to save one life on average. Table 10 reports three dollar figures (corresponding to the point estimate and the bounds of

[9]The test was performed as described in Wooldridge (2002). Such tests were first described in Hausman (1978).

a 90% confidence interval around it) of the cost of saving an expected life for each instrument-diagnosis combination. Negative dollar figures reflect the cost savings that would be expected along with saving a life in cases where the marginal impact of expenditure is estimated to be harmful.

Calculating cost-effectiveness ratios in terms of dollars per life year requires estimates of conditional life expectancy for each diagnosis. The availability of data on life expectancy conditional upon survival varies substantially depending upon the illness considered. Crude estimates of conditional life expectancy are presented in Table 11 for each of the eight diagnoses considered in this paper, with sources noted in the table. In addition to the problem that the conditional life expectancies are calculated using limited data, it is very possible that the marginal patients whose lives are saved by increasing expenditure will have life expectancy that differs from the average. The figures from Table 11 are used to calculate cost per life year values that are presented in the final rows of each panel of Table 10.

2.4.4 Detailed Results by Diagnosis

Acute Myocardial Infarction

The results for acute myocardial infarction, presented in Table 10(a), are broadly significant. The Wald estimate and two-staged least squares estimates are negative and of similar magnitude. While the first stage results suggest that the visitors' instruments are marginally weak, Hausman tests confirm that the IV estimates are significantly different from the OLS one. The results imply that the cost of saving an expected life among myocardial infarction patients would be on the order of $270,000, which corresponds to $45,000 per life year.

Acute Appendicitis

Table 10(b) presents the results for patients with acute appendicitis. While none of the IV estimates are significant, all have a negative sign, which is opposite to OLS. The instruments based upon procedures provided to visitors are too weak to be of any real use with F-statistics less than 2 so that they are not even significantly correlated with the endogenous regressor, let alone strongly correlated. The mean cost instruments have first stage F-statistics greater than 25 and Hausman tests suggest that the results do differ significantly from the OLS estimate. The magnitude of the estimates is low, suggesting that $5,000,000 would be required to save an expected life. Because patients with acute appendicitis tend to be young and live relatively normal lives conditional upon survival, this is equivalent to a marginally cost effective $106,000 per life year.

Cerebrovascular Accident

None of the IV estimates of the impact of additional spending on mortality from cerebrovascular accident, presented in Table 10(c), are statistically significant. The instruments based upon visitors' procedures are weak and the corresponding IV estimates are positive, like OLS. The cost instruments are both adequately strong and yield negative IV estimates, with the visitors' cost estimate differing significantly from OLS according to a Hausman test. The point estimates from the cost instruments vary by an order of magnitude with the implied cost of saving an expected life ranging from $400,000 to $4,000,000. The corresponding cost per life year figures range from a reasonable $50,000 to nearly $600,000.

Dysrhythmias

In Table 10(d), we see that the instruments based upon visitors' procedures are again weak. The cost instruments are adequately strong and both yield negative

point estimates, opposite to OLS. Only the estimate based upon locals' costs is significantly different from zero. The magnitude of this estimate suggests that an additional $600,000 would be required to save an expected life. The cost of a life year is a relatively cost-effective $80,000.

Gastrointestinal Bleed

The results for gastrointestinal bleed are presented in Table 10(e). Once again, the instruments based upon visitors' procedures are weak. The cost instruments are stronger, though the first stage F-statistic for the visitors' cost instrument is marginal at 8.2. The IV estimates corresponding to the cost instruments are negative, significant, and of similar magnitude. They imply that approximately $170,000 would save one expected life or a cost per life year of approximately $20,000. This figure meets any commonly used criteria for cost-effectiveness.

Acute Pancreatitis

All of the IV estimates for acute pancreatitis, presented in Table 10(f), are negative, opposite to OLS. While none are statistically significantly different from zero, three of the estimates are significantly different from the OLS result according to the Hausman test results. Only the locals' cost instrument seems adequately strong and its magnitude corresponds to a cost of saving an expected life that exceeds $12,000,000 or more than $550,000 per life year.

Pulmonary Embolism

The results for pulmonary embolism, presented in Table 10(g), are very imprecise, perhaps due to the comparatively small sample size of 17,854. The locals' cost and visitors' number of procedures instruments are strongest, but the corresponding estimates vary wildly. It would be unreasonable to draw any conclusions, even

tentative, from these results.

Vertebral Fracture

While none of the IV results for vertebral fracture, presented in Table 10(h), are significant, all are of negative sign, opposite to OLS. Only one of these differs significantly from the OLS result, however, based on Hausman tests. The sample size is small and the estimates are imprecise. The point estimates suggest millions of dollars would be required to save an expected life, corresponding to a cost of several hundred thousand dollars per life year.

2.4.5 Results for the Pooled Sample

It is important to break down this analysis by disease, as done above, because this can help determine how to optimally allocate resources among them. It is also interesting to consider what would happen if we simply changed spending on health care generally, without taking specific steps to alter the allocation. For the analysis presented here, this means estimating equation (1) including patients with any of the diagnoses and with fixed effects for diagnosis in the regression. The estimates obtained will give the marginal impact of expenditure on mortality during acute hospitalization averaged across the eight diagnoses considered.[10] An additional reason for doing this is that many of the estimates discussed above were imprecise. Pooling the sample may improve precision by increasing the sample size directly as well as increasing the number of clusters since the instruments will

[10]A pooled analysis could also include interaction terms of cost with the diagnosis fixed effects. This would allow the impact of cost to vary across diagnoses, but would differ from the separate analyses presented in Table 10 in that it constrains the impact of the covariates and the error term to be the same across diagnoses. The results of this approach are very similar to those already presented and so are omitted here.

now vary at the county-by-diagnosis level, rather than just the county level. Two separate analyses are performed, one using mortality as the dependent variable and one using conditional life expectancy, as discussed in Section 2.3.2.

The results, presented in Table 12, are considerably more consistent and robust than when diagnoses are considered individually. All four instruments have first stage F-statistics greater than 10. When mortality is the dependent variable, all four IV estimates are negative in sign and vary by less than a factor of two. Three of these are significantly different from zero, with the average implying that additional expenditure of approximately $320,000 would save one expected life. The results are similarly robust when life years is the dependent variable, with the average of three significant estimates suggesting that $45,000 will be required to save a life year.

The results for the pooled sample are very similar to those for acute myocardial infarction alone. Since the estimates for acute myocardial infarction were the most significant and robust when considered separately and so could be driving the pooled estimates, the pooled analysis was repeated omitting acute myocardial infarction patients. The results are presented in Table 13. While they do differ substantially in magnitude from those in Table 12, the estimates remain relatively robust and statistically significant. Three of the instruments have an adequately strong first stage and all three of these yield IV estimates that are opposite to OLS for both dependent variables. The estimates obtained using locals' and visitors' cost instruments are statistically significant and are of the same order of magnitude. The average of these two results suggests a cost of $890,000 for saving an expected life or $90,000 per life year.

2.4.6 Interpretation Issues

Possible Sources of Positive Bias

In interpreting the IV estimates, it is useful to think about what factors could lead them to be asymptotically biased. As previously discussed, the OLS estimates suffer from a positive bias[11], so we first consider factors that would cause the IV estimates to be biased similarly. The OLS estimates also turn out to have a positive sign, so that they provide positive upper bounds and the true sign of the coefficient remains unknown. The asymptotic bias term for the IV estimates is equal to the covariance of the instrument with the error term divided by the covariance of the instrument with the endogenous regressor. Each of the instruments is positively correlated with the endogenous regressor, cost, and cost is positively correlated with the illness severity portion of the error term. The most obvious way for the instruments to fail is if they are also positively correlated with illness severity. This could happen with the visitors' cost instrument, for example, if the unobserved characteristics of visitors were in fact positively correlated with those of the locals. The evidence presented in Table 5, and to a lesser extent in Table 6, suggests that this may in fact be a problem because observable characteristics of locals and visitors appear to be somewhat correlated. Because the IV estimates are uniformly lower than the OLS estimates, however, the bias appears to have been attenuated by this approach.

As mentioned earlier, an additional source of bias would exist if regional expenditure is correlated with regional quality of care. This bias would be positive if higher costs were associated with lower quality of care.

If either of these sources of positive bias is present, the estimates remain upper

[11]The bias is positive when mortality is the dependent variable and negative when life years is the dependent variable. Since most of the estimates used mortality as a dependent variable, the bias discussion is from this point of view. The conclusions are the same for life years with all signs of correlations reversed.

bounds. But because the sign of most of the estimates is negative, the sign of the relationship between cost and mortality will have been established.

Possible Sources of Negative Bias

Because most of the IV estimates have a negative sign, it is also important to consider under what conditions negative bias would be present. This would occur if an instrument is invalid because it correlates with a part of the error term with a sign opposite to the situations discussed in the previous section. The first possibility is that visitors' unobserved characteristics are negatively correlated with those of the locals. *A priori* this seems unlikely; it is much easier to think of reasons why a positive correlation would exist. The evidence presented in Table 7 also argues strongly against this possibility. If anything, the observable characteristics examined are positively correlated, so there seems little reason to think that the unobservable characteristics would be otherwise. The second source of negative bias that must be considered would occur if higher cost regions were also higher quality. This possibility cannot be ruled out and so must be considered in interpreting the results. If this turns out to be the case, then the estimates still establish that higher cost regions achieve better health outcomes, which is interesting in its own right. Whether this is due to quantity or quality of resources employed is a matter for further investigation.

2.5 Discussion

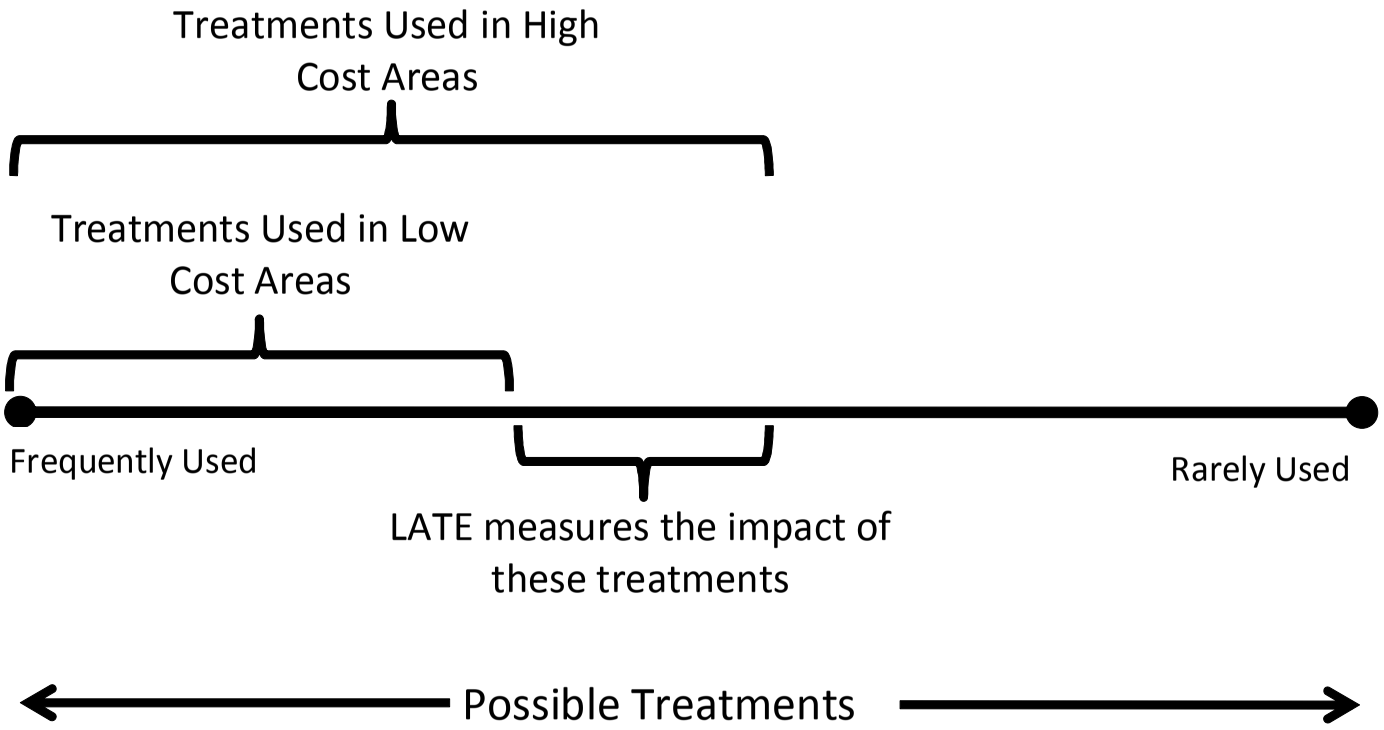
This study has provided evidence that greater use of health care is associated with improved outcomes near the margin for several conditions that require acute hospitalization. The result is broadly consistent with the view that health care is effective on average, but has low marginal effectiveness. Along with Doyle (2008), it stands

in contrast to work on regional variation that has shown no measurable benefit to the "extra" care provided in high use regions.

Although the measured benefit of health spending is relatively small, there is reason to think that the analysis may underestimate the impact of additional care. Because an important source of OLS bias is toward finding medical spending to be harmful, failures of the identifying assumptions for instrument validity would likely bias the IV estimates in this direction as well. The evidence presented suggests that the instruments do correlate with some observable variables, making it seem likely that they will correlate with some unobservable variables as well. Also, the instruments based on locals' mean costs tend to show benefit to additional care. This instrument will produce estimates that are asymptotically biased toward the OLS one if there is any regional variation in unobserved determinants of illness severity, which seems quite likely. Another factor that could have led to underestimation of benefits is the fact that costs are clearly measured with substantial error. It was argued that the measurement error was likely to be approximated by the classical description, which would imply that the estimates underestimate the true magnitude of the parameter. The estimates stated in terms of dollars per life year may include additional error in either direction due to the crudity of the data used for conditional life expectancy.

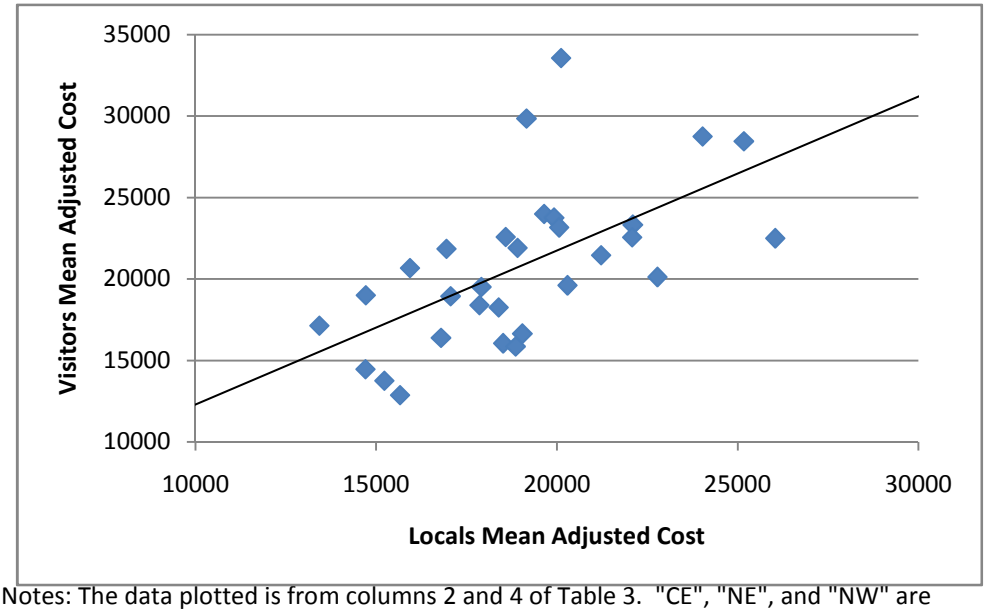
While this analysis provides evidence that higher spending is associated with better outcomes, it cannot distinguish whether this is due to the higher quantity of medical resources employed or some unobserved characteristic of high cost hospitals. If higher cost hospitals also tend to provide care that is higher quality in ways not captured by total costs, it could be that high costs are simply a marker for high quality. In either case, it is worth investigating what high and low cost regions do differently in treating these diseases.

Figure 1. Schematic of Local Average Treatment Effect



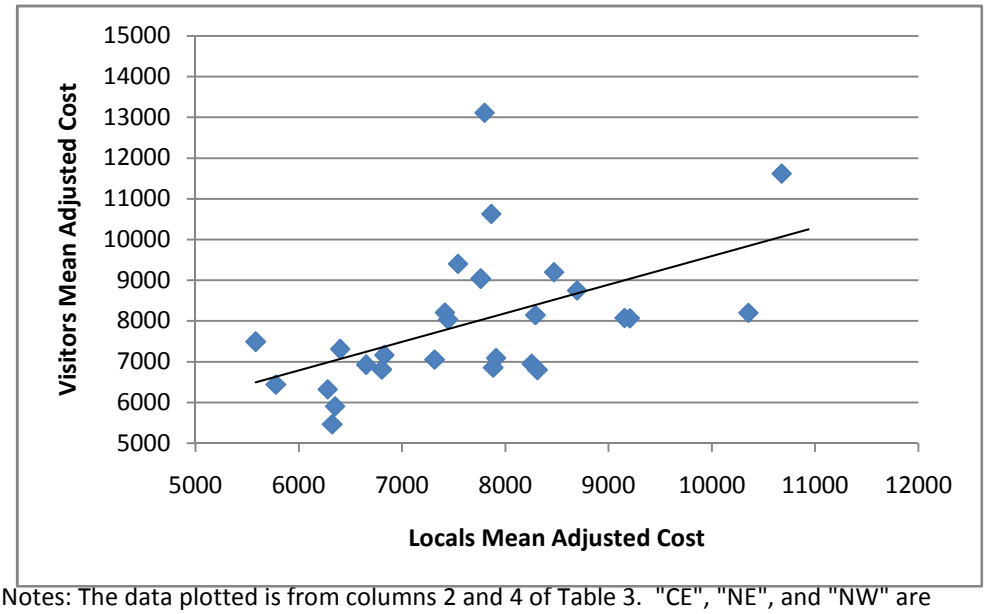
Notes: The figure supposes that all possible treatments for a given diagnosis are "lined up" from those most commonly used (presumably because they are thought to be most effective or cost-effective) at one end and those that are least commonly used at the other. The figure depicts the fact that some treatments are used in high cost areas, but not low cost ones. (In reality, they will likely be more commonly used in the high cost areas.) An instrument that uses the differences between the areas in costs and outcomes will assess the impact of these treatments that are used differentially.

Figure 2(a). Comparison of Locals and Visitors Mean Costs by County: Acute Myocardial Infarction



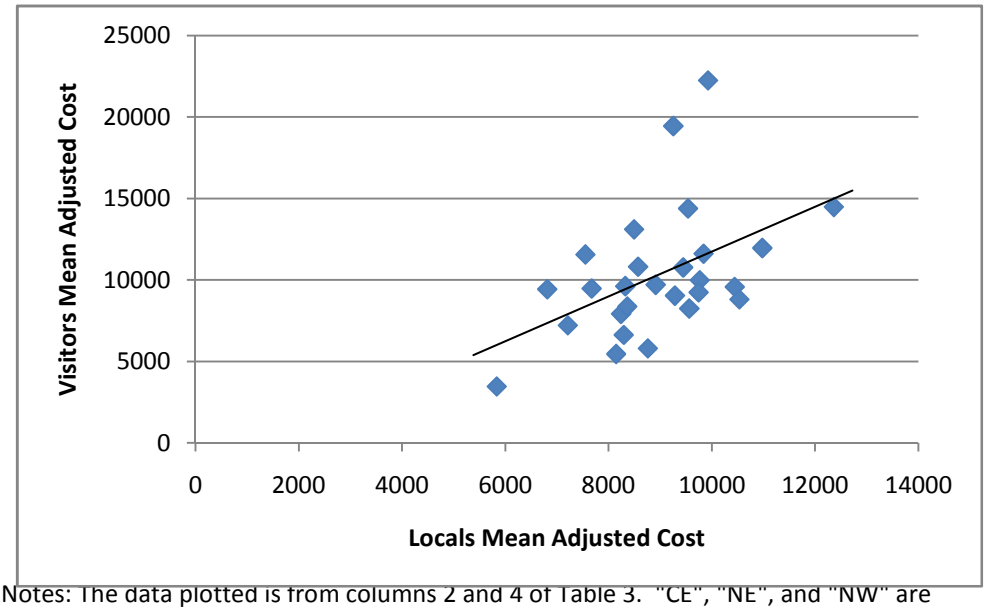
Notes: The data plotted is from columns 2 and 4 of Table 3. "CE", "NE", and "NW" are excluded from the figure. A linear trend line is included.

Figure 2(b). Comparison of Locals and Visitors Mean Costs by County: Appendicitis



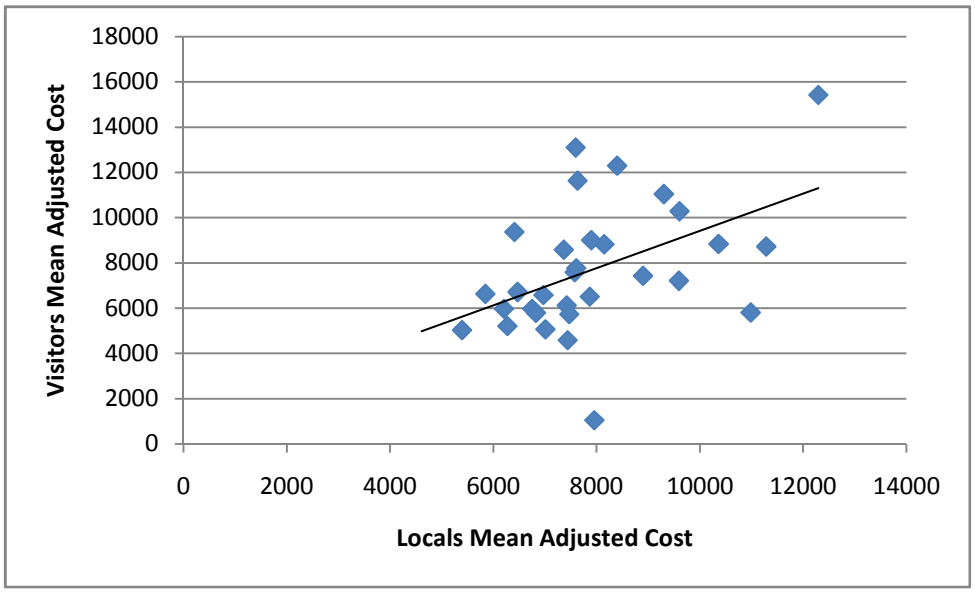
Notes: The data plotted is from columns 2 and 4 of Table 3. "CE", "NE", and "NW" are excluded from the figure. A linear trend line is included.

Figure 2(c). Comparison of Locals and Visitors Mean Costs by County: Cerebrovascular Accident



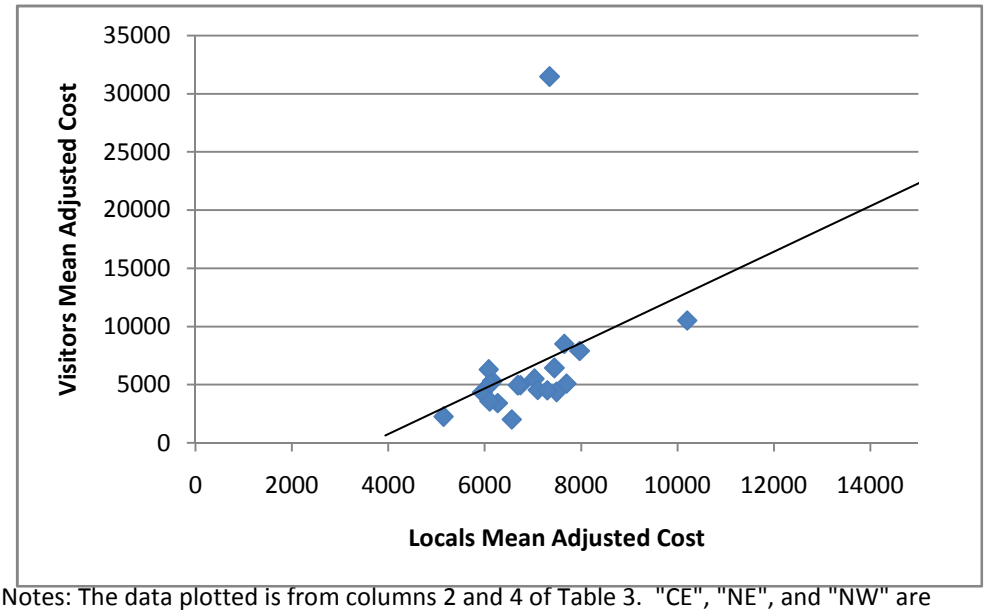
Notes: The data plotted is from columns 2 and 4 of Table 3. "CE", "NE", and "NW" are excluded from the figure. A linear trend line is included.

Figure 2(d). Comparison of Locals and Visitors Mean Costs by County: Dysrhythmias



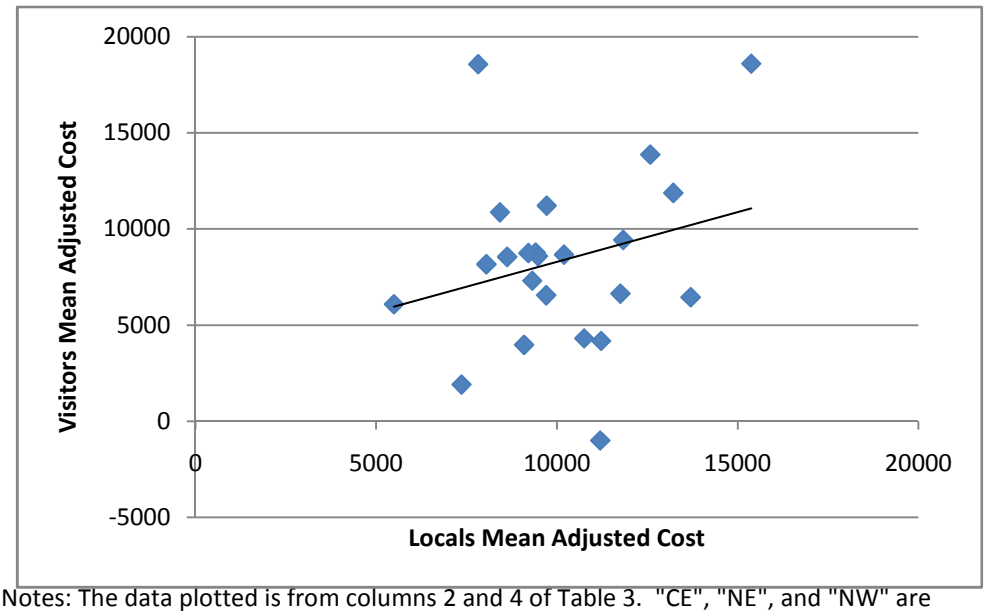
Notes: The data plotted is from columns 2 and 4 of Table 3. "CE", "NE", and "NW" are excluded from the figure. A linear trend line is included.

Figure 2(e). Comparison of Locals and Visitors Mean Costs by County: GI Bleed



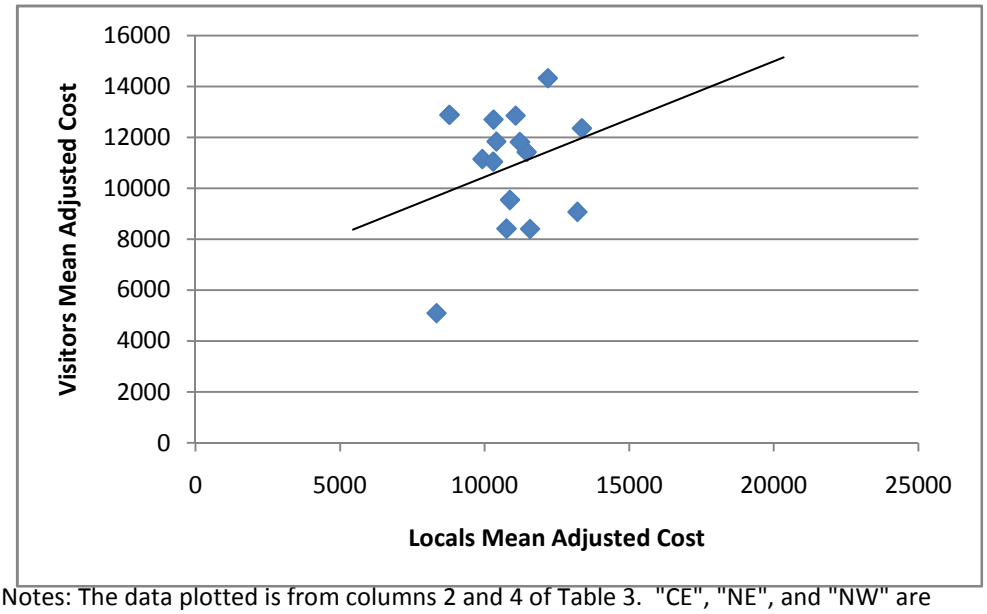
Notes: The data plotted is from columns 2 and 4 of Table 3. "CE", "NE", and "NW" are excluded from the figure. A linear trend line is included.

Figure 2(f). Comparison of Locals and Visitors Mean Costs by County: Pancreatitis



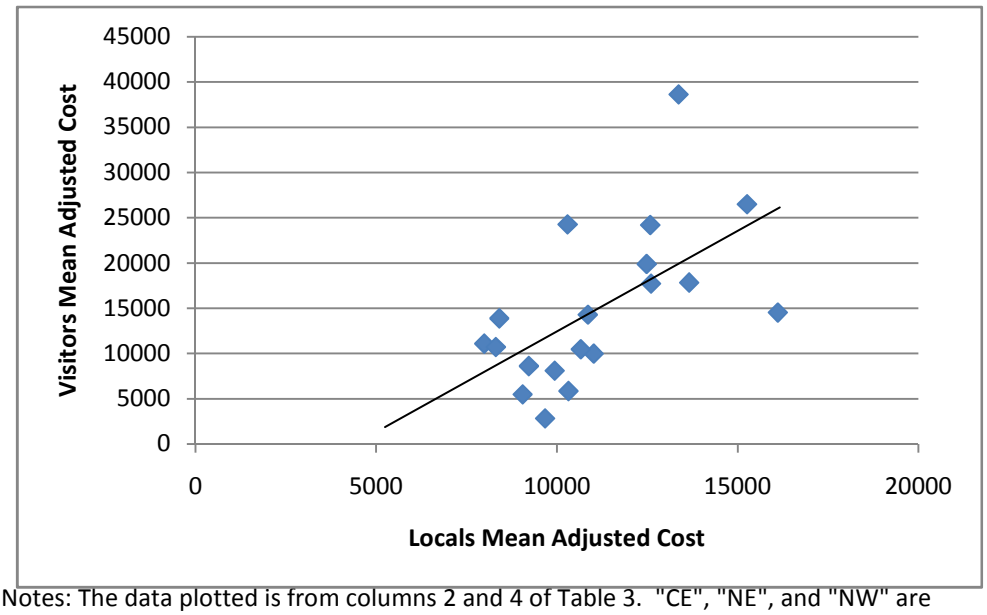
Notes: The data plotted is from columns 2 and 4 of Table 3. "CE", "NE", and "NW" are excluded from the figure. A linear trend line is included.

Figure 2(g). Comparison of Locals and Visitors Mean Costs by County: Pulmonary Embolism



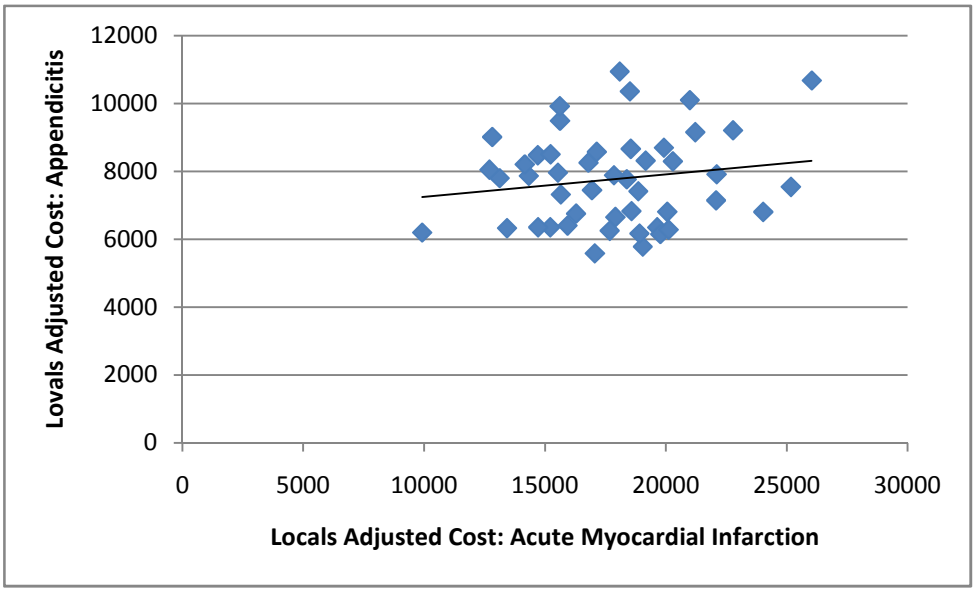
Notes: The data plotted is from columns 2 and 4 of Table 3. "CE", "NE", and "NW" are excluded from the figure. A linear trend line is included.

Figure 2(h). Comparison of Locals and Visitors Mean Costs by County: Vertebral Fracture



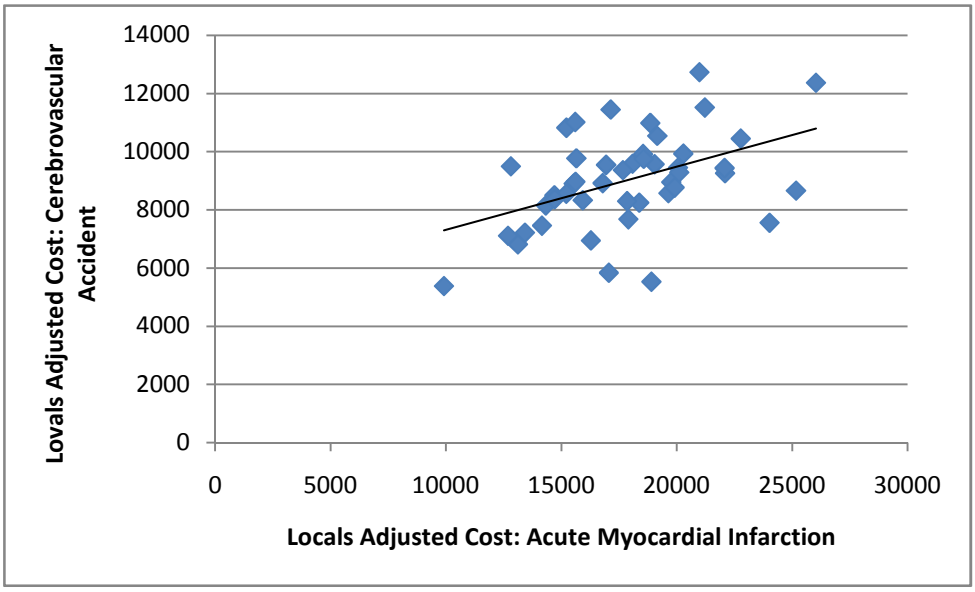
Notes: The data plotted is from columns 2 and 4 of Table 3. "CE", "NE", and "NW" are excluded from the figure. A linear trend line is included.

Figure 3(a). Comparison of Locals Mean County Costs by Diagnosis: Acute Myocardial Infarction vs. Appendicitis



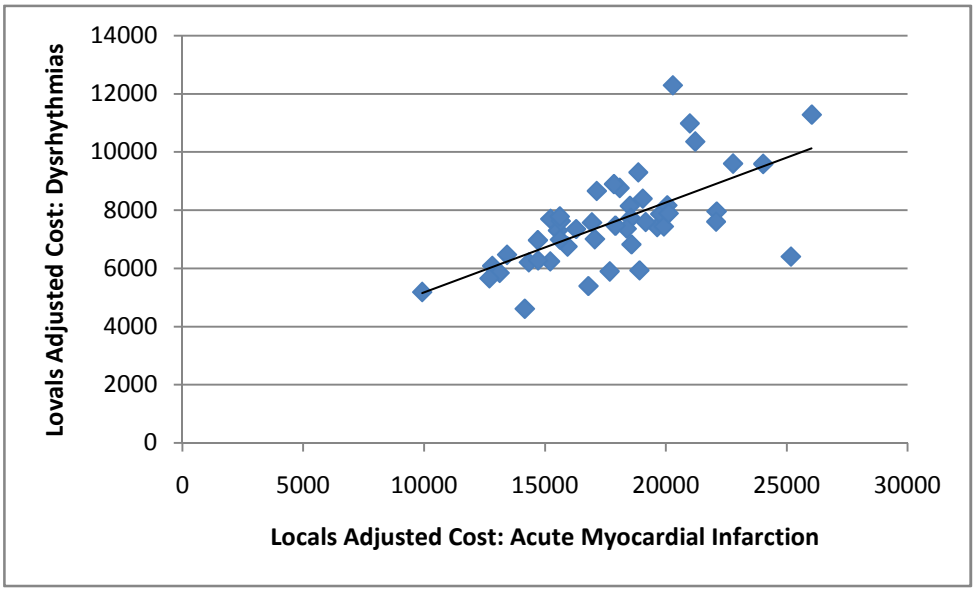
Notes: The data plotted is from Table 3. "CE", "NE", and "NW" are excluded. A linear trend line is shown.

Figure 3(b). Comparison of Locals Mean County Costs by Diagnosis: Acute Myocardial Infarction vs. Cerebrovascular Accident



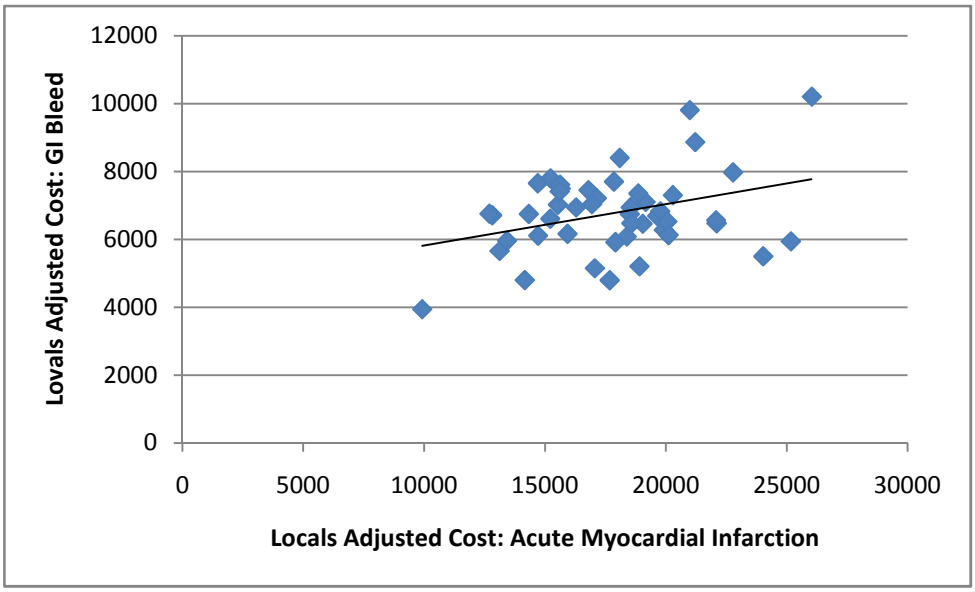
Notes: The data plotted is from Table 3. "CE", "NE", and "NW" are excluded. A linear trend line is shown.

Figure 3(c). Comparison of Locals Mean County Costs by Diagnosis: Acute Myocardial Infarction vs. Dysrhythmias



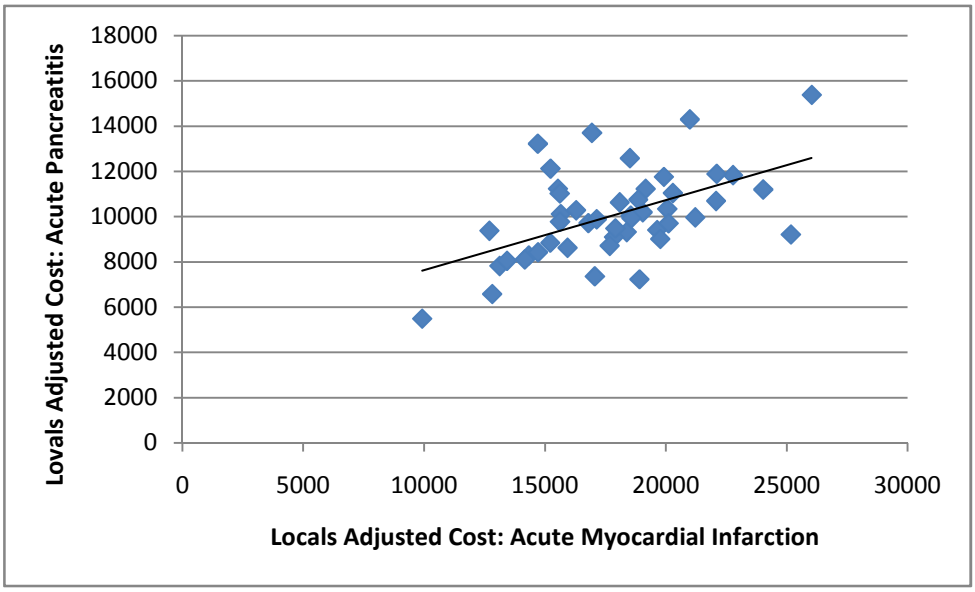
Notes: The data plotted is from Table 3. "CE", "NE", and "NW" are excluded. A linear trend line is shown.

Figure 3(d). Comparison of Locals Mean County Costs by Diagnosis: Acute Myocardial Infarction vs. GI Bleed



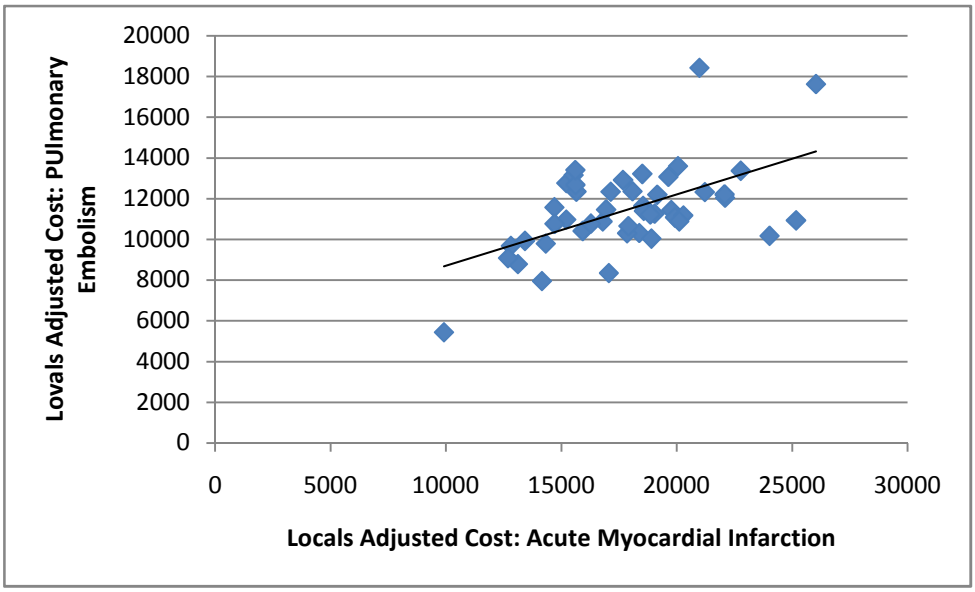
Notes: The data plotted is from Table 3. "CE", "NE", and "NW" are excluded. A linear trend line is shown.

Figure 3(e). Comparison of Locals Mean County Costs by Diagnosis: Acute Myocardial Infarction vs. Acute Pancreatitis



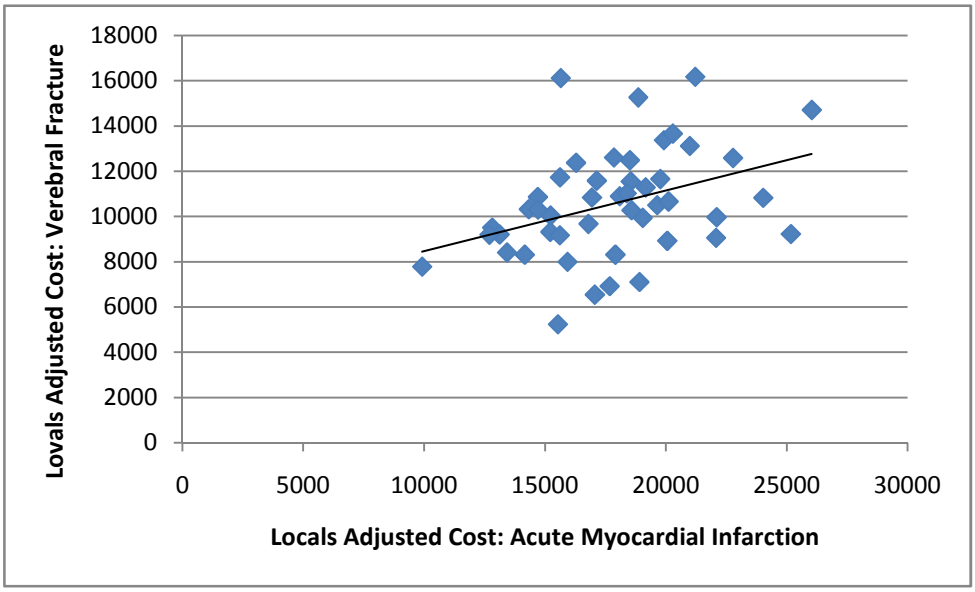
Notes: The data plotted is from Table 3. "CE", "NE", and "NW" are excluded. A linear trend line is shown.

Figure 3(f). Comparison of Locals Mean County Costs by Diagnosis: Acute Myocardial Infarction vs. Pulmonary Embolism



Notes: The data plotted is from Table 3. "CE", "NE", and "NW" are excluded. A linear trend line is shown.

Figure 3(g). Comparison of Locals Mean County Costs by Diagnosis: Acute Myocardial Infarction vs. Vertebral Fracture



Notes: The data plotted is from Table 3. "CE", "NE", and "NW" are excluded. A linear trend line is shown.

Table 1. Illness Definitions

Illness	ICD-9 Codes Used
Myocardial Infarction (Heart Attack)	410.XX, excluding fifth digit of 2
Acute Appendicitis	540, 540.X, 541
Cerebrovascular Accident (Stroke)	434, 434.X, 434.XX
Dysrhythmias (Heart Rhythm Disturbances)	427, 427.X, 427.XX
Gastrointestinal (GI) Bleeding	578, 578.X
Acute Pancreatitis	577
Pulmonary Embolism	415.19
Vertebral Fracture	805, 805.X

Table 2. Description of Variables Used to Construct the Cost-Charge Ratios

Cost: "Total Operating Expenses"

Total costs incurred by revenue-producing and non-revenue producing cost centers for providing patient care at the hospital. Excludes non-operating expenses, provisions for income taxes, and provisions for bad debts.

Charges: "Gross Patient Revenue"

The total charges at the hospital's full established rates for the provision of patient care services before deductions from revenue are applied. Includes charges related to hospital-based physician professional services. Other operating revenue, capitation premium revenue, and nonoperating revenue are excluded. Gross Patient Revenue is reported by the following revenue center groups: Daily Hospital Services, Ambulatory Services, and Ancillary Services.

Notes: Variable definitions are taken from OSHPD's Hospital Annual Financial Data Selected Data File Documentation, September 2005.

Table 3(a). Summary Statistics: Acute Myocardial Infarction

Variable	Sample		Variable	Sample	
	Locals	Visitors		Locals	Visitors
n	158269	1791			
Mortality	0.109	0.101	Self Pay	0.027	0.040
	(0.312)	(0.301)		(0.163)	(0.196)
Charges	61,904	63,626	Other Payor	0.007	0.005
	(81,809)	(74,056)		(0.084)	(0.071)
Cost	18,398	19,568	HMO	0.441	0.322
	(21,521)	(21,151)		(0.497)	(0.467)
Age	69.7	72.8	Comprehensive	0.033	0.059
	(13.3)	(11.7)	ER	(0.179)	(0.235)
Female	0.403	0.118	Basic ER	0.946	0.889
	(0.490)	(0.322)		(0.226)	(0.314)
Black	0.041	0.007	Standby ER	0.006	0.035
	(0.197)	(0.082)		(0.075)	(0.183)
Nat. Amer.	0.000	-	Hospital Beds	329.1	322.5
	(0.021)	-		(147.1)	(171.7)
Asian	0.044	0.007	Transfer	0.126	-
	(0.205)	(0.085)		(0.332)	-
Hispanic	0.088	0.007	Distance to Hosp.	6.9	-
	(0.283)	(0.085)		(11.0)	-
ZC Income	49,095	-	Distance to Hosp.	168.2	-
	(18,677)	-	Squared	(895.1)	-
ZC Pop.	40,327	-	DNR Status	0.090	0.064
	(19,560)	-		(0.286)	(0.245)
ZC Num. of	14,351	-	Num. Of	6.4	6.2
Households	(6,137)	-	Diagnoses	(3.6)	(3.6)
ZC Area	45.4	-	Num. Diagnoses	53.7	51.0
	(96.0)	-	Squared	(61.1)	(60.7)
ZC Density	5,508	-	Year 1999	0.191	0.199
	(6,239)	-		(0.393)	(0.400)
ZC Household	2.8	-	Year 2000	0.199	0.195
Size	(0.8)	-		(0.399)	(0.397)
Medicare	0.597	0.609	Year 2001	0.203	0.216
	(0.491)	(0.488)		(0.402)	(0.411)
MediCal	0.081	0.018	Year 2002	0.205	0.204
	(0.272)	(0.135)		(0.404)	(0.403)
Other Gov't	0.027	0.024	Year 2003	0.202	0.185
Insurance	(0.162)	(0.153)		(0.402)	(0.389)

Notes: Values are means with standard deviations in parentheses. Abbreviations: ZC = zip code; ER = Emergency Room, DNR = Do Not Resuscitate.

Table 3(b). Summary Statistics: Appendicitis

Variable	Sample		Variable	Sample	
	Locals	Visitors		Locals	Visitors
n	102448	1169			
Mortality	0.001	0.002	Self Pay	0.089	0.107
	(0.039)	(0.041)		(0.285)	(0.309)
Charges	22,560	21,851	Other Payor	0.010	0.015
	(29,712)	(17,204)		(0.097)	(0.120)
Cost	7,442	7,843	HMO	0.621	0.494
	(8,983)	(6,794)		(0.485)	(0.500)
Age	31.2	40.2	Comprehensive	0.044	0.040
	(18.1)	(21.2)	ER	(0.205)	(0.197)
Female	0.383	0.054	Basic ER	0.926	0.867
	(0.486)	(0.226)		(0.262)	(0.339)
Black	0.016	0.002	Standby ER	0.011	0.080
	(0.124)	(0.041)		(0.105)	(0.271)
Nat. Amer.	0.000	-	Hospital Beds	310.0	287.9
	(0.018)	-		(153.8)	(197.6)
Asian	0.030	0.002	Transfer	0.007	-
	(0.170)	(0.041)		(0.083)	-
Hispanic	0.248	0.003	Distance to Hosp.	5.6	-
	(0.432)	(0.058)		(6.9)	-
ZC Income	49,590	-	Distance to Hosp.	78.8	-
	(19,054)	-	Squared	(462.5)	-
ZC Pop.	44,577	-	DNR Status	0.005	0.005
	(20,960)	-		(0.073)	(0.071)
ZC Num. of	14,786	-	Num. Of	0.9	0.9
Households	(5,972)	-	Diagnoses	(1.6)	(1.6)
ZC Area	38.5	-	Num. Diagnoses	3.5	3.4
	(92.8)	-	Squared	(13.9)	(10.8)
ZC Density	6,211	-	Year 1999	0.169	0.164
	(6,471)	-		(0.375)	(0.371)
ZC Household	3.0	-	Year 2000	0.191	0.184
Size	(0.8)	-		(0.393)	(0.388)
Medicare	0.058	0.079	Year 2001	0.203	0.218
	(0.234)	(0.269)		(0.402)	(0.413)
MediCal	0.228	0.027	Year 2002	0.213	0.212
	(0.420)	(0.161)		(0.409)	(0.409)
Other Gov't	0.068	0.043	Year 2003	0.224	0.222
Insurance	(0.252)	(0.202)		(0.417)	(0.415)

Notes: Values are means with standard deviations in parentheses. Abbreviations: ZC = zip code; ER = Emergency Room.

Table 3(c). Summary Statistics: Cerebrovascular Accident

Variable	Sample		Variable	Sample	
	Locals	Visitors		Locals	Visitors
n	93450	1086			
Mortality	0.067	0.064	Self Pay	0.021	0.021
	(0.249)	(0.244)		(0.144)	(0.144)
Charges	29,580	30,960	Other Payor	0.005	0.006
	(48,618)	(55,816)		(0.074)	(0.074)
Cost	9,167	9,694	HMO	0.361	0.238
	(15,642)	(12,316)		(0.480)	(0.426)
Age	72.8	74.5	Comprehensive	0.038	0.059
	(12.3)	(10.8)	ER	(0.192)	(0.236)
Female	0.553	0.262	Basic ER	0.934	0.886
	(0.497)	(0.440)		(0.248)	(0.318)
Black	0.072	0.037	Standby ER	0.010	0.038
	(0.258)	(0.188)		(0.101)	(0.191)
Nat. Amer.	0.001	-	Hospital Beds	317.1	289.5
	(0.026)	-		(154.1)	(171.2)
Asian	0.072	0.015	Transfer	0.026	-
	(0.258)	(0.121)		(0.159)	-
Hispanic	0.109	0.021	Distance to Hosp.	5.1	-
	(0.312)	(0.144)		(8.0)	-
ZC Income	49,123	-	Distance to Hosp.	88.8	-
	(19,378)	-	Squared	(724.7)	-
ZC Pop.	40,984	-	DNR Status	0.105	0.095
	(20,025)	-		(0.307)	(0.293)
ZC Num. of	14,396	-	Num. Of	6.4	6.3
Households	(5,996)	-	Diagnoses	(3.3)	(3.2)
ZC Area	37.3	-	Num. Diagnoses	52.6	50.5
	(88.6)	-	Squared	(56.2)	(52.8)
ZC Density	6,269	-	Year 1999	0.205	0.206
	(6,734)	-		(0.404)	(0.405)
ZC Household	2.8	-	Year 2000	0.202	0.223
Size	(0.7)	-		(0.402)	(0.416)
Medicare	0.693	0.750	Year 2001	0.201	0.197
	(0.461)	(0.433)		(0.401)	(0.398)
MediCal	0.096	0.018	Year 2002	0.196	0.174
	(0.295)	(0.135)		(0.397)	(0.379)
Other Gov't	0.018	0.010	Year 2003	0.196	0.200
Insurance	(0.133)	(0.100)		(0.397)	(0.400)

Notes: Values are means with standard deviations in parentheses. Abbreviations: ZC = zip code; ER = Emergency Room.

Table 3(d). Summary Statistics: Dysrhythmias

Variable	Sample		Variable	Sample	
	Locals	Visitors		Locals	Visitors
n	154524	1901			
Mortality	0.034	0.028	Self Pay	0.018	0.024
	(0.181)	(0.165)		(0.133)	(0.154)
Charges	26,380	25,196	Other Payor	0.008	0.006
	(40,982)	(38,435)		(0.088)	(0.076)
Cost	8,058	8,276	HMO	0.401	0.280
	(12,036)	(11,798)		(0.490)	(0.449)
Age	70.6	71.2	Comprehensive	0.036	0.066
	(14.3)	(13.3)	ER	(0.185)	(0.248)
Female	0.515	0.180	Basic ER	0.935	0.846
	(0.500)	(0.384)		(0.247)	(0.361)
Black	0.041	0.008	Standby ER	0.011	0.075
	(0.198)	(0.089)		(0.103)	(0.264)
Nat. Amer.	0.000	-	Hospital Beds	313.5	290.8
	(0.021)	-		(161.9)	(194.1)
Asian	0.045	0.006	Transfer	0.031	-
	(0.207)	(0.076)		(0.175)	-
Hispanic	0.085	0.008	Distance to Hosp.	5.7	-
	(0.278)	(0.091)		(9.4)	-
ZC Income	50,590	-	Distance to Hosp.	120.1	-
	(19,553)	-	Squared	(904.8)	-
ZC Pop.	39,639	-	DNR Status	0.048	0.033
	(19,864)	-		(0.213)	(0.179)
ZC Num. of	14,193	-	Num. Of	5.3	4.9
Households	(6,110)	-	Diagnoses	(3.3)	(3.2)
ZC Area	42.1	-	Num. Diagnoses	39.6	34.4
	(98.2)	-	Squared	(49.5)	(44.2)
ZC Density	5,685	-	Year 1999	0.186	0.195
	(6,403)	-		(0.389)	(0.396)
ZC Household	2.8	-	Year 2000	0.198	0.209
Size	(0.7)	-		(0.399)	(0.407)
Medicare	0.650	0.642	Year 2001	0.206	0.203
	(0.477)	(0.479)		(0.404)	(0.402)
MediCal	0.080	0.013	Year 2002	0.208	0.195
	(0.271)	(0.114)		(0.406)	(0.396)
Other Gov't	0.023	0.019	Year 2003	0.202	0.199
Insurance	(0.150)	(0.136)		(0.401)	(0.399)

Notes: Values are means with standard deviations in parentheses. Abbreviations: ZC = zip code; ER = Emergency Room.

Table 3(e). Summary Statistics: GI Bleed

Variable	Sample		Variable	Sample	
	Locals	Visitors		Locals	Visitors
n	42416	484			
Mortality	0.052	0.031	Self Pay	0.036	0.072
	(0.222)	(0.173)		(0.185)	(0.259)
Charges	23,170	19,254	Other Payor	0.006	0.004
	(39,310)	(31,640)		(0.076)	(0.064)
Cost	7,111	6,525	HMO	0.356	0.209
	(11,709)	(13,237)		(0.479)	(0.407)
Age	68.0	66.7	Comprehensive	0.045	0.035
	(17.3)	(17.4)	ER	(0.207)	(0.184)
Female	0.496	0.200	Basic ER	0.919	0.826
	(0.500)	(0.401)		(0.273)	(0.379)
Black	0.067	0.014	Standby ER	0.013	0.134
	(0.250)	(0.120)		(0.115)	(0.341)
Nat. Amer.	0.001	-	Hospital Beds	319.7	250.1
	(0.030)	-		(160.3)	(183.5)
Asian	0.053	0.012	Transfer	0.024	-
	(0.224)	(0.111)		(0.152)	-
Hispanic	0.127	0.017	Distance to Hosp.	5.3	-
	(0.333)	(0.128)		(8.5)	-
ZC Income	48,792	-	Distance to Hosp.	101.6	-
	(19,168)	-	Squared	(804.3)	-
ZC Pop.	41,980	-	DNR Status	0.101	0.062
	(19,955)	-		(0.301)	(0.241)
ZC Num. of	14,732	-	Num. Of	7.1	6.4
Households	(6,046)	-	Diagnoses	(3.8)	(3.7)
ZC Area	32.3	-	Num. Diagnoses	64.9	54.8
	(85.8)	-	Squared	(67.7)	(61.9)
ZC Density	6,694	-	Year 1999	0.184	0.163
	(6,907)	-		(0.388)	(0.370)
ZC Household	2.8	-	Year 2000	0.199	0.238
Size	(0.7)	-		(0.399)	(0.426)
Medicare	0.613	0.599	Year 2001	0.205	0.209
	(0.487)	(0.491)		(0.404)	(0.407)
MediCal	0.127	0.035	Year 2002	0.210	0.202
	(0.332)	(0.184)		(0.408)	(0.402)
Other Gov't	0.041	0.037	Year 2003	0.202	0.188
Insurance	(0.197)	(0.189)		(0.401)	(0.391)

Notes: Values are means with standard deviations in parentheses. Abbreviations: ZC = zip code; ER = Emergency Room.

Table 3(f). Summary Statistics: Acute Pancreatitis

Variable	Sample		Variable	Sample	
	Locals	Visitors		Locals	Visitors
n	64700	798			
Mortality	0.017	0.015	Self Pay	0.070	0.091
	(0.127)	(0.122)		(0.255)	(0.288)
Charges	32,194	28,713	Other Payor	0.007	0.011
	(68,255)	(45,504)		(0.085)	(0.106)
Cost	10,506	9,473	HMO	0.427	0.336
	(21,942)	(14,538)		(0.495)	(0.473)
Age	51.7	55.1	Comprehensive	0.046	0.044
	(18.8)	(17.9)	ER	(0.210)	(0.205)
Female	0.509	0.194	Basic ER	0.920	0.833
	(0.500)	(0.396)		(0.271)	(0.373)
Black	0.091	0.021	Standby ER	0.011	0.103
	(0.287)	(0.144)		(0.106)	(0.304)
Nat. Amer.	0.001	-	Hospital Beds	318.3	269.6
	(0.032)	-		(153.5)	(178.1)
Asian	0.040	0.009	Transfer	0.019	-
	(0.195)	(0.093)		(0.137)	-
Hispanic	0.209	0.020	Distance to Hosp.	6.0	-
	(0.407)	(0.140)		(9.1)	-
ZC Income	46,586	-	Distance to Hosp.	117.8	-
	(17,866)	-	Squared	(829.8)	-
ZC Pop.	44,225	-	DNR Status	0.019	0.014
	(20,841)	-		(0.137)	(0.117)
ZC Num. of	14,844	-	Num. Of	4.6	4.2
Households	(6,062)	-	Diagnoses	(3.3)	(3.0)
ZC Area	38.3	-	Num. Diagnoses	31.7	26.6
	(88.2)	-	Squared	(46.7)	(37.1)
ZC Density	6,528	-	Year 1999	0.170	0.149
	(6,543)	-		(0.376)	(0.356)
ZC Household	3.0	-	Year 2000	0.188	0.180
Size	(0.7)	-		(0.390)	(0.385)
Medicare	0.296	0.332	Year 2001	0.202	0.199
	(0.456)	(0.471)		(0.402)	(0.400)
MediCal	0.227	0.045	Year 2002	0.212	0.222
	(0.419)	(0.208)		(0.409)	(0.416)
Other Gov't	0.086	0.053	Year 2003	0.228	0.249
Insurance	(0.281)	(0.223)		(0.420)	(0.433)

Notes: Values are means with standard deviations in parentheses. Abbreviations: ZC = zip code; ER = Emergency Room.

Table 3(g). Summary Statistics: Pulmonary Embolism

Variable	Sample		Variable	Sample	
	Locals	Visitors		Locals	Visitors
n	17854	348			
Mortality	0.065	0.052	Self Pay	0.022	0.046
	(0.246)	(0.222)		(0.146)	(0.210)
Charges	37,056	34,759	Other Payor	0.005	0.003
	(46,328)	(34,938)		(0.071)	(0.054)
Cost	11,618	11,379	HMO	0.472	0.287
	(14,373)	(8,427)		(0.499)	(0.453)
Age	64.0	66.3	Comprehensive	0.058	0.126
	(16.9)	(14.6)	ER	(0.235)	(0.333)
Female	0.563	0.178	Basic ER	0.921	0.816
	(0.496)	(0.383)		(0.270)	(0.388)
Black	0.088	0.014	Standby ER	0.001	0.020
	(0.283)	(0.119)		(0.034)	(0.141)
Nat. Amer.	0.001	-	Hospital Beds	354.6	318.5
	(0.024)	-		(165.8)	(189.5)
Asian	0.022	0.000	Transfer	0.028	-
	(0.146)	(0.000)		(0.166)	-
Hispanic	0.071	0.011	Distance to Hosp.	6.3	-
	(0.256)	(0.107)		(9.7)	-
ZC Income	52,181	-	Distance to Hosp.	133.2	-
	(20,931)	-	Squared	(999.9)	-
ZC Pop.	40,127	-	DNR Status	0.067	0.037
	(19,121)	-		(0.249)	(0.190)
ZC Num. of	14,607	-	Num. Of	6.0	5.2
Households	(5,959)	-	Diagnoses	(3.5)	(3.1)
ZC Area	32.4	-	Num. Diagnoses	48.0	36.9
	(77.5)	-	Squared	(56.0)	(41.4)
ZC Density	6,018	-	Year 1999	0.166	0.190
	(6,148)	-		(0.372)	(0.393)
ZC Household	2.7	-	Year 2000	0.184	0.144
Size	(0.6)	-		(0.388)	(0.351)
Medicare	0.529	0.523	Year 2001	0.209	0.184
	(0.499)	(0.500)		(0.407)	(0.388)
MediCal	0.103	0.034	Year 2002	0.214	0.259
	(0.304)	(0.183)		(0.410)	(0.439)
Other Gov't	0.031	0.032	Year 2003	0.227	0.224
Insurance	(0.174)	(0.175)		(0.419)	(0.418)

Notes: Values are means with standard deviations in parentheses. Abbreviations: ZC = zip code; ER = Emergency Room.

Table 3(h). Summary Statistics: Vertebral Fracture

Variable	Sample		Variable	Sample	
	Locals	Visitors		Locals	Visitors
n	14028	401			
Mortality	0.013	0.005	Self Pay	0.055	0.102
	(0.114)	(0.071)		(0.227)	(0.303)
Charges	34,370	44,950	Other Payor	0.010	0.025
	(67,887)	(74,941)		(0.100)	(0.156)
Cost	10,858	15,271	HMO	0.363	0.312
	(20,667)	(24,916)		(0.481)	(0.464)
Age	61.8	63.1	Comprehensive	0.080	0.105
	(23.3)	(21.6)	ER	(0.271)	(0.307)
Female	0.534	0.127	Basic ER	0.898	0.848
	(0.499)	(0.334)		(0.302)	(0.360)
Black	0.026	0.002	Standby ER	0.008	0.045
	(0.159)	(0.050)		(0.087)	(0.207)
Nat. Amer.	0.000	-	Hospital Beds	350.8	319.9
	(0.015)	-		(166.6)	(184.0)
Asian	0.038	0.010	Transfer	0.036	-
	(0.192)	(0.100)		(0.186)	-
Hispanic	0.092	0.002	Distance to Hosp.	8.0	-
	(0.290)	(0.050)		(12.9)	-
ZC Income	50,649	-	Distance to Hosp.	228.8	-
	(19,634)	-	Squared	(1205.8)	-
ZC Pop.	39,811	-	DNR Status	0.043	0.025
	(19,209)	-		(0.204)	(0.156)
ZC Num. of	14,335	-	Num. Of	4.7	3.7
Households	(5,939)	-	Diagnoses	(3.5)	(3.3)
ZC Area	40.4	-	Num. Diagnoses	34.0	24.8
	(91.0)	-	Squared	(48.6)	(43.2)
ZC Density	5,164	-	Year 1999	0.174	0.195
	(5,300)	-		(0.379)	(0.396)
ZC Household	2.8	-	Year 2000	0.186	0.172
Size	(0.6)	-		(0.389)	(0.378)
Medicare	0.515	0.302	Year 2001	0.197	0.185
	(0.500)	(0.460)		(0.398)	(0.388)
MediCal	0.088	0.025	Year 2002	0.217	0.192
	(0.283)	(0.156)		(0.412)	(0.394)
Other Gov't	0.082	0.075	Year 2003	0.227	0.257
Insurance	(0.274)	(0.263)		(0.419)	(0.437)

Notes: Values are means with standard deviations in parentheses. Abbreviations: ZC = zip code; ER = Emergency Room.

Table 4(a). Costs by County of Hospitalization: Acute Myocardial Infarction

County	Locals		Visitors		County	Locals		Visitors	
	Raw Cost	Adj. Cost	Raw Cost	Adj. Cost		Raw Cost	Adj. Cost	Raw Cost	Adj. Cost
Alameda	$17,916	$18,511	$16,702	$16,043	San Benito	$10,669	$17,141	-	-
Amador	$8,144	$12,815	-	-	San Bernardino	$15,099	$14,713	$17,255	$18,999
Butte	$15,797	$19,642	$19,645	$23,998	San Diego	$19,410	$17,855	$20,048	$18,389
Calaveras	$9,350	$18,547	-	-	San Francisco	$21,057	$16,944	$23,202	$21,851
Contra Costa	$22,110	$22,780	$19,931	$20,115	San Joaqin	$17,055	$20,058	$18,882	$23,157
Del Norte	$8,576	$16,796	$9,278	$16,390	San Luis Obispo	$12,377	$18,578	$17,419	$22,584
El Dorado	$8,178	$14,703	$11,043	$14,459	San Mateo	$21,033	$19,162	$31,143	$29,846
Fresno	$17,441	$17,063	$19,351	$18,948	Santa Barbara	$15,643	$17,912	$18,963	$19,514
Humboldt	$14,677	$19,770	-	-	Santa Clara	$22,192	$18,860	$20,480	$15,858
Imperial	$9,007	$14,328	-	-	Santa Cruz	$19,441	$22,101	$20,869	$23,315
Kern	$16,095	$19,045	$13,789	$16,633	Shasta	$23,875	$25,174	$25,327	$28,448
Kings	$7,190	$15,226	$7,128	$13,752	Siskiyou	$7,282	$16,286	-	-
Lake	$9,886	$18,091	-	-	Solano	$14,138	$20,992	-	-
Lassen	-	-	-	-	Sonoma	$15,642	$20,292	$13,448	$19,604
Los Angeles	$18,065	$15,933	$23,798	$20,672	Stanislaus	$22,418	$22,079	$20,959	$22,561
Madera	$8,893	$15,535	-	-	Sutter	$10,101	$12,697	-	-
Marin	$18,416	$21,220	$17,219	$21,457	Tehama	$7,470	$14,163	-	-
Mendocino	$7,047	$15,216	-	-	Tulare	$19,012	$18,909	$23,464	$21,915
Merced	$7,581	$9,920	-	-	Tuolomne	$7,398	$15,620	-	-
Monterey	$24,596	$26,037	$18,522	$22,490	Ventura	$18,957	$20,113	$32,848	$33,562
Napa	$22,526	$24,029	$27,005	$28,746	Yolo	$9,075	$15,609	-	-
Nevada	$7,858	$13,119	-	-	Yuba	$14,916	$17,678	-	-
Orange	$17,997	$18,383	$18,174	$18,258	CE	$10,480	$22,543	-	-
Placer	$10,631	$15,656	$10,909	$12,876	NE	$6,841	$18,594	-	-
Riverside	$12,998	$13,426	$16,672	$17,134	NW	$48,288	$59,003	-	-
Sacramento	$23,472	$19,921	$26,457	$23,749					

Notes: Values in "Adj. Cost" columns have been regression-adjusted for the variables listed in Table 1. Abbreviations: CE = Alpine, Inyo, Mariposa, Mono; NE = Modoc, Plumas, Sierra; NW = Colusa, Glenn, Trinity.

Table 4(b). Costs by County of Hospitalization: Appendicitis

County	Locals		Visitors		County	Locals		Visitors	
	Raw Cost	Adj. Cost	Raw Cost	Adj. Cost		Raw Cost	Adj. Cost	Raw Cost	Adj. Cost
Alameda	$10,460	$10,353	$6,998	$8,203	San Benito	$6,342	$8,574	-	-
Amador	$9,410	$9,011	-	-	San Bernardino	$6,655	$6,350	$8,181	$5,905
Butte	$6,045	$6,350	-	-	San Diego	$8,368	$7,884	$6,830	$6,856
Calaveras	$9,509	$8,660	-	-	San Francisco	$9,018	$7,445	$7,798	$8,034
Contra Costa	$9,326	$9,206	$8,202	$8,068	San Joaqin	$5,923	$6,805	$5,687	$6,810
Del Norte	$6,385	$8,253	$6,112	$6,950	San Luis Obispo	$5,737	$6,828	$5,269	$7,158
El Dorado	$7,489	$8,472	$7,468	$9,197	San Mateo	$8,578	$8,312	$6,212	$6,798
Fresno	$5,722	$5,584	$7,999	$7,489	Santa Barbara	$5,855	$6,651	$5,528	$6,924
Humboldt	$5,383	$6,148	-	-	Santa Clara	$7,528	$7,414	$8,408	$8,210
Imperial	$6,930	$7,864	$9,793	$10,631	Santa Cruz	$7,079	$7,910	$6,532	$7,094
Kern	$5,294	$5,780	$6,612	$6,438	Shasta	$8,282	$7,541	$7,677	$9,404
Kings	$7,258	$8,500	-	-	Siskiyou	$6,096	$6,754	-	-
Lake	$10,751	$10,937	-	-	Solano	$9,004	$10,097	-	-
Lassen	-	-	-	-	Sonoma	$7,628	$8,294	$7,424	$8,145
Los Angeles	$7,045	$6,400	$7,609	$7,309	Stanislaus	$6,966	$7,143	-	-
Madera	$7,695	$7,957	-	-	Sutter	$6,986	$8,047	-	-
Marin	$8,672	$9,152	$6,892	$8,074	Tehama	$7,258	$8,204	-	-
Mendocino	$6,558	$6,352	-	-	Tulare	$6,408	$6,166	-	-
Merced	$5,643	$6,195	-	-	Tuolomne	$8,747	$9,489	-	-
Monterey	$10,215	$10,675	$10,826	$11,617	Ventura	$5,648	$6,279	$6,130	$6,323
Napa	$6,488	$6,803	-	-	Yolo	$9,177	$9,915	-	-
Nevada	$7,669	$7,798	$11,915	$13,113	Yuba	$6,494	$6,249	-	-
Orange	$7,693	$7,763	$8,390	$9,039	CE	$13,880	$15,751	$17,281	$15,725
Placer	$6,519	$7,317	$5,336	$7,054	NE	$8,839	$8,771	-	-
Riverside	$6,190	$6,325	$6,650	$5,467	NW	$7,408	$7,647	-	-
Sacramento	$9,917	$8,695	$8,718	$8,752					

Notes: Values in "Adj. Cost" columns have been regression-adjusted for the variables listed in Table 1. Abbreviations: CE = Alpine, Inyo, Mariposa, Mono; NE = Modoc, Plumas, Sierra; NW = Colusa, Glenn, Trinity.

Table 4(c). Costs by County of Hospitalization: Cerebrovascular Accident

County	Locals		Visitors		County	Locals		Visitors	
	Raw Cost	Adj. Cost	Raw Cost	Adj. Cost		Raw Cost	Adj. Cost	Raw Cost	Adj. Cost
Alameda	$10,234	$9,840	$11,290	$11,608	San Benito	$9,593	$11,441	-	-
Amador	$8,603	$9,491	-	-	San Bernardino	$8,162	$8,364	$7,582	$8,367
Butte	$6,697	$8,572	$8,630	$10,810	San Diego	$9,239	$8,295	$8,088	$6,626
Calaveras	$6,847	$9,913	-	-	San Francisco	$11,000	$9,540	$16,204	$14,384
Contra Costa	$10,760	$10,444	$10,783	$9,572	San Joaqin	$7,746	$9,447	$9,265	$10,765
Del Norte	$7,261	$8,913	$7,535	$9,702	San Luis Obispo	$7,314	$9,745	$6,725	$9,239
El Dorado	$7,252	$8,496	$11,741	$13,101	San Mateo	$11,383	$10,536	$8,013	$8,804
Fresno	$6,792	$5,836	$5,294	$3,469	Santa Barbara	$6,682	$7,674	$8,348	$9,469
Humboldt	$6,829	$8,948	-	-	Santa Clara	$12,332	$10,979	$13,548	$11,955
Imperial	$6,873	$8,148	$4,028	$5,460	Santa Cruz	$8,862	$9,255	$16,564	$19,439
Kern	$8,160	$9,564	$7,272	$8,244	Shasta	$8,383	$8,657	-	-
Kings	$7,285	$10,816	-	-	Siskiyou	$5,389	$6,944	-	-
Lake	$5,950	$9,581	-	-	Solano	$10,596	$12,722	-	-
Lassen	-	-	-	-	Sonoma	$8,248	$9,927	$20,776	$22,232
Los Angeles	$9,622	$8,325	$11,992	$9,617	Stanislaus	$9,105	$9,432	-	-
Madera	$6,930	$8,894	-	-	Sutter	$8,209	$7,108	-	-
Marin	$10,717	$11,511	-	-	Tehama	$6,802	$7,453	-	-
Mendocino	$6,554	$8,547	-	-	Tulare	$6,163	$5,528	-	-
Merced	$6,680	$5,381	-	-	Tuolomne	$6,488	$8,961	-	-
Monterey	$11,613	$12,364	$12,596	$14,473	Ventura	$9,089	$9,286	$10,505	$9,034
Napa	$7,959	$7,554	$10,256	$11,560	Yolo	$8,612	$11,013	-	-
Nevada	$5,622	$6,813	$7,147	$9,429	Yuba	$9,228	$9,360	-	-
Orange	$8,184	$8,243	$9,191	$7,917	CE	$9,866	$12,485	-	-
Placer	$7,064	$9,767	$6,663	$9,982	NE	$5,854	$9,434	-	-
Riverside	$6,751	$7,213	$7,560	$7,213	NW	$7,201	$9,420	-	-
Sacramento	$10,399	$8,763	$6,954	$5,805					

Notes: Values in "Adj. Cost" columns have been regression-adjusted for the variables listed in Table 1. Abbreviations: CE = Alpine, Inyo, Mariposa, Mono; NE = Modoc, Plumas, Sierra; NW = Colusa, Glenn, Trinity.

Table 4(d). Costs by County of Hospitalization: Dysrhythmias

County	Locals		Visitors		County	Locals		Visitors	
	Raw Cost	Adj. Cost	Raw Cost	Adj. Cost		Raw Cost	Adj. Cost	Raw Cost	Adj. Cost
Alameda	$8,452	$8,148	$9,319	$8,819	San Benito	$6,514	$8,663	-	-
Amador	$5,436	$6,087	-	-	San Bernardino	$6,606	$6,272	$4,980	$5,203
Butte	$6,250	$7,420	$4,825	$6,117	San Diego	$10,017	$8,899	$9,506	$7,424
Calaveras	$5,007	$7,729	-	-	San Francisco	$9,349	$7,577	$8,913	$7,588
Contra Costa	$10,159	$9,604	$12,148	$10,279	San Joaqin	$6,764	$8,168	-	-
Del Norte	$4,081	$5,395	$4,203	$5,026	San Luis Obispo	$5,097	$6,825	$3,730	$5,792
El Dorado	$5,734	$6,970	$6,300	$6,578	San Mateo	$8,703	$7,594	$14,207	$13,096
Fresno	$7,607	$7,008	$7,453	$5,059	Santa Barbara	$7,376	$7,471	$5,674	$5,727
Humboldt	$6,257	$7,868	$4,724	$6,502	Santa Clara	$10,487	$9,301	$13,850	$11,041
Imperial	$4,495	$6,207	$3,625	$5,965	Santa Cruz	$7,534	$7,955	$4,740	$1,044
Kern	$7,276	$8,396	$13,551	$12,294	Shasta	$7,619	$6,409	$10,979	$9,365
Kings	$4,333	$7,701	-	-	Siskiyou	$5,028	$7,352	-	-
Lake	$6,126	$8,765	-	-	Solano	$8,523	$10,983	$5,941	$5,804
Lassen	-	-	-	-	Sonoma	$11,413	$12,291	$17,198	$15,420
Los Angeles	$7,839	$6,752	$9,249	$5,971	Stanislaus	$7,749	$7,607	$9,396	$7,762
Madera	$5,051	$7,304	-	-	Sutter	$5,588	$5,659	-	-
Marin	$9,096	$10,360	$9,491	$8,833	Tehama	$4,445	$4,615	-	-
Mendocino	$3,950	$6,242	-	-	Tulare	$6,115	$5,934	-	-
Merced	$4,962	$5,189	-	-	Tuolomne	$5,223	$6,991	-	-
Monterey	$10,838	$11,284	$7,923	$8,720	Ventura	$8,028	$7,896	$9,604	$9,004
Napa	$10,847	$9,593	$10,966	$7,208	Yolo	$5,653	$7,785	-	-
Nevada	$5,038	$5,846	$4,865	$6,627	Yuba	$5,463	$5,897	-	-
Orange	$7,146	$7,363	$9,438	$8,580	CE	$6,632	$9,348	$4,787	$6,632
Placer	$5,493	$7,631	$10,791	$11,632	NE	$4,200	$8,154	-	-
Riverside	$5,991	$6,469	$8,102	$6,709	NW	$4,571	$8,162	-	-
Sacramento	$10,238	$7,440	$7,127	$4,583					

Notes: Values in "Adj. Cost" columns have been regression-adjusted for the variables listed in Table 1. Abbreviations: CE = Alpine, Inyo, Mariposa, Mono; NE = Modoc, Plumas, Sierra; NW = Colusa, Glenn, Trinity.

Table 4(e). Costs by County of Hospitalization: GI Bleed

County	Locals		Visitors		County	Locals		Visitors	
	Raw Cost	Adj. Cost	Raw Cost	Adj. Cost		Raw Cost	Adj. Cost	Raw Cost	Adj. Cost
Alameda	$7,092	$6,740	$5,662	$4,956	San Benito	$6,146	$7,209	-	-
Amador	$6,232	$6,708	-	-	San Bernardino	$6,312	$6,106	$5,595	$3,573
Butte	$5,492	$6,688	$4,814	$4,942	San Diego	$8,473	$7,698	$6,339	$5,095
Calaveras	$5,454	$6,942	-	-	San Francisco	$8,343	$7,034	$6,364	$5,491
Contra Costa	$8,529	$7,972	$7,239	$7,895	San Joaqin	$5,438	$6,521	-	-
Del Norte	$5,579	$7,448	$4,866	$6,433	San Luis Obispo	$4,705	$6,472	-	-
El Dorado	$7,626	$7,650	$6,947	$8,500	San Mateo	$7,837	$7,098	$6,984	$4,549
Fresno	$5,741	$5,147	$4,031	$2,251	Santa Barbara	$5,358	$5,914	-	-
Humboldt	$5,357	$6,826	-	-	Santa Clara	$8,509	$7,348	$29,292	$31,458
Imperial	$5,674	$6,745	-	-	Santa Cruz	$6,083	$6,471	-	-
Kern	$5,448	$6,457	-	-	Shasta	$6,497	$5,940	-	-
Kings	$5,691	$7,792	-	-	Siskiyou	$4,164	$6,940	-	-
Lake	$6,509	$8,397	-	-	Solano	$7,837	$9,806	-	-
Lassen	-	-	-	-	Sonoma	$6,004	$7,300	$4,805	$4,514
Los Angeles	$7,047	$6,159	$7,163	$5,299	Stanislaus	$6,632	$6,560	$4,096	$2,017
Madera	$5,754	$7,020	-	-	Sutter	$5,773	$6,752	-	-
Marin	$8,678	$8,863	-	-	Tehama	$4,738	$4,798	-	-
Mendocino	$4,651	$6,604	-	-	Tulare	$5,771	$5,202	-	-
Merced	$5,056	$3,941	-	-	Tuolomne	$5,801	$7,607	-	-
Monterey	$9,312	$10,201	$8,605	$10,509	Ventura	$6,595	$6,125	$4,530	$5,099
Napa	$6,364	$5,498	-	-	Yolo	$5,783	$7,410	-	-
Nevada	$5,476	$5,657	-	-	Yuba	$5,389	$4,792	-	-
Orange	$6,226	$6,082	$6,119	$6,292	CE	$5,490	$8,801	-	-
Placer	$6,224	$7,492	$3,469	$4,364	NE	$4,819	$6,986	-	-
Riverside	$5,811	$5,955	$5,624	$4,341	NW	$54,798	$56,549	-	-
Sacramento	$7,778	$6,274	$4,760	$3,418					

Notes: Values in "Adj. Cost" columns have been regression-adjusted for the variables listed in Table 1. Abbreviations: CE = Alpine, Inyo, Mariposa, Mono; NE = Modoc, Plumas, Sierra; NW = Colusa, Glenn, Trinity.

Table 4(f). Costs by County of Hospitalization: Acute Pancreatitis

County	Locals		Visitors		County	Locals		Visitors	
	Raw Cost	Adj. Cost	Raw Cost	Adj. Cost		Raw Cost	Adj. Cost	Raw Cost	Adj. Cost
Alameda	$12,738	$12,582	$15,470	$13,869	San Benito	$8,380	$9,882	-	-
Amador	$6,146	$6,577	-	-	San Bernardino	$9,173	$8,423	$8,450	$10,869
Butte	$8,353	$9,409	$5,915	$8,774	San Diego	$11,112	$9,091	$9,362	$3,979
Calaveras	$8,565	$10,038	-	-	San Francisco	$17,001	$13,701	$9,947	$6,453
Contra Costa	$13,223	$11,832	$12,345	$9,433	San Joaqin	$8,013	$10,337	-	-
Del Norte	$7,591	$9,715	$4,907	$11,215	San Luis Obispo	$7,336	$9,932	-	-
El Dorado	$12,622	$13,221	$8,214	$11,879	San Mateo	$12,607	$11,224	$7,216	$4,184
Fresno	$7,963	$7,358	$3,420	$1,914	Santa Barbara	$9,212	$9,477	$6,360	$8,588
Humboldt	$7,095	$9,008	-	-	Santa Clara	$13,484	$10,752	$10,281	$4,314
Imperial	$6,344	$8,278	-	-	Santa Cruz	$11,763	$11,887	-	-
Kern	$9,530	$10,193	$9,129	$8,671	Shasta	$10,877	$9,208	$7,211	$8,749
Kings	$8,508	$12,121	-	-	Siskiyou	$8,090	$10,279	-	-
Lake	$7,608	$10,629	-	-	Solano	$11,272	$14,296	-	-
Lassen	-	-	-	-	Sonoma	$9,946	$11,043	-	-
Los Angeles	$9,687	$8,620	$13,530	$8,553	Stanislaus	$11,262	$10,690	-	-
Madera	$10,076	$11,235	-	-	Sutter	$9,780	$9,374	-	-
Marin	$8,471	$9,963	-	-	Tehama	$8,635	$8,103	-	-
Mendocino	$6,358	$8,841	-	-	Tulare	$7,318	$7,227	-	-
Merced	$7,518	$5,489	$7,019	$6,089	Tuolomne	$7,354	$9,771	-	-
Monterey	$14,329	$15,377	$16,755	$18,596	Ventura	$11,044	$9,703	$6,230	$6,557
Napa	$11,927	$11,198	$6,582	-$992	Yolo	$9,807	$11,023	-	-
Nevada	$7,722	$7,817	$12,190	$18,570	Yuba	$9,018	$8,708	-	-
Orange	$9,797	$9,317	$8,683	$7,309	CE	$11,488	$14,050	-	-
Placer	$8,195	$10,115	-	-	NE	$6,571	$9,851	-	-
Riverside	$8,280	$8,044	$8,488	$8,168	NW	$5,779	$9,527	-	-
Sacramento	$14,922	$11,757	$10,652	$6,641					

Notes: Values in "Adj. Cost" columns have been regression-adjusted for the variables listed in Table 1. Abbreviations: CE = Alpine, Inyo, Mariposa, Mono; NE = Modoc, Plumas, Sierra; NW = Colusa, Glenn, Trinity.

Table 4(g). Costs by County of Hospitalization: Pulmonary Embolism

County	Locals		Visitors		County	Locals		Visitors	
	Raw Cost	Adj. Cost	Raw Cost	Adj. Cost		Raw Cost	Adj. Cost	Raw Cost	Adj. Cost
Alameda	$13,628	$13,210	$9,633	$9,073	San Benito	$9,996	$12,334	-	-
Amador	$8,644	$9,683	-	-	San Bernardino	$10,905	$10,761	$7,789	$8,417
Butte	$10,841	$13,066	-	-	San Diego	$11,054	$10,301	$10,821	$11,047
Calaveras	$7,357	$11,639	-	-	San Francisco	$13,680	$11,460	$10,778	$11,424
Contra Costa	$14,205	$13,364	$11,324	$12,358	San Joaqin	$11,196	$13,590	-	-
Del Norte	$8,918	$10,879	$9,395	$9,543	San Luis Obispo	$8,071	$11,391	-	-
El Dorado	$9,505	$11,571	$8,528	$8,400	San Mateo	$13,125	$12,190	$14,955	$14,324
Fresno	$8,959	$8,343	$7,578	$5,097	Santa Barbara	$9,150	$10,651	-	-
Humboldt	$8,832	$11,431	-	-	Santa Clara	$12,207	$11,223	$12,678	$11,819
Imperial	$7,930	$9,790	-	-	Santa Cruz	$10,997	$12,042	-	-
Kern	$9,390	$11,257	-	-	Shasta	$11,104	$10,932	-	-
Kings	$8,303	$12,759	-	-	Siskiyou	$7,131	$10,770	-	-
Lake	$9,643	$12,356	-	-	Solano	$15,723	$18,413	-	-
Lassen	-	-	-	-	Sonoma	$8,848	$11,169	-	-
Los Angeles	$12,125	$10,411	$13,127	$11,837	Stanislaus	$11,795	$12,202	-	-
Madera	$10,476	$13,153	-	-	Sutter	$9,705	$9,081	-	-
Marin	$10,361	$12,323	-	-	Tehama	$8,915	$7,952	-	-
Mendocino	$8,354	$10,970	-	-	Tulare	$10,658	$10,037	-	-
Merced	$7,416	$5,442	-	-	Tuolomne	$8,376	$12,675	-	-
Monterey	$16,378	$17,619	-	-	Ventura	$11,557	$10,885	-	-
Napa	$10,531	$10,172	-	-	Yolo	$10,077	$13,400	-	-
Nevada	$7,000	$8,788	$10,589	$12,887	Yuba	$13,202	$12,911	-	-
Orange	$10,480	$10,310	$12,412	$12,701	CE	$16,659	$20,335	-	-
Placer	$8,991	$12,345	-	-	NE	$9,772	$16,321	-	-
Riverside	$9,551	$9,924	$11,617	$11,147	NW	$11,322	$17,102	-	-
Sacramento	$13,112	$11,075	$11,422	$12,854					

Notes: Values in "Adj. Cost" columns have been regression-adjusted for the variables listed in Table 1. Abbreviations: CE = Alpine, Inyo, Mariposa, Mono; NE = Modoc, Plumas, Sierra; NW = Colusa, Glenn, Trinity.

Table 4(h). Costs by County of Hospitalization: Vertebral Fracture

County	Locals		Visitors		County	Locals		Visitors	
	Raw Cost	Adj. Cost	Raw Cost	Adj. Cost		Raw Cost	Adj. Cost	Raw Cost	Adj. Cost
Alameda	$10,325	$12,484	$59,391	$19,888	San Benito	$6,212	$11,581	-	-
Amador	$5,206	$9,509	-	-	San Bernardino	$13,262	$10,298	$19,064	$24,269
Butte	$7,766	$10,497	-	-	San Diego	$14,609	$12,605	$18,586	$17,725
Calaveras	$4,714	$11,544	-	-	San Francisco	$12,058	$10,840	-	-
Contra Costa	$11,816	$12,583	$24,470	$24,199	San Joaqin	$5,073	$8,926	-	-
Del Norte	$5,850	$9,675	$4,174	$2,844	San Luis Obispo	$5,928	$10,276	-	-
El Dorado	$5,737	$10,859	$12,475	$14,293	San Mateo	$8,967	$11,283	-	-
Fresno	$6,882	$6,547	-	-	Santa Barbara	$6,754	$8,313	$4,489	$10,726
Humboldt	$8,108	$11,653	-	-	Santa Clara	$17,418	$15,259	$24,563	$26,488
Imperial	$5,853	$10,322	$5,384	$5,858	Santa Cruz	$6,729	$9,968	-	-
Kern	$7,957	$9,941	$6,035	$8,102	Shasta	$9,835	$9,226	$8,339	$8,615
Kings	$3,790	$10,038	-	-	Siskiyou	$6,141	$12,372	-	-
Lake	$5,905	$10,893	-	-	Solano	$6,656	$13,112	-	-
Lassen	-	-	-	-	Sonoma	$11,541	$13,659	$16,200	$17,841
Los Angeles	$8,159	$7,994	$11,425	$11,096	Stanislaus	$9,559	$9,055	$6,101	$5,483
Madera	$3,564	$5,241	-	-	Sutter	$5,419	$9,194	-	-
Marin	$12,258	$16,166	-	-	Tehama	$4,489	$8,311	-	-
Mendocino	$3,864	$9,318	-	-	Tulare	$5,641	$7,106	-	-
Merced	$4,979	$7,781	-	-	Tuolomne	$7,409	$11,730	-	-
Monterey	$11,176	$14,704	-	-	Ventura	$9,106	$10,662	$7,714	$10,477
Napa	$7,702	$10,822	-	-	Yolo	$4,657	$9,171	-	-
Nevada	$4,485	$9,205	-	-	Yuba	$5,468	$6,921	-	-
Orange	$9,601	$11,021	$7,904	$9,987	CE	$6,282	$12,223	-	-
Placer	$12,063	$16,110	$16,237	$14,531	NE	$6,154	$10,495	-	-
Riverside	$9,307	$8,409	$15,490	$13,889	NW	$3,590	$11,747	-	-
Sacramento	$18,828	$13,368	$44,423	$38,612					

Notes: Values in "Adj. Cost" columns have been regression-adjusted for the variables listed in Table 1. Abbreviations: CE = Alpine, Inyo, Mariposa, Mono; NE = Modoc, Plumas, Sierra; NW = Colusa, Glenn, Trinity.

Table 5(a). Locals OLS Relationships: Acute Myocardial Infarction

Explanatory Variable	Dependent Variable		Explanatory Variable	Dependent Variable	
	Mortality	Cost		Mortality	Cost
n	158269	158269			
Age	**0.00205**	**-105.02**	Other Payor	0.0102	**-1854.7**
	(0.00011)	**(9.35)**		(0.0146)	**(579.3)**
Female	**-0.0060**	**-1626.28**	HMO	**-0.0100**	**-1864.1**
	(0.0015)	**(157.98)**		**(0.0034)**	**(329.9)**
Black	**-0.0074**	**-1457.74**	Comprehensive	**0.0273**	1696.3
	(0.0036)	**(509.46)**	ER	**(0.0097)**	(2669.2)
Nat. Amer.	-0.0578	-2486.86	Basic ER	**0.0147**	-1754.7
	(0.0266)	(2107.31)		**(0.0072)**	(922.4)
Asian	-0.0012	**1533.05**	Standby ER	-0.0018	-3592.0
	(0.0037)	**(313.49)**		(0.0243)	(1310.8)
Hispanic	**-0.0091**	155.33	Hospital Beds	**-6.08E-05**	**18.9**
	(0.0033)	(455.79)		**(1.36E-05)**	**(2.1)**
ZC Income	**-3.47E-07**	**0.0381**	Transfer	**-0.0162**	**2038.3**
	(1.00E-07)	**(0.0171)**		**(0.0033)**	**(472.6)**
ZC Pop.	**7.45E-07**	-0.0205	Distance to Hosp.	**-0.0010**	**63.8**
	(1.56E-07)	(0.0267)		**(0.0003)**	**(33.4)**
ZC Num. of	**-2.27E-06**	0.0619	Distance to Hosp.	**6.62E-06**	-0.3067
Households	**(4.65E-07)**	(0.0834)	Squared	**(3.16E-06)**	(0.2380)
ZC Area	1.10E-06	-0.72	DNR Status	**0.2503**	**-6866.6**
	(9.25E-06)	(1.49)		**(0.0210)**	**(559.1)**
ZC Density	**5.21E-07**	0.0145	Num. Of	**0.0065**	**577.4**
	(2.34E-07)	(0.0413)	Diagnoses	**(0.0009)**	**(131.1)**
ZC Household	0.0001	232.7363	Num. Diagnoses	**0.0002**	**30.1**
Size	(0.0014)	(165.11)	Squared	**(0.0000)**	**(8.0)**
Medicare	-0.0022	-383.03	Year 2000	-0.0036	1453.5
	(0.0031)	(429.71)		(0.0034)	(1221.3)
MediCal	**0.0137**	**1118.05**	Year 2001	-0.0062	**581.0**
	(0.0061)	**(511.95)**		(0.0038)	**(312.9)**
Other Gov't	**-0.0131**	-1160.54	Year 2002	**-0.0123**	**2263.6**
Insurance	**(0.0026)**	(703.73)		**(0.0038)**	**(371.4)**
Self Pay	**0.0177**	**-2864.21**	Year 2003	**-0.0208**	**2411.6**
	(0.0050)	**(551.82)**		**(0.0030)**	**(557.6)**

Notes: Entries are coefficients from OLS regressions with standard errors in parentheses. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Coefficients that are statistically significant at the p<0.10 level are highlighted in bold. Abbreviations: ZC = Zip code, ER = Emergency Room, DNR = Do Not Resuscitate.

Table 5(b). Locals OLS Relationships: Appendicitis

Explanatory Variable	Dependent Variable		Explanatory Variable	Dependent Variable	
	Mortality	Cost		Mortality	Cost
n	102448	102448			
Age	**0.00005**	-3.37	Other Payor	-0.0004	-245.6
	(0.00001)	(6.31)		(0.0006)	(484.0)
Female	**-0.0005**	**-162.68**	HMO	0.0003	-404.6
	(0.0002)	**(37.83)**		(0.0006)	(203.3)
Black	**0.0019**	**1511.24**	Comprehensive	-0.0009	1918.2
	(0.0012)	**(667.59)**	ER	(0.0015)	(1563.8)
Nat. Amer.	-0.0006	1255.13	Basic ER	-0.0010	-199.2
	(0.0006)	(804.11)		(0.0015)	(875.0)
Asian	-0.0016	-24.26	Standby ER	-0.0023	-17.6
	(0.0011)	(214.42)		(0.0033)	(988.9)
Hispanic	-0.0002	**259.13**	Hospital Beds	-4.73E-07	2.1
	(0.0002)	**(108.15)**		(7.89E-07)	(1.2)
ZC Income	**-2.10E-08**	**0.0151**	Transfer	0.0015	**2065.2**
	(1.12E-08)	**(0.0059)**		(0.0017)	**(1073.2)**
ZC Pop.	-1.26E-08	-0.0179	Distance to Hosp.	0.0000	**72.9**
	(2.10E-08)	(0.0100)		(0.0000)	**(14.1)**
ZC Num. of	2.82E-08	**0.0590**	Distance to Hosp.	3.77E-07	**-0.3518**
Households	(6.58E-08)	**(0.0360)**	Squared	(3.26E-07)	**(0.1117)**
ZC Area	-2.24E-06	-1.07	DNR Status	**0.0286**	902.6
	(1.45E-06)	(1.01)		**(0.0091)**	(552.5)
ZC Density	-5.31E-09	**0.0528**	Num. Of	**-0.0017**	**1252.3**
	(1.56E-08)	**(0.0189)**	Diagnoses	**(0.0004)**	**(89.4)**
ZC Household	-0.0001	78.7234	Num. Diagnoses	**0.0006**	**61.5**
Size	(0.0002)	(76.48)	Squared	**(0.0001)**	**(12.3)**
Medicare	**0.0063**	**873.99**	Year 2000	-0.0002	**1070.4**
	(0.0017)	**(291.23)**		(0.0003)	**(542.9)**
MediCal	0.0003	**1056.32**	Year 2001	-0.0004	**749.2**
	(0.0004)	**(131.05)**		(0.0003)	**(76.4)**
Other Gov't	0.0000	**1308.50**	Year 2002	-0.0005	**1210.5**
Insurance	(0.0005)	**(375.63)**		(0.0003)	**(102.8)**
Self Pay	0.0003	-20.76	Year 2003	**-0.0010**	**1590.3**
	(0.0007)	(211.81)		**(0.0003)**	**(113.9)**

Notes: Entries are coefficients from OLS regressions with standard errors in parentheses. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Coefficients that are statistically significant at the p <0.10 level are highlighted in bold. Abbreviations: ZC = Zip code, ER = Emergency Room.

Table 5(c). Locals OLS Relationships: Cerebrovascular Accident

Explanatory Variable	Dependent Variable		Explanatory Variable	Dependent Variable	
	Mortality	Cost		Mortality	Cost
n	93450	93450			
Age	**0.0004**	**-71.90**	Other Payor	0.0011	213.9
	(0.0001)	**(7.50)**		(0.0129)	(647.9)
Female	**-0.0078**	**-569.13**	HMO	-0.0051	**-1524.0**
	(0.0018)	**(68.88)**		(0.0030)	**(210.9)**
Black	**-0.0162**	**1038.50**	Comprehensive	**0.0206**	1191.1
	(0.0028)	**(231.81)**	ER	**(0.0095)**	(1158.1)
Nat. Amer.	-0.0073	**-2815.12**	Basic ER	0.0134	-2345.3
	(0.0223)	**(485.34)**		(0.0099)	(943.6)
Asian	-0.0060	320.65	Standby ER	**-0.0401**	-2270.6
	(0.0053)	(391.48)		**(0.0196)**	(1015.3)
Hispanic	**-0.0081**	59.56	Hospital Beds	-1.53E-08	**7.1**
	(0.0031)	(364.45)		(8.42E-06)	**(1.0)**
ZC Income	**-1.23E-07**	**0.0262**	Transfer	**0.0192**	**1205.5**
	(8.09E-08)	**(0.0097)**		**(0.0063)**	**(648.6)**
ZC Pop.	-1.76E-07	-0.0097	Distance to Hosp.	-0.0004	-4.4
	(1.59E-07)	(0.0200)		(0.0003)	(17.5)
ZC Num. of	3.54E-07	0.0300	Distance to Hosp.	2.64E-06	**0.2966**
Households	(4.47E-07)	(0.0618)	Squared	(2.04E-06)	**(0.1740)**
ZC Area	2.50E-06	-0.66	DNR Status	**0.1843**	-190.7
	(1.47E-05)	(0.54)		**(0.0090)**	(219.4)
ZC Density	2.78E-07	**0.0553**	Num. Of	0.0022	**372.7**
	(1.77E-07)	**(0.0159)**	Diagnoses	(0.0017)	**(67.6)**
ZC Household	0.0072	**489.4582**	Num. Diagnoses	**0.0002**	**33.2**
Size	(0.0027)	**(232.16)**	Squared	**(0.0001)**	**(6.0)**
Medicare	-0.0043	**-163.60**	Year 2000	0.0000	734.1
	(0.0032)	**(115.58)**		(0.0029)	(730.2)
MediCal	**0.0066**	**2382.23**	Year 2001	0.0010	**429.0**
	(0.0041)	**(322.70)**		(0.0023)	**(165.3)**
Other Gov't	**-0.0120**	**-680.88**	Year 2002	**-0.0039**	**875.5**
Insurance	**(0.0055)**	**(320.97)**		**(0.0026)**	**(113.4)**
Self Pay	**0.0268**	448.01	Year 2003	**-0.0091**	**986.0**
	(0.0073)	(358.14)		**(0.0027)**	**(144.3)**

Notes: Entries are coefficients from OLS regressions with standard errors in parentheses. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Coefficients that are statistically significant at the p <0.10 level are highlighted in bold. Abbreviations: ZC = Zip code, ER = Emergency Room.

Table 5(d). Locals OLS Relationships: Dysrhythmias

Explanatory Variable	Dependent Variable		Explanatory Variable	Dependent Variable	
	Mortality	Cost		Mortality	Cost
n	154524	154524			
Age	**-0.0004**	**-8.65**	Other Payor	-0.0028	-620.2
	(0.0000)	**(3.88)**		(0.0059)	(387.6)
Female	**-0.0103**	**-861.03**	HMO	0.0005	**-1017.7**
	(0.0011)	**(76.45)**		(0.0021)	**(134.2)**
Black	**0.0105**	**716.53**	Comprehensive	**0.0091**	-2182.2
	(0.0025)	**(187.97)**	ER	**(0.0051)**	(1041.3)
Nat. Amer.	0.0229	**-2426.99**	Basic ER	**0.0093**	**-1755.8**
	(0.0298)	**(796.47)**		**(0.0056)**	**(528.1)**
Asian	**0.0067**	**633.92**	Standby ER	-0.0376	-1492.7
	(0.0020)	**(342.76)**		(0.0177)	(516.9)
Hispanic	-0.0008	367.87	Hospital Beds	**-1.55E-05**	**7.6**
	(0.0014)	(282.78)		**(4.38E-06)**	**(0.8)**
ZC Income	**-7.59E-08**	**0.0179**	Transfer	-0.0006	**5637.7**
	(3.20E-08)	**(0.0077)**		(0.0039)	**(702.0)**
ZC Pop.	**2.27E-07**	-0.0135	Distance to Hosp.	**-0.0007**	**65.3**
	(6.99E-08)	(0.0085)		**(0.0001)**	**(20.2)**
ZC Num. of	**-6.36E-07**	**0.0643**	Distance to Hosp.	**4.43E-06**	-0.1091
Households	**(1.85E-07)**	**(0.0212)**	Squared	**(1.22E-06)**	(0.1680)
ZC Area	3.90E-06	0.42	DNR Status	**0.2108**	**-788.8**
	(9.39E-06)	(0.67)		**(0.0210)**	**(325.0)**
ZC Density	**2.76E-07**	0.0188	Num. Of	**0.0026**	**398.3**
	(8.13E-08)	(0.0173)	Diagnoses	**(0.0007)**	**(52.4)**
ZC Household	-0.0003	**187.5333**	Num. Diagnoses	**0.0003**	**35.3**
Size	(0.0011)	**(94.85)**	Squared	**(0.0001)**	**(3.7)**
Medicare	0.0002	-164.64	Year 2000	**-0.0021**	846.8
	(0.0018)	(121.05)		**(0.0011)**	(820.1)
MediCal	**0.0071**	**758.96**	Year 2001	**-0.0062**	**418.9**
	(0.0029)	**(149.55)**		**(0.0017)**	**(116.6)**
Other Gov't	-0.0036	-162.50	Year 2002	**-0.0097**	**1068.1**
Insurance	(0.0026)	(314.93)		**(0.0017)**	**(149.2)**
Self Pay	**0.0250**	**-1178.93**	Year 2003	**-0.0116**	**1188.9**
	(0.0037)	**(222.73)**		**(0.0020)**	**(220.9)**

Notes: Entries are coefficients from OLS regressions with standard errors in parentheses. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Coefficients that are statistically significant at the p <0.10 level are highlighted in bold. Abbreviations: ZC = Zip code, ER = Emergency Room.

Table 5(e). Locals OLS Relationships: GI Bleed

Explanatory Variable	Dependent Variable Mortality	Cost	Explanatory Variable	Dependent Variable Mortality	Cost
n	42416	42416			
Age	**0.0005**	**-23.68**	Other Payor	-0.0251	**-985.0**
	(0.0001)	**(5.29)**		(0.0117)	**(471.5)**
Female	**-0.0171**	**-473.74**	HMO	-0.0034	**-1182.6**
	(0.0025)	**(241.84)**		(0.0025)	**(216.1)**
Black	-0.0012	**605.76**	Comprehensive	-0.0079	-119.3
	(0.0024)	**(337.07)**	ER	(0.0124)	(1201.0)
Nat. Amer.	-0.0227	-497.86	Basic ER	0.0005	-946.1
	(0.0227)	(1044.83)		(0.0042)	(692.7)
Asian	0.0093	**630.62**	Standby ER	**-0.0326**	-759.0
	(0.0110)	**(272.10)**		**(0.0146)**	(782.3)
Hispanic	-0.0059	201.07	Hospital Beds	1.16E-06	**6.1**
	(0.0033)	(178.04)		(1.23E-05)	**(0.8)**
ZC Income	-1.10E-07	**0.0194**	Transfer	**0.0194**	423.5
	(9.22E-08)	**(0.0032)**		**(0.0096)**	(577.9)
ZC Pop.	7.74E-07	0.0021	Distance to Hosp.	**-0.0007**	16.5
	(2.43E-07)	(0.0211)		**(0.0003)**	(31.5)
ZC Num. of	-2.17E-06	0.0137	Distance to Hosp.	5.06E-06	0.3625
Households	(7.35E-07)	(0.0545)	Squared	(2.97E-06)	(0.5487)
ZC Area	1.18E-05	1.21	DNR Status	**0.1652**	-273.9
	(1.54E-05)	(0.76)		**(0.0153)**	(218.9)
ZC Density	1.78E-07	0.0168	Num. Of	**0.0021**	**249.7**
	(4.32E-07)	(0.0148)	Diagnoses	**(0.0015)**	**(146.7)**
ZC Household	**-0.0076**	167.0208	Num. Diagnoses	0.0001	**24.7**
Size	**(0.0053)**	(228.45)	Squared	(0.0001)	**(7.9)**
Medicare	-0.0089	-198.79	Year 2000	0.0032	1099.5
	(0.0056)	(262.66)		(0.0038)	(1138.2)
MediCal	**0.0060**	**803.61**	Year 2001	-0.0005	**176.5**
	(0.0044)	**(332.43)**		(0.0025)	**(150.4)**
Other Gov't	**-0.0144**	-154.42	Year 2002	**-0.0051**	**730.9**
Insurance	**(0.0034)**	(844.53)		**(0.0035)**	**(117.9)**
Self Pay	**0.0175**	**-1069.40**	Year 2003	**-0.0076**	**652.8**
	(0.0061)	**(358.86)**		**(0.0031)**	**(212.5)**

Notes: Entries are coefficients from OLS regressions with standard errors in parentheses. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Coefficients that are statistically significant at the p <0.10 level are highlighted in bold. Abbreviations: ZC = Zip code, ER = Emergency Room.

Table 5(f). Locals OLS Relationships: Acute Pancreatitis

Explanatory Variable	Dependent Variable		Explanatory Variable	Dependent Variable	
	Mortality	Cost		Mortality	Cost
n	64700	64700			
Age	**0.0004**	**-35.10**	Other Payor	-0.0017	1153.6
	(0.0001)	**(6.02)**		(0.0055)	(1739.9)
Female	**-0.0062**	**-1198.53**	HMO	**0.0027**	**-1095.7**
	(0.0007)	**(373.67)**		**(0.0013)**	**(339.5)**
Black	**-0.0075**	**-2134.21**	Comprehensive	-0.0034	1887.3
	(0.0009)	**(279.10)**	ER	(0.0049)	(3463.9)
Nat. Amer.	**-0.0127**	-1394.39	Basic ER	-0.0024	-2321.5
	(0.0031)	(3741.87)		(0.0039)	(2807.9)
Asian	-0.0004	**1052.91**	Standby ER	-0.0101	-2610.9
	(0.0018)	**(450.50)**		(0.0097)	(3074.3)
Hispanic	-0.0005	**762.19**	Hospital Beds	**4.44E-06**	**8.7**
	(0.0021)	**(385.50)**		**(3.54E-06)**	**(1.3)**
ZC Income	**-8.43E-08**	**0.0539**	Transfer	**0.0253**	**8531.4**
	(4.14E-08)	**(0.0129)**		**(0.0037)**	**(2972.2)**
ZC Pop.	-2.79E-07	-0.0244	Distance to Hosp.	0.0001	**148.8**
	(1.17E-07)	(0.0240)		(0.0001)	**(30.7)**
ZC Num. of	7.93E-07	0.0813	Distance to Hosp.	-5.65E-07	-0.3947
Households	(3.56E-07)	(0.0680)	Squared	(9.28E-07)	(0.2549)
ZC Area	**8.81E-06**	0.58	DNR Status	**0.1309**	162.1
	(5.97E-06)	(1.75)		**(0.0150)**	(1010.8)
ZC Density	-9.96E-08	0.0405	Num. Of	0.00004	**637.0**
	(8.91E-08)	(0.0360)	Diagnoses	(0.0005)	**(156.4)**
ZC Household	0.0039	**670.1488**	Num. Diagnoses	**0.0003**	**64.8**
Size	(0.0022)	**(428.93)**	Squared	**(0.0001)**	**(12.2)**
Medicare	0.0010	**-991.00**	Year 2000	0.0029	1216.9
	(0.0021)	**(299.49)**		(0.0011)	(852.9)
MediCal	**0.0037**	**1108.51**	Year 2001	-0.0003	383.0
	(0.0014)	**(305.15)**		(0.0016)	(323.4)
Other Gov't	**-0.0021**	535.46	Year 2002	**-0.0036**	542.0
Insurance	**(0.0015)**	(1042.66)		**(0.0019)**	(297.0)
Self Pay	**0.0031**	**-1865.31**	Year 2003	**-0.0046**	268.7
	(0.0015)	**(432.90)**		**(0.0012)**	(270.8)

Notes: Entries are coefficients from OLS regressions with standard errors in parentheses. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Coefficients that are statistically significant at the p <0.10 level are highlighted in bold. Abbreviations: ZC = Zip code, ER = Emergency Room.

Table 5(g). Locals OLS Relationships: Pulmonary Embolism

Explanatory Variable	Dependent Variable		Explanatory Variable	Dependent Variable	
	Mortality	Cost		Mortality	Cost
n	17854	17854			
Age	**0.0006**	**-49.41**	Other Payor	0.0168	**-1183.5**
	(0.0001)	**(13.83)**		(0.0270)	**(817.7)**
Female	**-0.0102**	-263.12	HMO	-0.0031	**-1949.5**
	(0.0033)	(232.68)		(0.0072)	**(364.5)**
Black	-0.0013	706.09	Comprehensive	-0.0031	-1800.1
	(0.0047)	(525.11)	ER	(0.0246)	(4010.5)
Nat. Amer.	-0.0580	1489.01	Basic ER	-0.0029	-2813.4
	(0.0162)	(1233.50)		(0.0180)	(2609.8)
Asian	**0.0445**	-297.58	Standby ER	0.0183	56.3
	(0.0136)	(718.81)		(0.0953)	(2536.5)
Hispanic	**0.0097**	632.63	Hospital Beds	-1.28E-05	**8.4**
	(0.0062)	(306.37)		(1.08E-05)	**(2.1)**
ZC Income	-1.32E-08	0.0233	Transfer	**0.0160**	1340.6
	(1.19E-07)	(0.0111)		**(0.0106)**	(798.7)
ZC Pop.	3.81E-07	-0.0205	Distance to Hosp.	-0.0001	19.0
	(4.23E-07)	(0.0397)		(0.0004)	(33.5)
ZC Num. of	-4.57E-07	0.1041	Distance to Hosp.	4.60E-06	0.1182
Households	(1.14E-06)	(0.1230)	Squared	(3.52E-06)	(0.2385)
ZC Area	-5.81E-06	-1.50	DNR Status	**0.2107**	**-1737.2**
	(2.38E-05)	(1.46)		**(0.0177)**	**(515.0)**
ZC Density	3.40E-07	**0.0627**	Num. Of	**0.0085**	**705.7**
	(4.46E-07)	**(0.0263)**	Diagnoses	**(0.0020)**	**(110.1)**
ZC Household	0.0005	378.1373	Num. Diagnoses	-0.0001	**35.4**
Size	(0.0076)	(557.23)	Squared	(0.0001)	**(8.1)**
Medicare	**-0.0111**	-565.83	Year 2000	-0.0070	1021.1
	(0.0061)	(407.68)		(0.0076)	(914.6)
MediCal	-0.0012	**1904.01**	Year 2001	-0.0009	193.0
	(0.0083)	**(534.81)**		(0.0056)	(434.3)
Other Gov't	-0.0146	745.33	Year 2002	**-0.0195**	**270.6**
Insurance	(0.0099)	(1369.56)		**(0.0058)**	**(289.0)**
Self Pay	**0.0269**	-658.76	Year 2003	**-0.0224**	**513.1**
	(0.0164)	(730.70)		**(0.0066)**	**(348.1)**

Notes: Entries are coefficients from OLS regressions with standard errors in parentheses. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Coefficients that are statistically significant at the p <0.10 level are highlighted in bold. Abbreviations: ZC = Zip code, ER = Emergency Room.

Table 5(h). Locals OLS Relationships: Vertebral Fracture

Explanatory Variable	Dependent Variable		Explanatory Variable	Dependent Variable	
	Mortality	Cost		Mortality	Cost
n	14028	14028			
Age	**0.0002**	**-127.15**	Other Payor	**-0.0045**	2721.3
	(0.0001)	**(8.96)**		**(0.0030)**	(3299.3)
Female	**-0.0102**	**-2345.73**	HMO	0.0007	-585.5
	(0.0020)	**(426.52)**		(0.0023)	(409.0)
Black	-0.0003	1749.34	Comprehensive	**0.0116**	**3657.8**
	(0.0043)	(1960.93)	ER	**(0.0053)**	**(2561.0)**
Nat. Amer.	-0.0068	**-5986.76**	Basic ER	**0.0044**	-1878.1
	(0.0031)	**(3204.13)**		**(0.0052)**	(1260.2)
Asian	-0.0017	565.40	Standby ER	-0.0191	516.6
	(0.0047)	(759.63)		(0.0226)	(2357.9)
Hispanic	**-0.0044**	-786.54	Hospital Beds	**8.66E-06**	**13.7**
	(0.0016)	(828.59)		**(6.74E-06)**	**(3.2)**
ZC Income	-9.93E-08	**0.0115**	Transfer	-0.0024	**4908.5**
	(5.88E-08)	**(0.0158)**		(0.0049)	**(1891.7)**
ZC Pop.	3.42E-07	**-0.0729**	Distance to Hosp.	0.0002	**217.1**
	(2.60E-07)	**(0.0382)**		(0.0001)	**(36.5)**
ZC Num. of	-8.60E-07	**0.2441**	Distance to Hosp.	**-2.08E-06**	**-0.8988**
Households	(6.74E-07)	**(0.1244)**	Squared	**(1.23E-06)**	**(0.5399)**
ZC Area	-8.40E-06	**-4.39**	DNR Status	**0.0622**	-693.0
	(1.00E-05)	**(1.55)**		**(0.0150)**	(911.1)
ZC Density	**-3.65E-07**	-0.1345	Num. Of	0.0006	**1684.0**
	(2.72E-07)	(0.0359)	Diagnoses	(0.0010)	**(223.1)**
ZC Household	-0.0058	**1093.019**	Num. Diagnoses	0.0002	-10.4
Size	(0.0052)	**(638.29)**	Squared	(0.0001)	(23.5)
Medicare	**0.0065**	**-2576.82**	Year 2000	-0.0063	400.8
	(0.0022)	**(848.23)**		(0.0031)	(647.4)
MediCal	0.0007	**2601.83**	Year 2001	-0.0015	327.3
	(0.0024)	**(1020.38)**		(0.0035)	(476.9)
Other Gov't	-0.0006	**1298.44**	Year 2002	0.0016	**2494.3**
Insurance	(0.0029)	**(743.81)**		(0.0037)	**(704.0)**
Self Pay	-0.0011	**-1976.75**	Year 2003	-0.0029	**1462.5**
	(0.0033)	**(804.16)**		(0.0029)	**(563.5)**

Notes: Entries are coefficients from OLS regressions with standard errors in parentheses. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Coefficients that are statistically significant at the p <0.10 level are highlighted in bold. Abbreviations: ZC = Zip code, ER = Emergency Room.

Table 6(a). Correlation of Instrument with County Characteristics: Acute Myocardial Infarction

County Characteristic	County Level Instrument			
	Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n	50	30	30	30
Median Income	0.007	0.376	0.705	0.479
	(0.935)	(0.545)	(0.735)	(0.494)
Population	0.330	0.254	0.199	0.072
	(0.569)	(0.618)	(0.997)	(0.790)
Locals Adjusted Mean Cost		**15.807**	**3.426**	**5.755**
		(0.000)	**(0.011)**	**(0.023)**

Notes: Values are F-statistics for the regression of the row variable on the column variable(s) with p-values in parentheses below. The number of observations for each regression in a column is presented at the top of the column. Results with $p<0.10$ are highlighted in bold.

Table 6(b). Correlation of Instrument with County Characteristics: Appendicitis

County Characteristic	County Level Instrument			
	Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n	50	28	28	28
Median Income	1.709	0.076	1.823	1.769
	(0.197)	(0.785)	(0.170)	(0.195)
Population	1.523	1.202	1.391	0.011
	(0.223)	(0.283)	(0.270)	(0.919)
Locals Adjusted Mean Cost		**34.425**	0.658	1.449
		(0.000)	(0.586)	(0.240)

Notes: Values are F-statistics for the regression of the row variable on the column variable(s) with p-values in parentheses below. The number of observations for each regression in a column is presented at the top of the column. Results with $p<0.10$ are highlighted in bold.

Table 6(c). Correlation of Instrument with County Characteristics: Cerebrovascular Accident

County Characteristic	County Level Instrument			
	Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n	50	27	27	27
Median Income	**8.156**	**4.523**	**2.619**	**6.473**
	(0.006)	**(0.043)**	**(0.054)**	**(0.018)**
Population	0.456	0.722	0.692	0.298
	(0.503)	(0.404)	(0.635)	(0.590)
Locals Adjusted Mean Cost		**7.161**	0.956	1.637
		(0.013)	(0.466)	(0.213)

Notes: Values are F-statistics for the regression of the row variable on the column variable(s) with p-values in parentheses below. The number of observations for each regression in a column is presented at the top of the column. Results with $p<0.10$ are highlighted in bold.

Table 6(d). Correlation of Instrument with County Characteristics: Dysrhythmias

County Characteristic	County Level Instrument			
	Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n	50	32	32	32
Median Income	**12.200**	**5.031**	1.195	1.769
	(0.001)	**(0.032)**	(0.330)	(0.194)
Population	0.014	0.108	2.159	0.070
	(0.907)	(0.745)	(0.115)	(0.794)
Locals Adjusted Mean Cost		**7.639**	**3.332**	**4.885**
		(0.010)	**(0.034)**	**(0.035)**

Notes: Values are F-statistics for the regression of the row variable on the column variable(s) with p-values in parentheses below. The number of observations for each regression in a column is presented at the top of the column. Results with $p<0.10$ are highlighted in bold.

Table 6(e). Correlation of Instrument with County Characteristics: GI Bleed

County Characteristic	County Level Instrument			
	Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n	50	20	20	20
Median Income	0.365	**3.157**	1.358	2.683
	(0.548)	**(0.093)**	(0.302)	(0.119)
Population	0.292	0.000	0.608	0.767
	(0.591)	(0.992)	(0.721)	(0.393)
Locals Adjusted Mean Cost		2.264	0.397	0.066
		(0.150)	(0.868)	(0.800)

Notes: Values are F-statistics for the regression of the row variable on the column variable(s) with p-values in parentheses below. The number of observations for each regression in a column is presented at the top of the column. Results with $p<0.10$ are highlighted in bold.

Table 6(f). Correlation of Instrument with County Characteristics: Acute Pancreatitis

County Characteristic	County Level Instrument			
	Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n	50	23	23	23
Median Income	**6.732**	0.620	0.192	0.412
	(0.013)	(0.440)	(0.974)	(0.528)
Population	0.547	0.133	0.184	0.231
	(0.463)	(0.719)	(0.977)	(0.636)
Locals Adjusted Mean Cost		1.449	0.531	0.007
		(0.242)	(0.777)	(0.935)

Notes: Values are F-statistics for the regression of the row variable on the column variable(s) with p-values in parentheses below. The number of observations for each regression in a column is presented at the top of the column. Results with $p<0.10$ are highlighted in bold.

Table 6(g). Correlation of Instrument with County Characteristics: Pulmonary Embolism

County Characteristic	County Level Instrument			
	Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n	50	15	15	15
Median Income	0.194	**6.347**	1.451	**3.938**
	(0.662)	**(0.026)**	(0.295)	**(0.069)**
Population	1.021	0.324	0.950	0.998
	(0.317)	(0.579)	(0.494)	(0.336)
Locals Adjusted Mean Cost		0.995	1.133	2.620
		(0.337)	(0.409)	(0.130)

Notes: Values are F-statistics for the regression of the row variable on the column variable(s) with p-values in parentheses below. The number of observations for each regression in a column is presented at the top of the column. Results with $p<0.10$ are highlighted in bold.

Table 6(h). Correlation of Instrument with County Characteristics: Vertebral Fracture

County Characteristic	County Level Instrument			
	Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n	50	19	19	19
Median Income	**27.569**	**5.337**	**2.558**	**8.236**
	(0.000)	**(0.034)**	**(0.094)**	**(0.011)**
Population	0.171	0.058	0.561	0.737
	(0.681)	(0.813)	(0.649)	(0.403)
Locals Adjusted Mean Cost		**8.993**	0.717	**4.269**
		(0.008)	(0.557)	**(0.054)**

Notes: Values are F-statistics for the regression of the row variable on the column variable(s) with p-values in parentheses below. The number of observations for each regression in a column is presented at the top of the column. Results with $p<0.10$ are highlighted in bold.

Table 7(a). Correlation of Locals and Visitors Observed Characteristics: Acute Myocardial Infarction

Number of Counties Compared: 30

County-Level Characteristic	Correlation Coefficient	p-value
Unadjusted Values		
Age	**0.403**	**0.034**
Female	**0.484**	**0.007**
Hispanic	0.192	0.310
Adjusted Values		
Cost	**0.601**	**0.000**
Mortality	0.296	0.112
Num. of Diagnoses	**0.736**	**0.000**
Hypertension	**0.553**	**0.002**
Diabetes	0.299	0.109
COPD	0.269	0.150
Cancer	**0.357**	**0.053**

Notes: Entries are correlation coefficients with corresponding p-values for the comparison of county means for visitors and locals. Comparisons with $p<0.10$ are highlighted in bold. Abbreviations: COPD = chronic obstructive pulmonary disease.

Table 7(b). Correlation of Locals and Visitors Observed Characteristics: Appendicitis

Number of Counties Compared: 28

County-Level Characteristic	Correlation Coefficient	p-value
Unadjusted Values		
Age	-0.182	0.533
Female	0.111	0.572
Hispanic	0.061	0.760
Adjusted Values		
Cost	**0.755**	**0.000**
Mortality	0.285	0.142
Num. of Diagnoses	0.276	0.154
Hypertension	**0.345**	**0.072**
Diabetes	0.200	0.308
COPD	**0.436**	**0.020**
Cancer	0.114	0.563

Notes: Entries are correlation coefficients with corresponding p-values for the comparison of county means for visitors and locals. Comparisons with $p<0.10$ are highlighted in bold. Abbreviations: COPD = chronic obstructive pulmonary disease.

Table 7(c). Correlation of Locals and Visitors Observed Characteristics: Cerebrovascular Accident

Number of Counties Compared: 27

County-Level Characteristic	Correlation Coefficient	p-value
Unadjusted Values		
Age	0.118	0.556
Female	**0.691**	**0.000**
Hispanic	**0.590**	**0.001**
Adjusted Values		
Cost	**0.472**	**0.013**
Mortality	-0.056	0.782
Num. of Diagnoses	**0.520**	**0.005**
Hypertension	**0.359**	**0.066**
Diabetes	**0.368**	**0.059**
COPD	**-0.346**	**0.077**
Cancer	0.208	0.297

Notes: Entries are correlation coefficients with corresponding p-values for the comparison of county means for visitors and locals. Comparisons with $p<0.10$ are highlighted in bold. Abbreviations: COPD = chronic obstructive pulmonary disease.

Table 7(d). Correlation of Locals and Visitors Observed Characteristics: Dysrhythmias

Number of Counties Compared: 32

County-Level Characteristic	Correlation Coefficient	p-value
Unadjusted Values		
Age	-0.098	0.608
Female	**0.394**	**0.025**
Hispanic	-0.097	0.598
Adjusted Values		
Cost	**0.451**	**0.010**
Mortality	-0.113	0.537
Num. of Diagnoses	**0.443**	**0.011**
Hypertension	0.156	0.394
Diabetes	**0.506**	**0.003**
COPD	0.108	0.557
Cancer	0.229	0.208

Notes: Entries are correlation coefficients with corresponding p-values for the comparison of county means for visitors and locals. Comparisons with $p<0.10$ are highlighted in bold. Abbreviations: COPD = chronic obstructive pulmonary disease.

Table 7(e). Correlation of Locals and Visitors Observed Characteristics: GI Bleed

Number of Counties Compared: 20

County-Level Characteristic	Correlation Coefficient	p-value
Unadjusted Values		
Age	0.215	0.362
Female	0.026	0.915
Hispanic	0.122	0.609
Adjusted Values		
Cost	0.334	0.150
Mortality	0.125	0.601
Num. of Diagnoses	**0.659**	**0.002**
Hypertension	-0.052	0.827
Diabetes	**-0.513**	**0.021**
COPD	-0.212	0.370
Cancer	0.111	0.641

Notes: Entries are correlation coefficients with corresponding p-values for the comparison of county means for visitors and locals. Comparisons with $p<0.10$ are highlighted in bold. Abbreviations: COPD = chronic obstructive pulmonary disease.

Table 7(f). Correlation of Locals and Visitors Observed Characteristics: Acute Pancreatitis

Number of Counties Compared: 23

County-Level Characteristic	Correlation Coefficient	p-value
Unadjusted Values		
Age	0.153	0.507
Female	**0.480**	**0.020**
Hispanic	0.297	0.168
Adjusted Values		
Cost	0.254	0.242
Mortality	-0.084	0.704
Num. of Diagnoses	**0.568**	**0.005**
Hypertension	0.213	0.329
Diabetes	0.145	0.510
COPD	-0.194	0.374
Cancer	-0.231	0.290

Notes: Entries are correlation coefficients with corresponding p-values for the comparison of county means for visitors and locals. Comparisons with $p<0.10$ are highlighted in bold. Abbreviations: COPD = chronic obstructive pulmonary disease.

Table 7(g). Correlation of Locals and Visitors Observed Characteristics: Pulmonary Embolism

Number of Counties Compared: 15

County-Level Characteristic	Correlation Coefficient	p-value
Unadjusted Values		
Age	0.338	0.217
Female	-0.169	0.547
Hispanic	**0.640**	**0.010**
Adjusted Values		
Cost	0.267	0.337
Mortality	-0.057	0.841
Num. of Diagnoses	-0.018	0.948
Hypertension	0.281	0.310
Diabetes	0.441	0.100
COPD	0.030	0.917
Cancer	-0.009	0.976

Notes: Entries are correlation coefficients with corresponding p-values for the comparison of county means for visitors and locals. Comparisons with $p<0.10$ are highlighted in bold. Abbreviations: COPD = chronic obstructive pulmonary disease.

Table 7(h). Correlation of Locals and Visitors Observed Characteristics: Vertebral Fracture

Number of Counties Compared: 19

County-Level Characteristic	Correlation Coefficient	p-value
Unadjusted Values		
Age	-0.056	0.837
Female	0.139	0.571
Hispanic	-0.065	0.793
Adjusted Values		
Cost	**0.588**	**0.008**
Mortality	0.299	0.214
Num. of Diagnoses	0.377	0.111
Hypertension	-0.067	0.784
Diabetes	0.004	0.986
COPD	0.322	0.178
Cancer	-0.073	0.767

Notes: Entries are correlation coefficients with corresponding p-values for the comparison of county means for visitors and locals. Comparisons with $p<0.10$ are highlighted in bold. Abbreviations: COPD = chronic obstructive pulmonary disease.

Table 8(a) Part I. Relationship of Local Characteristics to Instrument: Acute Myocardial Infarction

	Instrument: Locals Adjusted Mean Cost			Instrument: Visitors Adjusted Mean Cost		
	County Mean for Locals:			County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	**0.847**	**0.881**	**0.024**	0.874	0.859	0.324
Cost	**11,185**	**18,988**	**0.000**	15,141	15,063	0.967
Age	**72.754**	**70.573**	**0.029**	**70.462**	**72.178**	**0.084**
Female	**0.453**	**0.414**	**0.033**	0.417	0.441	0.135
Black	0.017	0.020	0.683	0.026	0.015	0.278
Nat. Amer.	0.002	0.001	0.737	0.001	0.002	0.382
Asian	0.021	0.029	0.497	0.026	0.025	0.980
Hispanic	0.097	0.048	0.105	0.069	0.074	0.819
ZC Income	**40,201**	**47,702**	**0.026**	48,390	42,049	0.109
ZC Pop.	28,468	30,418	0.601	**35,475**	**26,857**	**0.011**
ZC Num. H'holds	10,420	11,103	0.571	**12,882**	**9,853**	**0.005**
ZC Area	165	124	0.403	104	162	0.182
ZC Density	1,970	2,207	0.821	2,527	1,900	0.482
ZC H'hold Size	2.701	2.644	0.617	2.765	2.632	0.212
Medicare	**0.735**	**0.652**	**0.023**	**0.645**	**0.714**	**0.065**
MediCal	0.058	0.057	0.909	0.058	0.057	0.948
Other Gov't	0.028	0.030	0.765	0.034	0.027	0.336
Self Pay	0.024	0.022	0.826	0.023	0.023	0.970
Other Payor	0.004	0.006	0.686	0.012	0.002	0.147
HMO	**0.234**	**0.331**	**0.053**	**0.405**	**0.230**	**0.001**
Comprehens. ER	0.012	0.013	0.921	0.023	0.009	0.363
Basic ER	0.911	0.888	0.750	0.949	0.878	0.180
Standby ER	0.014	0.093	0.166	0.017	0.069	0.202
Hospital Beds	170	215	0.181	**244**	**170**	**0.040**
Transfer	**0.041**	**0.117**	**0.001**	0.104	0.068	0.128
Dist. To Hosp.	6.306	7.589	0.210	7.769	6.595	0.254
DNR Status	0.197	0.150	0.159	**0.127**	**0.193**	**0.026**
Num. Diagnoses	**6.723**	**6.165**	**0.041**	6.180	6.557	0.161

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(a) Part II. Relationship of Local Characteristics to Instrument: Acute Myocardial Infarction

	Instrument: Visitors Number of Procedures		
	County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.881	0.857	0.125
Cost	17,067	14,238	0.134
Age	71	72	0.139
Female	**0.414**	**0.442**	**0.094**
Black	0.031	0.014	0.125
Nat. Amer.	0.001	0.002	0.380
Asian	0.042	0.019	0.175
Hispanic	0.064	0.076	0.628
ZC Income	**52,134**	**40,445**	**0.005**
ZC Pop.	**33,728**	**27,606**	**0.064**
ZC Num. H'holds	**12,442**	**10,041**	**0.030**
ZC Area	**90**	**168**	**0.072**
ZC Density	**4,077**	**1,236**	**0.076**
ZC H'hold Size	2.740	2.643	0.327
Medicare	**0.644**	**0.715**	**0.053**
MediCal	0.056	0.058	0.895
Other Gov't	0.030	0.029	0.803
Self Pay	0.024	0.022	0.683
Other Payor	0.012	0.002	0.129
HMO	**0.369**	**0.246**	**0.010**
Comprehens. ER	0.015	0.012	0.819
Basic ER	**0.968**	**0.870**	**0.059**
Standby ER	0.009	0.073	0.122
Hospital Beds	**253**	**166**	**0.014**
Transfer	0.108	0.066	0.118
Dist. To Hosp.	6.877	6.977	0.925
DNR Status	**0.135**	**0.190**	**0.062**
Num. Diagnoses	6.274	6.517	0.303

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(b) Part I. Relationship of Local Characteristics to Instrument: Appendicitis

	Instrument: Locals Adjusted Mean Cost			Instrument: Visitors Adjusted Mean Cost		
	County Mean for Locals:			County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.999	0.998	0.511	0.999	0.998	0.510
Cost	**6,571**	**8,636**	**0.000**	**6,500**	**8,033**	**0.000**
Age	32.000	31.883	0.924	31.547	32.095	0.628
Female	0.378	0.376	0.857	**0.389**	**0.372**	**0.057**
Black	0.007	0.009	0.492	0.009	0.007	0.660
Nat. Amer.	0.002	0.002	0.851	0.001	0.002	0.338
Asian	0.019	0.016	0.718	0.016	0.018	0.797
Hispanic	0.161	0.159	0.961	0.203	0.144	0.145
ZC Income	42,910	45,921	0.371	46,157	43,738	0.491
ZC Pop.	32,443	29,535	0.460	**37,940**	**28,286**	**0.011**
ZC Num. H'holds	11,558	10,679	0.468	**12,979**	**10,394**	**0.018**
ZC Area	110	180	0.153	96	164	0.130
ZC Density	2,843	1,527	0.215	2,877	1,916	0.322
ZC H'hold Size	2.760	2.711	0.696	**2.884**	**2.677**	**0.041**
Medicare	0.071	0.072	0.940	0.066	0.073	0.299
MediCal	0.211	0.219	0.745	0.209	0.217	0.755
Other Gov't	0.064	0.058	0.610	0.058	0.062	0.717
Self Pay	**0.099**	**0.075**	**0.049**	0.090	0.086	0.730
Other Payor	0.019	0.007	0.242	0.015	0.012	0.763
HMO	0.526	0.523	0.952	**0.605**	**0.493**	**0.004**
Comprehens. ER	0.024	0.013	0.511	0.011	0.021	0.445
Basic ER	0.901	0.874	0.704	**0.966**	**0.857**	**0.032**
Standby ER	0.056	0.067	0.840	**0.012**	**0.081**	**0.095**
Hospital Beds	**218**	**150**	**0.028**	**243**	**161**	**0.015**
Transfer	0.004	0.003	0.576	0.004	0.003	0.556
Dist. To Hosp.	6.067	5.757	0.720	5.920	5.908	0.989
DNR Status	0.012	0.020	0.617	0.005	0.020	0.192
Num. Diagnoses	1.007	1.047	0.686	**0.842**	**1.098**	**0.001**

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(b) Part II. Relationship of Local Characteristics to Instrument: Appendicitis

	Instrument: Visitors Number of Procedures		
	County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.999	0.998	0.293
Cost	7,631	7,593	0.942
Age	33	32	0.321
Female	**0.390**	**0.371**	**0.063**
Black	0.008	0.008	0.912
Nat. Amer.	0.001	0.002	0.269
Asian	0.023	0.015	0.399
Hispanic	0.155	0.162	0.875
ZC Income	**52,566**	**41,246**	**0.006**
ZC Pop.	**35,624**	**29,186**	**0.075**
ZC Num. H'holds	**12,734**	**10,490**	**0.051**
ZC Area	**79**	**171**	**0.041**
ZC Density	3,749	1,577	0.187
ZC H'hold Size	2.816	2.704	0.334
Medicare	0.068	0.073	0.466
MediCal	**0.176**	**0.230**	**0.023**
Other Gov't	0.074	0.056	0.152
Self Pay	0.082	0.089	0.570
Other Payor	0.010	0.014	0.612
HMO	**0.609**	**0.492**	**0.002**
Comprehens. ER	0.044	0.008	0.193
Basic ER	0.939	0.867	0.187
Standby ER	**0.012**	**0.081**	**0.095**
Hospital Beds	**227**	**167**	**0.091**
Transfer	0.003	0.003	0.981
Dist. To Hosp.	**4.972**	**6.277**	**0.070**
DNR Status	0.009	0.019	0.419
Num. Diagnoses	**0.904**	**1.074**	**0.031**

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(c) Part I. Relationship of Local Characteristics to Instrument: Cerebrovascular Accident

	Instrument: Locals Adjusted Mean Cost			Instrument: Visitors Adjusted Mean Cost		
	County Mean for Locals:			County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.926	0.928	0.833	0.930	0.926	0.413
Cost	**7,391**	**8,976**	**0.001**	8,244	8,160	0.880
Age	73.733	73.741	0.988	73.080	73.993	0.116
Female	0.553	0.569	0.247	0.548	0.566	0.115
Black	0.026	0.037	0.438	0.036	0.029	0.593
Nat. Amer.	0.002	0.003	0.607	0.001	0.003	0.115
Asian	**0.019**	**0.047**	**0.075**	0.037	0.032	0.748
Hispanic	0.095	0.067	0.360	0.120	0.066	0.233
ZC Income	**39,718**	**48,482**	**0.009**	47,151	42,913	0.256
ZC Pop.	30,032	28,976	0.779	**35,861**	**27,031**	**0.014**
ZC Num. H'holds	11,018	10,543	0.693	**12,784**	**10,001**	**0.013**
ZC Area	154	136	0.719	**88**	**167**	**0.057**
ZC Density	1,606	2,688	0.315	2,743	1,915	0.376
ZC H'hold Size	2.676	2.622	0.649	2.779	2.599	0.117
Medicare	0.772	0.748	0.338	**0.717**	**0.777**	**0.011**
MediCal	0.064	0.065	0.937	0.072	0.062	0.407
Other Gov't	0.021	0.020	0.790	0.019	0.022	0.567
Self Pay	0.018	0.016	0.569	0.020	0.015	0.184
Other Payor	0.004	0.004	0.859	**0.010**	**0.002**	**0.092**
HMO	0.204	0.248	0.307	**0.325**	**0.188**	**0.003**
Comprehens. ER	0.018	0.009	0.465	0.031	0.007	0.228
Basic ER	0.912	0.882	0.664	0.950	0.876	0.154
Standby ER	**0.006**	**0.106**	**0.084**	0.015	0.072	0.152
Hospital Beds	199	170	0.378	**257**	**156**	**0.003**
Transfer	0.018	0.015	0.462	0.018	0.016	0.516
Dist. To Hosp.	6.324	5.363	0.110	6.193	5.708	0.425
DNR Status	0.182	0.194	0.716	**0.131**	**0.210**	**0.002**
Num. Diagnoses	**6.675**	**6.177**	**0.033**	6.477	6.406	0.741

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(c) Part II. Relationship of Local Characteristics to Instrument: Cerebrovascular Accident

	Instrument: Visitors Number of Procedures		
	County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.926	0.927	0.925
Cost	8,100	8,216	0.841
Age	74	74	0.918
Female	0.552	0.565	0.329
Black	0.023	0.035	0.306
Nat. Amer.	0.002	0.003	0.617
Asian	0.030	0.034	0.803
Hispanic	0.106	0.071	0.462
ZC Income	44,670	43,878	0.823
ZC Pop.	30,589	29,082	0.649
ZC Num. H'holds	11,250	10,598	0.551
ZC Area	119	155	0.439
ZC Density	2,110	2,161	0.954
ZC H'hold Size	2.714	2.624	0.438
Medicare	0.756	0.762	0.813
MediCal	0.059	0.067	0.521
Other Gov't	0.020	0.021	0.806
Self Pay	0.021	0.015	0.108
Other Payor	0.007	0.003	0.379
HMO	**0.289**	**0.202**	**0.099**
Comprehens. ER	0.028	0.008	0.310
Basic ER	0.946	0.878	0.190
Standby ER	0.021	0.070	0.238
Hospital Beds	224	169	0.129
Transfer	0.015	0.017	0.569
Dist. To Hosp.	6.126	5.734	0.515
DNR Status	0.159	0.199	0.173
Num. Diagnoses	6.390	6.440	0.821

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(d) Part I. Relationship of Local Characteristics to Instrument: Dysrhythmias

	Instrument: Locals Adjusted Mean Cost			Instrument: Visitors Adjusted Mean Cost		
	County Mean for Locals:			County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.971	0.965	0.113	0.966	0.969	0.282
Cost	**6,069**	**7,627**	**0.006**	6,581	6,974	0.481
Age	70.863	71.200	0.557	71.114	70.993	0.838
Female	**0.524**	**0.507**	**0.050**	0.518	0.514	0.649
Black	0.015	0.020	0.519	0.022	0.016	0.554
Nat. Amer.	0.002	0.001	0.539	0.003	0.000	0.120
Asian	0.018	0.026	0.415	0.017	0.024	0.487
Hispanic	0.072	0.057	0.578	0.077	0.058	0.607
ZC Income	**39,687**	**49,380**	**0.004**	41,711	45,862	0.184
ZC Pop.	27,560	30,219	0.470	28,720	28,969	0.947
ZC Num. H'holds	10,299	10,946	0.587	10,759	10,558	0.864
ZC Area	154	127	0.532	164	130	0.523
ZC Density	2,169	1,878	0.778	1,711	2,170	0.611
ZC H'hold Size	2.637	2.647	0.935	2.594	2.665	0.542
Medicare	0.703	0.694	0.661	0.700	0.698	0.896
MediCal	0.064	0.059	0.674	0.067	0.059	0.472
Other Gov't	0.027	0.023	0.499	0.023	0.026	0.509
Self Pay	0.016	0.014	0.558	0.014	0.015	0.772
Other Payor	0.006	0.006	0.960	0.008	0.005	0.578
HMO	0.238	0.307	0.111	0.285	0.267	0.698
Comprehens. ER	0.022	0.006	0.239	0.025	0.009	0.378
Basic ER	0.907	0.868	0.588	0.933	0.866	0.267
Standby ER	**0.012**	**0.117**	**0.079**	0.038	0.077	0.453
Hospital Beds	192	176	0.628	194	180	0.677
Transfer	0.021	0.021	0.957	0.026	0.018	0.438
Dist. To Hosp.	**6.828**	**5.358**	**0.015**	6.251	6.018	0.734
DNR Status	0.081	0.085	0.873	0.064	0.092	0.143
Num. Diagnoses	**5.467**	**5.022**	**0.064**	5.298	5.219	0.738

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(d) Part II. Relationship of Local Characteristics to Instrument: Dysrhythmias

	Instrument: Visitors Number of Procedures		
	County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.966	0.969	0.450
Cost	7,190	6,687	0.424
Age	71	71	0.450
Female	0.515	0.515	0.981
Black	0.019	0.017	0.830
Nat. Amer.	0.003	0.001	0.192
Asian	0.029	0.019	0.469
Hispanic	0.070	0.062	0.836
ZC Income	46,732	43,499	0.381
ZC Pop.	28,715	28,971	0.946
ZC Num. H'holds	10,832	10,524	0.803
ZC Area	150	136	0.806
ZC Density	2,956	1,585	0.348
ZC H'hold Size	2.617	2.654	0.750
Medicare	0.706	0.695	0.594
MediCal	0.061	0.062	0.956
Other Gov't	0.023	0.026	0.519
Self Pay	0.014	0.016	0.471
Other Payor	0.009	0.005	0.497
HMO	0.269	0.274	0.924
Comprehens. ER	0.025	0.008	0.363
Basic ER	0.936	0.865	0.241
Standby ER	0.039	0.077	0.461
Hospital Beds	194	180	0.693
Transfer	0.027	0.018	0.376
Dist. To Hosp.	5.734	6.261	0.438
DNR Status	0.067	0.090	0.199
Num. Diagnoses	5.264	5.235	0.901

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(e) Part I. Relationship of Local Characteristics to Instrument: GI Bleed

	Instrument: Locals Adjusted Mean Cost			Instrument: Visitors Adjusted Mean Cost		
	County Mean for Locals:			County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.947	0.950	0.524	0.945	0.949	0.458
Cost	5,904	8,580	0.183	6,492	7,429	0.461
Age	69.025	69.056	0.971	69.102	69.025	0.928
Female	0.499	0.479	0.149	**0.512**	**0.483**	**0.028**
Black	0.031	0.026	0.691	0.047	0.024	0.273
Nat. Amer.	**0.001**	**0.008**	**0.063**	0.002	0.005	0.101
Asian	0.023	0.026	0.764	0.036	0.021	0.421
Hispanic	0.113	0.070	0.176	0.082	0.094	0.656
ZC Income	41,287	46,297	0.144	46,049	43,228	0.522
ZC Pop.	32,124	26,787	0.151	**33,629**	**28,412**	**0.094**
ZC Num. H'holds	11,566	10,009	0.192	**12,486**	**10,363**	**0.032**
ZC Area	126	163	0.425	**63**	**165**	**0.002**
ZC Density	2,068	2,279	0.847	3,161	1,927	0.205
ZC H'hold Size	2.724	2.609	0.316	2.691	2.660	0.749
Medicare	0.673	0.681	0.759	0.651	0.684	0.285
MediCal	0.103	0.102	0.986	0.105	0.102	0.825
Other Gov't	0.036	0.046	0.227	0.033	0.043	0.160
Self Pay	0.030	0.029	0.837	0.033	0.029	0.471
Other Payor	0.006	0.005	0.789	**0.002**	**0.007**	**0.059**
HMO	0.252	0.208	0.272	**0.340**	**0.202**	**0.003**
Comprehens. ER	0.016	0.016	0.983	0.035	0.012	0.392
Basic ER	0.934	0.830	0.142	0.922	0.872	0.338
Standby ER	0.020	0.110	0.120	0.036	0.073	0.368
Hospital Beds	**214**	**150**	**0.044**	**269**	**160**	**0.004**
Transfer	0.021	0.020	0.947	0.024	0.019	0.379
Dist. To Hosp.	6.321	5.428	0.131	6.271	5.775	0.491
DNR Status	0.127	0.151	0.230	0.130	0.141	0.607
Num. Diagnoses	**7.419**	**6.327**	**0.000**	6.981	6.846	0.592

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(e) Part II. Relationship of Local Characteristics to Instrument: GI Bleed

	Instrument: Visitors Number of Procedures		
	County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.950	0.948	0.820
Cost	6,558	7,413	0.508
Age	69	69	0.497
Female	0.505	0.485	0.214
Black	0.044	0.025	0.375
Nat. Amer.	0.006	0.004	0.691
Asian	0.023	0.025	0.911
Hispanic	0.075	0.096	0.477
ZC Income	44,878	43,520	0.749
ZC Pop.	32,849	28,607	0.238
ZC Num. H'holds	12,180	10,439	0.142
ZC Area	99	156	0.264
ZC Density	2,585	2,071	0.580
ZC H'hold Size	2.695	2.659	0.703
Medicare	0.669	0.679	0.718
MediCal	0.097	0.104	0.613
Other Gov't	**0.032**	**0.043**	**0.093**
Self Pay	0.031	0.029	0.776
Other Payor	0.006	0.005	0.864
HMO	0.307	0.211	0.063
Comprehens. ER	0.015	0.016	0.934
Basic ER	0.938	0.868	0.159
Standby ER	0.033	0.073	0.324
Hospital Beds	227	170	0.124
Transfer	0.022	0.020	0.757
Dist. To Hosp.	5.671	5.925	0.734
DNR Status	0.125	0.142	0.457
Num. Diagnoses	6.997	6.842	0.553

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(f) Part I. Relationship of Local Characteristics to Instrument: Acute Pancreatitis

	Instrument: Locals Adjusted Mean Cost			Instrument: Visitors Adjusted Mean Cost		
	County Mean for Locals:			County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.983	0.984	0.746	0.982	0.984	0.177
Cost	**8,284**	**10,911**	**0.000**	**11,279**	**9,067**	**0.027**
Age	52.315	51.488	0.370	51.809	51.931	0.874
Female	0.503	0.478	0.119	0.502	0.487	0.276
Black	**0.024**	**0.069**	**0.013**	0.062	0.041	0.263
Nat. Amer.	0.003	0.002	0.385	**0.001**	**0.003**	**0.032**
Asian	**0.013**	**0.030**	**0.079**	**0.049**	**0.013**	**0.018**
Hispanic	0.175	0.127	0.283	0.185	0.141	0.254
ZC Income	**38,878**	**47,750**	**0.005**	**50,016**	**41,198**	**0.041**
ZC Pop.	28,695	31,452	0.481	**41,841**	**26,357**	**0.000**
ZC Num. H'holds	10,136	11,515	0.251	**14,588**	**9,638**	**0.000**
ZC Area	164	114	0.252	**56**	**165**	**0.002**
ZC Density	1,530	2,841	0.204	**5,738**	**1,063**	**0.018**
ZC H'hold Size	2.715	2.703	0.924	**2.888**	**2.653**	**0.036**
Medicare	**0.340**	**0.293**	**0.010**	0.304	0.321	0.261
MediCal	0.222	0.215	0.732	0.199	0.224	0.215
Other Gov't	0.074	0.100	0.117	0.097	0.084	0.402
Self Pay	0.073	0.067	0.494	0.067	0.071	0.618
Other Payor	0.015	0.005	0.152	0.004	0.012	0.061
HMO	**0.291**	**0.383**	**0.016**	**0.437**	**0.306**	**0.000**
Comprehens. ER	0.008	0.032	0.206	**0.085**	**0.000**	**0.029**
Basic ER	0.836	0.918	0.256	0.854	0.884	0.625
Standby ER	0.095	0.043	0.396	**0.016**	**0.086**	**0.089**
Hospital Beds	176	190	0.663	**313**	**142**	**0.000**
Transfer	0.009	0.013	0.261	**0.019**	**0.008**	**0.003**
Dist. To Hosp.	6.136	6.113	0.973	5.963	6.175	0.706
DNR Status	0.028	0.060	0.208	**0.020**	**0.052**	**0.062**
Num. Diagnoses	4.714	4.411	0.147	4.779	4.494	0.131

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(f) Part II. Relationship of Local Characteristics to Instrument: Acute Pancreatitis

Variable	Instrument: Visitors Number of Procedures County Mean for Locals: Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.982	0.984	0.490
Cost	**11,204**	**9,091**	**0.043**
Age	53	52	0.150
Female	0.501	0.487	0.357
Black	0.047	0.046	0.958
Nat. Amer.	0.002	0.003	0.684
Asian	0.039	0.016	0.151
Hispanic	0.121	0.161	0.315
ZC Income	47,887	41,870	0.149
ZC Pop.	34,260	28,751	0.146
ZC Num. H'holds	**12,817**	**10,197**	**0.033**
ZC Area	107	149	0.366
ZC Density	4,246	1,535	0.151
ZC H'hold Size	2.667	2.723	0.634
Medicare	0.326	0.314	0.543
MediCal	0.197	0.225	0.129
Other Gov't	0.101	0.083	0.382
Self Pay	0.059	0.073	0.142
Other Payor	0.007	0.011	0.575
HMO	0.390	0.320	0.113
Comprehens. ER	**0.079**	**0.002**	**0.047**
Basic ER	0.899	0.870	0.616
Standby ER	**0.013**	**0.087**	**0.073**
Hospital Beds	**277**	**153**	**0.009**
Transfer	**0.016**	**0.009**	**0.097**
Dist. To Hosp.	5.955	6.178	0.729
DNR Status	0.023	0.051	0.101
Num. Diagnoses	4.831	4.478	0.102

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(g) Part I. Relationship of Local Characteristics to Instrument: Pulmonary Embolism

	Instrument: Locals Adjusted Mean Cost			Instrument: Visitors Adjusted Mean Cost		
	County Mean for Locals:			County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.932	0.940	0.352	0.927	0.938	0.233
Cost	**9,669**	**11,378**	**0.008**	10,775	10,475	0.708
Age	64.318	65.303	0.381	64.436	64.882	0.668
Female	0.553	0.570	0.400	0.551	0.563	0.489
Black	0.025	0.041	0.323	0.076	0.025	0.151
Nat. Amer.	0.001	0.002	0.654	0.000	0.002	0.208
Asian	0.008	0.016	0.145	0.019	0.011	0.439
Hispanic	0.059	0.046	0.546	0.048	0.054	0.762
ZC Income	43,572	46,034	0.498	44,793	44,805	0.997
ZC Pop.	29,986	27,225	0.453	**34,303**	**27,521**	**0.090**
ZC Num. H'holds	11,054	10,176	0.466	**13,114**	**10,139**	**0.046**
ZC Area	146	147	0.994	109	154	0.448
ZC Density	1,759	2,265	0.607	4,839	1,474	0.220
ZC H'hold Size	2.635	2.551	0.453	2.608	2.590	0.857
Medicare	0.565	0.585	0.562	0.560	0.578	0.645
MediCal	0.085	0.087	0.878	0.103	0.083	0.209
Other Gov't	0.044	0.033	0.407	0.051	0.036	0.584
Self Pay	0.016	0.011	0.242	0.016	0.013	0.508
Other Payor	0.006	0.006	0.997	**0.002**	**0.007**	**0.075**
HMO	0.347	0.342	0.905	0.377	0.338	0.541
Comprehens. ER	0.027	0.005	0.168	0.035	0.013	0.307
Basic ER	0.890	0.905	0.837	0.943	0.889	0.256
Standby ER	0.013	0.087	0.196	**0.002**	**0.059**	**0.094**
Hospital Beds	**217**	**162**	**0.096**	**269**	**174**	**0.084**
Transfer	0.019	0.015	0.475	0.021	0.017	0.526
Dist. To Hosp.	**7.544**	**5.758**	**0.013**	6.309	6.716	0.719
DNR Status	0.113	0.103	0.698	**0.066**	**0.116**	**0.004**
Num. Diagnoses	6.095	5.146	0.003	**5.936**	**5.560**	**0.089**

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(g) Part II. Relationship of Local Characteristics to Instrument: Pulmonary Embolism

	Instrument: Visitors Number of Procedures		
	County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.926	0.938	0.175
Cost	10,268	10,572	0.744
Age	65	65	0.885
Female	0.547	0.564	0.364
Black	0.071	0.026	0.207
Nat. Amer.	0.000	0.002	0.141
Asian	0.018	0.011	0.538
Hispanic	0.041	0.055	0.466
ZC Income	43,938	44,968	0.790
ZC Pop.	30,752	28,197	0.531
ZC Num. H'holds	11,968	10,357	0.273
ZC Area	119	152	0.563
ZC Density	4,391	1,559	0.305
ZC H'hold Size	2.545	2.602	0.604
Medicare	0.573	0.576	0.943
MediCal	0.096	0.084	0.536
Other Gov't	0.050	0.036	0.626
Self Pay	0.015	0.013	0.784
Other Payor	**0.001**	**0.007**	**0.072**
HMO	0.323	0.349	0.692
Comprehens. ER	0.029	0.014	0.482
Basic ER	0.958	0.886	0.129
Standby ER	**0.002**	**0.059**	**0.094**
Hospital Beds	238	180	0.282
Transfer	0.016	0.017	0.781
Dist. To Hosp.	6.424	6.694	0.814
DNR Status	**0.075**	**0.114**	**0.044**
Num. Diagnoses	**5.988**	**5.550**	**0.051**

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(h) Part I. Relationship of Local Characteristics to Instrument: Vertebral Fracture

	Instrument: Locals Adjusted Mean Cost			Instrument: Visitors Adjusted Mean Cost		
	County Mean for Locals:			County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.984	0.988	0.324	0.983	0.987	0.364
Cost	**6,354**	**9,440**	**0.001**	8,198	7,822	0.631
Age	64.668	65.734	0.579	**62.346**	**65.915**	**0.074**
Female	0.552	0.574	0.351	**0.531**	**0.571**	**0.082**
Black	0.010	0.010	0.912	0.009	0.010	0.827
Nat. Amer.	0.000	0.001	0.740	0.000	0.001	0.983
Asian	**0.010**	**0.031**	**0.063**	0.014	0.022	0.462
Hispanic	0.079	0.043	0.129	0.101	0.051	0.226
ZC Income	**39,082**	**50,179**	**0.001**	43,373	44,945	0.699
ZC Pop.	29,732	29,409	0.932	32,912	28,735	0.238
ZC Num. H'holds	10,699	11,146	0.718	11,763	10,712	0.367
ZC Area	163	126	0.436	144	145	0.982
ZC Density	**1,206**	**3,033**	**0.093**	2,482	2,029	0.686
ZC H'hold Size	**2.711**	**2.528**	**0.087**	**2.779**	**2.580**	**0.063**
Medicare	0.596	0.616	0.644	**0.519**	**0.628**	**0.011**
MediCal	0.089	0.068	0.206	0.095	0.074	0.213
Other Gov't	0.067	0.073	0.609	0.068	0.070	0.852
Self Pay	0.037	0.038	0.923	**0.057**	**0.033**	**0.027**
Other Payor	0.010	0.010	0.922	0.024	0.006	0.163
HMO	0.229	0.277	0.318	0.289	0.244	0.405
Comprehens. ER	0.009	0.047	0.142	0.033	0.027	0.801
Basic ER	0.867	0.884	0.825	**0.945**	**0.858**	**0.082**
Standby ER	0.055	0.066	0.844	0.016	0.072	0.125
Hospital Beds	188	203	0.681	**251**	**182**	**0.094**
Transfer	0.026	0.019	0.405	0.035	0.020	0.215
Dist. To Hosp.	7.756	6.601	0.302	8.367	6.881	0.285
DNR Status	0.081	0.115	0.228	**0.048**	**0.111**	**0.002**
Num. Diagnoses	4.842	4.882	0.887	4.646	4.916	0.407

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 8(h) Part II. Relationship of Local Characteristics to Instrument: Vertebral Fracture

	Instrument: Visitors Number of Procedures		
	County Mean for Locals:		
Variable	Below Median Instrument Value	Above Median Instrument Value	t-Test for Mean Equality (p-value)
Mortality	0.984	0.987	0.626
Cost	8,087	7,849	0.791
Age	62	66	0.107
Female	0.532	0.571	0.114
Black	0.008	0.011	0.608
Nat. Amer.	0.000	0.001	0.983
Asian	0.009	0.023	0.146
Hispanic	0.085	0.055	0.479
ZC Income	43,495	44,915	0.715
ZC Pop.	30,204	29,412	0.812
ZC Num. H'holds	11,007	10,901	0.920
ZC Area	153	142	0.828
ZC Density	1,950	2,162	0.838
ZC H'hold Size	2.727	2.593	0.231
Medicare	**0.531**	**0.625**	**0.049**
MediCal	0.098	0.073	0.131
Other Gov't	0.058	0.073	0.244
Self Pay	**0.054**	**0.034**	**0.064**
Other Payor	0.022	0.007	0.230
HMO	0.275	0.248	0.629
Comprehens. ER	**0.005**	**0.034**	**0.086**
Basic ER	**0.975**	**0.851**	**0.009**
Standby ER	0.016	0.072	0.121
Hospital Beds	217	190	0.527
Transfer	0.028	0.021	0.602
Dist. To Hosp.	8.518	6.844	0.201
DNR Status	**0.055**	**0.109**	**0.006**
Num. Diagnoses	4.572	4.934	0.309

Notes: This table evaluates how well balanced various observable variables of the locals are with respect to instrument values. The county mean of each variable among the locals is presented for counties that have lower-than-median and higher-than-median instrument values. The third column of each set contains the p-value that results from a t-test for mean equality with unequal variances. Results with $p<0.10$ are highlighted in bold.

Table 9. Significance of Relationships of Local Characteristics to the Instruments

Diagnosis	Instrument	Number of Comparisons	Number with p<0.10	Binomial Probability
AMI	Locals Cost	24	6	0.007
AMI	Visitors Cost	24	5	0.028
AMI	Vis. Num. Proc.	24	9	0.000
Appendicitis	Locals Cost	24	2	0.436
Appendicitis	Visitors Cost	24	8	0.000
Appendicitis	Vis. Num. Proc.	24	10	0.000
CVA (Stroke)	Locals Cost	24	4	0.085
CVA (Stroke)	Visitors Cost	24	6	0.007
CVA (Stroke)	Vis. Num. Proc.	24	1	0.708
Dysrhythmias	Locals Cost	24	5	0.028
Dysrhythmias	Visitors Cost	24	0	0.920
Dysrhythmias	Vis. Num. Proc.	24	0	0.920
GI Bleed	Locals Cost	24	3	0.214
GI Bleed	Visitors Cost	24	6	0.007
GI Bleed	Vis. Num. Proc.	24	1	0.708
Pancreatitis	Locals Cost	24	4	0.085
Pancreatitis	Visitors Cost	24	13	0.000
Pancreatitis	Vis. Num. Proc.	24	4	0.085
PE	Locals Cost	24	2	0.436
PE	Visitors Cost	24	6	0.007
PE	Vis. Num. Proc.	24	4	0.085
Vertebral Fx	Locals Cost	24	4	0.085
Vertebral Fx	Visitors Cost	24	7	0.002
Vertebral Fx	Vis. Num. Proc.	24	4	0.085

Note: This table shows the binomial probabilities of getting the observed (or greater) number of statistically significant comparisons for each diagnosis/instrument pair in Table 6 under a null hypothesis of n=24, p=0.10. Because a binomial random variable assumes independence, the Medicare variable (which is highly correlated with age) and number of households variable (which is highly correlated with population) are omitted. Because the independent and explanatory variable-of-interest (survival and cost) are also omitted, the number of comparisons is 24. Bold text is used to highlight binomial probabilities less that 0.10. Abbreviations: AMI = acute myocardial infarction; CVA = cerebrovascular accident; GI = gastrointestinal; PE = Pulmonary Embolism.

Table 10(a). Effect of Spending on Survival: Acute Myocardial Infarction

		Instrument Used			
		Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n		158269	158269	158269	158269
OLS	Coefficient	**8.76E-07**	**8.76E-07**	**8.76E-07**	**8.76E-07**
	(std err)	**(9.61E-08)**	**(9.61E-08)**	**(9.61E-08)**	**(9.61E-08)**
Number of Instruments		1	1	13	1
Wald Estimate	Coefficient	**-4.36E-06**	-1.91E-04	-	-8.56E-06
	(std err)	**(2.05E-06)**	(5.50E-03)	-	(7.99E-06)
IV 2SLS- First Stage	Coefficient	**1.004**	**0.264**	-	**1129.9**
	(std err)	**(0.027)**	**(0.096)**	-	**(406.8)**
	F Statistic	1393.9	7.6	8.4	7.7
IV 2SLS- Second Stage	Coefficient	**-3.15E-06**	**-7.25E-06**	**-2.76E-06**	-3.39E-06
	(std err)	**(8.36E-07)**	**(3.53E-06)**	**(9.71E-07)**	(2.54E-06)
Hausman Test	F Statistic	**23.6**	**18.0**	**14.1**	**3.5**
	(p value)	**(0.000)**	**(0.000)**	**(0.001)**	**(0.070)**
Cost of One Expected Life Saved	Low Est.	$221,188	$76,692	$229,756	$132,352
	Point Est.	$317,460	$137,931	$362,319	$294,985
	High Est.	$562,126	$684,556	$856,487	-$1,289,324
Cost per Life-Year Saved	Low Est.	$36,865	$12,782	$38,293	$22,059
	Point Est.	$52,910	$22,989	$60,387	$49,164
	High Est.	$93,688	$114,093	$142,748	-$214,887

Notes: The dependent variable is survival and the coefficient on the cost explanatory variable is presented for each of the four instruments. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Bold text indicates statistical significance at the p <0.10 level. The OLS estimate is presented in each column for ease of reference. The Wald estimates are constructed using the data in the first two rows of Table 6. The F-statistic that results from a test of the significance of the instrument(s) in the first stage regression is also shown. The Hausman test result evaluates the significance of the difference between the OLS and 2SLS estimates under the assumption that the instrument is valid. The 2SLS estimates are extrapolated to calculate the cost of one expected life saved. The range of costs were obtained from a 90% confidence interval around the 2SLS estimate. Negative costs imply that the marginal impact of additional spending is to cause harm and indicate how much money could be saved along with a life.

Table 10(b). Effect of Spending on Survival: Appendicitis

		Instrument Used			
		Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n		102448	102448	102448	102448
OLS	Coefficient	**7.37E-07**	**7.37E-07**	**7.37E-07**	**7.37E-07**
	(std err)	**(2.08E-07)**	**(2.08E-07)**	**(2.08E-07)**	**(2.08E-07)**
Number of Instruments		1	1	3	1
Wald Estimate	Coefficient	1.97E-07	2.23E-07	-	-1.42E-05
	(std err)	(3.04E-07)	(4.59E-07)	-	(1.99E-04)
IV 2SLS- First Stage	Coefficient	**0.997**	**0.612**	-	-165.1
	(std err)	**(0.019)**	**(0.117)**	-	(1247.1)
	F Statistic	2722.8	27.3	1.3	0.0
IV 2SLS- Second Stage	Coefficient	-2.05E-07	-2.09E-07	-1.17E-07	-2.71E-06
	(std err)	(1.34E-07)	(1.81E-07)	(3.86E-07)	(1.77E-05)
Hausman Test	F Statistic	**14.1**	**6.7**	1.6	0.1
	(p value)	**(0.001)**	**(0.015)**	(0.221)	(0.770)
Cost of One Expected Life Saved	Low Est.	$2,354,271	$1,976,910	$1,333,262	$31,508
	Point Est.	$4,878,049	$4,784,689	$8,547,009	$369,004
	High Est.	-$67,750,678	-$11,384,335	-$1,937,834	-$37,997
Cost per Life-Year Saved	Low Est.	$51,629	$43,353	$29,238	$691
	Point Est.	$106,975	$104,927	$187,434	$8,092
	High Est.	-$1,485,760	-$249,656	-$42,496	-$833

Notes: The dependent variable is survival and the coefficient on the cost explanatory variable is presented for each of the four instruments. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Bold text indicates statistical significance at the p <0.10 level. The OLS estimate is presented in each column for ease of reference. The Wald estimates are constructed using the data in the first two rows of Table 6. The F-statistic that results from a test of the significance of the instrument(s) in the first stage regression is also shown. The Hausman test result evaluates the significance of the difference between the OLS and 2SLS estimates under the assumption that the instrument is valid. The 2SLS estimates are extrapolated to calculate the cost of one expected life saved. The range of costs were obtained from a 90% confidence interval around the 2SLS estimate. Negative costs imply that the marginal impact of additional spending is to cause harm and indicate how much money could be saved along with a life.

Table 10(c). Effect of Spending on Survival: Cerebrovascular Accident

		Instrument Used			
		Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n		93450	93450	93450	93450
OLS	Coefficient	**1.72E-06**	**1.72E-06**	**1.72E-06**	**1.72E-06**
	(std err)	**(3.11E-07)**	**(3.11E-07)**	**(3.11E-07)**	**(3.11E-07)**
Number of Instruments		1	1	5	1
Wald Estimate	Coefficient	-9.27E-07	-5.36E-05	-	-5.15E-06
	(std err)	(4.41E-06)	(3.75E-04)	-	(7.29E-05)
IV 2SLS- First Stage	Coefficient	**1.008**	**0.233**	-	**484.0**
	(std err)	**(0.036)**	**(0.068)**	-	**(285.1)**
	F Statistic	803.7	11.7	4.0	2.9
IV 2SLS- Second Stage	Coefficient	-2.27E-07	-2.65E-06	4.05E-06	4.65E-07
	(std err)	(1.46E-06)	(2.32E-06)	(3.49E-06)	(6.58E-06)
Hausman Test	F Statistic	1.9	**4.6**	0.6	0.0
	(p value)	(0.183)	**(0.040)**	(0.455)	(0.852)
Cost of One Expected Life Saved	Low Est.	$381,476	$154,923	$597,514	$96,841
	Point Est.	$4,405,286	$377,358	-$246,914	-$2,150,538
	High Est.	-$461,382	-$865,951	-$102,316	-$88,840
Cost per Life-Year Saved	Low Est.	$50,194	$20,385	$78,620	$12,742
	Point Est.	$579,643	$49,652	-$32,489	-$282,966
	High Est.	-$60,708	-$113,941	-$13,463	-$11,689

Notes: The dependent variable is survival and the coefficient on the cost explanatory variable is presented for each of the four instruments. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Bold text indicates statistical significance at the p <0.10 level. The OLS estimate is presented in each column for ease of reference. The Wald estimates are constructed using the data in the first two rows of Table 6. The F-statistic that results from a test of the significance of the instrument(s) in the first stage regression is also shown. The Hausman test result evaluates the significance of the difference between the OLS and 2SLS estimates under the assumption that the instrument is valid. The 2SLS estimates are extrapolated to calculate the cost of one expected life saved. The range of costs were obtained from a 90% confidence interval around the 2SLS estimate. Negative costs imply that the marginal impact of additional spending is to cause harm and indicate how much money could be saved along with a life.

Table 10(d). Effect of Spending on Survival: Dysrhythmias

		Instrument Used			
		Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n		154524	154524	154524	154524
OLS	Coefficient	**8.53E-07**	**8.53E-07**	**8.53E-07**	**8.53E-07**
	(std err)	**(1.98E-07)**	**(1.98E-07)**	**(1.98E-07)**	**(1.98E-07)**
Number of Instruments		1	1	3	1
Wald Estimate	Coefficient	3.63E-06	-9.33E-06	-	5.17E-06
	(std err)	(2.36E-06)	(1.99E-05)	-	(8.64E-06)
IV 2SLS- First Stage	Coefficient	**1.004**	**0.319**	-	**852.6**
	(std err)	**(0.021)**	**(0.088)**	-	**(466.2)**
	F Statistic	2183.7	13.1	3.4	3.3
IV 2SLS- Second Stage	Coefficient	**-1.73E-06**	-4.96E-07	-1.78E-06	1.54E-06
	(std err)	**(9.87E-07)**	(2.24E-06)	(2.17E-06)	(3.87E-06)
Hausman Test	F Statistic	**6.1**	0.3	1.2	0.0
	(p value)	**(0.019)**	(0.599)	(0.278)	(0.850)
Cost of One Expected Life Saved	Low Est.	$298,625	$239,831	$187,308	$208,039
	Point Est.	$578,035	$2,016,129	$561,798	-$649,351
	High Est.	$8,983,112	-$314,703	-$562,177	-$126,794
Cost per Life-Year Saved	Low Est.	$41,476	$33,310	$26,015	$28,894
	Point Est.	$80,283	$280,018	$78,028	-$90,188
	High Est.	$1,247,654	-$43,709	-$78,080	-$17,610

Notes: The dependent variable is survival and the coefficient on the cost explanatory variable is presented for each of the four instruments. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Bold text indicates statistical significance at the p <0.10 level. The OLS estimate is presented in each column for ease of reference. The Wald estimates are constructed using the data in the first two rows of Table 6. The F-statistic that results from a test of the significance of the instrument(s) in the first stage regression is also shown. The Hausman test result evaluates the significance of the difference between the OLS and 2SLS estimates under the assumption that the instrument is valid. The 2SLS estimates are extrapolated to calculate the cost of one expected life saved. The range of costs were obtained from a 90% confidence interval around the 2SLS estimate. Negative costs imply that the marginal impact of additional spending is to cause harm and indicate how much money could be saved along with a life.

Table 10(e). Effect of Spending on Survival: GI Bleed

		Instrument Used			
		Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n		42416	42416	42416	42416
OLS	Coefficient	**2.23E-06**	**2.23E-06**	**2.23E-06**	**2.23E-06**
	(std err)	**(4.96E-07)**	**(4.96E-07)**	**(4.96E-07)**	**(4.96E-07)**
Number of Instruments		1	1	6	1
Wald Estimate	Coefficient	-1.42E-06	-3.97E-06	-	1.69E-06
	(std err)	(2.31E-06)	(1.22E-05)	-	(1.05E-05)
IV 2SLS- First Stage	Coefficient	**1.008**	**0.041**	-	-372.0
	(std err)	**(0.028)**	**(0.015)**	-	(328.9)
	F Statistic	1285.8	8.2	2.4	1.3
IV 2SLS- Second Stage	Coefficient	**-5.82E-06**	**-6.32E-06**	-4.63E-06	4.86E-06
	(std err)	**(1.53E-06)**	**(2.28E-06)**	(2.85E-06)	(9.94E-06)
Hausman Test	F Statistic	**24.3**	**4.0**	**4.8**	0.1
	(p value)	**(0.000)**	**(0.060)**	**(0.040)**	(0.753)
Cost of One Expected Life Saved	Low Est.	$120,060	$99,411	$107,481	$87,400
	Point Est.	$171,821	$158,228	$215,983	-$205,761
	High Est.	$302,042	$387,477	-$22,727,273	-$47,255
Cost per Life-Year Saved	Low Est.	$14,641	$12,123	$13,107	$10,659
	Point Est.	$20,954	$19,296	$26,339	-$25,093
	High Est.	$36,834	$47,253	-$2,771,619	-$5,763

Notes: The dependent variable is survival and the coefficient on the cost explanatory variable is presented for each of the four instruments. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Bold text indicates statistical significance at the p <0.10 level. The OLS estimate is presented in each column for ease of reference. The Wald estimates are constructed using the data in the first two rows of Table 6. The F-statistic that results from a test of the significance of the instrument(s) in the first stage regression is also shown. The Hausman test result evaluates the significance of the difference between the OLS and 2SLS estimates under the assumption that the instrument is valid. The 2SLS estimates are extrapolated to calculate the cost of one expected life saved. The range of costs were obtained from a 90% confidence interval around the 2SLS estimate. Negative costs imply that the marginal impact of additional spending is to cause harm and indicate how much money could be saved along with a life.

Table 10(f). Effect of Spending on Survival: Acute Pancreatitis

		Instrument Used			
		Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n		64700	64700	64700	64700
OLS	Coefficient	**1.06E-06**	**1.06E-06**	**1.06E-06**	**1.06E-06**
	(std err)	**(8.34E-08)**	**(8.34E-08)**	**(8.34E-08)**	**(8.34E-08)**
Number of Instruments		1	1	6	1
Wald Estimate	Coefficient	-2.75E-07	1.02E-06	-	1.00E-06
	(std err)	(8.58E-07)	(1.18E-06)	-	(1.24E-06)
IV 2SLS- First Stage	Coefficient	**1.000**	**0.195**	-	544.6
	(std err)	**(0.039)**	**(0.114)**	-	(355.4)
	F Statistic	642.8	3.0	2.7	2.3
IV 2SLS- Second Stage	Coefficient	-8.22E-08	-1.78E-06	-1.12E-06	-2.13E-06
	(std err)	(4.26E-07)	(1.80E-06)	(1.23E-06)	(3.21E-06)
Hausman Test	F Statistic	**7.1**	**7.0**	**4.5**	1.1
	(p value)	**(0.014)**	**(0.015)**	**(0.044)**	(0.314)
Cost of One Expected Life Saved	Low Est.	$1,280,672	$211,327	$318,756	$135,237
	Point Est.	$12,165,450	$561,798	$892,857	$469,484
	High Est.	-$1,622,218	-$853,242	-$1,114,579	-$319,040
Cost per Life-Year Saved	Low Est.	$59,290	$9,784	$14,757	$6,261
	Point Est.	$563,215	$26,009	$41,336	$21,735
	High Est.	-$75,103	-$39,502	-$51,601	-$14,770

Notes: The dependent variable is survival and the coefficient on the cost explanatory variable is presented for each of the four instruments. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Bold text indicates statistical significance at the p <0.10 level. The OLS estimate is presented in each column for ease of reference. The Wald estimates are constructed using the data in the first two rows of Table 6. The F-statistic that results from a test of the significance of the instrument(s) in the first stage regression is also shown. The Hausman test result evaluates the significance of the difference between the OLS and 2SLS estimates under the assumption that the instrument is valid. The 2SLS estimates are extrapolated to calculate the cost of one expected life saved. The range of costs were obtained from a 90% confidence interval around the 2SLS estimate. Negative costs imply that the marginal impact of additional spending is to cause harm and indicate how much money could be saved along with a life.

Table 10(g). Effect of Spending on Survival: Pulmonary Embolism

		Instrument Used			
		Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n		17854	17854	17854	17854
OLS	Coefficient	**1.77E-06**	**1.77E-06**	**1.77E-06**	**1.77E-06**
	(std err)	**(3.63E-07)**	**(3.63E-07)**	**(3.63E-07)**	**(3.63E-07)**
Number of Instruments		1	1	5	1
Wald Estimate	Coefficient	-4.86E-06	3.65E-05	-	-3.98E-05
	(std err)	(5.19E-06)	(1.23E-04)	-	(1.17E-04)
IV 2SLS- First Stage	Coefficient	**0.974**	0.063	-	**1220.4**
	(std err)	**(0.047)**	(0.177)	-	**(416.9)**
	F Statistic	429.7	0.1	3.4	8.6
IV 2SLS- Second Stage	Coefficient	1.78E-06	-3.70E-05	-1.13E-06	-8.25E-06
	(std err)	(3.30E-06)	(1.21E-04)	(6.28E-06)	(5.74E-06)
Hausman Test	F Statistic	0.0	**4.8**	0.2	**3.7**
	(p value)	(0.998)	**(0.046)**	(0.655)	**(0.074)**
Cost of One Expected Life Saved	Low Est.	$275,330	$4,259	$87,495	$56,614
	Point Est.	-$561,798	$27,027	$884,956	$121,212
	High Est.	-$139,043	-$6,220	-$109,061	-$859,402
Cost per Life-Year Saved	Low Est.	$14,340	$222	$4,557	$2,949
	Point Est.	-$29,260	$1,408	$46,091	$6,313
	High Est.	-$7,242	-$324	-$5,680	-$44,761

Notes: The dependent variable is survival and the coefficient on the cost explanatory variable is presented for each of the four instruments. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Bold text indicates statistical significance at the p <0.10 level. The OLS estimate is presented in each column for ease of reference. The Wald estimates are constructed using the data in the first two rows of Table 6. The F-statistic that results from a test of the significance of the instrument(s) in the first stage regression is also shown. The Hausman test result evaluates the significance of the difference between the OLS and 2SLS estimates under the assumption that the instrument is valid. The 2SLS estimates are extrapolated to calculate the cost of one expected life saved. The range of costs were obtained from a 90% confidence interval around the 2SLS estimate. Negative costs imply that the marginal impact of additional spending is to cause harm and indicate how much money could be saved along with a life.

Table 10(h). Effect of Spending on Survival: Vertebral Fracture

		Instrument Used			
		Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates	Visitors Number of Procedures
n		14028	14028	14028	14028
OLS	Coefficient	**5.10E-07**	**5.10E-07**	**5.10E-07**	**5.10E-07**
	(std err)	**(1.80E-07)**	**(1.80E-07)**	**(1.80E-07)**	**(1.80E-07)**
Number of Instruments		1	1	3	1
Wald Estimate	Coefficient	-1.41E-06	1.07E-05	-	9.51E-06
	(std err)	(1.52E-06)	(3.76E-05)	-	(5.37E-05)
IV 2SLS- First Stage	Coefficient	**0.987**	**0.196**	-	**1423.0**
	(std err)	**(0.043)**	**(0.079)**	-	**(609.5)**
	F Statistic	521.1	6.2	2.0	5.5
IV 2SLS- Second Stage	Coefficient	-2.81E-07	-3.48E-07	-9.05E-07	-9.58E-07
	(std err)	(7.74E-07)	(9.85E-07)	(1.32E-06)	(1.28E-06)
Hausman Test	F Statistic	1.1	1.0	1.9	**3.3**
	(p value)	(0.304)	(0.342)	(0.187)	**(0.085)**
Cost of One Expected Life Saved	Low Est.	$645,011	$509,321	$325,754	$327,097
	Point Est.	$3,558,719	$2,873,563	$1,104,972	$1,043,841
	High Est.	-$1,011,777	-$789,017	-$793,777	-$876,271
Cost per Life-Year Saved	Low Est.	$64,501	$50,932	$32,575	$32,710
	Point Est.	$355,872	$287,356	$110,497	$104,384
	High Est.	-$101,178	-$78,902	-$79,378	-$87,627

Notes: The dependent variable is survival and the coefficient on the cost explanatory variable is presented for each of the four instruments. Standard errors are heteroskedasticity-robust and clustered by county of hospitalization. Bold text indicates statistical significance at the p <0.10 level. The OLS estimate is presented in each column for ease of reference. The Wald estimates are constructed using the data in the first two rows of Table 6. The F-statistic that results from a test of the significance of the instrument(s) in the first stage regression is also shown. The Hausman test result evaluates the significance of the difference between the OLS and 2SLS estimates under the assumption that the instrument is valid. The 2SLS estimates are extrapolated to calculate the cost of one expected life saved. The range of costs were obtained from a 90% confidence interval around the 2SLS estimate. Negative costs imply that the marginal impact of additional spending is to cause harm and indicate how much money could be saved along with a life.

Table 11. Conditional Life Expectancy

Diagnosis	n	Mean Age	Unconditional Life Expectancy	Conditional Life Expectancy	Source Notes
Myocardial Infarction	158269	70	14.9	6.0	(1)
Acute Appendicitis	102448	31	48.0	*45.6*	(2)
Cerebrovascular Accident	93450	73	13.0	7.6	(3)
Dysrhythmias	154524	71	14.3	*7.2*	(4)
GI Bleeding	42416	68	16.3	*8.2*	(5)
Acute Pancreatitis	64700	52	28.8	*21.6*	(6)
Pulmonary Embolism	17854	64	19.2	19.2	(7)
Vertebral Fracture	14028	63	19.9	10.0	(8)
Weighted Mean	647689	62.3	21.4	14.9	
Weighted Mean Excluding Myocardial Infarction	489420	59.8	23.5	17.8	

Notes: Number of observations and age are taken from Table 1. The unconditional life expectancy is the life expectancy for the US population at the given age as reported by the Centers for Disease Contol, 2003. Entries in italics are crude estimates obtained by making significant assumptions. The detailed sources for the entries in the "Conditional Life Expectancy" column are as follows: (1) Cutler, et al. (1998). (2) No good estimates were found. Assumed eqaul to 95% of unconditional life expectancy because there are few long-term sequelae. (3) Hannerz and Nielsen (2001). (4) This is a heterogeneous group of disorders, so good estimates were not easily obtainable. Dysrhythmias are often indicative of substantial underlying cardiovascular disease, so an estimate of 50% of the unconditional life expectancy was used. (5) GI Bleeding has numerous causes with highly variable outcomes. An estimate of 50% of the unconditional life expectancy was used. (6) Mortality from acute pancreatitis returns to levels comparable to the general population after 6 months (Goldacre and Roberts, 2004). However, acute pancreatitis is frequently associated with alcohol abuse or underlyig biliary disease and recurrence is frequent if these factors are not treated (Pleskow, 2004). For these reasons, an estimate of 75% of the unconditional life expectancy was used. (7) Even after massive pulmonary embolism, mortality is not increased after the first few days (Miniati, et al., 2006), so the unconditional life expactancy is used. (8) Mortality for those suffering from a vertebral fracture is 18% at five years (Francis, et al., 2004). This compares to a five-year mortality of approximately 9% among the US population for those age 63 (Centers for Disease Control, 2003). An estimate of 50% of the unconditional life expectancy is used.

Table 12(a). Effect of Spending on Survival: All Diagnoses

		Instrument Used			
		Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates (Sum)	Visitors Number of Procedures
n		647689	647689	647689	647689
OLS	Coefficient	**-9.81E-07**	**-9.81E-07**	**-9.81E-07**	**-9.81E-07**
	(std err)	**(6.76E-08)**	**(6.76E-08)**	**(6.76E-08)**	**(6.76E-08)**
Number of Instruments		1	1	1	1
IV 2SLS- First Stage	Coefficient	**0.935**	**0.215**	-	**756.3**
	(std err)	**(0.038)**	**(0.055)**	-	**(220.7)**
	F Statistic	614.7	15.1	15.3	11.7
IV 2SLS- Second Stage	Coefficient	**2.38E-06**	**3.55E-06**	**3.87E-06**	2.02E-06
	(std err)	**(5.80E-07)**	**(1.50E-06)**	**(1.83E-06)**	(1.72E-06)
Hausman Test	F Statistic	**33.6**	**9.3**	**5.0**	2.4
	(p value)	**(0.000)**	**(0.003)**	**(0.027)**	(0.124)
Cost of One Expected Life Saved	Low Est.	$300,192	$166,389	$145,535	$206,577
	Point Est.	$420,168	$281,690	$258,398	$495,050
	High Est.	$699,888	$917,431	$1,151,013	-$1,248,751

Notes: The dependent variable is survival and the coefficient on the cost explanatory variable is presented for each of the four instruments. Standard errors are heteroskedasticity-robust and clustered at the diagnosis-by-county of hospitalization level. Bold text indicates statistical significance at the p <0.10 level. The OLS estimate is presented in each column for ease of reference. The F-statistic that results from a test of the significance of the instrument(s) in the first stage regression is also shown. The Hausman test result evaluates the significance of the difference between the OLS and 2SLS estimates under the assumption that the instrument is valid. The 2SLS estimate are extrapolated to calculate the cost of one expected life saved. The range of costs were obtained from a 90% confidence interval around the 2SLS estimate. Negative costs imply that the marginal impact of additional spending is to cause harm and indicate how much money could be saved along with a life.

Table 12(b). Effect of Spending on Life Years: All Diagnoses

		Instrument Used			
		Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates (Sum)	Visitors Number of Procedures
n		647689	647689	647689	647689
OLS	Coefficient	**-1.21E-05**	**-1.21E-05**	**-1.21E-05**	**-1.21E-05**
	(std err)	**(1.58E-06)**	**(1.58E-06)**	**(1.58E-06)**	**(1.58E-06)**
Number of Instruments		1	1	1	1
IV 2SLS- First Stage	Coefficient	**0.935**	**0.215**	-	**756.3**
	(std err)	**(0.038)**	**(0.055)**	-	**(220.7)**
	F Statistic	614.7	15.1	15.3	11.7
IV 2SLS- Second Stage	Coefficient	**1.55E-05**	**2.68E-05**	**2.82E-05**	1.69E-05
	(std err)	**(3.83E-06)**	**(1.02E-05)**	**(1.29E-05)**	(1.32E-05)
Hausman Test	F Statistic	**51.5**	**12.6**	**6.7**	**3.7**
	(p value)	**(0.000)**	**(0.000)**	**(0.010)**	**(0.055)**
Cost of One Life Year Saved	Low Est.	$45,911	$22,974	$20,261	$25,942
	Point Est.	$64,516	$37,313	$35,461	$59,172
	High Est.	$108,474	$99,285	$141,965	-$210,615

Notes: The dependent variable is life years and the coefficient on the cost explanatory variable is presented for each of the four instruments. Standard errors are heteroskedasticity-robust and clustered at the diagnosis-by-county of hospitalization level. Bold text indicates statistical significance at the p <0.10 level. The OLS estimate is presented in each column for ease of reference. The F-statistic that results from a test of the significance of the instrument(s) in the first stage regression is also shown. The Hausman test result evaluates the significance of the difference between the OLS and 2SLS estimates under the assumption that the instrument is valid. The 2SLS estimate are extrapolated to calculate the cost of one life year saved. The range of costs were obtained from a 90% confidence interval around the 2SLS estimate. Negative costs imply that the marginal impact of additional spending is to cause harm and indicate how much money could be saved along with a year of life.

Table 13(a). Effect of Spending on Survival: All Diagnoses Except Acute Myocardial Infarction

		Instrument Used			
		Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates (Sum)	Visitors Number of Procedures
n		489420	489420	489420	489420
OLS	Coefficient	**-1.19E-06**	**-1.19E-06**	**-1.19E-06**	**-1.19E-06**
	(std err)	**(9.15E-08)**	**(9.15E-08)**	**(9.15E-08)**	**(9.15E-08)**
Number of Instruments		1	1	1	1
IV 2SLS- First Stage	Coefficient	**1.041**	**0.194**	-	**671.6**
	(std err)	**(0.024)**	**(0.058)**	-	**(198.6)**
	F Statistic	1843.2	11.3	3.3	11.4
IV 2SLS- Second Stage	Coefficient	**8.68E-07**	**1.60E-06**	-2.13E-06	7.34E-07
	(std err)	**(4.05E-07)**	**(8.80E-07)**	(4.19E-06)	(1.92E-06)
Hausman Test	F Statistic	**27.5**	**8.2**	0.1	0.9
	(p value)	**(0.000)**	**(0.005)**	(0.814)	(0.347)
Cost of One Expected Life Saved	Low Est.	$652,656	$328,601	$210,899	$257,546
	Point Est.	$1,152,074	$625,000	-$469,484	$1,362,398
	High Est.	$4,906,771	$6,377,551	-$111,091	-$414,113

Notes: The dependent variable is survival and the coefficient on the cost explanatory variable is presented for each of the four instruments. Standard errors are heteroskedasticity-robust and clustered at the diagnosis-by-county of hospitalization level. Bold text indicates statistical significance at the p <0.10 level. The OLS estimate is presented in each column for ease of reference. The F-statistic that results from a test of the significance of the instrument(s) in the first stage regression is also shown. The Hausman test result evaluates the significance of the difference between the OLS and 2SLS estimates under the assumption that the instrument is valid. The 2SLS estimate are extrapolated to calculate the cost of one expected life saved. The range of costs were obtained from a 90% confidence interval around the 2SLS estimate. Negative costs imply that the marginal impact of additional spending is to cause harm and indicate how much money could be saved along with a life.

Table 13(b). Effect of Spending on Life Years: All Diagnoses Except Acute Myocardial Infarction

		Instrument Used			
		Locals Adjusted Mean Cost	Visitors Adjusted Mean Cost	Visitors Adjusted Procedure Rates (Sum)	Visitors Number of Procedures
n		489420	489420	489420	489420
OLS	Coefficient	**-1.75E-05**	**-1.75E-05**	**-1.75E-05**	**-1.75E-05**
	(std err)	**(2.15E-06)**	**(2.15E-06)**	**(2.15E-06)**	**(2.15E-06)**
Number of Instruments		1	1	1	1
IV 2SLS- First Stage	Coefficient	**1.041**	**0.194**	-	**671.6**
	(std err)	**(0.024)**	**(0.058)**	-	**(198.6)**
	F Statistic	1843.2	11.3	3.3	11.4
IV 2SLS- Second Stage	Coefficient	**8.12E-06**	**1.79E-05**	-5.81E-06	1.11E-05
	(std err)	**(4.26E-06)**	**(9.23E-06)**	(3.63E-05)	(1.93E-05)
Hausman Test	F Statistic	**35.5**	**9.2**	0.1	1.8
	(p value)	**(0.000)**	**(0.003)**	(0.761)	(0.177)
Cost of One Life Year Saved	Low Est.	$66,197	$30,269	$18,614	$23,391
	Point Est.	$123,153	$55,866	-$172,117	$90,090
	High Est.	$882,145	$361,952	-$15,304	-$48,657

Notes: The dependent variable is life years and the coefficient on the cost explanatory variable is presented for each of the four instruments. Standard errors are heteroskedasticity-robust and clustered at the diagnosis-by-county of hospitalization level. Bold text indicates statistical significance at the p <0.10 level. The OLS estimate is presented in each column for ease of reference. The F-statistic that results from a test of the significance of the instrument(s) in the first stage regression is also shown. The Hausman test result evaluates the significance of the difference between the OLS and 2SLS estimates under the assumption that the instrument is valid. The 2SLS estimate are extrapolated to calculate the cost of one life year saved. The range of costs were obtained from a 90% confidence interval around the 2SLS estimate. Negative costs imply that the marginal impact of additional spending is to cause harm and indicate how much money could be saved along with a year of life.

Chapter 3

One Chance in a Million: Altruism and the Bone Marrow Registry

(Written with Ted Bergstrom and Rod Garratt)

3.1 Introduction

For patients who suffer from leukemia or other blood diseases, a stem cell transplant frequently offers the best chance of survival. Such a transplant is likely to be a life saving event. According to the web site of the London Health Sciences Centre (2006):

> "Long-term survival may be greater than 80 per cent, ... depending on the type of disease treated, the patient's age, and the severity of illness. For patients with acute leukemia, long-term survival is 50-60 per cent but this is much better than 20-25 per cent survival when patients are treated with chemotherapy alone. ... recipients eventually return to a normal lifestyle."

The most effective treatment for many blood diseases is radiation that destroys all blood cells in the body, both diseased and healthy. The blood cells must then be replaced with healthy ones. This is accomplished by transplanting blood-forming stem cells from a healthy donor whose immune system is compatible with that of the recipient. One's best prospect for a donor is a brother or sister. The probability that two siblings are acceptable matches is one-fourth. Those who lack a sibling donor must search among the population at large. Finding a compatible stem cell donor is vastly more difficult than finding a blood donor. The probability that two randomly selected white Americans are of matching type is less than one in ten thousand. About twenty percent of white Americans are of types that are shared by less than one person in a million. The African-American population is genetically even more diverse. The probability that two randomly selected African-Americans will match is less than one in one hundred thousand.

A remarkable set of institutions has developed for matching needy patients with compatible donors. These institutions, known as bone marrow registries, collect a list of potential volunteer stem cell donors. Those who join a registry must express their willingness to donate to any patient in need of a transplant. At the time of registration, a saliva sample is collected from the potential donor for DNA testing. The registrant's type is stored along with the donor's contact information. The United States National Marrow Donor Program (NMDP) began to operate in 1986 and currently maintains a registry of more than six million potential donors whose type has been determined.[1] The NMDP has expanded its scope internationally to include approximately 1.5 million registrants from the German bone marrow registry and smaller numbers from the registries of Sweden, Norway, the Netherlands, and Israel. Other countries have national registries that are not incorporated in the

[1]See McCullough, Perkins and Hansen (2006) and Fisher (2007) for discussions of the history of bone marrow registries in the United States.

NMDP, but are at least partially linked by a worldwide clearing house. There are approximately eleven million registrants in bone marrow registries throughout the world.

The existence of bone marrow registries raises interesting questions: How does the size and racial composition of the current registry compare with that of an optimal registry? What motivates people to join the registry? What financial and/or social incentives would be suitable for increasing registry size? This paper will address each of these questions.

Everyone in society faces a risk that they or a loved one will at some time need a stem cell transplant. Thus, everyone benefits from the existence of bone marrow registries. But an efficient registry would not include everyone. As the registry size increases, there is diminishing probability that adding another registrant will add an unrepresented type. Eventually, the value of marginal benefits from an additional registrant will fall below the marginal cost. This will determine the optimal size and racial composition of the registry.

We apply biologists' estimates of the probability distribution of immunity types and medical data on survival probabilities of transplant recipients to estimate the probability that an additional registrant will save a life. We then use economic estimates of the money value of a statistical life to calculate the expected value of an additional registrant. Finally, we compare this value to the marginal cost of adding an additional person to the registry.

Our estimates indicate that there is a strong case for increasing the number of registrants of all races, with the greatest net benefit coming from additional African-Americans. We estimate the size and racial make-up of an optimal registry. The current registry includes between two and three percent of the eligible U.S. population of whites, African-Americans, and Hispanics, and more than six percent of eligible Asian-Americans. An optimal registry would include approximately one-

fourth of all eligible African-Americans and Asian-Americans, fourteen percent of eligible Hispanics, and seven percent of eligible whites.

The probability that a white American will fail to find a match in the current registry is less than ten percent, while for African-Americans, this probability is nearly forty percent. In an optimally constituted registry, the probability of finding no match would be about three percent for whites, nine percent for Asian-Americans and twelve percent for African-Americans. The persistence of racial differences in no-match probabilities in an optimal registry results in part from the greater genetic diversity of the Asian-American and African-American populations and in part from the fact that these populations are smaller than the white population and hence have fewer patients seeking matches.

Those who donate stem cells bear a significant cost. Stem cells can be contributed by either of two procedures.[2] The more traditional method is a bone marrow transplant. Bone marrow is "harvested" from the donor's pelvis by means of insertions of a needle that reaches the center of the bone. This operation is performed under general or regional anesthesia. A more recently developed procedure transfers stem cells collected by a filtering process from the donor's bloodstream. This process, known as peripheral blood stem cell (PBSC) donation, requires the same type of genetic match as marrow transplants. Before the transfer, the donor is given a drug that produces a higher-than-normal number of stem cells in the bloodstream. This procedure does not require anesthesia. Both procedures impose

[2]A third source of stem cells is umbilical cord blood collected from newborns' placentas at delivery. Cord blood storage is unlikely to replace the bone marrow registry on a large scale because it is dramatically more expensive to store frozen cord blood than to store data about potential donors. The number of cord blood units stored is less than one percent of the number of persons in the registry.

serious inconvenience and discomfort, along with temporary side effects.[3] Neither procedure is likely to have long term health effects on the donor.

The biology of stem cell donations poses an unusual free-rider problem. Some who would willingly incur the costs of a donation if there were no other way to save the patient's life might prefer to let someone else bear this cost if another donor is available. If a registrant is asked to donate, the registry may or may not contain other suitable donors for the same patient. If other matching registrants are available, the net effect of one's own donation is simply to displace another donor. Joining the registry will be more attractive if it is likely that one will be the only available match when asked to donate.

The probability, conditional on being asked to donate, that one is the only match for the patient depends on one's race and on the number of persons of each race who are currently in the registry. With the existing registry, this probability is about eight percent for whites and almost eighty percent for African-Americans. In an optimal registry these percentages would fall to about three percent for whites and twenty percent for African-Americans.

Not only would an optimal registry have to attract more volunteers of all races than the current registry, but it would have to attract them despite the fact that in an optimal registry, a donor will be less likely to be the only available match for the recipient. It is therefore unclear whether a large enough registry can be obtained solely from unpaid volunteers. We consider the incentive problems that are likely to attend alternative forms of financial and social inducements and we suggest that payments to donors are more likely to be effective than payments to new registrants.

[3]According to the NMDP web site, "Marrow donors can expect to feel some soreness in their lower back for a few days or longer... Some may take two to three weeks before they feel completely recovered." The web site reports that PBSC donors often experience bone pain and flu-like symptoms, as well as occasional insomnia, headaches, fatigue, nausea, and vomiting.

3.2 Some Genetic Background

The body's immune system uses proteins known as human leukocyte antigens (HLA) to distinguish cells that belong to the body from those that do not. A stem cell transplant is likely to be successful only if the donor's HLA type is sufficiently close to that of the recipient. A person's HLA type is determined by genes located on chromosome 6, one copy of which is inherited from each parent. Until recently, the medical standard for an HLA match compared the specific contents, or *alleles*, of the three genes HLA-A, HLA-B, and HLA-DRB1 at a low level of resolution. Using this standard, there are about twenty million HLA-types.[4]

Two siblings have matching HLA types with probability one-fourth, since they match only if they both inherit the same version of chromosome 6 from each parent. A specific combination of alleles for HLA-A, HLA-B, and HLA-DRB1 on one chromosome is known as a *haplotype*. An individual's HLA compatibility is determined by the full list of six alleles on her two copies of chromosome 6. This is known as her *phenotype*. We obtained data on the population distribution of HLA types from a study by Mori, Beatty, Graves, Boucher and Milford (1997), which is based on a sample of about 400,000 individuals who were registered with the National Marrow Donor Program in 1995 and whose HLA-A,-B,-DR phenotypes were recorded. The distribution of HLA types is markedly different across races, and sample observations have accordingly been partitioned into five racial groups: whites, African-Americans, Asian-Americans, Hispanics, and Native Americans.

Because the sample is small relative to the number of possible phenotypes, direct estimation of the population distribution of phenotypes would not be effective. However, with an elegant application of statistics and genetic theory, geneticists are

[4]Recent research indicates that outcomes are improved by using higher resolution matching and by considering at least one additional gene from chromosome 6. We will discuss the effect of more refined matching later in this paper.

Table 3.1: Probability of HLA Match by Race

	White	African-Am	Asian-Am	Hispanic	Native Am
White	1/11,000				
African-Am	1/113,000	1/98,000			
Asian-Am	1/223,000	1/1,310,000	1/29,000		
Hispanic	1/44,000	1/259,000	1/254,000	1/34,000	
Native Am	1/13,000	1/116,000	1/173,000	1/36,000	1/11,000

Notes: Probabilities are calculated with Matlab, using our construction of phenotype distribution for each race, based on the Mori et al. (1997) estimates of haplotype distribution.

able to exploit this data much more powerfully. Mori et al. (1997) assume that within racial groups, mating is random with respect to HLA type. Based on this assumption, they use the observed distribution of phenotypes to construct a maximum likelihood distribution of haplotypes for each of the five racial groups. This process assigns positive estimated frequencies to about eleven thousand haplotypes. With this estimate of haplotype frequencies and the assumption of random mating within races, it is possible to estimate the frequency distributions of genetic types that are not directly observed in the sample. We use the haplotype distribution published by Mori et al. (1997) to construct such an estimate of the distribution of phenotypes in each group.[5] This process assigns positive probabilities to more than ten million distinct phenotypes.

Table 3.1 shows the probabilities by race that two randomly selected persons would have matching HLA types. Although two people are more likely to match if they are of the same race, the probability of matches across races is not negligible. The distribution of types is far from uniform. Some types are relatively common and some are extremely rare. The probability is about one in eleven thousand that two randomly selected white Americans are of matching types. But about half of

[5]An individual's phenotype is determined by the contents of his or her two haplotypes. The distribution of phenotypes is not the same as that of haplotype pairs (genotypes) because phenotypes do not distinguish how alleles are divided between the two chromosomes.

the white population are of types that occur with frequency less than one in one hundred thousand, and about one-fifth are in groups with frequency less than one in a million. The African-American population is even more heterogeneous. The probability that two randomly selected African-Americans have matching types is about one tenth of the corresponding probability for two whites.

3.3 Benefit-Cost Analysis

The welfare economics of the bone marrow registry is simplified and symmetrized by a "veil of ignorance" that shrouds knowledge of our medical futures. Nobody knows whether they or their loved ones will ever need a stem cell transplant. Hardly anyone knows whether they have a rare or a common HLA type. Additions to the registry are public goods that benefit everyone by increasing the probability of finding a donor if one is needed. Although the HLA type of registrants is not known until after they are enrolled and tested, the frequency distribution of types is known to differ by race. Thus we treat the number of registrants of each race as a distinct public good. We estimate the summed willingness-to-pay of persons of each race for adding an additional person of any specified race to the registry.

3.3.1 Estimating Probabilities of Finding a Match

Our first step in measuring benefits is to estimate the effect of an additional registrant of specified race on the probability that individuals who seek transplants will find a match in the registry. We estimate this effect using probability distributions of HLA types by race that we constructed from the Mori estimates of haplotype distribution. Since about ten million types have non-zero probabilities, the estimated probability distributions of HLA types are vectors with ten million components. This calculation is made possible by the remarkable computational

power of Matlab.

A significant fraction of those listed in the bone marrow registry are not available to donate when called upon. Some have moved without leaving forwarding addresses, some have health conditions that prevent them from donating, and some are no longer willing to contribute. To estimate probabilities of finding a match, we use "effective" registry sizes, which are expected numbers of registrants who are available to donate if called. Table 3.2 reports, by race, the number of persons in the registry, the fraction available, the effective number in the registry, and the probability that a randomly selected person lacks an HLA-match in the registry.[6]

Table 3.2: Registry size and probability of no match, by race, in 2006

Race	Number in Registry	Fraction Available	Effective No. in Registry	Probability of No Match
White	4,444,335	.65	2,888,818	.08
African-Am	485,791	.34	165,169	.38
Asian-Am	432,293	.44	190,209	.21
Hispanic	594,801	.47	279,556	.16
Native Am	70,781	.48	33,975	.11

Notes: Registration statistics are obtained from NMDP Registry and Transplant Statistics (NMDP, 2007a). The published table includes 1.5 million registrants of "unknown" race. According to the NMDP, almost all of these are recruited through international registries in Germany, the Netherlands, Sweden, Norway, and Israel, which do not collect information on race. Since the racial composition of these countries is almost entirely white, we count all of the unknowns as white. After 2002, the NMDP began to ask those listed as Hispanic to specify whether they were white, African-American, Asian-American, or Native American. We treat Hispanic as a racial group because our data on HLA distributions does so. This requires an imputation to avoid double-counting of registrants as being both Hispanic and a member of one of our other racial groups.

We calculate the probability that a person of specified race will find a match as follows. Let R be a vector listing the effective number of persons of each of the five races, white, African-American, Asian-American, Hispanic, and Native American,

[6]The estimated fractions of registrants available when asked are based on NMDP experience as reported by Craig Kollman *et al* (Kollman et al., 2004).

in the registry. For each race x, R_x is the number of persons of race x in the registry. Let p_i^x be the fraction of the population of race x that is of HLA type i. We assume that within races, a person's HLA type does not influence the probability of joining the registry. The probability that no type i's are found among registrants of race x is the probability that no type i's are selected in R_x random draws from the population of race x. This probability is

$$(1 - p_i^x)^{R_x}. \tag{3.1}$$

A registry with enrollment vector R contains no persons of type i if there are no type i's among registrants of any race. Therefore, when R is the vector of registrants by race, the probability that a person of type i has no match of any race in the registry is

$$p_i^0(R) = \prod_x (1 - p_i^x)^{R_x}. \tag{3.2}$$

The probability that a person of race x has no match in the registry is therefore

$$\sum_i p_i^x p_i^0(R). \tag{3.3}$$

Let us define $G_{xy}(R)$ to be the increase in the probability that a random member of race y has a match in the registry if one adds one registrant of race x to a registry of composition R. The probability that someone of race y is of type i and has no match in the registry is $p_i^y p_i^0(R)$, and the probability that a new registrant of race x is of type i is p_i^x. Therefore the probability that a person of race y is of type i, has no match in the current registry, and will have a match if an additional person of race x is added to the registry is $p_i^x p_i^y p_i^0(R)$. Summing these probabilities over the types, we have

$$G_{xy}(R) = \sum_i p_i^y p_i^x p_i^0(R). \tag{3.4}$$

It is interesting to see that $G_{xy}(R)$ is symmetric in x and y. Thus the effect of adding a registrant of race x on the probability that a person of race y will find a match is the same as that of adding a registrant of race y on the probability that a person of race x will find a match. Since we have estimated the type frequencies, p_i^x and p_i^y, for any two races x and y and the probabilities $p_i^0(R)$ that a member of type i will have no match, we can calculate the effects $G_{xy}(R)$ for any pair of races. Table 3.3 shows the increased probability of finding a registered match by race of the registrant and of the recipient.

Table 3.3: Gain in match probability from adding one registrant (Figures in table must be multiplied by 10^{-7})

Gain to a member of this Race	**Race of Added registrant**				
	White	African-Am	Asian-Am	Hispanic	Native Am
White	0.143	0.136	0.094	0.146	0.132
African-Am	0.136	6.043	0.154	0.547	0.287
Asian-Am	0.094	0.154	3.727	0.212	0.207
Hispanic	0.146	0.547	0.212	1.124	0.305
Native Am	0.132	0.287	0.207	0.305	1.012

Notes: Entries are calculated with Matlab using Equations 3.3 and 3.4 above, with estimated frequency distribution of phenotypes based on Mori's haplotype distribution (Mori et al., 1997). Numbers reported in table are 10^7 times actual effects of one person.

3.3.2 Estimating the Number of Lives Saved

To estimate the number of lives saved by an additional registrant, we first estimate the number of patients of each race who seek transplants. We then calculate the expected increased probabilities of finding a compatible donor that result from adding one more donor of a given race. Finally, we multiply the increased probabilities of

finding a compatible donor by the increase in long term survival probability that results from obtaining a transplant.

The first column of Table 3.4 reports the number of persons of each race who received transplants in 2006. The second column estimates the numbers who would have obtained transplants had a match been available, but who were unable to find a match. The third column estimates the total number of persons seeking transplants.

Table 3.4: Numbers of Actual and Potential Transplants (2006)

Race	Actual Transplants	Number with No Match	Potential Transplants
White	2394	203	2597
African-Am	120	72	192
Asian-Am	83	22	105
Hispanic	191	38	229
Native Am	12	1	13
All Races	2800	336	3136

Notes: The NMDP report *Number of Allogenic Transplants Performed* (NMDP, 2007b), shows that in 2006, approximately 2,800 patients received transplants through the NMDP, either from bone marrow or peripheral stem cell donations. We apply the proportions of all transplants performed since 1987 by race, as reported in the *2004 Biennial Report of the NMDP* (NMDP, 2006a), to estimate numbers of patients of each race in 2006. To estimate the number of potential transplants of each race, we divide the number of actual transplants by the probability that someone of that race finds a match in the registry. The probability of finding a match is just one minus the "probability of no match" reported in table 3.2.

We next estimate the expected annual increase in the number of transplants to persons of race y that would result from an additional registrant of race x. To obtain this estimate, we multiply the number of potential transplants to persons of race y found in Table 3.4 by the estimate in Table 3.3 of the increased match probability for persons of race y resulting from an additional registrant of race x. In Table 3.5, we report the expected number of additional transplants that result from adding 1,000 new registrants of each specified race.

Not every transplant saves a life. With some probability, the recipient will die

shortly after receiving the transplant. With some probability, a patient would survive without a transplant. To obtain the effect of an additional registrant on the expected number of lives saved, we need to multiply the increase in the expected number of transplants by the probability that a transplant saves an additional life. The biennial report of the NMDP (2006a, page 3-37), reports that the probability that a transplant recipient survives for at least ten years after a transplant is about thirty percent. Survival probabilities of patients who do and do not receive transplants depend on the medical condition for which they are treated. We have surveyed the medical literature on each of the most common conditions treated by stem cell transplants. Appendix B of this paper reports for each condition an estimate of the long term survival probability of those who receive transplants and of those who receive the next best available treatment. We estimate that the availability of an HLA compatible donor increases long term survival probability of a patient seeking a transplant by an average of twenty-one percentage points. Therefore we calculate the expected number of lives saved by an additional registrant as twenty-one percent of the probability that the additional registrant is a match for a patient who had no other match in the registry. Table 3.5 reports the expected number of lives saved by adding 1,000 new registrants of each specified race.

Table 3.5: Expected annual additional transplants and lives saved by adding 1,000 effective registrants

Race of New Registrants	Expected Annual Transplants Added	Expected Annual Lives Saved
White	0.044	0.009
African-Am	0.166	0.035
Asian-Am	0.072	0.015
Hispanic	0.077	0.016
Native Am	0.050	0.010

3.3.3 Valuing Lives Saved

The benefits of the bone marrow registry are well suited to measurement using the value of statistical life approach. This method was introduced by Mishan (1971), and further developed for analysis of public projects by Bergstrom (1982) and Dehez and Drèze (1982). The underlying theory and its empirical implications are lucidly explained in a survey by Viscusi and Aldy (2003). An individual's "value of statistical life" (VSL) is her marginal rate of substitution between survival probability and wealth—the rate at which she is willing to make exchanges between monetary wealth and small changes in survival probability. For example, someone who would pay \$1000 to eliminate a one-time fatality risk of .0001 would have a value of statistical life of approximately $\$1000 \div .0001 = \$10,000,000$. A larger registry benefits each person in society by contributing a small increment to the survival probability of each. The marginal rate of substitution of an individual between this public good and private consumption is the product of the effect on her survival probability times her value of statistical life. The Samuelson condition for efficient provision of a public good compares the sum of individual marginal rates of substitution between the public good and private goods to the marginal cost of the public good relative to private goods. If individuals' values of statistical life are uncorrelated with their gains in survival probability from a larger registry, then the sum of marginal rates of substitution is equal to the average VSL times the expected number of lives saved.

Many efforts have been made to estimate the value of a statistical life using a wide variety of methods, including ingeniously designed surveys (Jones-Lee, Hammerton and Philips, 1985; Johannesson, Johansson and Löfgren, 1997), studies of market wage premiums for dangerous work, consumer decisions about purchasing consumer safety devices, health care decisions, and decision rules used by government agencies. Viscusi and Aldy (2003) review a large number of these studies. Estimated valuations vary widely across studies and methodologies, but according

to Viscusi and Aldi, are mainly concentrated in the range from four to nine million U.S. dollars. We assume a value of statistical life of $6.5 million, the midpoint of this range. This is consistent with the policies of the U.S. Environmental Protection Agency, as reported in their publication "Guidelines for Preparing Economic Analyses" (U.S. Environmental Protection Agency, 1997), which recommends a VSL equivalent to 6.75 million 2004 dollars.

After joining the registry, potential donors can remain in the registry until they reach age 61. According to the NMDP 2004 biennial report (NMDP, 2006a, Table 2-1, page 2-24), the median age of new registrants is 35 years. We therefore assume that new registrants will remain in the registry for 25 years and we discount the annual flow of benefits at a rate of 2 percent per year. Table 3.6 reports our estimate of the present value of an additional (effective) registrant under these assumptions.

Table 3.6: Present value of an additional effective registrant

Total present value to this group	**Race of the additional effective registrant**				
	White	African-Am	Asian-Am	Hispanic	Native Am
White	$1012	$961	$664	$1,028	$928
African-Am	$71	$3155	$81	$285	$150
Asian-Am	$27	$44	$1,063	$60	$59
Hispanic	$91	$341	$132	$701	$190
Native Am	$5	$10	$8	$11	$37
Total Value	$1,206	$4,512	$1,947	$2,085	$1,364

The entries in the first row show that the white population benefits substantially from additional registrants of other races. This is true mainly because there is a large population of whites who are potential beneficiaries.

3.3.4 Costs of An Additional Registrant

The NMDP web-site reports a cost of $52 for tissue-typing an additional registrant in 2007. Personal communication with sources at the NMDP indicates that the total cost of obtaining sample material, tissue-typing, and maintaining a record of a new potential donor's contact information is approximately $105. We have calculated benefits for an additional *effective* registrant–one who is able and willing to make a donation if called upon. Since not all registrants are available when called upon, our cost estimates must include the cost of registering more than one person per effective registrant. Kollman et al. (2004) report that, based on NMDP experience, the fractions of recent registrants who can be located, pass the physical examination, and who consent to make a donation are .70 for white registrants, .42 for African-Americans, .50 for Asian-Americans, and .52 for Hispanics.[7]

Increasing the number of registrants increases the expected number of transplants and hence the expected total hospital and physician costs of performing these transplants. We estimate total hospital and physician costs for a transplant at about $166,000.[8] Multiplying this cost by the expected number of additional transplants resulting from an additional registrant (see Table 3.5), we find that the expected annual hospitalization costs resulting from adding a registrant range from about $7 for whites to about $28 for African-American registrants.

[7]These fractions are larger for recent registrants than for earlier registrants because HLA types were misclassified for a significant number of earlier registrants. Current DNA testing methods have largely eliminated this problem for new registrants.

[8]This estimate is based on a survey of costs in 2001 (Redaelli, Botteman, Stephens and Pashos, 2004) and converted to 2007 dollars.

3.3.5 Comparing Benefits and Costs

Table 3.7 shows estimated marginal benefits and costs from adding an effective registrant to the bone marrow registry. Marginal benefits exceed costs for all races and the benefit-cost ratio is highest for African-Americans. The 2004 Biennial Report of the NMDP (NMDP, 2006a, page 2.27) announced that the NMDP has "changed its strategy in recent years to focus more on recruiting minority volunteer donors and less on recruiting Caucasian volunteers." The report shows that the number of new white registrants diminished by about twenty five percent from 1996 until 2004, while the number of new registrants from minority groups was roughly constant. The NMDP's emphasis on recruiting African-American donors, particularly given a fixed budget, is consistent with our estimates of benefit-cost ratios. However, our results indicate that there is a strong case for increasing the total budget of the NMDP to allow increased recruitment of registrants from all races.

Table 3.7: Benefit-cost comparison for an additional registrant

	Race of the additional registrant				
	White	African-Am	Asian-Am	Hispanic	Native Am
Benefit	\$1206	\$4,512	\$1,947	\$2,078	\$1364
Total Cost	\$297	\$800	\$446	\$455	\$359
B/C Ratio	4.1	5.6	4.4	4.6	3.8

3.4 Optimal Registry Size and Composition

3.4.1 Calculating the Optimal Registry

We have seen that the expected present value of benefits exceeds the cost of adding registrants to the current NMDP registry. We next investigate the size and racial composition of an optimal registry–one that maximizes the difference between total

benefits and total costs. Our task is made more complex by the differences in type distribution across races and by the fact that a significant number of matches occur across races. Fortunately, it turns out that the difference between total benefits and total costs is a strictly concave function of the vector of numbers of registrants of each race. (We prove this in Appendix A.) Therefore a local optimum is also a unique global optimum and so we can use straightforward numerical methods to find the number of persons of each race in an optimal registry. Table 3.8 reports the number of persons of each race[9] in an optimal registry and compares it to the existing registry size[10] By our calculations, the optimal registry size is more than two-and-a-half times as large as the current registry for all races, and nearly ten times as large for African-Americans.

Table 3.8: Actual and optimal registry size (in millions)

Race	Number in registry	Optimal number in registry	Ratio optimal to actual
White	4.44	12.11	2.72
African-Am	0.49	4.73	9.75
Asian-Am	0.43	1.76	4.07
Hispanic	0.59	2.93	4.93

The bone marrow registry is less than twenty years old, and registrants remain eligible on average for about twenty-five years after joining. Therefore, the registry has continued to grow, although the number of new registrants has diminished in recent years.[11] Current registration rates, however, do not appear to be sufficient

[9]We omit estimates for Native Americans. The distribution of HLA types of Native Americans is very similar to that of whites. As a result, the calculation of the optimal number of Native American registrants is volatile.

[10]The figures reported are total registry sizes, not effective registry sizes.

[11]The number of new registrants was 630,000 in 1996 and was approximately 500,000 in 2004. In 2004, approximately 85,000 registrants turned 61 and were removed from the registry.

to achieve the optimal registry size, even in the long run. If registrants remain in the registry for an average of 25 years, then in long run equilibrium, the number of new registrants per year would have to be about four percent of the optimal registry size. Table 3.9 compares current registration rates with steady state optimal rates for each race.

Table 3.9: Current and steady state optimal registrations per year

Race	Current annual new registrants	Annual registrants for optimal steady state	Ratio optimal to current
White	340,000	480,000	1.4
African-Am	30,000	189,000	6.3
Asian-Am	40,000	70,000	1.8
Hispanic	45,000	117,000	2.6

Notes: Current annual new registrants is estimated by the average number of new registrants in 2003 and 2004, as reported in the NMDP Biennial Report (NMDP, 2006a, Table 2.19). Annual registrants for optimal steady state is calculated as four percent of the optimal registry size reported in Table 3.8.

Table 3.10 shows for each race the percentage of the population of eligible age who are enrolled in the current registry and who would be enrolled in an optimal registry. We see that current enrollments are between two and three percent for whites, African-Americans and Asian-Americans and larger for Asian-Americans. An optimal registry would have more than seven percent of all whites, fourteen percent of Hispanics, and nearly twenty-five percent of all African-Americans and Asian-Americans. This table also shows the probability that a patient seeking a transplant will fail to find a match in the current registry and in an optimal registry. Although an optimal registry includes larger fractions of the African-American and Asian-American populations, they would still be less likely to find a match in the optimal registry than would whites. This discrepancy arises because the African-American and Asian-American populations are both smaller and more genetically diverse than the white population. We have calculated that even if all eligible African-Americans

were added to the registry and the number of whites left unchanged, the probability of finding a match in the registry would be lower for an African-American patient than for a white.

Table 3.10: Percent of population in registry and probability of no match

Race	Pct of eligible population in actual registry	Pct of eligible population in optimal registry	Prob no match in actual registry	Prob no match in optimal registry
White	2.7	7.1	.08	.03
African-Am	2.4	23.8	.38	.12
Asian-Am	6.5	26.5	.21	.09
Hispanic	2.9	14.3	.11	.06

Notes: Figures in the first and second columns represent the ratio of U.S. registrations in the NMDP to U.S. population aged 18-61, by race.

3.4.2 Sensitivity to Quantitative Assumptions

Our benefit-cost comparisons are sensitive to two quantitative estimates about which there must be much uncertainty. The first of these is prediction of future medical technology. The expected benefit from an additional registrant depends critically on the number of patients seeking transplants over the next twenty-five years. But how medical innovations will affect the demand for transplants over this period? We have assumed that the number of transplants will remain constant at 2006 levels. This assumption seems conservative. Over the past decade, the number of transplants facilitated by the NMDP has grown steadily, and has increased by almost ten percent per year in the years, 2005-2007. The NMDP attributes much of this growth to the availability of improved techniques that make transplants feasible for more patients (NMDP, 2008). If the number of patients seeking transplants were to continue to grow at ten percent annually, the present value of expected benefits from an additional registrant would be nearly four times as large as our estimates. If this number were to grow at five percent per year, this number would be twice

our estimate. It is also possible that future medical discoveries will reduce the need for stem cell transplants or make it possible for patients to accept transplants from donors who are less closely matched. Benefits from adding new registrants to the current registry would continue to exceed costs so long as the rate of decrease in number of patients is less than thirty percent per year.

Another critical assumption about which there is significant room for disagreement is the value attributed to saving a statistical life. According to Viscusi and Aldy (2003), estimates of the VSL vary over the range from $4-$9 million. We used the middle of this range, $6.5 million. Changing the valuation to the lower or upper end of this range would reduce or increase benefits by about forty percent. Even with a forty percent reduction in the VSL, benefits would exceed costs for adding registrants of all races.

Our estimates treat the population served by the NMDP as a closed system. We do not account for the possibility that patients in the countries served by the NMDP may get transplants from other registries or that residents of other countries may obtain transplants form the NMDP. If the world clearing house for registrants operated entirely smoothly, the number of available registrants would be almost twice the number in the NMDP, but the population served and hence the number of patients seeking transplants would also be much larger. We do not have data on the number of persons receiving or seeking transplants from non-NMDP countries, nor on the racial composition of these populations and registries. We have made crude estimates of expected benefits, assuming that the ratio of the number of registrants to the number of persons seeking transplants in the non-NMDP countries is the same as for the NMDP. With these assumptions, the present value of benefits remains more than three times the present value of costs for all races and more than five times that of costs for those of African ancestry.

3.4.3 Finer Classification

The traditional medical standard for an HLA match focused on whether the alleles of the genes HLA-A, HLA-B, and HLA-DRB1 were similar at a "low" resolution. Recent research has suggested that outcomes are improved by also matching the gene HLA-C and possibly HLA-DQB1 and HLA-DRB1 (Shaw et al., 2007; Lee et al., 2007; Loiseau, Busson, Balere, Dormoy, Bignon and Gagne, 2007). There also appears to be benefit to matching alleles at higher genetic resolution than was done previously (Flomenberg et al., 2004). Our study uses the traditional matching standard. We do so because the best publicly available data on the population distribution of HLA types is compatible with this standard and because most studies that have evaluated the effectiveness of stem cell transplants relative to other treatment options were carried out using the traditional standard. As more rigorous matching standards are applied, the benefits from a larger registry are likely to be greater than those that we have calculated. When more comprehensive data on the population distribution of higher resolution HLA types and on the incremental effectiveness of closer matches become available, it will be useful to recalculate these benefits. In the mean time, our estimates serve as a useful lower bound for the value of an increased registry.

Fève and Florens (2005) consider the possibility of a two-step testing process involving a cheap genetic "pretest." The pretest would be only partially informative about a volunteer's HLA type. Volunteers could then be selected for full testing and introduction into the registry depending on the results of the pretest.[12] A simple implementation of a pretest would be to determine volunteers' national and regional

[12]In a related paper (Fève, Cambon-Thomsen, Eliaou, Raffoux and Florens, 2007), the authors evaluate the optimality of a proposed recruitment plan for the French registry, assuming that that there is no sharing of stem cells across national boundaries, and assuming that the registry can draw donors from an optimized distribution of types.

origins on a finer basis than is currently done. A recent report by the NMDP (NMDP, 2006b) states that "preliminary findings indicate that HLA distribution may vary considerably by region and reinforces the value of focusing our recruitment efforts on minority racial and ethnic communities." For ideological reasons, the major European bone marrow registries do not collect data on race. Nevertheless, each country supplies separate statistics on registration by its own nationals and the distribution of HLA phenotypes within European countries is known (BMDW, 2006).

Although HLA distributions differ between countries, patients needing transplants are quite likely to find their only match in the registry of another country. In 2004, approximately thirty five percent of all stem cell donations were from donors in one country to recipients in another (WMDA, 2004). For small countries, international transfers are especially important. Approximately ninety percent of the donations received by Swiss patients come from outside Switzerland and ninety percent of the donations made by Swiss residents are received by non-Swiss (Morell, Kern, Salvisberg and Wenger, 1999).

The methods that we have developed for dealing with differing HLA type distributions across races are well-suited to the study of regional and national differences. Our benefit-cost estimates include the benefits of adding a registrant of any race to persons of any other race. This method, as applied to national registries, can be used to estimate the probability that a new registrant in one country will be the only match for a patient in another. Thus we can study the effects of national registry sizes on the export and import of stem cells between nations and regions. This in turn permits an analysis of the incentive problems that arise in the interaction between national bone marrow registries.

3.5 What Motivates Potential Donors?

Those who join the bone marrow registry are told that if called upon to donate, they will bear risk, inconvenience and discomfort, they will receive no monetary reward, and the beneficiary will almost certainly be a stranger. Yet millions of people have voluntarily joined bone marrow registries. Why have they done so?

The decision faced by stem cell donors is qualitatively different from that in standard Nash equilibrium models of private provision of public goods (see Bergstrom, Blume and Varian (1986)). In these models, potential contributors care only about the sum of individual contributions. Thus one person's donation is a perfect substitute for that of another. The biology of immune systems ensures that stem cell contributions by two people of different HLA types can not be substituted for each other.[13] For someone who is the only representative of an HLA type in the registry, a donation will critically determine the survival of a patient of this type. However if there are others of the same type in the registry, one's own donation is not essential, since another equally suitable donor is available.

The number of patients needing transplants is small relative to the number of persons in the registry and hence the probability that a registrant will ever be asked to donate is small. The lifetime probability for a white person who remains in the registry for twenty five years is only about one percent. For other races this probability is even lower. If the bone marrow registry contains more than one HLA match for a patient, only one donor will be needed. If there is no one else of a person's HLA type in the registry, we define a registrant as *pivotal*. In Appendix A, we show how to calculate the conditional probability that a donor of specified race will be pivotal.

[13]Although the standard public goods model does not apply well to donation of stem cells, it does apply to financial support of costs of operating the bone marrow registry.

Table 3.11: Probabilities of being asked and of being pivotal if asked

	Current Registry		Optimal Registry	
	P(Asked|Reg)	P(Pivotal|Asked)	P(Asked|Reg)	P(Pivotal|Asked)
Race	π	h	π	h
White	.013	.08	.004	.03
African-Am	.005	.78	.001	.19
Asian-Am	.006	.30	.002	.11
Hispanic	.008	.22	.003	.08

For each race, Table 3.11 reports the probability π that a registrant will be asked to donate and the probability h that a registrant is pivotal, conditional on being asked to donate. We see that h is about eight percent for a white registrant, thirty percent for an Asian-American and almost eighty percent for an African-American. If the registry size were increased to optimal levels, the conditional probabilities of being pivotal would be much lower for members of all races but would remain larger for other races than for whites.

Blood donors and kidney donors also face free-rider problems, though these differ from the free-rider problem that arises with stem cell donation. While blood donation is much less traumatic than stem cell donation, blood donors encounter a more standard free-rider problem. There are millions of other potential donors whose blood is a perfect substitute for one's own. The blood type with the fewest compatible donors (O negative) can accept transfusions from about seven percent of the population. Kidney donations require the same compatibility as blood donations, with a few additional complications, but the cost of donating a kidney is much greater than that of donating blood.[14] The waiting list for kidney transplants

[14]People are much more likely to be willing to sacrifice a kidney for a loved one than for a stranger. Roth, Sönmez and Ünver (2007) devised exchange networks to facilitate multilateral kidney trades that allow people to donate kidneys for the benefit of specific patients with whom they are not themselves donor-compatible.

is currently more than three times as large as the number of transplants that are annually performed. Therefore, kidney donors, unlike stem cell or blood donors, can be certain that their donation will increase the number of transplants performed and not simply displace the contribution of another suitable donor.

3.5.1 Meditations of a Consequentialist Altruist

At present, those who join the registry can not be expected to know the probability h of being pivotal. Perhaps many donors would not be interested in this number if they were told. Nevertheless, it is likely that more people would be willing to join the registry if the likelihood that a donor is pivotal in saving a life is higher. It is therefore useful to consider the decision problem faced by a potential donor who is aware of the relevant probabilities.

We will consider a rational potential donor whose choices are consistent with a von Neumann Morgenstern utility function. Let us assume that this person is a "consequentialist altruist," who values actions only by their results.[15] Three distinct possible states of the world are of concern to the decision-maker. One possibility is that she is never asked to donate. A second is that she is asked to donate and is the only person of her type in the registry. The third possibility is that she is asked to donate and the registry contains at least one other person of her type. Let π_i be the probability i will be asked to donate if registered, and let h_i be i's perceived probability that if asked to donate, she is the only registrant of her type.[16]

[15]The *Stanford Encyclopedia of Philosophy* (Zalta, 2006) defines consequentialism as "the view that normative properties depend only on consequences."

[16]The NMDP does not reveal to potential donors whether they are the only person of their HLA type in the registry. Although we have estimated the probability h for persons of each race, no such estimates have been publicly available, and perceptions about this probability are likely to vary widely.

Assume that signing up to join the registry is costless. Then a consequentialist altruist will assign the same utility U_{0i} to joining the registry and not being asked to donate as to not joining the registry. Suppose that i assigns a utility cost C_i to the risk, pain, and inconvenience of making a donation and that making a pivotal donation adds B_i to i's utility, where $B_i > C_i$. Then i attaches a utility of $U_{0i} + B_i - C_i > U_{0i}$ to making a pivotal donation. If i makes a donation when there is at least one other willing registrant of her type, then i's participation has no effect on the patient's survival probability, but simply saves another registrant the cost of donating. Let V_i be the utility that i attaches to saving someone else the trouble of donating and suppose that $V_i < C_i$. Then in the event that there is another compatible donor in the registry, i would prefer not to donate since $U_{0i} + V_i - C_i < U_{0i}$.

The NMDP asks registrants to promise that they are "willing to donate to any person in need," though there is no contractual obligation to do so. A consequentialist altruist would join only if she intended to donate if asked. The expected utility of i for joining the registry is

$$(1 - \pi_i)U_{0i} + \pi_i \left(h_i(U_{0i} + B_i - C_i) + (1 - h_i)(U_{0i} + V_i - C_i)\right), \tag{3.5}$$

and i will prefer to join the registry if and only if the utility in Expression 3.5 exceeds U_{0i}. This is the case if and only if

$$h_i(B_i - C_i) + (1 - h_i)(V_i - C_i) > 0. \tag{3.6}$$

Let us simplify by assuming that $V_i = 0$. Then Condition 3.6 becomes

$$\frac{B_i}{C_i} > \frac{1}{h_i}. \tag{3.7}$$

As shown in Table 3.11, we estimate that the probability h of being pivotal is .08 for white Americans. If this were the probability perceived by all potential donors, then Condition 3.7 tells us that those who join the registry must have benefit-cost ratios $B_i/C_i > 12.5$. According to Table 3.10, about 2.7 percent of the eligible white population is enrolled in the registry. This means that the current registry of white Americans can be supported by motives of consequentialist altruism if 2.7 percent of the population have benefit-cost ratios exceeding 12.5 for making a pivotal stem cell donation to a stranger. An African-American who is asked to donate is much more likely to be pivotal than a white. For African-Americans, the current African-American enrollment could be maintained if 2.4 percent of the population have personal benefit-cost ratios exceeding 1.25. For Asian-Americans, maintaining the current registry would require 6.5 percent of the population to have benefit-cost ratios of at least 3.3, and for Hispanics, this would require 2.9 percent to have benefit-cost ratios of at least 5.

An optimal registry of well-informed consequentialist altruists would require much more intense and widespread altruism than is needed to maintain the current registry. According to Table 3.8, an optimal registry would have about twice as many whites, about four times as many Hispanics and Asian-Americans, and almost ten times as many African-Americans as the current registry. Not only would the registry have to be much larger, but we see from Table 3.11 that with the optimal registry, each person's probability of being pivotal would be less than half of what it is in the current registry. These considerations suggest that to achieve an optimal registry with a population of consequentialist altruists, it may be necessary to offer additional inducements for potential registrants.

3.5.2 More Complex Motivations

Economists, whose usual fare is the study of rational, selfish agents, are less experienced with predicting behavior of those who act with generosity. Some useful insights can be captured by upgrading the sensibilities of our familiar workhorse, *homo economicus*, to those of a consequentialist altruist. But this modest upgrade is unlikely to capture the full variety of motives that underlie much of altruistic behavior.

In recent years, economists have developed models and experiments that explore alternative motives for altruistic behavior. Bergstrom et al. (1986) and Andreoni (1989) proposed that people feel a "warm glow" that depends on the size of their own gift, independent of the ultimate stock of public goods. Duncan (2004) introduced the notion of "impact philanthropy," where people take pleasure in the difference made by their own actions. Benabou and Tirole (2006) suggested that "people perform good deeds and refrain from selfish ones because of social pressure and norms that attach honor to the former and shame to the latter." Benabou and Tirole show that to determine motives from actions requires a somewhat subtle signal extraction model where good actions may or may not impress others. As Ellingsen and Johannesson (2007) put it, "some people are generous, but everyone wants to appear generous." Benabou and Tirole also suggest that people perform prosocial acts in order to improve their own self-image, using concrete actions to signal to their future selves the kind of person that they really are.

A series of papers (Dana, Weber and Kuang, 2007; Dana, Cain and Dawes, 2006; Broberg, Ellingson and Johannesson, 2007; Lazear, Malmendier and Weber, 2006) indicates that while people often act generously when the consequences of their actions are clearly spelled out, they are adept at finding "moral wiggle room." These papers report evidence from laboratory experiments in which people who would behave generously with full information are willing to conceal information

from themselves or from potential recipients so that they can behave selfishly without making their motives transparent. This is the case even though the potential recipient never learns who has behaved selfishly or unselfishly toward him.

Titmuss (1970) argued that paying people for blood "donations" might reduce the supply of blood from those who would otherwise contribute for free. Many donors are motivated either by social acclaim or by self-satisfaction. Benabou and Tirole (2006) suggest that if blood donors are paid, the value of blood donation as a signal of generosity will be weakened, possibly producing the "Titmuss effect." In a field experiment conducted in Gothenberg, Sweden, Mellström and Johannesson (2005) gave subjects an opportunity to donate blood. In a control treatment they offered no monetary payment. In a second treatment they offered to pay subjects about $7 for contributing blood. In a third treatment they offered potential contributors a money payment but allowed them to specify that the payment be given to a charity. For men, they found no significant difference among the treatments. But when women were offered a payment in the second treatment, only about half as many were willing to contribute as when they were not paid. In the third treatment, with the option to give the payment to charity, the proportion of contributors was restored to that with no payment.

A desire to signal altruism may be a useful motivator for blood donations, which occur as soon as one agrees to donate. This motivation serves the bone marrow registry less well. A bone marrow registrant could signal altruism by joining the registry, while realizing that the probability is small that he will be asked to donate. Since the registry cannot make binding contracts, one could gain acclaim by registering, while intending to refuse to donate if called upon.

Motives and ethical views that guide generous actions are likely to differ widely. There is likely to be wide variation in perceptions of the cost and danger of stem cell donations. The current registry contains less than four percent of the eligible

population, while an optimal registry would contain almost ten percent. Much as crime-prevention policies must focus on the actions of those who believe they are least likely to be caught and who are least troubled by conscience, membership in the bone marrow registry is likely to come from those who most strongly believe that their gifts will be pivotal and who have the strongest altruistic feelings.

3.5.3 An Enriched Model

Our model of consequentialist altruists assigned the same utility U_{0i} to joining the registry and not being asked to donate as to not joining the registry at all. If there is no social acclaim and no payment for joining the registry, people would join only if they hope to be called on to donate. Those who register would certainly intend to donate if asked. But if joining the registry is rewarded, either with money or status, some may choose to register although they hope never to be asked to donate. Since registrants are under no contractual obligation to donate if asked, some may register to gain social acclaim (or money if registrants are paid), while intending to decline if asked to donate.[17] Others are likely to regard it as shameful not to keep their promise and would donate even if they regretted having joined the registry.

We employ a simple additive utility model to keep track of these interacting effects. Let x_i be the net time-and-money cost of joining the registry. (If there are payments for joining the registry, x_i could be negative.) Let $a_i(x_i)$ represent i's utility valuation of the social acclaim for joining. The social acclaim that one receives for joining the registry may be greater if joining the registry is more expensive and

[17] According to Kollman et al. (2004), approximately 30 percent of white registrants, 60 percent of African-American registrants, and 50 percent of Asian-American and Hispanic registrants who are asked to donate either are not able to or do not agree to make a donation. Not all of these are direct refusals. Some are unable to donate for medical reasons and some cannot be found at the address listed with the registry.

may be reduced if one is paid to join. Person i receives a net utility increment of $a_i(x_i) - x_i$ from joining the registry, whether or not i is asked to donate.

If the net gain $a_i(x_i) - x_i$ from registering is positive, i might join with the intention to decline if asked to donate. Refusing to donate after promising to do so may entail shame, which we quantify as S_i. Then if called on to donate, i will donate only if

$$S_i > C_i - h_i B_i - (1 - h_i)V_i. \tag{3.8}$$

Taking account of the option to refuse when asked to donate, a necessary and sufficient condition for i to join the registry is

$$a_i(x_i) - x_i > \pi_i \min\{S_i, C_i - h_i B_i - (1 - h_i)V_i\}. \tag{3.9}$$

Expression 3.9 tells us that i compares the net direct benefit from joining the registry with the expected cost of being asked to donate if registered. If asked to donate, i will do so only if Condition 3.8 is satisfied.

3.5.4 Should registrants or donors be paid?

We have argued that the current bone marrow registry falls short of optimal size for all races. When resources are undersupplied, it is natural for economists to consider using the price mechanism to remedy the shortage. Roth (2007) observed that many people view the sale of human organs and tissue with repugnance and, in response, governments frequently outlaw such sales. Becker and Elías (2007) argued that such prejudices are not well founded and that a strong humanitarian case can be made for using markets to increase the supply of organs and tissue. Roth notes that current distinctions often seem arbitrary. In the U.S. it is illegal to buy and sell human kidneys, livers, and other organs, although it is legal to pay financial expenses that the donor incurs in the process. In contrast, the sale of human eggs

and sperm is permitted, as are "womb-rental payments" to surrogate mothers. Sale of blood for transfusions is illegal, but sale of blood for plasma extraction is legal and commonly practiced.

Not only are bone marrow registrants and donors currently unpaid; joining the registry entails significant costs in time and money. The internet has reduced the time cost of joining. New registrants no longer need to travel to a collection center. An eligible donor can simply go to the NMDP's web site, complete an online form, and order a tissue-typing kit. When the kit arrives, the registrant takes a swab of his or her cheek cells, and mails the swab to the registry for testing. Although the time costs have fallen, the money cost of registering has increased. Until recently, potential donors could join the bone marrow registry without paying a fee. This is no longer the case. Those who join the registry by the internet must pay a fee of $52 when they order the tissue-typing kit.[18] It is not surprising that the NMDP must charge fees to recover its costs. The major source of government funding for the NMDP is the US Department of Health and Social Services. Funds received from this source decreased from $25 million in 2005 and 2006 to $23 million in 2007. Given that there are currently too few registrants of all races, these fees seem an unfortunate impediment to recruitment.[19]

Would greater recruitment efforts and free registration be sufficient to attract a registry of optimal size? Comparison of registration rates among prosperous industrialized countries suggests that the number of voluntary registrations may be

[18]The registry web site states that: "For volunteers who join in person, sometimes all or part of the tissue-typing costs may be covered by a patient family, community group, or corporation." The US Department of Defense pays all costs for military personnel who join at a designated collection center.

[19]If fees were eliminated, new registrants could be encouraged to make voluntary cash donations designated to recruit more registrants.

quite sensitive to recruitment effort. The United States registry currently includes less than three percent of the white population aged 18-61 while an optimal registry would include about seven percent. Two countries, Israel with ten percent, and Germany with seven percent, register larger proportions of the eligible population. In the UK, approximately two percent, in Canada, Denmark, and Norway approximately one percent, and in France, the Netherlands, and Switzerland less than one-half of one percent of the eligible population is registered.[20] If a voluntary bone marrow registry in the United States could achieve the registration rates of Germany, the number of white Americans registered would be reasonably close to optimal.

Attracting an optimal number of Asian-American registrants is a more formidable task. About six and a half percent of Asian-Americans of eligible age are currently registered. An optimal registry would require registration of approximately twenty-five percent. The countries of Asia are a potential alternative source of stem cell donors for Asian-Americans. The largest bone marrow registries in Asia are in Japan, which has about three hundred thousand registrants, and Taiwan, which has about two hundred seventy thousand. This compares with four hundred thirty thousand Asian-Americans in the U.S. registry. Mainland China currently has only six thousand registrants and India has only one thousand. Expansion of the Asian registries and international sharing agreements would greatly improve the prospects of Asian-Americans seeking stem-cell transplants.

The current registry includes two and a half percent of African-Americans of eligible ages, while an optimal registry would contain nearly twenty-five percent. It is difficult to see how the registry can attract sufficient numbers of African-American registrants without providing much stronger incentives than are currently

[20]The size of national registries is published online by Bone Marrow Donors Worldwide (BMDW, 2006).

available. African-Americans seeking a stem cell donor have little chance of finding one in Africa. In Africa, the only country with a registry is South Africa, which has registered about sixty thousand persons, most of whom are white.

Paying new registrants may attract some who join for the money and expect to refuse if asked to donate. A more effective system of rewards would make payments only to those who actually make a donation. As is seen from Equation 3.9, payments to donors increase not only the incentive to register, but also the incentive for registrants to donate if asked. Thus payments to donors could be expected to increase the fraction of effective registrants as well as the number of registrants.

It has been argued that people wish to signal their altruism to others (or perhaps to themselves), that paying contributors of organs or tissue reduces the effect of a contribution as a signal, and hence that payments to contributors may reduce contributions from those who were willing to do it for free. The blood donation experiments of Mellström and Johannesson (2005) suggest that payments sometimes deter donations, but they also suggest a simple way to overcome this effect. When Mellström and Johannesson offered subjects the opportunity to donate their payments to charity, the deterrent effect of payments disappeared. This suggests that if stem cell donors are paid, they should be allowed an opportunity to publicly waive any payment for themselves, with the understanding that the registry would use the money saved to recruit more donors.

Paying donors raises another interesting question. Our benefit-cost analysis did not count the pain and inconvenience of donors as costs. This seems appropriate for unpaid volunteers. The fact that donors choose to donate without pay indicates that the pleasure they feel from contributing outweighs the costs. For the marginal donor, these unmeasured benefits and costs are equal. If donors must be paid to achieve an adequate registry, then the costs to marginal donors must exceed the benefits by the amount of payments. Thus marginal costs of adding registrants would have to

include expected payments made to these registrants if they are asked to donate. An optimal U.S. registry requires much larger proportions of the population for minority groups than for whites. If donor payments are used to achieve a nearly optimal registry, payment rates would have to be higher for African-Americans than for whites. Higher payments to African-American donors imply a higher marginal cost of adding African-American donors than of adding white donors. A more refined calculation of optimal registry sizes would need to take this into account.

3.6 Conclusion

Our benefit-cost analysis indicates that for every racial group, marginal benefits from an additional registrant exceed marginal costs, and that the benefit-cost ratio is highest for African-Americans. The NMDP currently focuses on recruitment of minority donors and has allowed the annual number of new white registrants to decline. Although a focus on African-American and minority registration appears to be justified by the relative benefit-cost ratios, our calculations indicate that the current registry has fewer people of all races than is optimal.

We estimated optimal registry sizes for each race. An optimal registry would have almost ten times as many African-Americans, between four and five times as many Asian-Americans and Hispanics, and three times as many whites as the current registry. Even with an optimal registry, African-Americans would be less likely to find a match than persons of other races. This is a consequence of the relatively small size and great genetic diversity of the African-American population.

The bone marrow registry confronts us with an interesting variant of the standard free-rider problem. Donations by people of different HLA types are not substitutes. Each potential donor will, with some probability, be the only person who can save the life of one particular stranger. As the size of the registry increases, it becomes

less likely that a new registrant will be the only potential donor of her type. In an optimal registry, these probabilities would be less than half as large as in the current registry.

The bone marrow registry has attracted almost three percent of the eligible US population. Despite the impressive generosity displayed by these volunteers, it would be difficult to achieve an optimal registry in the U.S. solely by increased recruitment effort. This difficulty is compounded by the fact that as the registry approaches optimal size, the free rider problem becomes more severe, since new registrants are less likely to be unique in the registry.

Some of the current shortfall can be made up by increases in the size of foreign registries, particularly in wealthy countries where stem cell transplants are commonly practiced. For African-Americans however, it seems highly unlikely that an optimal registry can be achieved by voluntary means or by expansion of international registries. We have argued that if money payments are used to increase the size of the registry, it would be more effective to pay only those who are called upon and consent to contribute rather than to pay all new registrants.

Appendix A

Proofs and Derivations

A.1 Net social benefit is a strictly concave function

Let $R = (R_1 \dots R_k)$ be the vector of numbers of effective registrants of each of k races. Let S_x be the number of persons of race x who seek bone marrow transplants and let p_i^x be the probability that a person of race x is of HLA type i. The expected number of persons of HLA type i who seek bone marrow transplants is

$$N_i = \sum_{x=1}^{k} S_x p_i^x. \tag{A-1}$$

The probability that a person of HLA type i has a match in the registry is $1 - p_i^0(R)$, where $p_i^0(R)$ is the probability given in Equation 3.2 that a registrant of type i is the only registrant of this type. The expected total number of bone marrow transplants administered is

$$T(R) = \sum_i N_i \left(1 - p_i^0(R)\right). \tag{A-2}$$

We will show that $T(\cdot)$ is a concave function. We first show that the functions $p_i^0(\cdot)$ are concave. The second order partial derivative of $p_i^0(\cdot)$ with respect to R_x

and R_y is

$$\frac{\partial p_i^0(R)}{\partial R_x \partial R_y} = \ln(1-p_i^x)\ln(1-p_i^y)p_i^0(R). \tag{A-3}$$

Therefore the Hessian matrix of the function $p_i^0(R)$ can be written as

$$H_i(R) = p_i^0(R)x^T x \tag{A-4}$$

where x_i is the k-vector $(\ln(1-p_i^1, \ldots, \ln(1-p_i^k))$. Since $x \neq 0$, it must be that the matrix $x^T x$ is positive definite, and since $p_i^0(R) > 0$, it follows that $H_i(R)$ is positive definite. The function $p_i^0(\cdot)$ is therefore a convex function and hence $1 - p_i^0(\cdot)$ is a concave function. Then $T(R) = \sum_i N_i\,(1 - p_i^0(R))$ is a positively weighted linear combination of concave functions and hence must be concave.

Let s be the probability that a bone marrow transplant will save the life of a patient, V the value of a statistical life and m the hospital costs of performing a transplant. Assume that $sV > m$. Let c_x be the cost of registering and typing enough registrants of race x to add one effective registrant, and let $c(R) = \sum_x c_x R_x$. The net social benefit of the bone marrow registry is then $NSB(R) = (sV - m)T(R) - c(R)$. Since $T(R)$ is concave and $c(R)$ is linear in R, $NSB(R)$ must be a concave function of the vector R.

A.2 Probability of being pivotal if asked to donate

Let R_x and S_x be the number of registrants and the number of transplant seekers of race x and let R and S be the corresponding vectors of registrants and transplant seekers. Let $h_x(R, S)$ be the conditional probability that a registrant of race x is the only person of his type in the registry, given that he is asked to make a donation.

Define $\pi_x(R, S)$ as the annual probability that a registrant of race x will be

chosen to make a donation and $\varphi_x^0(R,S)$ to be the probability that a registrant of race x is chosen to donate and is the only registrant of his HLA type in the registry. Then by Bayes' law,

$$h_x(R,S) = \frac{\varphi_x^0(R,S)}{\pi_x(R,S)}. \tag{A-5}$$

We estimate $\varphi_x^0(R,S)$ and $\pi_x(R,S)$ as follows. Let

$$n_i(S) = 1 - \prod_x (1 - p_i^x)^{S_x} \tag{A-6}$$

be the probability that there is at least one patient of type i seeking a donation. The probability that a donor of type i is pivotal in saving a life is

$$p_i^0(R) n_i(S) \tag{A-7}$$

where $p_i^0(R)$ is the probability given in Equation 3.2 that a registrant of type i is the only registrant of this type. The probability that a registrant of race x is pivotal in saving a life is now

$$\varphi_x^0(R,S) = \sum_i p_i^x p_i^0(R) n_i(S). \tag{A-8}$$

Let

$$m_i(S) = \sum_x p_i^x S_x, \tag{A-9}$$

which is the expected number of type i persons seeking a transplant. The fraction of type i registrants that are of race x is

$$r_i^x(R) = \frac{p_i^x R_x}{\sum_y p_i^y R_y}. \tag{A-10}$$

The expected number of registrants of race x who are asked to donate is then

$$\sum_i m_i(S) r_i^x(R). \tag{A-11}$$

The probability that a registrant of race x is asked to donate is therefore

$$\pi_x(R, S) = \frac{\sum_i m_i(S) r_i^x(R)}{R_x}. \tag{A-12}$$

We can now use equations A-5, A-8, and A-12 to calculate $h_x(R, S)$.

Appendix B

Gain in Survival Probability from a Transplant

We estimate the expected gain in survival probability from receiving a stem cell transplant rather than the next best treatment. Transplants are used to treat many conditions and data varies across diseases in availability, quality, and generality. Using available studies, we estimate the expected number of lives saved by an additional transplant for each of the most common conditions. We then calculate an average net gain in long term survival probability, weighted by the frequency of ailments. This figure, which is 0.21, is our estimate of the expected number of lives saved by an additional transplant facilitated by the bone marrow registry.

More than twenty thousand patients with various conditions have been treated by bone marrow transplantation using NMDP donors between 1987 and 2004. The numbers by disease as reported by the NMDP (2006a), are listed in Table B.1.

Table B.1: Net Survival Gains From Transplants, by Disease

Disease	Number of Transplants	Fraction of Transplants	Net Survival Gain
Acute myelogenous leukemia	4,800	0.24	0.16
Chronic myelogenous leukemia	4,686	0.23	0.15
Acute lymphoblastic leukemia	3,815	0.19	0.42
Myelodysplastic syndromes	2,110	0.10	0.25
Non-Hodgkin's lymphomas	1,344	0.07	0.00
Severe aplastic anemia	733	0.04	0.20
Other	2,886	0.14	0.21

B.1 Disease-by-disease review

B.1.1 Acute Myelogenous Leukemia

An examination of long-term survival for patients with acute myelogenous leukemia (AML) observed 5-year survival rates of 45% for bone marrow transplantation and 29% for an alternative chemotherapeutic approach (Bennett et al., 1997). We therefore use a value of 0.16 as the change in survival probability attributable to bone marrow transplantation for patients with AML. This value is consistent with those found in other studies (e.g. Zittoun et al. (1995)).

B.1.2 Chronic Myelogenous Leukemia

The bone marrow registry notes that use of bone marrow transplantation to treat chronic myelogenous leukemia (CML) decreased after the 2001 introduction of the drug imatinib mesylate (NMDP, 2006a). A more recent review article (Savona and Talpaz, 2006) concludes that while imatinib mesylate improves outcomes, it is not curative for CML and there remains a role for bone marrow transplantation. We therefore include CML in our calculation. A textbook discussion of treatment for CML (Garcia-Manero, Talpaz, Faderi and Kantarjian, 2003) refers to four studies comparing bone marrow transplantation with chemotherapy. We use the arithmetic

mean survival advantage of these studies, 0.15, as the change in survival probability attributable to bone marrow transplantation for patients with CML.

B.1.3 Acute Lymphoblastic Leukemia

A recent study found 68% 15-year survival for patients with acute lymphoblastic leukemia (ALL) who received a bone marrow transplant from an unrelated donor (Chim, Lie, Liang, Au and Kwong, 2007) . Two studies that assess the effectiveness of chemotherapy in treating ALL found long term survival rates of 20% and 32% (Sebban et al., 1994; Zhang et al., 1995). We take the arithmetic mean of these two studies to compute a change in survival probability attributable to bone marrow transplantation of 0.42.

B.1.4 Myelodysplastic Syndromes

There is no curative chemotherapy available for myelodysplastic syndromes and ten year survival is on the order of 2% (Gilliland and Dunbar, 2003). Among patients treated with bone marrow transplants facilitated by the national registry, 10 year survival is approximately 27% (NMDP, 2006a). We attribute a change in survival probability of 0.25 to bone marrow transplantation for myelodysplastic syndrome. This value is consistent with at least one study directly assessing the impact of bone marrow transplantation in patients with myelodysplastic syndrome (Anderson et al., 1996).

B.1.5 Non-Hodgkin's Lymphomas

According to a recent review article (Peggs, Mackinnon and Linch, 2004) on the subject, "the role of [bone marrow] transplantation in the management of lymphomas remains uncertain." A recent textbook describes the use of bone marrow transplan-

tation in Non-Hodgkin's Lymphoma as "controversial" and concludes that "only a fraction of the most advanced patients... may be salvaged by the use of [bone marrow transplantation]" (Gilliland and Dunbar, 2006). Because years of research have failed to elucidate the benefit of bone marrow transplantation for patients with Non-Hodgkins Lymphoma, we assume here that there is currently no associated gain in survival.

B.1.6 Aplastic Anemia

A recent textbook presents a summary of 13 studies comparing bone marrow transplantation to immunosuppressive therapy, a primary alternative, for the treatment of aplastic anemia (Young and Shimamura, 2003). Because the studies vary in the age of participants, we separately computed average survival advantage (weighted by study size) attributable to bone marrow transplantation for adults and children. We then weight the results by the number of adults and children who have been transplanted from donors through the registry to compute an overall average change in survival probability of 0.20.

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