PHYSICIAN SOCIAL NETWORKS AND GEOGRAPHICAL VARIATION IN MEDICAL CARE *

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Abstract

This paper shows how social influences on individual decisions help resolve a public health puzzle—the inordinate effect of geography on treatment. To explain geographical variations, we construct a model in which physician choices are subject to social influence. Small regional differences in the patient population mix give rise to divergent treatment patterns—the treatment a patient receives depends on where she lives. The empirical analysis uses data from Florida on coronary patients and their doctors. The data reveal significant geographic variation in the treatment rates. We find empirical support for the claim that local social influences determine treatment choice.

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I Introduction

This paper deals with a general question and a specific puzzle. The general question is related to the effect of the social environment on individual decisions. Are medical decisions influenced by social and cultural forces and, if they are, what is the cost to society of departures from strict scientific standards? The specific puzzle in question is the well–documented effect of geography on treatment. The treatment that a patient receives depends, beyond reasonable limits, on where she lives. We use the idea that decisions are subject to social influence to provide an explanation of this public health puzzle. Conversely, the rich detail with which medical decisions are documented presents us with a unique opportunity to deepen our understanding of the effects of the social environment on individual choices. For, if medical decisions are influenced by social and cultural forces, why should other kinds of decisions be immune?

The extent of geographical variation in the United States is quite striking. Consider the case of two procedures used to treat heart conditions. In a comparison of hospital referral regions across the country, rates of Coronary Artery Bypass Grafting among Medicare enrollees varied by a factor of more than 3.5, while the rates of Coronary Angioplasty ranged from 2.5 to 16.9 per 1,000 enrollees (The Dartmouth Atlas of Health Care, 1999). Such patterns occur for a number of other procedures as well, with uniformity of treatment styles within regions, but significant differences across regions. The study of geographical variations has a long history, going back at least to Glover's pioneering study of tonsillectomy in Britain (Glover, 1938). In the United States, Wennberg and his colleagues (e.g. Wennberg and Gittelsohn, 1973) have documented the phenomenon comprehensively over a number of years. Geographical variations appear to be both extensive and persistent, even after controlling for demographic and illness conditions. A number of explanations have been proposed but, for reasons discussed below, the puzzle remains largely unresolved.

While attempts have been made to explain the puzzle away based on variations in patient characteristics and economic incentives, such explanations have not stood up to rigorous scrutiny (Phelps and Mooney 1993). In our own study, the data on coronary care in Florida is extensive, enabling us to control for such factors. It is equally unlikely that treatment variations reflect gross error or physician ignorance. Practice guidelines and quality indicators are widely disseminated and easily available, accessible even on the Internet. Nor do regional variations appear to be an artifact of physician self-selection, whereby doctors migrate to hospitals or locations based on their practice style. Previous studies have attempted to quantify a physician's "practice style" (roughly, her preference for intensity of treatment). The evidence points towards great variability of styles within regions (Phelps, 2000). With such stylized facts in mind, we construct a model in which equilibrium choices display geographical variation and practice norms emerge from the dynamic interaction of physicians within social networks.

The key ingredient of our model is local social interaction among doctors. In this we are guided by the recent work of Becker and Murphy (2001), Brock and Durlauf (2001), Glaeser and Scheinkman (2002), Young (1998) and others. We consider two sources of social influence on medical decisions—local increasing returns and pure conformity effects. The former arise when knowledge spillovers are present. The correct diagnosis and treatment for a patient can be complicated, and there may be an opportunity to take advantage of the experience of others. The success rate of a procedure is then likely to depend on the extent to which close colleagues use the same procedure and it could be rational for a physician to choose a procedure that is used with greater frequency within her local social sphere. Alternatively, a physician may tend to mimic the choices of her colleagues even in the absence of increasing returns. This could arise from a preference for conformity (Bernheim, 1994), or because the prevailing legal standard in malpractice cases is believed to be conformity to local norms. Conformity could also result if physicians give greater weight to the direct experience of colleagues than to general practice guidelines. Either type of social influence can explain the emergence of local uniformity in procedure choice. However, as we discuss in some detail in the paper, the welfare implications of the two forms of influence are different.

To explain variation in treatment norms *across* regions we introduce (possibly small) demographic differences. It is often the case with medical procedures that their appropriate use depends upon the characteristics of patients. We find this in procedure guidelines, and also in an analysis of the data. For instance, bypass surgery is used more sparingly in the treatment of older patients. Our main theoretical result asserts that the mix of patients in a region can influence the practice norm that emerges. As a consequence, the treatment a patient receives depends on where she is treated.

We test our model with data from Florida patient discharge records, focusing on patients over 35 with primary diagnoses of coronary atherosclerosis and acute myocardial infarction (AMI, or heart attack). In total we draw on a large sample (over 80,000) of inpatient stays during the period between 1993 and 2000. Each record reports the patient's age, race, sex, principal and secondary diagnoses, treatments received, the attending physician, the hospital name and county location, and the length of stay. We also employ county-level demographic information from the 1990 and 2000 Census and other public sources. The combined data provide a rich picture of the sources of variation in coronary treatments, and in particular allow us to test for local interactions among physician choices.

Empirically we assume that physicians interact within social networks determined by where they work. Specifically, we say physician P belongs to physician Q's *social network* if there is some hospital at which they both have admitting privileges. We find direct evidence of interactions within such networks: the likelihood of a given procedure's being chosen by some doctor increases in its recent rate of use by physicians in her social network, even when controlling for possible endogeneity in the network treatment rates. Such endogeneity might be expected, for example, if there are unobserved similarities among either the patients or the doctors in the same social network, or because of the shared local economic environment. To identify the network interaction effects we adopt an instrumental variables technique similar to that of Goolsbee and Klenow (2002) in their study of network externalities in computer adoption.

We also find uniformity of treatment within regions exceeding what could be explained on the basis of patient similarities alone, and we find that similar patients may be treated differently in different places. A subtle implication of our geographical variation result is that the likelihood of a procedure being used on a patient depends on the population mix. For instance, if bypass surgery is (globally) less likely to be used on older patients then it will be used less often on younger patients in regions where the population of old patients is larger. This appears to be the case. The evidence of discrepancies in the quality of care across regions is mixed. We find that an indirect measure of the quality of care–giving patients risky surgery at low-volume hospitals–may be substantially affected by the network's treatment tendencies. At the same time, however, treatment variations across regions are not systematically related to differences in the length of hospital stay.

The paper draws upon several different lines of research. The theoretical roots extend back as far as Schelling's (1971) work on segregation, which showed how interdependent preferences can produce much greater racial uniformity within neighborhoods than any individual would prefer. Our paper is more directly related to recent work on evolutionary games and local interaction models, such as Ellison (1993), Ellison and Fudenberg (1993), Kandori, Mailath and Rob (1993), Morris (2000), Young (1993), Young (1996) and, most closely, Young and Burke (2001). The latter paper treats contracting norms in sharecropping and develops an explanation for the prevalence of conventional arrangements that seem not to vary sufficiently with the relevant fundamentals. Incorporating preferences for conformity and local influence, the stable contracting pattern exhibits local uniformity together with global diversity.[1]

In the health economics literature, Phelps (2000) provides an extensive survey of empirical and theoretical studies of regional variations, including his own explanation (Phelps and Mooney 1993). In the latter, physicians update their beliefs about proper treatment rules by observing local treatment patterns. Local norms, once in place, tend to persist because the learning rule pulls beliefs in the direction of dominant practice. The story in this model is not inconsistent with ours, but there are significant differences. In particular, our model can explain the *emergence* of local treatment norms in addition to their persistence. We allow for many forms of social influence to investigate whether welfare losses are an inevitable consequence of treatment variations.

The medical literature is extensive, even after we limit attention to cardiac care. In addition to the works cited above, the phenomenon is also described in *The Dartmouth Atlas of Cardiovascular Health Care* (1999), in O'Connor *et. al.* (1999), and Pilote *et. al.* (1995).

The rest of the paper is organized as follows. In section II, we describe the theoretical model and results. The efficiency of the outcome is examined, and we establish results on convergence and selection. Section III contains the empirical analysis. We begin with a discussion of the data,describe the econometric model, present results from the analysis of coronary angiography, and of surgical interventions. Concluding remarks are in section IV.

II A Model of Procedure Choice

The model contains two essential features—local interaction and social influence—which combine to yield the characteristic combination of local uniformity and global diversity of treatment. We imagine a population of physicians, at fixed locations along a line, who treat randomly arriving patients. A patient may be one of two types, and the physician must choose between two alternative treatments. The payoffs to the treatments depend on patient characteristics as well as on the past treatment choices of the physician's 'neighbors', defined in the model as the physicians at adjacent locations. The social influence may be viewed as deriving from local increasing returns, or from doctors' taste for conformity. The geometric structure implies that the neighborhoods overlap, a feature that permits influence to percolate across the line of physicians. We define distinct regions of the line which differ in their respective arrival probabilities of the two patient types (i.e. demographic mix). These regions are *not* isolated. Absent social influence each physician would switch treatment depending on a patient's type. But the interdependent payoff structure leads eventually to a single procedure being applied to all patients in a given region regardless of type, while the regional demographic variation implies that this single dominant procedure will differ across regions. The differences in the patient distributions across regions do not have to be extreme to produce this sort of choice pattern.

II-A Theoretical Model

The pattern of use of procedures arises as a steady state of a stochastic dynamic process. We begin by describing the process. Physicians are indexed by their location on $\mathbb{Z}$, the set of integers. For each $x \in \mathbb{Z}$, $\{x-1, x+1\}$ denotes the set of neighbors of x. There are two types of patients, denoted α and β, and two procedures A and B. Let $\pi_z(h, L, R)$ denote the quality of the outcome when the physician uses procedure $z \in \{A, B\}$ on a patient of type $h \in \{\alpha, \beta\}$, assuming her neighbors use $\{L, R\}$ (L and R belong to $\{A, B\}$). It will be convenient to think of the outcome as being characterized by a single number, the likelihood of success of the procedure. Then $\pi_A(\alpha, A, B)$ will denote the likelihood of success of procedure A on an α-patient when one neighbor uses A and the other B. We assume functions π_A and π_B are the same for all physicians. The utility of a physician will depend upon π_A and π_B, but is likely to depend upon other things as well. First, the quality of outcomes will depend upon the quality of complementary inputs like hospital services, and also upon unobservable physician effort or investment. Second, physicians may incur different costs in their choice of procedures, either from the inherent riskiness of certain procedures or else because of incentives in the insurance and payment system. Finally, the presence of preference for conformity, whereby physicians get utility when their choices agree with those of their neighbors, could lead to regional variations even if spillovers are absent.

We use the following specification of preferences:

$$U(z, h, L, R, \ldots) = \pi_z(h, L, R),$$

so that physicians care only about the quality of outcomes. In particular, by assuming that physician and patient interests are perfectly aligned, we neglect the important role of incentives. However, our results rely on qualitative features of preferences that survive generalization. Moreover, many different kinds of social interaction have these features. The essential assumption about payoffs is the following:[2]

Property P. Preferences satisfy the following two conditions:

(a) Procedure A is optimal for α–patients if one or more neighbors use A, but B is optimal if both neighbors use B.

(b) Procedure B is optimal for β–patients if one or more neighbors use B, but A is optimal if both neighbors use A.

Three properties of payoffs can generate this feature: (1) payoffs from using a procedure increase with the number of neighbors who use the same procedure, (2) neither procedure dominates the other, and (3) for any fixed neighborhood, A yields higher payoffs when used on an α type than when used on a β type (and B yields higher payoffs when used on a β type than on an α type). However, it is not true that procedure A is always better than procedure B for an α type, nor that B is better than A for β types. We present, and graph, an example of such preferences:

$$\pi_A(\alpha, B, B) = 0.3 \quad \pi_A(\beta, B, B) = 0.2$$
$$\pi_A(\alpha, A, B) = 0.4 \quad \pi_A(\beta, A, B) = 0.3$$
$$\pi_A(\alpha, A, A) = 0.5 \quad \pi_A(\beta, A, A) = 0.4$$

Similarly, for procedure B the payoffs are

$$\pi_B(\alpha, B, B) = 0.4 \quad \pi_B(\beta, B, B) = 0.5$$
$$\pi_B(\alpha, A, B) = 0.3 \quad \pi_B(\beta, A, B) = 0.4$$
$$\pi_B(\alpha, A, A) = 0.2 \quad \pi_B(\beta, A, A) = 0.3$$

Figure 1 illustrates physician payoffs from using each procedure on an α-patient. Observe that the preferences satisfy property $\mathbf{P}$(a).

Figure 1 here.

Patients arrive randomly at each location, with inter-arrival times that are exponential with parameter λ. Without loss of generality we take $\lambda = 1$. The concentration of patient types varies by region. We partition $\mathbb{Z}$ into two regions, East and West. The negative integers constitute the West, while the non-negative integers constitute the East. The probability that a patient who arrives at any given location in the East (West) is of type α will be given by p_E (p_W). The *state* of the system is a function from integers to $\{A, B\}$ ($\omega : \mathbb{Z} \to \{A, B\}$). An '$A$' at any location indicates that the physician there used procedure A on her most recent patient. A 'B' denotes the use of procedure B on the most recent patient. The set of states is denoted by Ω.

Consider a specific location $x \in \mathbb{Z}$. When a patient arrives at x, the physician makes a choice between A and B. The choice depends on the type of patient, as well as the choices made (in the recent past) by neighboring physicians. We can imagine an infinite sequence, with values at each location indicating the most recent choice made by the physician there:

$$\cdots AABBBABAAABA \cdots .$$

At random dates there is a transition: the value at one location changes from A to B or vice versa. The process is a continuous time Markov chain, X_t, and we are interested in the invariant (equivalently stationary, or equilibrium) distributions of this process.

Let $\mathbf{A} \in \Omega$ denote the state ω with $\omega(i) = A$ for all $i \in \mathbb{Z}$. In other words,

$$\mathbf{A} \equiv \cdots AAAAAAAAAAAA \cdots .$$

Similarly, $\mathbf{B} \in \Omega$ denotes the state ω with $\omega(i) = B$ for all $i \in \mathbb{Z}$:

$$\mathbf{B} \equiv \cdots BBBBBBBBBBBB \cdots .$$

The configuration at a particular date t will be identified by ω_t.

Let δ_ω be the probability that puts all of its mass on ω. Clearly, $\delta_{\mathbf{A}}$ and $\delta_{\mathbf{B}}$ are invariant measures. If we somehow reach the configuration $\mathbf{A}$ (or $\mathbf{B}$), the process can never escape from this state. Following Liggett (1999), we say the process *coexists* if there is an invariant measure that is not a mixture of $\delta_{\mathbf{A}}$ and $\delta_{\mathbf{B}}$. Alternatively, the process coexists if for i and j, $\lim_{t\to\infty}\text{Prob}\{\omega_t(i) \neq \omega_t(j)\} > 0$. We show that the process X_t defined above coexists by identifying an invariant distribution in which both procedures are used with strictly positive probability at the same dates.

Define the set of states $S \subset \Omega$ as follows: $\omega \in S$ if there exists $m \in \mathbb{Z}$ such that $\omega(i) = A$ for all $i < m$ and $\omega(i) = B$ for all $i \geq m$. In other words, S consists of states such as

$$\cdots AAAAAABBBBBB \cdots .$$

S is *irreducible*—every state in S is reached with positive probability from any other state in S. It is *closed*—once in S, we can never escape. It is *recurrent*—we eventually return to every state in S—but not periodic.[3]

We prove the existence of an invariant distribution that has S as its support. For simplicity, the distribution is characterized in terms of the location of the boundary point between the region in which procedure A is used and the region in which procedure B is the norm. In the proposition below, $\rho(\cdot)$ specifies the probability distribution of this boundary point. The proof is in the appendix.

Proposition 1. *Suppose preferences satisfy property* **P**. *Let $p_W > 1/2$ and $p_E < 1/2$. Then the physician choice process coexists. Specifically, there is an invariant measure ρ, with support $\mathbb{Z}$, such that*

$$\rho(m) = \frac{1}{K}\left(\frac{1-p_W}{p_W}\right)^{-m} \qquad \textit{if } m < 0$$

$$\rho(m) = \frac{1}{K}\left(\frac{p_E}{1-p_E}\right)^{m} \qquad \textit{if } m \geq 0.$$

K is a real number constant which can be chosen to ensure that ρ is a probability.

The proposition above tells us that the location of the East–West boundary is random. The probability $\rho(m)$ gives us the likelihood that the boundary will be m. Imagine the process as follows: each state consists of an infinite string of A's followed by infinitely many B's, but the boundary between the two regions keeps moving around, according to the probabilities governed by $\rho(\cdot)$. We refer to *the long-run outcome* ρ to describe the steady state in which the states from S appear according to probability ρ.

Remarks. (1) In case $p_W < 1/2$ and $p_E > 1/2$, we get a similar result, only the support now consists of a string of B's followed by A's. In case $p_W < 1/2$ and $p_E < 1/2$, the invariant distribution is $\delta_{\mathbf{B}}$. If $p_W > 1/2$ and $p_E > 1/2$, it is $\delta_{\mathbf{A}}$. (2) When $p_W = p_E = 1/2$ the state always remains in S and the boundary performs a symmetric random walk. This process is like the one-dimensional linear voter model (see Liggett). Despite the fact that the state always remains in S, the process does not coexist. This is because $\lim_{t \to \infty} \Pr\{\omega_t(i) \neq \omega_t(j)\} = 0$. (3) The proof of Proposition 1, as well as Proposition 2 below, requires infinitely many locations (i.e. $\mathbb{Z}$). In the finite case we would reach either $\mathbf{A}$ or $\mathbf{B}$ with positive probability, and then be trapped there. It seems likely that one can recover geographical variation by adding small noise to the model, but the analysis of such a process is beyond our scope here.

The model has interesting observable implications. It suggests that the procedure performed on a patient depends on the demographic mix of the region. For instance, the procedure performed on a 50 year old patient could depend on the proportion of the local population that is 70 years or older (in cases where a specific procedure is considered medically more appropriate for the aged). In cardiac care, expert panels and procedure guidelines differ in their recommendation for different groups of patients (our empirical analysis can pick this up as well). In our empirical investigation, one of our robust findings is the effect of local demographics on procedure use.

II-B Emergence of Norms

We show here how, starting from almost any initial state, the dynamic evolution of the system leads to regional norms of practice. In other words, since the process has several invariant distributions, we would like to identify the distribution which is most likely to be selected in the long run from randomly chosen initial conditions. Proposition 2 suggests that the uniform states $\mathbf{A}$ and $\mathbf{B}$ are, in a well-defined sense, exceptional. Typically, we would expect the system's behavior to be described by the invariant distribution ρ from Proposition 1.

We assume the initial value (procedure choice) at each location is picked by tossing a θ-coin, where $\theta \in (0,1)$—i.e. the initial distribution is the Bernoulli product measure with density θ. Let π^t denote the distribution of the Markov chain at time t. We consider the behavior of the sequence $\{\pi^t\}$ as $t \to \infty$. In the long run, the behavior of π^t is closely approximated by ρ.

Proposition 2. *Suppose the initial distribution is ν_θ, the Bernoulli product measure with density $\theta \in (0,1)$, $p_W > 1/2$ and $p_E < 1/2$. Let π^t denote the distribution of the Markov chain at time t. Then π^t converges weakly to ρ as $t \to \infty$.*

The proposition shows that from "most" initial configurations the process will evolve to display geographical variation. The proof is patterned after Durrett (1988) and Bramson and Griffeath (1981), who investigate the so-called "biased voter model". The process discussed in our paper is not identical to the biased voter model, but the differences are inconsequential for the main arguments. One difference is the presence of regions with different "bias"; another is the transition rate at a site where both neighbors make the opposite choice.[4]

II-C Efficiency

In our model, regional variations can arise either from scale effects in technology (as a result of knowledge spillovers, for instance) or else because of the presence of peer effects. While this has no significant implication for long-run outcomes, the distinction *is* pertinent for efficiency. With scale effects, some patients are likely to benefit from local uniformity of practice, since the likelihood of success of a procedure increases when others choose the same procedure. If regional variations arise because of physicians' desire to conform with one another then patients must suffer. The distinction is also important for comparisons of policy. For instance, is strict enforcement of procedure guidelines (matching patient characteristics to procedure) necessarily a good thing from the point of view of patients and physicians? More generally, are the long-run outcomes of section II-A efficient? These questions are addressed next.

Suppose that physician preferences are not subject to peer effects and, as in section II-A, utility equals the likelihood of success of the procedure used. We consider a policy which involves enforcement of procedure guidelines requiring the use of A on α-patients and B on β-patients.[5]Under such a policy, at any given state, some patients will be worse off and some better off than in the long-run coexistent steady state. The more interesting question is whether the policy improves *expected* outcomes for the population as a whole.[6]We provide an illustration of the tradeoffs introduced by a policy of procedure guidelines, and its desirability from the perspective of patients and physicians. Since a physician's expected utility at a location equals the expected likelihood of success for the population profile at that location, we can speak of patient welfare in terms of these same payoffs.

Assume initially we are in the long-run coexistent steady state, with choice A blanketing the region to the left of the (stochastic) boundary location, and choice B blanketing the region right of the boundary. Consider the fate of a β type arriving in the region to the left of the boundary: formerly she would have faced a payoff of either $\pi_A(\beta, A, A)$ or $\pi_B(\beta, A, B)$, the latter occurring only at the rightmost location in the region. Under the guidelines, she will get a payoff of either $\pi_B(\beta, A, A)$ or $\pi_B(\beta, A, B)$, or even $\pi_B(\beta, B, B)$. The first of these is less than $\pi_A(\beta, A, A)$, what she would have received formerly when surrounded by choice A. However, under guidelines it will become more likely that she arrives at a location with at least one neighboring choice of B, since β types are now always treated with procedure B. Thus the payoffs $\pi_B(\beta, A, B)$ and $\pi_B(\beta, B, B)$ might alternately replace payoff $\pi_A(\beta, A, A)$. If the technology is such that each of these first two exceeds the third, β types might be made better off from the guidelines, depending on the differences between the various payoff possibilities, and on the arrival probability of β types in the west. The latter probability matters because the greater it is, the greater will be the increase in the frequency of (A, B) and (B, B) neighborhoods in the west under the guidelines policy.

We must consider also the fate of an α type arriving in the region to the left of the steady-state boundary when guidelines are suddenly imposed: if one arrives at a location surrounded by choice A she will receive the same treatment under the guidelines as formerly, and similarly if she arrives at a heterogeneous location (with choice A on one side and B on the other). But since heterogeneity becomes more probable, she will more often face the lower payoff $\pi_A(\alpha, A, B)$ than the payoff $\pi_A(\alpha, A, A)$. In addition the possibility arises that an α arrives at a location surrounded by B choices, in which case she will receive (suboptimally) choice A. Thus we can see that α types arriving in the region which would have been dominated by choice A in the long-run steady state will be made unambiguously worse off by the imposition of procedure guidelines. Inverting this analysis to consider the region to the east of the boundary, it should be easy to see that β types will be made unambiguously worse off and α types may be (but are not necessarily) made better off.

Given these contingencies, we want to know whether the net effect of procedure guidelines on the expected success probability at any given location can ever be positive. We find that it can, as we state in the following proposition:

Proposition 3. *The long-run outcome ρ need not be efficient. In particular, it may be dominated by a policy of enforced procedure guidelines.*

In the appendix we prove the proposition by identifying a plausible technology for which the guidelines policy proves superior to the long-run outcome ρ. We show that in general guidelines are more likely to dominate the long-run outcome (a) the more similar are the population profiles in the different regions (both p_W and p_E are close to $1/2$), (b) the greater the payoff advantage to neighborhood heterogeneity over homogeneity, and (c) the smaller the losses from reversing procedure choices at locations with homogeneous neighborhoods. Note that following procedure guidelines when others do so is not a best response—the policy requires enforcement. Individually rational doctors do not take into account the fact that a heterogeneity of skills in the population creates external benefits.

Preferences that display a desire to conform to the actions of peers raise a different set of questions. When are decisions more likely to be subject to social pressures? How does one design policy to diminish negative social influences? We can only frame these questions here. This paper is an analysis of the *effects* of social influence on individual actions. It is not clear that we understand the *causes* of social influence well enough to say something concrete about the way in which policy might influence it.

III Empirical analysis

Using the Florida data on coronary patients, we examine the effects of physician interactions and regional demographics on discrete treatment choices. We find that doctors in likely proximity influence each others' choices at the margin, with the result that diverse patients are treated similarly within regions, while similar patients are treated differently in regions with different patient demographics, as the model predicts. We also find some evidence to support the model's predictions on patient welfare in the presence of local social interactions.

Identification of local knowledge spillovers and conformity effects presents a challenge because of the possibility of alternative sources of local treatment uniformity. For example, the patients treated in a given locale may have traits in common that affect their treatment, and the physicians may have similar innate treatment tendencies. The shared economic environment may contribute further to such uniformity. We adopt a number of strategies to control for these possibilities, including the use of instrumental variables, and find our results to be robust.

The Florida patient discharge data comes from a legally mandated and audited census of inpatient stays, reported quarterly by Florida hospitals. We use records from the years 1993 to 2000, combining each year's quarterly reports in two half-year reports. Each record gives the patient's age, race, sex, principal diagnosis and (where applicable) secondary diagnoses, treatments received, the attending physician, the hospital name and county location, the length of stay, and several other facts.[7] A limitation of the data is that each observation is a single hospital stay rather than a longitudinal patient record. Repeat hospitalizations are masked, so a patient's complete treatment record may be censored.

To focus on coronary care we restrict our attention to the records of patients over 35 years old, with a principal diagnosis of either acute myocardial infarction (AMI) or coronary atherosclerosis. We include emergency and non-emergency patients, but omit maternity admissions and patients transferred from other facilities. As described below, we also employ county-level demographic information from the 1990 and 2000 Census and other public sources. We also compute a measure of mortality risk for each patient, the *Charlson index*, based on the discharge information.[8]

Table 1 here

Before turning to the econometric models, we describe some salient features of the uncontrolled treatment rates. Table 1 displays the basic statistical frequencies of treatment for heart disease patients in regions of Florida. For example, the probability of a younger (under 55) patient's receiving heart surgery is lower in those regions of Florida with relatively many older patients than in regions with relatively few older patients. Specifically, the contrast is great between these rates in the youngest region, District 2, and those of the oldest, District 9. Conversely the surgery rates for older patients are higher in younger districts. We also observe that surgery rates decline on average with age, a natural pattern reflecting the fact that, holding other things the same, surgery-related risks increase with age. These facts suggest exactly the type of effect predicted by the model: treatment in a region follows the choice best suited to the dominant patient type. In this case, younger patients are treated like older patients when their doctors (and their doctors' colleagues) treat older patients most of the time, and vice-versa for older patients in young regions. The controlled econometric tests that follow reinforce this finding and suggest that social interactions among physicians contribute to its formation.

III-A Probit analysis of treatment choice

For each of two binary treatment choices, we estimate the probability of a patient's receiving a given treatment as a function of variables capturing physician interactions, regional demographics, and individual patient characteristics. The first model estimates the incidence of coronary angiography, an invasive diagnostic procedure, and the second examines the choice of heart surgery (either CABG—coronary artery bypass grafting—or PTCA—percutaneous transluminal coronary angioplasty) over non-invasive drug treatments. In each model, the dependent variable is an indicator of whether the invasive procedure (angiography or surgery, respectively) was performed on the given patient.

Let Y_i^* be a latent variable describing the (unobserved) relative payoff of the specific treatment for patient i. Recall that physician choices are assumed to follow patient welfare, at least as the physician perceives it. There is some threshold value $\bar{Y}_i^*$ such that the treatment is chosen if and only if Y_i^* meets or exceeds this value. Y_i is given the value 1 if patient i is observed to have received the treatment, and the value zero if she did not. We express the basic econometric model as follows:

$$Y_i^* = \alpha + N_{j_i}\beta + X_i'\gamma + R_{k_i}'\delta + P_i'\theta_i + \epsilon_i. \tag{1}$$

$$Y_i = \ I(Y_i^* \geq \overline{Y}_i^*), \qquad\qquad i = 1, ..., N \tag{2}$$

In the equation, N_{j_i} is the treatment rate in the social network (defined below) associated with the patient's physician, the latter denoted j_i. Note that other patients treated by the same physician during the same period will have the same value for N_{j_i}. X_i is the vector of patient characteristics, R_{k_i} is the vector of demographic variables and district dummies for the region, k_i, in which the patient was treated, and P_i is the vector of dummy variables indicating the patient's provider type.

According to the theoretical model, the choice made by a doctor at a given location depends on the recent choices at neighboring locations and on the patient's type. To capture the latter we include the patient's race, sex, and age, fifteen discrete indicators of secondary diagnoses or 'comorbidities', and the age-adjusted Charlson index, a measure of the risk of mortality derived from the patient diagnostics (Charlson, et. al. 1987). To capture recent local treatment choices we construct a variable called the 'network rate', described in detail below, indicating the (lagged) use of the invasive procedure among the peers of the acting physician. Further sources of spillovers could include the hospital's absolute volume in the given procedure, as well as demographic factors that proxy for average health factors in the local region. For the former we define a dummy variable taking a value of one if the hospital of treatment performed more than 200 angiographies (or 100 surgeries, respectively) in the same six-month period.[9]For the latter we include the population over age 65, the percent high school graduates, population growth rate, physicians per capita, and income per capita, all measured at the district level from the most recent census and other public sources. We also include a set of dummy variables to capture fixed effects across the 11 administrative planning districts in Florida.

To construct an empirical counterpart to the model's social network, we assume that doctors practicing in the same hospital are more likely to interact and influence each other's decisions than doctors working at different hospitals. On this assumption a physician's *social network* will consist of the set of all physicians practicing at any one of the same hospitals as the given physician during the period of observation. We impose the requirements, however, that each included physician must have treated no fewer than 10 patients total during the period, and no fewer than 5 at each hospital at which he showed any activity. Patient records of doctors not meeting these requirements are excluded when computing network treatment rates because we take low activity to mean a low level of social influence.

Note that a given social network (or *network* for short) is specific to a given doctor and a given time period, and does not include the doctor himself. The networks of different physicians, however, may overlap substantially. If Doctor A practiced at Hospital 1 and Hospital 2, and Doctor B practiced at Hospital 1 and Hospital 3, Doctors A and B are in each other's respective networks for the relevant period, and both networks contain all physicians besides A and B who worked at Hospital 1. Doctors who practiced at Hospital 2 are in A's network but not in B's, and vice-versa for doctors at Hospital 3.

To measure a social network's use of a procedure, we compute the proportion of instances of a specific treatment out of the total volume of patient treatments by doctors in the given network for the given period. This measure, called the *network rate*, includes all relevant treatments chosen by all physicians in the given network, even those administered at a 'non-network' hospital. Referring to the example above, when computing the rates of A's network we count Doctor B's procedures at both Hospital 1 and Hospital 3, even though Doctor A treated no patients at Hospital 3.[10]

The term 'network effects' will refer here to interactions among physicians—based on knowledge spillovers, increasing returns, or pure conformity—that produce relative uniformity of treatment choice. The model predicts a positive relationship between the probability that a given patient receives a given treatment and the tendency of her physician's social network to administer such treatment. That is, we predict a positive coefficient on our network rate variable when estimating the probability of a given choice.

Identification of network effects is difficult given that factors affecting treatment—patient characteristics, physician practice styles, economic incentives—may be correlated within the network regardless of direct interaction effects. Residential sorting on age, wealth, education, or a number of other factors may produce local patient populations with similar health factors requiring similar treatments. Physicians might sort into hospitals on the basis of predetermined treatment styles, or factors associated with treatment styles such as medical school or residency affiliation. The matching of patients with physicians may produce similar and reinforcing effects, depending on the degree of control patients exert over the choice of physician. For example, physicians with a propensity to order angiography may attract patients who desire angiography, and any network bias in favor of angiography will be strengthened. Alternatively, a given demographic and economic climate may select for a particular type of physician, inducing a kind of unintended sorting. In each of these cases, treatments could be correlated regardless of any direct network effects, and the coefficient on the network variable will be biased when the relevant factors are unobserved.

Drawing on the approach of Goolsbee and Klenow (2002), we use an instrumental variables (IV) model to identify the network effects. In the IV model the instruments are the average values, among the other patients treated in the given social network, of the Charlson index and the reported comorbidities. These average patient characteristics should help predict the network's aggregate treatment rates, but should not directly affect individual treatment choices. The instrumental network variable should then isolate network effects, provided the instruments are uncorrelated with the errors. To ensure such independence, we include as regressors the individual patient characteristics (including age, race, and sex, in addition to the Charlson index and comorbidity dummies), the patient's insurance type, and the five regional demographic factors listed above. With these controls in the model, the coefficient on the instrumental network rate will be biased only if the *average* patient traits are correlated with relevant unobserved factors, in excess of any correlations between the included variables and the errors. For example, suppose an individual's Charlson index value (observed) is correlated with her smoking behavior (unobserved), as well as correlated with the average Charlson index value in the network's patient population (an instrument). For identification to be compromised, the network's average Charlson index number must predict her smoking behavior, *after controlling for her own Charlson number*.

We can express the IV probit model as follows:

$$Y_i^* = \alpha + IVN_{j_i}\beta + X_i'\gamma + R_{k_i}'\delta + P_i'\theta + \epsilon_{k_i} + \epsilon_{j_i} + \epsilon_i. \tag{3}$$

$$Y_i = I(Y_i^* \geq \overline{Y}_i^*), \qquad i = 1, ..., N \tag{4}$$

In equation 3, the variables are defined as before except that the instumental variable IVN_{j_i} replaces N_{j_i}. The error is decomposed to indicate a hierarchy of unobserved variation: ϵ_{k_i} denotes unobserved factors common to the region, ϵ_{j_i} common disturbances at the network level, and ϵ_i an idiosyncratic error, all presumed independent of each other. Each error is normally distributed with mean zero, but the variances may differ.

The error structure captures the various sorting possibilities, and renders more explicit the requirements for identification of network effects. A positive value of ϵ_{j_i} could represent, for example, the effect of a common (exogenous) practice style among physicians in the network, an effect that would bias the coefficient on the uncorrected network variable. However, by construction the ϵ_{j_i} represent only sorting effects not predictable on the basis of the traits of the patients in the network (traits which might be correlated with physician practice style), nor on the basis of the regional demographic factors. The patient and demographic factors may therefore absorb a portion of the effect of unobserved sorting, but the residual portion is independent of these regressors, and therefore likely to be independent of the instruments as well. A similar argument applies to region-level effects, captured by ϵ_{k_i}. To reiterate the argument above, identification is threatened only if the network's average patient traits are correlated with the errors, controlling for correlations between the individual patient and demographic factors and the errors.

In addition to providing econometric controls, we actually test directly for physician sorting. While we can't observe practice styles, we do observe each doctor's age and residency hospital. Research in medical sociology (Wilkes, et al. 1998, Yedidia et al. 1996) suggests that residency training affects the formation of beliefs and practice styles among new physicians. We might expect that the timing of residency would matter as well as the location. Hence any sorting on residency location or cohort (proxied by age) could contribute to regional treatment variations. To measure the extent to which doctors sort into hospitals on the basis of either residency location or age, we employ an *assortativity index* (Newman 2002). Based on this measure, we find no systematic tendency for physicians to locate on the basis of residency, nor on the basis of age. The index is described in detail in the Appendix.

III-B Analysis of Angiography

We begin by investigating the binary choice of whether or not to perform coronary angiography[11], a diagnostic procedure that is used to identify, locate and measure the severity of coronary artery disease. While it is extremely accurate, the procedure is invasive and risky, and may be dominated in terms of cost-effectiveness by other, non-invasive diagnostics such as echocardiography and SPECT (Garber and Solomon 1999).

Table 2 shows the coefficient estimates from the full model for 1994, using instrumental variables probit estimation.[12],[13]Results in Table 2 are broadly consistent with the hypothesis that variations in regions and their demographics, patient characteristics and networks rates are important in the choice of this diagnostic treatment. For example, patients who are admitted from the emergency room or who are transferred to another hospital are less likely to receive the procedure. Variations in treatment rates across regions remain, even factoring into account education levels and other demographics. Older patients and black patients are substantially less likely to receive the procedure. Finally, the results are consistent with the hypothesis that the economies of scale in performing these procedures may influence the decision, at the margin, to choose the angiography procedure.

Table 2 here

These considerations held constant, the lagged rate of angiography procedures within the physician social network is highly significant, in both the IV model and the standard probit model. The robustness of the network rate coefficient to the IV specification lends critical support to the claim that we are witnessing true network effects. We take this as strong evidence that the transmission of experience via informal contacts with peers helps explain the readiness to order this diagnostic test.

III-C Choice of Surgery over Non-invasive Treatment

Patients who are hospitalized with AMI and coronary atherosclerosis may be given intensive surgical interventions such as bypass surgery or angioplasty, or may simply be held for observation, diagnostic testing and drug therapy. The data reveal that the two surgical interventions plus non-surgery inpatient stays account for the preponderance of patient care given in our data.

The econometric model is analogous to the angiography case, with the latent dependent variable capturing the payoff to surgical intervention. The instruments for the network surgery rate are the same as the instruments for the network angiography rate. The results are reported in Table 2, again for the IV probit model. The results show that the decision to perform the expensive surgical procedure is correlated with patients admitted from emergency and those who are discharged as a transfer to another hospital. The tendency to promote surgery in hospitals that do relatively large numbers of surgeries is confirmed by the significant coefficients on the economies of scale for coronary angioplasties and for bypass operations. But after controlling for these factors, detailed patient comorbidities and the regional variations, there remain in the evidence substantial effects associated with the propensity to choose surgery within the physician's social network.

Relatively high rates of surgery in the attending physician's network are associated with a higher probability that the patient will be given surgery.

III-D Predicted treatment patterns across regions

The model predicts that treatment patterns may diverge across regions when local interaction effects couple with regional differences in the patient mix. Looking at Table 3, we find substantial empirical support for this prediction for a 'representative' patient who has sample mean characteristics. The first columns of the table gives the estimated probabilities of a representative patient's receiving angiography (and surgery) in each of the 11 districts.[14]We see that the same patient's treatment would vary substantially across the districts. This result is precisely what our theoretical model would expect in the presence of peer effects. Absent peer influence and knowledge spillovers, we might still observe regional treatment variations, but we should not expect the same patient to be treated differently at different locations.

Table 3 here

Our results indicate that local interactions are a significant factor in treatment patterns. We argue that the observed network or peer effects are genuine, not mere proxies for unobserved correlations, given the robustness of the coefficient estimates to instrumental variables estimation and extensive controls.

III-E Analysis of patient outcomes

We conduct a number of tests to discern the impact of network effects on patient outcomes. Does conformity imply that patients get the wrong treatment? Or do knowledge spillovers imply that uniformity need not have deleterious effects?

It would be desirable to look directly at outcomes and determine whether the patients' survival rates or quality of life varies across regions. Direct tests prove impractical in this study, however, because of the unavailability of quality measures, such as mortality rates in the period following the hospital stay. One observable, albeit weak, proxy for outcome quality is the length of hospital stay for patients who are given surgery. Longer hospital stays are generally associated with complications or slower recovery from surgery. In a large sample, controlling for patient age, demographics and illness characteristics, we would not expect to see systematic variations in length of stay if the quality of outcomes were similar. Indeed, the right column of Table 3 reports the predictions of a least-squares model of the length of stay, in logs, across regions and again for 'representative' patient. [15]The extent of regional variations is quite small in Table 3. This result would suggest that the impact of network effects is minimal, despite the appearance of large regional variations.

A second test of this hypothesis is an indirect one and asks whether the network effects encourage treatments at low volume facilities. Recent medical research has shown extensively that risky operations such as bypass surgery and angioplasty, when conducted at low volume hospitals, produce worse outcomes than when conducted at high volume facilities (Birkmeyer, 2000). We cannot observe the bad outcomes, but would expect them to be more likely at these facilities. Thus, it is interesting to ask whether there is a correlation between the network rate and the probability that a patient is given surgery at the low quality hospital. We re-estimated our IV probit models of angiography and surgery, using a subsample of patients treated in hospitals classified as low volume, i.e. the hospital of treatment performed less than 200 angiographies (or surgeries, respectively) in the same six-month period. The results in Tables 4 reveal that the network effects are highly significant even in this subsample of patients who are admitted to facilities without appropriate economies of scale in performing these procedures.[16]We cannot be sure that this result means that doctors interacting in networks with high rates of surgery are induced into recommending, at the margin, surgery at the wrong facility, or if they are reacting to knowledge spillovers from the network that mitigate the facility disadvantages. These last results, if substantial, further suggest that there is a risk of adverse effects to patients when social interaction induces network effects in low volume hospitals.

Table 4 here

IV Conclusion

Our study of medical practice, like many others, finds variations in the rates of diagnostic and treatment choices for patients across regions. These variations are sustained, even between regions of a single state, after controlling for demographic and illness conditions in some detail. Our theoretical model attempts to develop an explanation of the phenomenon in terms of social influences. We show, in Proposition 1, how the observed pattern of regional practice norms could arise in equilibrium. But perhaps the more striking result is Proposition 2, where we find that, starting from almost any initial condition, simple adaptive behavior leads to the emergence of co-existent norms.

Although our model is designed with the health care problem in mind, there are other applications. Consider corruption of government officials, for instance. Let A denote the risky act of soliciting a bribe, while B denotes not demanding a bribe. People who are likely to accede to the demand are the α-types, and β-types are likely to refuse. Now our results can be used to illustrate how regional governance norms emerge.

Regional variation does not necessarily imply unwarranted or welfare-reducing choices. If knowledge spillovers are significant, patients could, on the whole, be better off when physicians utilize the local pool of expertise in a particular procedure. On the other hand, as Proposition 3 illustrates, there are also benefits associated with a heterogeneity of skills in the local physician population, so that a policy of enforced procedure guidelines could dominate the equilibrium outcome. Our empirical results on patient welfare are mixed, yet they do provide some evidence that network effects may contribute systematically to adverse outcomes. Variations in the length of hospital stay are not systematically linked to treatment variations, but network effects appear to promote surgical intervention in the risky setting of a low-volume hospital. A limitation of our study of outcomes is that we do not have access to longitudinal patient records, and the question needs to be addressed with richer data.

There have been significant innovations in cardiac care in the last several years. While we assume a fixed technology, our model can be extended to account for innovations. Innovations in medicine often make a procedure viable for new segments of the patient population. In a version of our model with multiple types, this leads to regional differences in the propensity to adopt new technologies. Depending again on the population mix, quick shifts to the new innovation arise in some regions, while others remain resistant.

To examine social interaction among physicians in hospital settings for advanced treatment such as this one, we traced the aggregate treatment tendencies of a hypothetical social network by identifying the most likely points of mutual contact between physicians. In doing so, we have found that, controlling for patient characteristics, a patient will be more likely to receive angiography or the surgical options if the attending physician is in a group prone to recommend those options. While our construction of social networks is merely suggestive of what in reality is a much richer and more subtle set of interactions, it contains information that is empirically relevant to treatment choices, and its explanatory power appears robust across patient populations.

Appendix

Proof of Proposition 1

Proof. Since the process on Z is irreducible and aperiodic, it has an essentially unique invariant distribution. Each state can be specified in terms of m, the location of the first zero. First we define the probabilities $b(m)$ and $d(m)$ of transition $m \to m+1$ and $m \to m-1$ respectively. Recalling that the rate of arrival of patients is one, these are given by:

$$b(m) = \begin{cases} p_W & \text{if } m < 0 \\ \\ p_E & \text{otherwise.} \end{cases}$$

In other words, m moves to the right if an α-patient arrives at m, which happens with probability p_W in the West and p_E in the East.

$$d(m) = \begin{cases} 1 - p_W & \text{if } m \leq 0 \\ \\ 1 - p_E & \text{otherwise.} \end{cases}$$

In other words, m moves to the left if a β-patient arrives at $m-1$, which happens with probability $1 - p_W$ in the West and $1 - p_E$ in the East. The process is reversible, so that invariant distributions can be obtained from the detailed balance conditions:

$$b(m-1)\rho(m-1) = d(m)\rho(m).$$

We can confirm that these are satisfied. In case $m \leq 0$, we can substitute for ρ and confirm that

$$\frac{b(m-1)}{d(m)} = \frac{p_W}{1 - p_W} = \frac{\rho(m)}{\rho(m-1)}.$$

When $m > 0$,

$$\frac{b(m-1)}{d(m)} = \frac{p_E}{1-p_E} = \frac{\rho(m)}{\rho(m-1)}.$$

So $\rho(\cdot)$ is an invariant distribution. It is not a mixture of δ_0 and δ_1, hence the process coexists. $\square$

Proof of Proposition 2.

Proof. Let ξ_t^x denote the process at time t when the initial configuration has A at site x, and B elsewhere. In this case the A-region will always constitute an interval, unless ξ_t^x has no A's at all. Let $L_t \equiv \min_i\{i|\xi_t^x(i) = A\}$ and $R_t \equiv \max_i\{i|\xi_t^x(i) = A\}$, so that $[L_t, R_t]$ denotes the A-region (initially, $L_0 = R_0 = x$). We first show that for $x \in$ West, and conditioning on the event

$$\Omega = \{R_t \geq L_t \text{ for all } t > 0\},$$

ξ_t^x, grows linearly in time until R_t reaches the East/West boundary (specifically, until $R_t = -1$). Thereafter, only L_t extends westwards. Given $p_W > 1/2$, $p_E < 1/2$, and if $0 > R_t > L_t$, R_t and L_t perform independent random walks according to:

$$R_t \rightarrow \begin{cases} R_t + 1 & \text{at rate } \lambda \\ \\ R_t - 1 & \text{at rate } 1 \end{cases} \tag{5}$$

$$L_t \rightarrow \begin{cases} L_t - 1 & \text{at rate } \lambda \\ \\ L_t + 1 & \text{at rate } 1 \end{cases} \tag{6}$$

where $\lambda = p_W/(1-p_W) > 1$. Then, following Durrett (p. 38), and conditioning on Ω,

$$\frac{R_t - x}{t} \rightarrow (\lambda - 1) \quad \text{and} \quad \frac{L_t - x}{t} \rightarrow -(\lambda - 1) \quad a.s.$$

Once $R_t = -1$, conditional on Ω, R_t evolves like the boundary in Proposition 1. An analogous statement holds for the evolution of B regions in the East. Next we consider an arbitrary configuration ξ and index the A and B regions as follows. Let A^0 denote the easternmost A-region that still occupies sites in the West: i.e. A^0 is a set of contiguous sites with $A^0 \cap$ West $\neq \emptyset$ and $[i > \max A^0 \;\&\; i < 0] \Rightarrow \xi(i) = B$. Similarly B^0 denotes the set of contiguous sites with $B^0 \cap$ East $\neq \emptyset$ and $[i < \min B^0 \;\&\; i > 0] \Rightarrow \xi(i) = A$. If ξ is chosen according to ν_θ then, with probability one, both A^0 and B^0 will exist, and share a common boundary (defined as in Proposition 1, as the location of the first B in B^0). Label the A-region immediately to the west of A^0 by A^{-1} and the nearest eastern region by A^{+1}, and so on. We do the same for B-regions, with Eastern regions having positive indices and western regions having negative ones. Now A regions grow in the West, B-regions grow in the East, and the A^0/B^0 boundary evolves like the boundary of states in the sub-chain on S in Proposition 1, unless one of A^0 or B^0 becomes extinct (the right boundary becomes smaller than its left boundary). In case A^0 or B^0 becomes extinct, we relabel indices according to the scheme above and get a new A^0/B^0 boundary. Since, with probability one, there are initially infinitely many A and B regions, there are always A and B regions available to be relabelled. As $t \to \infty$, $|A^0| \to \infty$ and $|B^0| \to \infty$ and their extinction probability becomes zero. All B-regions in the West and A-regions in the East become extinct. As $t \to \infty$ the probability, for $x \in$ West, that $\xi_t(x) = B$ approaches the probability that the A^0/B^0 boundary is at $y \leq x$, which converges to $\rho(x)$:

$$\text{Prob}\ \{\xi_t(x) = B\} = \sum_{i \leq x} \rho(i).$$

So, observing that $\Omega = \{A, B\}^{\mathbb{Z}}$ carries the product topology, all the finite dimensional distributions converge as well, implying weak convergence of π^t to ρ. □

Proof of Proposition 3

Proof. First we describe the expected utility at location x in the long-run co-existent outcome ρ. Suppose $x < 0$ (x is in the West). Expected utility at x is a weighted sum of three terms:

$$U_1 \equiv p_W \pi_A(\alpha, A, A) + (1 - p_W)\pi_A(\beta, A, A) \tag{7}$$

$$U_2 \equiv p_W \pi_B(\alpha, B, B) + (1 - p_W)\pi_B(\beta, B, B) \tag{8}$$

$$U_3 \equiv p_W \pi_A(\alpha, A, B) + (1 - p_W)\pi_B(\beta, A, B) \tag{9}$$

with corresponding weights (1) the probability that x is in the interior of a region of A's, (2) the probability that x is in the interior of a region of B's, and (3) the probability that x is at a boundary. These probabilities can be explicitly computed from Proposition 1. The expected utility for a location in the East can be obtained in a similar manner. With enforced procedure guidelines the expected utility at $x < -1$ (interior West) is a weighted sum of

$$V_1 \equiv p_W \pi_A(\alpha, A, A) + (1 - p_W)\pi_B(\beta, A, A) \tag{10}$$

$$V_2 \equiv p_W \pi_A(\alpha, B, B) + (1 - p_W)\pi_B(\beta, B, B) \tag{11}$$

$$V_3 \equiv p_W \pi_A(\alpha, A, B) + (1 - p_W)\pi_B(\beta, A, B) \tag{12}$$

with weights (1) p_W^2, (2) $(1-p_W)^2$, and (3) $2p_W(1-p_W)$ respectively. In the interior East the weights are p_E^2, $(1-p_E)^2$, and $2p_E(1-p_E)$ respectively. At $x \in \{-1, 0\}$, one neighbor is in the East and one is in the West so that the weights are $p_E p_W$, $(1 - p_E)(1 - p_W)$, and $p_E(1 - p_W) + p_W(1 - p_E)$ respectively. In the interior West, from the returns to scale assumption, $U_1 > V_1$, $U_2 > V_2$, and $U_3 = V_3$. Procedure guidelines can do better if $U_1 - V_1$ and $U_2 - V_2$ are small, $U_3 = V_3$ is larger than U_1 and U_2 and has much greater weight under procedure guidelines than at the long-run outcome. These conditions can be satisfied by non-pathological technologies, e.g.

$$\pi_A(\alpha, B, B) = 0.1 \quad \pi_A(\beta, B, B) = 0$$

$$\pi_A(\alpha, A, B) = 0.4 \quad \pi_A(\beta, A, B) = 0.1$$

$$\pi_A(\alpha, A, A) = 0.5 \quad \pi_A(\beta, A, A) = 0.11$$

and similarly, for B,

$$\begin{aligned} \pi_B(\alpha, B, B) &= 0.11 \quad \pi_B(\beta, B, B) = 0.5 \\ \pi_B(\alpha, A, B) &= 0.1 \quad \pi_B(\beta, A, B) = 0.4 \\ \pi_B(\alpha, A, A) &= 0 \quad \pi_B(\beta, A, A) = 0.1, \end{aligned}$$

when p_E and p_W are close to $1/2$.[17] For expected utility at the long-run outcome, the weight of the term U_3 becomes small as p_E and p_W become close to $1/2$. For procedure guidelines the weight of V_3 becomes close to $1/2$, and so guidelines do better. This argument applies to the interior East with appropriate change of notation. For the case of $x \in -1, 0$, assuming p_W and p_E are both close to $1/2$, expected utility under the guidelines is approximately equal to the expected utility in either the interior East or the interior West under guidelines. Therefore the long-run outcome ρ is dominated by the policy of procedure guidelines. $\square$

The Assortativity Index

We measure the extent of assortative selection based on physician residency for each of eleven Florida districts and for each year between 1993 and 2000 by means of an *assortativity coefficient* (Newman 2002). Given the set of physicians practicing in a given district, any two physicians are said to have a *link* between them if they have practiced at the same hospital in the observed year. If a given pair of physicians have two hospitals in common we only count one link between them. There are two kinds of links: links between two doctors who completed residency at the same hospital (in which case the doctors are said to be of the same *type*), and links between those who did not. The assortativity coefficient tells us whether, and to what extent, the observed proportion of links between matching types exceeds that which we would get on average by randomly assigning links within the same set of physicians. The value of the coefficient is normalized to vary from a minimum of -1 (perfect disassortativity) to a maximum of 1 (perfect assortativity). A value of zero indicates an apparently random network structure.

Consider a simple example. There is a population of individuals, 50% of type A, and 50% of type B. If A types have links only with other A types, and B types only with other B's, the assortativity coefficient for the population will be 1, provided also that there is at least one link between two A types and one link between two B's. If on the other hand every link pairs a type A with a type B, the coefficient will take the value -1.

The explicit computation can be described as follows. Each physician can be one of N types, where N is the total number of distinct types represented in the district. Let m represent a symmetric NxN matrix, the ij-th entry of which indicates the number of links between a physician of type i and a physician of type j. However, if $i \neq j$, we divide this number by two to avoid double counting across the ij-th and ji-th entries. A doctor is not counted as linked to herself, and if no link exists for a given type pair, the relevant matrix entry (or entries) are zero. Define the normalized matrix $e = \frac{m}{||m||}$, where $||m||$ denotes the sum of the elements of m. The value of the coefficient is given by (Newman 2002):

$$a = \frac{Tr(e) - ||e^2||}{1 - ||e^2||}$$

Our calculations do not indicate a high degree of assortativity within the districts. The values for all years range from -0.12 to 0.05, averaging -0.016. Physicians simply do not appear to locate with strong preferences regarding the residency cohort of their potential peers.

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Endnotes

1. The details of medical procedure choice are sufficiently different that a direct application of their result seems not to be possible here. The necessary departure, along lines suggested by Ellison (1993) and Morris (2000), introduces significant conceptual and technical differences.

2. This is similar to the risk-dominance property in the theory of finite games (see Ellison, 1993).

3. For formal definitions of these properties, see Norris, (1997).

4. While we deal with the much simpler one-dimensional case, in light of Bramson and Griffeath our results should generalize to $\mathbb{Z}^2$ and higher dimensions).

5. The policy alternative of moving patients to regions based on their characteristics is considered infeasible. We look for policies that seek to improve welfare without relaxing the institutional constraints imposed in the model.

6. The requirement that all patients be better off, in every state, is too stringent a standard, and quite removed from public policy debates. We may think of expected outcomes as the expected utility of a patient before she becomes aware of her type (the probabilities p_E and p_W now correspond to the likelihood of developing characteristic α in the East and West respectively).

7. The CCS Diagnosis Categories were used to identify the 56 ICD-9CM categories relevant to these patients and to identify broad categories of comorbidities.

8. Charlson Index is computed according to a standard algorithm (Charlson et. al. 1987). Authors are grateful to Charles Burchill of the University of Manitoba for supplying the macro to compute the Charlson index.

9. These thresholds distinguishing high volume from low volume hospitals are sometimes used in the medical literature. See, e.g. Birkmeyer, 2000.

10. For our purposes a 'patient's doctor' means her attending physician, typically a cardiologist, who is the party primarily responsible for the choice of treatment. The frequency of a procedure (such as corrective surgery) for a given attending physician represents the number of his patients who received heart surgery on his recommendation, regardless of who performed the surgery.

11. This procedure is also frequently referred to as cardiac catheterization, although the two are not technically the same thing. Coronary angiography consists of viewing the coronary arteries with an X-ray technique called fluoroscopy. Catheterization is the means by which the dyes required for angiography are delivered to the aorta. We loosely use the general term angiography to refer specifically to coronary angiography.

12. Results for a separate sample from the year 2000 are reported in the appendix, Table A2. These results are qualitatitively identical with respect to the focal variables.

13. The regressions creating the IV for the network rates yielded adjusted r-squares of .68 and .65 for angiography and surgery, respectively.

14. In deriving the predicted probabilities we hold individual patient characteristics fixed at the statewide means, but use district-specific means for demographic variables and for physician network rates of angiography and surgery, respectively.

15. The model is specified with the same regressors as in Table 2, except for the omission of physician network rate of surgery. The sample includes only individuals who receive surgery and the network effects are thus predetermined.

16. Results for a separate sample from the year 2000 are reported in the appendix, Table A4. Again, these results are qualitatitively similar with respect to the focal variables.

17. In contrast, for the technology given in section II-A, the long-run outcome is always superior to enforced procedure guidelines.

Figure 1. Physician payoffs for procedures A and B and an α-patient

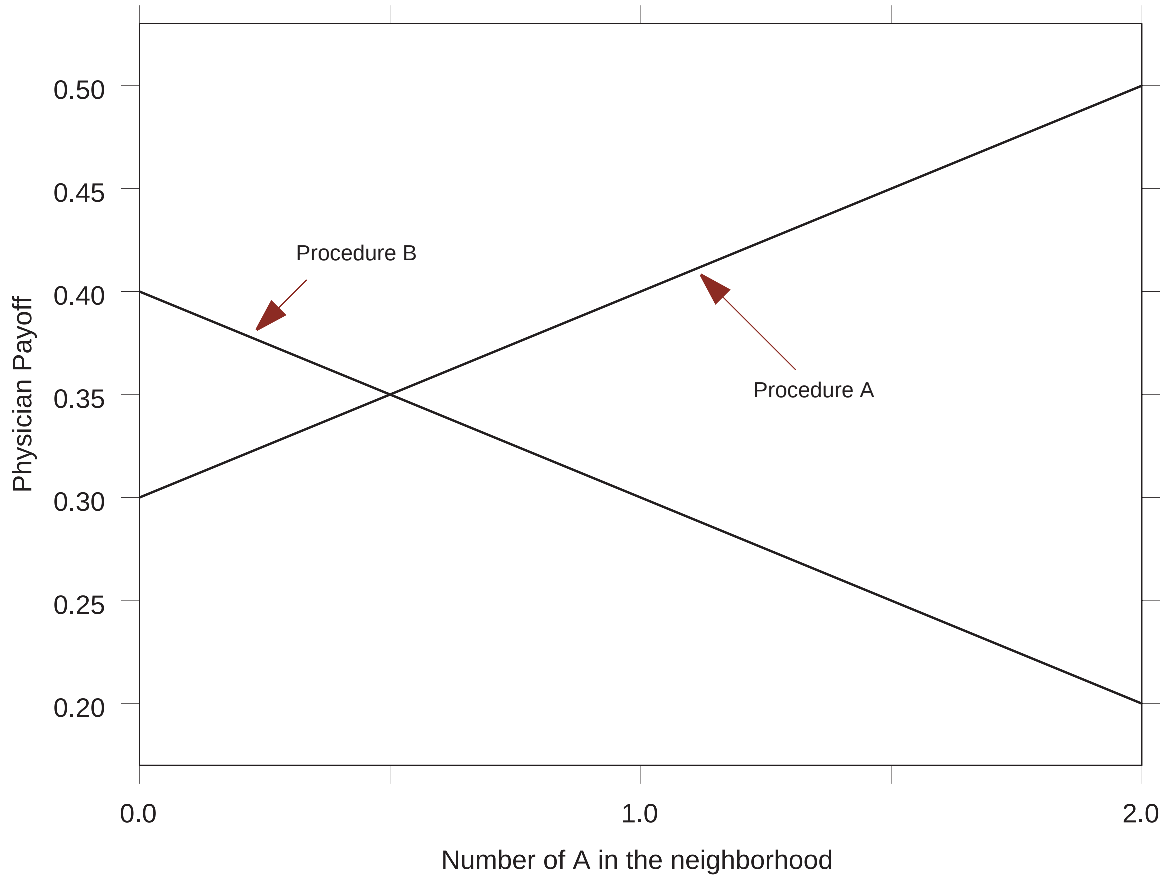

Table 1 Patterns of Regional Variation

		1994 Sample					
		Proportion Receiving Angiography			Proportion Receiving Surgery		
Districts	Mean Age	All ages	age<55	age>74	All ages	age<55	age > 74
1	66	0.49	0.63	0.42	0.60	0.74	0.50
2	65	0.63	0.61	0.47	0.80	0.89	0.56
3	69	0.30	0.39	0.20	0.44	0.53	0.29
4	67	0.50	0.58	0.36	0.77	0.87	0.56
5	70	0.25	0.43	0.16	0.54	0.70	0.41
6	68	0.45	0.49	0.32	0.65	0.69	0.47
7	67	0.53	0.58	0.44	0.67	0.67	0.55
8	70	0.36	0.49	0.24	0.54	0.64	0.36
9	71	0.29	0.46	0.20	0.32	0.50	0.22
10	71	0.36	0.44	0.26	0.48	0.61	0.33
11	70	0.28	0.43	0.16	0.39	0.56	0.22
Statewide	69	0.39	0.50	0.26	0.56	0.69	0.39
Observations	19192	19192	2369	6208	19192	2369	6208

		2000 Sample					
		Proportion Receiving Angiography			Proportion Receiving Surgery		
Districts	Mean Age	All ages	age<55	age>74	All ages	age<55	age > 74
1	68	0.65	0.73	0.52	0.73	0.75	0.60
2	66	0.66	0.66	0.61	0.87	0.87	0.76
3	69	0.45	0.57	0.37	0.74	0.77	0.66
4	67	0.63	0.70	0.56	0.87	0.90	0.80
5	71	0.50	0.56	0.43	0.86	0.89	0.79
6	70	0.60	0.70	0.47	0.71	0.81	0.57
7	68	0.43	0.50	0.38	0.67	0.70	0.59
8	70	0.56	0.61	0.43	0.62	0.67	0.45
9	70	0.36	0.31	0.32	0.52	0.41	0.48
10	72	0.36	0.41	0.28	0.64	0.68	0.50
11	69	0.56	0.70	0.45	0.68	0.82	0.53
Statewide	69	0.52	0.60	0.43	0.74	0.77	0.62
Observations	15251	15251	1914	5427	15251	1914	5427

Table 2. Treatment Choice Models, 1994
Instrumental Variables Probit, second stage estimates

Dependent Variable:	Angiography			Surgery		
	Estimated coefficient*	Std. Err.	Marginal Effects	Estimated coefficient*	Std. Err.	Marginal Effects
i.v., network rate	2.490 [a]	0.164	0.890	2.933 [a]	0.138	1.147
scale economies, angiography	0.632 [a]	0.031	0.222			
scale economies, bipass surgery				0.350 [a]	0.038	0.135
scale economies, angioplasty				0.611 [a]	0.041	0.235
<u>Regional Characteristics</u>						
district1	-1.937 [a]	0.168	-0.336	-2.082 [a]	0.212	-0.574
district2	-0.723 [a]	0.103	-0.207	-0.761 [a]	0.142	-0.293
district3	-0.753 [a]	0.095	-0.221	-0.947 [a]	0.115	-0.359
district4	-0.913 [a]	0.097	-0.259	-1.497 [a]	0.138	-0.517
district5	-0.658 [a]	0.093	-0.202	-0.788 [a]	0.123	-0.305
district6	-0.350 [a]	0.076	-0.116	-0.367 [a]	0.105	-0.145
district7	-0.930 [a]	0.111	-0.256	-1.187 [a]	0.147	-0.432
district8	-1.355 [a]	0.109	-0.336	-1.823 [a]	0.144	-0.588
district9	-0.530 [a]	0.119	-0.164	-0.467 [a]	0.153	-0.185
district10	-0.554 [a]	0.127	-0.173	-0.605 [a]	0.175	-0.237
population 65 and over	-0.001 [a]	0.000	-0.001	-0.003 [a]	0.001	-0.001
income per capita	-0.001	0.005	0.000	0.008	0.006	0.003
population growth	0.010 [a]	0.002	0.004	0.005 [a]	0.002	0.002
mds per capita	-0.033 [c]	0.018	-0.012	-0.168 [a]	0.025	-0.066
high school graduation rate	0.047 [a]	0.005	0.017	0.066 [a]	0.006	0.026
<u>Patient Characteristics</u>						
emergency room admission	-0.162 [a]	0.023	-0.058	-1.789 [a]	0.038	-0.570
transferred to another facility	-1.209 [a]	0.092	-0.295	-1.329 [a]	0.091	-0.466
male	0.102 [a]	0.023	0.036	0.242 [a]	0.028	0.095
black	-0.364 [a]	0.063	-0.118	-0.465 [a]	0.074	-0.184
hispanic	-0.048	0.057	-0.017	-0.026	0.069	-0.010
other race	-0.204 [b]	0.082	-0.069	0.216 [b]	0.110	0.082
age	-0.022 [a]	0.002	-0.008	-0.034 [a]	0.002	-0.013
patient insured by medicare	0.025	0.032	0.009	-0.038	0.041	-0.015
index of risk of mortality	0.075 [a]	0.017	0.027	0.134 [a]	0.021	0.052
deficiency anemias	-0.088	0.063	-0.031	-0.288 [a]	0.075	-0.114
chronic pulmonary disease	-0.210 [a]	0.035	-0.072	-0.273 [a]	0.043	-0.108
coagulopthy	0.290 [a]	0.089	0.109	0.885 [a]	0.137	0.283
depression	-0.499 [a]	0.126	-0.154	-0.884 [a]	0.140	-0.333
diabetes	-0.101 [a]	0.034	-0.036	-0.161 [a]	0.043	-0.064
diabetes w/ chronic complications	-0.344 [a]	0.079	-0.112	-0.406 [a]	0.093	-0.161
hypertension	-0.031	0.024	-0.011	-0.035	0.030	-0.014
hypothyroidism	-0.087	0.062	-0.030	-0.175 [b]	0.073	-0.069
fluid and electrolyte disorders	0.059 [c]	0.035	0.021	0.168 [a]	0.043	0.065
other neurological disorders	-0.181 [b]	0.090	-0.062	-0.237 [b]	0.104	-0.094
obesity	0.083	0.072	0.030	-0.164 [b]	0.084	-0.065
peripheral vascular disease	-0.093 [c]	0.052	-0.033	-0.253 [a]	0.063	-0.100
renal failure	-0.323 [a]	0.077	-0.106	-0.327 [a]	0.091	-0.130
solid tumor w/out metastasis	-0.280 [a]	0.071	-0.093	-0.357 [a]	0.082	-0.142
peptic ulcer disease x bleeding	-0.049	0.103	-0.017	-0.346 [a]	0.119	-0.137
intercept	-3.233 [a]	0.251		-2.243 [a]	0.310	
Observed Proportion	0.385			0.564		
Predicted Proportion	0.319	(at x-bar)		0.579	(at x-bar)	
Number of Observations	19192			19192		
Log Likelihood	-10034			-6137.438		

*Significance Level: a=1%,b=5% c=10%

Table 3 Estimated Regional Variations*

	Treatment				Outcomes	
	Angiography		Surgery		Length of Stay [a]	
District	**1994**	**2000**	**1994**	**2000**	**1994**	**2000**
1	0.40	0.66	0.63	0.84	1.84	1.03
2	0.58	0.72	0.80	0.92	1.64	1.33
3	0.21	0.58	0.36	0.80	1.88	1.44
4	0.42	0.66	0.61	0.94	1.77	1.42
5	0.19	0.58	0.40	0.91	1.66	1.07
6	0.40	0.65	0.67	0.87	1.81	1.28
7	0.51	0.69	0.79	0.79	1.59	1.32
8	0.29	0.61	0.49	0.81	1.54	1.42
9	0.21	0.58	0.33	0.65	1.86	1.26
10	0.34	0.63	0.57	0.76	1.63	1.52
11	0.23	0.59	0.39	0.75	1.57	1.36
coef. Var.	0.38	0.24	0.31	0.10	0.07	0.12

* Predicted values from each model, holding individual covariates at statewide means

[a] Expressed in natural logarithms

Table 4. Treatment Choice Models in Low Volume Hospitals, 1994
Instrumental Variables Probit, second stage estimates

Dependent Variable:	Angiography			Surgery		
	Estimated coefficient*	Std. Err.	Marginal Effects	Estimated coefficient*	Std. Err.	Marginal Effects
i.v., network rate	2.322 [a]	0.237	0.424	3.115 [a]	0.183	0.537
Regional Characteristics						
district1	-4.358 [a]	0.338	-0.123	-4.109 [a]	0.346	-0.128
district2	-1.086 [a]	0.175	-0.100	-1.398 [a]	0.211	-0.104
district3	-2.096 [a]	0.174	-0.201	-1.936 [a]	0.196	-0.170
district4	-1.666 [a]	0.175	-0.127	-1.951 [a]	0.218	-0.116
district5	-1.486 [a]	0.199	-0.140	-1.852 [a]	0.262	-0.145
district6	-0.973 [a]	0.158	-0.100	-0.830 [a]	0.183	-0.087
district7	-2.452 [a]	0.226	-0.153	-2.511 [a]	0.264	-0.143
district8	-3.035 [a]	0.218	-0.195	-3.065 [a]	0.250	-0.177
district9	-1.793 [a]	0.236	-0.126	-1.556 [a]	0.333	-0.114
district10	-2.163 [a]	0.257	-0.141	-2.499 [a]	0.342	-0.140
population 65 and over	-0.003 [a]	0.001	-0.001	-0.001	0.001	0.000
income per capita	0.001	0.007	0.000	-0.008	0.008	-0.001
population growth	0.013 [a]	0.003	0.002	0.020 [a]	0.003	0.004
mds per capita	-0.069 [b]	0.028	-0.013	-0.220 [a]	0.036	-0.038
high school graduation rate	0.108 [a]	0.009	0.020	0.139 [a]	0.010	0.024
Patient Characteristics						
emergency room admission	-0.177 [a]	0.043	-0.034	-1.782 [a]	0.064	-0.520
transferred to another facility	-1.151 [a]	0.122	-0.126	-1.246 [a]	0.115	-0.125
male	0.117 [a]	0.039	0.021	0.306 [a]	0.049	0.052
black	-0.535 [a]	0.101	-0.071	-0.526 [a]	0.114	-0.066
hispanic	0.106	0.090	0.020	0.376 [a]	0.110	0.079
other race	-0.042	0.179	-0.008	0.245	0.198	0.049
age	-0.026 [a]	0.003	-0.005	-0.030 [a]	0.003	-0.005
patient insured by medicare	0.047 [a]	0.055	0.008	-0.096	0.069	-0.017
index of risk of mortality	0.084 [a]	0.029	0.015	0.153 [a]	0.036	0.026
deficiency anemias	-0.047	0.106	-0.008	-0.206 [c]	0.124	-0.031
chronic pulmonary disease	-0.149 [b]	0.061	-0.025	-0.290 [a]	0.072	-0.044
coagulopthy	0.284 [c]	0.171	0.061	0.690 [a]	0.225	0.174
depression	-0.412 [b]	0.203	-0.058	-0.622 [b]	0.259	-0.071
diabetes	-0.052	0.059	-0.009	-0.074	0.076	-0.012
diabetes w/ chronic complications	-0.346 [b]	0.147	-0.051	-0.338 [b]	0.158	-0.047
hypertension	-0.030	0.041	-0.005	0.014	0.051	0.002
hypothyroidism	-0.114	0.115	-0.019	-0.081	0.132	-0.013
fluid and electrolyte disorders	0.076	0.061	0.014	0.265 [a]	0.074	0.052
other neurological disorders	-0.271 [c]	0.159	-0.042	-0.349 [c]	0.182	-0.048
obesity	-0.035	0.120	-0.006	0.046	0.134	0.008
peripheral vascular disease	-0.223 [b]	0.091	-0.036	-0.336 [a]	0.107	-0.047
renal failure	-0.471 [a]	0.144	-0.064	-0.497 [a]	0.164	-0.062
solid tumor w/out metastasis	-0.351 [a]	0.133	-0.052	-0.409 [a]	0.151	-0.055
peptic ulcer disease x bleeding	-0.157	0.168	-0.026	-0.274	0.176	-0.040
intercept	-6.427 [a]	0.512		-7.094 [a]	0.574	
Observed Proportion	0.209			0.267		
Predicted Proportion	0.106	(at x-bar)		0.098	(at x-bar)	
Number of Observations	9273			8717		
Log Likelihood	-3431.074			-2237.908		

*significance level a=1%,b=5% c=10%

Appendix: Results for 2000 sample

Table A2. Treatment Choice Models, 2000
Instrumental Variables Probit, second stage estimates

Dependent Variable:	Angiography			Surgery		
	Estimated coefficient*	Std. Err.	Marginal Effects	Estimated coefficient*	Std. Err.	Marginal Effects
i.v., network angiography rate	2.631 [a]	0.184	1.050	2.286 [a]	0.188	0.545
scale economies, angiography	0.815 [a]	0.036	0.308			
scale economies, bipass surgery				0.150 [a]	0.044	0.036
scale economies, angioplasty				1.282 [a]	0.067	0.405
Regional Characteristics						
district1	0.690 [a]	0.199	0.259	-0.875 [a]	0.280	-0.283
district2	0.535 [a]	0.103	0.206	-0.644 [a]	0.153	-0.195
district3	0.634 [a]	0.129	0.243	-0.377 [b]	0.148	-0.102
district4	0.503 [a]	0.115	0.196	-0.414 [a]	0.156	-0.114
district5	0.372 [a]	0.109	0.146	-0.142	0.148	-0.036
district6	0.225 [a]	0.076	0.089	-0.323 [a]	0.106	-0.087
district7	0.527 [a]	0.159	0.203	-0.696 [a]	0.193	-0.215
district8	0.391 [a]	0.139	0.153	-0.222	0.194	-0.058
district9	0.099	0.115	0.039	0.403 [a]	0.137	0.080
district10	0.018	0.136	0.007	0.019	0.165	0.005
population 65 and over	0.002 [a]	0.000	0.001	-0.001 [c]	0.001	0.000
income per capita	0.000	0.004	0.000	-0.032 [a]	0.006	-0.008
population growth	0.007 [a]	0.002	0.003	0.008 [a]	0.003	0.002
mds per capita	0.060 [a]	0.016	0.024	-0.110 [a]	0.022	-0.026
high school graduation rate	-0.033 [a]	0.006	-0.013	0.044 [a]	0.008	0.011
Patient Characteristics						
emergency room admission	0.075 [a]	0.025	0.030	-1.594 [a]	0.042	-0.380
transferred to another facility	-1.260 [a]	0.108	-0.406	-1.394 [a]	0.129	-0.482
male	0.034	0.024	0.014	0.154 [a]	0.034	0.037
black	-0.103 [c]	0.054	-0.041	-0.285 [a]	0.070	-0.077
hispanic	-0.057	0.058	-0.023	-0.134 [c]	0.078	-0.034
other race	0.078	0.077	0.031	0.053	0.119	0.012
age	-0.018 [a]	0.002	-0.007	-0.031 [a]	0.002	-0.007
patient insured by medicare	0.011	0.035	0.004	-0.088 [c]	0.052	-0.021
index of risk of mortality	0.019	0.017	0.007	0.105 [a]	0.024	0.025
deficiency anemias	0.018	0.059	0.007	0.065	0.082	0.015
chronic pulmonary disease	-0.187 [a]	0.036	-0.074	-0.237 [a]	0.050	-0.061
coagulopthy	0.235 [a]	0.071	0.093	0.666 [a]	0.118	0.111
depression	-0.277 [a]	0.094	-0.109	-0.475 [a]	0.110	-0.139
diabetes	-0.098 [a]	0.033	-0.039	-0.208 [a]	0.047	-0.053
diabetes w/ chronic complications	-0.171 [b]	0.080	-0.068	-0.436 [a]	0.107	-0.125
hypertension	-0.066 [a]	0.023	-0.026	-0.027	0.034	-0.007
hypothyroidism	0.017	0.054	0.007	-0.147 [b]	0.069	-0.037
fluid and electrolyte disorders	-0.137 [a]	0.048	-0.055	-0.174 [a]	0.061	-0.045
other neurological disorders	-0.307 [a]	0.111	-0.120	-0.264 [b]	0.131	-0.071
obesity	0.034	0.056	0.013	0.062	0.082	0.014
peripheral vascular disease	0.017	0.047	0.007	-0.117 [c]	0.065	-0.029
renal failure	0.027	0.072	0.011	-0.007	0.094	-0.002
solid tumor w/out metastasis	-0.090	0.061	-0.036	-0.208 [b]	0.083	-0.055
peptic ulcer disease x bleeding	0.035	0.119	0.014	-0.178	0.147	-0.046
intercept	0.555 [c]	0.320		-0.908 [c]	0.479	
Observed Proportion	0.522			0.737		
Predicted Proportion	0.494	(at x-bar)		0.845	(at x-bar)	
Number of Observations	15251			15251		
Log Likelihood	-8684.8224			-3920.485		

*Significance Level: a=1%,b=5% c=10%

Appendix: Results for 2000 sample

Table A4. Treatment Choice Models in Low Volume Hospitals, 2000
Instrumental Variables Probit, second stage estimates

Dependent Variable:	Angiography			Surgery		
	Estimated coefficient*	Std. Err.	Marginal Effects	Estimated coefficient*	Std. Err.	Marginal Effects
i.v., network rate	1.570 [a]	0.423	0.206	0.962 [c]	0.517	0.171
Regional Characteristics						
district1	-0.790	0.885	-0.062	-4.292 [a]	1.392	-0.180
district2	0.473	0.392	0.081			
district3	-0.757	0.647	-0.073			
district4	0.038	0.569	0.005	-3.131 [a]	1.004	-0.141
district5	-0.216	0.560	-0.025	-2.225 [b]	0.928	-0.147
district7	-0.737	0.769	-0.060	-4.717 [a]	1.300	-0.192
district8	-0.367	0.730	-0.038	-3.402 [a]	1.233	-0.206
district9	-1.549 [a]	0.580	-0.106	-2.608 [b]	1.091	-0.247
district10	-1.054	0.743	-0.077	-3.238 [b]	1.259	-0.212
population 65 and over	0.003	0.002	0.000	0.002	0.004	0.000
income per capita	-0.035	0.026	-0.005	-0.092 [c]	0.048	-0.016
population growth	0.028 [a]	0.007	0.004	0.036 [a]	0.011	0.006
mds per capita	0.175 [a]	0.058	0.023	-0.192	0.172	-0.034
high school graduation rate	0.031	0.030	0.004	0.186 [a]	0.049	0.033
Patient Characteristics						
emergency room admission	-0.285 [a]	0.075	-0.042	-1.794 [a]	0.160	-0.528
transferred to another facility	-2.282 [a]	0.401	-0.146			
male	0.133 [c]	0.069	0.017	0.324 [a]	0.112	0.057
black	0.087	0.120	0.012	-0.045	0.200	-0.008
hispanic	-0.312	0.201	-0.033	-0.555 [b]	0.240	-0.073
other race	0.096	0.208	0.014	-0.126	0.365	-0.021
age	-0.022 [a]	0.004	-0.003	-0.033 [a]	0.007	-0.006
patient insured by medicare	-0.051	0.096	-0.007	0.035	0.160	0.006
index of risk of mortality	0.072	0.047	0.009	0.118	0.075	0.021
deficiency anemias	-0.030	0.149	-0.004	0.107	0.266	0.020
chronic pulmonary disease	-0.113	0.106	-0.014	-0.246	0.180	-0.040
coagulopthy	0.758 [a]	0.218	0.162	0.774 [b]	0.350	0.205
depression	-0.486	0.315	-0.045	-0.879	0.762	-0.089
diabetes	-0.046	0.092	-0.006	-0.142	0.148	-0.024
diabetes w/ chronic complications	-0.247	0.249	-0.027	-0.175	0.386	-0.028
hypertension	-0.102	0.067	-0.013	-0.082	0.113	-0.014
hypothyroidism	0.051	0.141	0.007	-0.242	0.261	-0.037
fluid and electrolyte disorders	-0.069	0.130	-0.009	0.077	0.203	0.014
other neurological disorders	-0.087	0.310	-0.011	-0.016	0.415	-0.003
obesity	-0.087	0.170	-0.011	0.213	0.299	0.043
peripheral vascular disease	-0.119	0.138	-0.014	-0.246	0.253	-0.038
renal failure	-0.045	0.207	-0.006	-0.118	0.303	-0.019
solid tumor w/out metastasis	0.034	0.181	0.005	-0.113	0.318	-0.019
peptic ulcer disease x bleeding	0.047	0.328	0.006	-0.217	0.665	-0.033
intercept	-2.488 [b]	1.133		-7.244 [a]	2.038	
Observed Proportion	0.214			0.245		
Predicted Proportion	0.068	(at x-bar)		0.101	(at x-bar)	
Number of Observations	3314			1880		
Log Likelihood	-1095.569			-500.646		

*significance level a=1%,b=5% c=10%