Geographic Variations in a Model of Physician Treatment Choice with Social Interactions

Mary A. Burke*
Gary M. Fournier†
Kislaya Prasad‡

March 2, 2007

Abstract

Region-specific norms of behavior are a widespread phenomenon. For instance, several studies have found an inordinate effect of geography on the choice of medical procedures. We show how the presence of social influence on individual decisions can help explain such regularities. To explain geographical variations we construct a theoretical model, derived from interacting particle systems, in which physician choices are subject to either knowledge spillovers or a desire to conform. When optimal treatment depends on patient characteristics, regional differences in the patient mix will give rise to divergent treatment patterns—the treatment a patient receives depends on where she lives. The pattern of medical practice depends in predictable ways on regional demographic differences. Investigation of Florida data reveals significant geographic variation in treatment rates consistent with the predictions of our model. Implications for patient welfare are explored.

JEL Codes: C73, Z13, I10, I11

Keywords: Geographic variations in medicine, Evolutionary game theory, Interacting particle systems, Social influence, Local interactions, Medical practice guidelines

*Federal Reserve Bank of Boston, Boston, MA 02205.
†Department of Economics, Florida State University, Tallahassee, FL 32306.
‡Robert H. Smith School of Business, University of Maryland, College Park, MD 20742.

Geographic Variations in a Model of Physician Treatment Choice with Social Interactions

March 2, 2007

Abstract

Region-specific norms of behavior are a widespread phenomenon. For instance, several studies have found an inordinate effect of geography on the choice of medical procedures. We show how the presence of social influence on individual decisions can help explain such regularities. To explain geographical variations we construct a theoretical model, derived from interacting particle systems, in which physician choices are subject to either knowledge spillovers or a desire to conform. When optimal treatment depends on patient characteristics, regional differences in the patient mix will give rise to divergent treatment patterns—the treatment a patient receives depends on where she lives. The pattern of medical practice depends in predictable ways on regional demographic differences. Investigation of Florida data reveals significant geographic variation in treatment rates consistent with the predictions of our model. Implications for patient welfare are explored.

JEL Codes: C73, Z13, I10, I11

Keywords: Geographic variations in medicine, Evolutionary game theory, Interacting particle systems, Social influence, Local interactions, Medical practice guidelines

1 Introduction

This paper develops a general theory of the emergence of region-specific norms of behavior and uses it to suggest a possible resolution of a famous public health puzzle—the well-documented effect of geography on the choice of medical procedures. Over the years, a number of studies have found that medical choices tend to be relatively uniform within regions and yet quite diverse across regions. Surprisingly, the phenomenon persists today despite vast improvements in communication technology. In this paper, we show that the observed geographic treatment patterns are likely to be a consequence of *local social interactions* among physicians—interactions that result in a positive correlation between the choices of a given physician and the choices of her local colleagues. We expect such a relationship to arise in the medical context for (at least) two reasons: (1) physicians may learn and acquire skills from one another, and (2) there may be social pressure to conform to local practice norms. We posit that both of these mechanisms are grounded in face-to-face encounters and therefore should operate most strongly at the local level. A model adapted from the theory of *interacting particle systems* represents medical treatment choice in the presence of local social interactions and reproduces the stylized facts of the geographic variations puzzle. The theoretical model, although tailored to the requirements of the puzzle at hand, is quite general. However, for concreteness, we will stick with the language of the medical procedure choice example. The model predicts that, within a region, patients of all ages will tend to receive the treatment that is best suited to the patient of modal age for that region. As a result, a given patient will be treated differently in different regions, depending on the dominant age group in the region. We find strong support for these predictions among extensive data on coronary patients from Florida. We also use the model to show that patient welfare need not improve under a system of procedure guidelines designed to eliminate regional treatment variations.

The extent of geographical variation in medical care 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 (see Wennberg and Cooper, 1999). Such high variation has been recorded for many procedures and treatments, spanning all areas of medicine, and often persisting over time. The systematic study of treatment variations appears to begin with Glover's (1938) presentation to the Royal Society of Medicine. In the United States, Wennberg and his colleagues have documented the phenomenon comprehensively over a number of years (e.g. Wennberg and Gittelsohn, 1973; Wennberg and Birkmeyer (1999); O'Connor *et. al.*, 1999, and Pilote *et. al.*, 1995). The variations have proved remarkably robust to controls for incidence of illness and demographic and socioeconomic factors (Phelps and Mooney, 1993; Wennberg and Gittelsohn, 1982). Wennberg and Gittelsohn (1982) stressed the importance of physician "practice style," defined as a set of beliefs about the efficacy and appropriateness of alternative forms of care. However, subsequent inquiries into the role of practice style in treatment variations have yielded mixed results about its importance (e.g. contrast Grytten and Sorensen, 2002 with Folland and Stano, 1987). Among economists, Phelps and Mooney (1993) present a model, based on Bayesian updating, of how regional norms might persist once they are in place. However it does not explain how such norms might arise in the first place. More recently, Chandra and Staiger (2004) attribute medical treatment variations to local productivity spillovers. Although this explanation overlaps with our own, we show that conformity effects can just as readily explain treatment variations. Furthermore, the empirical evidence to date cannot neatly distinguish between these two sources of choice interactions.

We develop a model to explain how geographical variations in medical care arise, and why there may be resistance to efforts towards standardization of practice. Formally, we model the social system as a one-dimensional stochastic interacting particle system, as in Liggett (1999). Such systems are now used to study problems in evolutionary game theory. In this paper we build upon ideas in Ellison (1993), Morris (2000), Young (1998), Young and Burke (2001), and Burke, Fournier and Prasad (2006). Our particular theoretical contribution is to generalize Ellison's model so as to account for the dependence of the optimal choice on characteristics of patients who are randomly selected from the local population. Physicians occupy locations on a lattice and interact only with their nearest neighbors, by whom they may be influenced. Patients, who differ in characteristics such as age, arrive randomly at physician locations. Physicians then choose a medical procedure to maximize their payoffs (which are taken to be positively related with the likelihood of success of the procedure). Payoffs vary with patient characteristics, as well as with the recent treatment choices of neighbors. The patient mix differs across regions of the lattice. Starting from a random configuration of choices in the population of physicians, and given a random patient arrival process, we determine the emergent long-run behavior patterns. Burke, Fournier and Prasad (2006) considered a finite version of this model, but were only able to obtain simulation results. Here, we are able to prove theorems that characterize precisely the long-run behavior of the system. In addition, we obtain welfare results and generate testable implications of the theory, which are subjected to rigorous testing with data.

Local social interactions among physicians play a central role in our analysis. The choices of a physician's nearby colleagues exert an influence on her own choices, either because of local increasing returns or because of pure conformity effects. Local increasing returns will arise if there are knowledge spillovers across physicians, for example if a surgeon's own expertise in a given operation improves as his peers gain experience in the same procedure and share their insights. Under such conditions, a given treatment will yield better outcomes, and so become increasingly favored within a group of interacting peers, the more frequently it has been used in the past. Even in the absence of increasing returns, choice may be self-reinforcing within a group due to conformity effects. Conformity within a group can arise because individuals have an innate preference for social esteem, as in Bernheim (1994), or it might occur as a calculated response to institutional constraints. For example, in the United States, malpractice claims are judged by comparing a doctor's actions to standard practices within the local medical community, thereby discouraging deviation from such practices.[1] Either form of social influence gives rise to geographical variations—although the welfare implications will be quite different between these two cases.[2]

Another feature of our model is heterogeneity in patient characteristics. The "ideal" treatment for a patient is assumed to depend not just on symptoms, but also on general patient traits such as age. For instance, heart bypass surgery is much less likely to be used in elderly patients than in younger patients with the same medical conditions. This assumption is borne out in our data as well as in published procedure guidelines. The intuition for our main result can be seen by considering the fate of a younger patient in a region in which the proportion of elderly patients is relatively high. Her physician's peers are more likely to be using procedures better suited to the elderly. In the presence of social influence, the same procedure is more likely to be used on the younger patient as well. The dynamic feedback between physician choice and patient types produces a distinctive stable treatment pattern: regional treatment norms emerge, each of which represents the "ideal" treatment for the modal patient type in the region. Therefore, patients of diverse types in the same region all receive the same treatment (the local norm), while a patient of a given type receives different treatment depending on where she lives due to regional variation in average patient characteristics.

We test these predictions using a census of Florida patient discharge records, focusing on patients over 25 with a primary diagnosis of either coronary atherosclerosis or acute myocardial infarction (AMI, or "heart attack"). The usable sample covers over 500,000 inpatient stays during the periods 1995-2001. To test for the predicted relationship between average patient characteristics and treatment choice, we look at the rate of angioplasty and other surgical treatments of "elderly" patients at a hospital, and determine if it depends upon the proportion of "younger" patients being treated at the same hospital. Conversely, we examine whether the treatment rate of "younger" patients depends on the proportion of "elderly" patients at the hospital. Our panel regression model includes fixed effects for hospital and time, as well as controls for hospital volume, race, income, and insurance status. We find strong support for our predictions. Younger patients are less likely to get an angioplasty or surgery at hospitals with a larger proportion of older patients. Older patients are more likely to get an angioplasty at hospitals

[1] This is the dominant legal standard in the U.S. In Florida, "the prevailing professional standard of care for a given health care provider shall be that level of care, skill, and treatment which, in light of all relevant surrounding circumstances, is recognized as acceptable and appropriate by reasonably prudent similar health care providers." "Similar health care providers" are, inter alia, ones who practice in the same or similar medical community. (Florida Statutes 766.102).

[2] It is worth noting that other forms of social influence exist. In another study, of the adoption of new technologies in medicine, Burke, Fournier and Prasad (2007) found a significant influence of the choices of "star" physicians.

with a larger proportion of young patients (the effect has the expected sign but is not statistically significant in the case of surgery).

Is it fair to assume that regional variations are bad for patients? This would certainly be the case if variations resulted from pressures towards conformity. But the situation is unclear if regional variations are caused by local increasing returns. In the presence of increasing returns, a patient of a given type is best served by living in a region where the local norm matches the procedure ideal for her characteristics. In this case, she reaps the advantages of accumulated local expertise, advantages which would not accrue to the same extent if physicians were forced to apply different treatments to different patients depending on individual type only and ignoring spillover effects. We establish conditions under which mandated procedure guidelines improve patient outcomes, and conditions under which they don't. Procedure guidelines are often proposed as a way to improve medical outcomes. Our results suggest a need for caution. Guidelines that neglect social dimensions of medical procedure choice could well end up being counter-productive.

In principle, it is possible to tell whether patients suffer because of regional variations in procedure choice. Our data has two variables that are indicative of the quality of care that patients receive—mortality and length of hospital stay (the limitation being that long-term patient outcomes, following release from the hospital, are unavailable). We regress the outcome measures, for each patient group, against hospital demographic variables. We find little systematic evidence to suggest that patient welfare is adversely affected by the propensity of physicians to follow norms induced by the local age distribution. This is somewhat reassuring, and would seem to suggest that knowledge spillovers rather than conformity effects are the source of geographical variation.

2 A Model of Procedure Choice

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. In general the patient type could refer to any characteristic that systematically affects standard treatment recommendations, but it will be useful to think of type as age, such that some patients are 'old' and some are 'young.' The payoffs to the treatments depend not only on the patient's type but also on the recent treatment choices of the physician's two adjacent neighbors. The social influence may be viewed as deriving from local increasing returns, or from imitation or conformity effects as discussed above. The geometric structure implies that the neighborhoods overlap, a feature that permits influence to percolate across the line of physicians. The line is assumed to consist of two (connected) regions, each with a distinct age mix. We show that social influence leads eventually to a single procedure being applied to all patients in a given region regardless of age, while the regional demographic variation implies that this single dominant procedure will differ across regions. The difference in the age distributions across regions does not have to be extreme to produce this sort of choice pattern.

Here the threshold value is one-half: if there is a better than fifty percent chance that an arriving patient in a region is of a given type, the local norm will be to use the procedure "ideal" for them. If there are two regions, one above the threshold, and the other below, they will have different norms of practice.

2.1 *Theoretical Model*

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. This formulation can capture knowledge spillovers, because a procedure's success rate depends on the treatment choices of local neighbors. We abstract from unobservable factors that might affect the outcome of a given choice, such as the quality of complementary inputs, and the physician's skill and effort levels. We also assume (for now) that physicians care only about the likelihood of a procedure's success as described by this function $\pi_z(\cdot)$, that is we identify the physician's utility for a given treatment choice with its success probability:

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

In general physician utility may depend on a number of factors. For example, physicians may incur different costs for different procedures as a result of the payment system (e.g. Medicare reimbursement may bias choice in a particular direction), or they may care about the variability of treatment outcomes. As mentioned above, a taste for conformity might also affect individual physician payoffs. Our payoff structure abstracts from the former considerations (cost differences and risk preferences), but we can capture conformity effects simply by shifting the interpretation of the payoffs. The finding of persistent regional variation survives this generalization because it depends on qualitative features of the model that can capture a broad range of situations involving social interactions. The essential assumption about payoffs is the following:[3]

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.

[3] This definition is closely related to the concept of risk dominance in game theory.

(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:

$$\begin{array}{rr} \pi_A(\alpha, B, B) = 0.3 & \pi_A(\beta, B, B) = 0.2 \\ \pi_A(\alpha, A, B) = 0.4 & \pi_A(\beta, A, B) = 0.3 \\ \pi_A(\alpha, A, A) = 0.5 & \pi_A(\beta, A, A) = 0.4 \end{array}$$

Similarly, for procedure B the payoffs are

$$\begin{array}{rr} \pi_B(\alpha, B, B) = 0.4 & \pi_B(\beta, B, B) = 0.5 \\ \pi_B(\alpha, A, B) = 0.3 & \pi_B(\beta, A, B) = 0.4 \\ \pi_B(\alpha, A, A) = 0.2 & \pi_B(\beta, A, A) = 0.3 \end{array}$$

Figure 1 illustrates physician payoffs from using each procedure on an α-patient. Observe that the preferences satisfy property $\mathbf{P}$(a). Even if the success probability, π, does not depend on neighbors' choices, a desire for conformity could lead to payoffs with Property P. Pure conformity can be modelled by introducing a term in the utility function that penalizes agents by the extent to which they depart from the average behavior of neighbors (as in Brock and Durlauf, 2001). Such preferences, under mild conditions, will satisfy Property P and yield identical results.

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 location x (i.e. $\omega(x) = A$) indicates that the physician at x 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.

When a patient arrives at a specific location $x \in \mathbb{Z}$, the physician must make 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. Following the norm in the evolutionary game theory literature, we assume best-response dynamics — physicians maximize $\pi_z(h, L, R)$. The state of the system can be visualized as 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.[4]

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. Proofs are 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*,*

[4]For formal definitions of these properties, see Norris (1998).

with support $\mathbb{Z}$, such that

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

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

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, 1999). 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 (see Burke, Fournier and Prasad (2007) for suggestive simulation results). (4) If $p_E = p_W = 1$ then only α patients arrive at each location. This case corresponds to the model studied in Ellison (1993), and the risk dominant equilibrium $\mathbf{A}$ will be played.

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.

2.2 *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 (as opposed to global uniformity). 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 **A** and **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.[5]

2.3 *Welfare*

In our model, regional variations can arise either from local increasing returns (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 welfare. With scale effects, since the likelihood of success of a procedure increases when others choose the same procedure, some patients are likely to benefit from local uniformity of practice. If regional variations arise because of physicians' desire to conform with one another then patients are likely to 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? (Official guidelines are widely disseminated but not systematically enforced. For examples of guidelines in coronary care see Eagle, et al., 1999, and Gunnar et al., 1990.) A partial answer to this question is provided in Propositions 3 and 4 below.

Suppose that physician preferences are not subject to pure conformity effects and, as in section 2.1, 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-

[5] 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.

patients and B on β-patients.[6] 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 patient population as a whole.[7] Note that, from our definition of physician payoffs, the long-run average utility of the physician at location x (in equilibrium ρ) is a measure of the success rate of treatments for the patient population population. We prove

Proposition 3. *The long-run outcome ρ need not maximize the success rate of treatments for the patient population. In particular, it may be dominated, at every location $x \in \mathbb{Z}$, by the policy of enforced procedure guidelines.*

The proof of the proposition involves identifying a plausible technology for which the guidelines policy proves superior to the long-run outcome ρ at every location. In general, guidelines are more likely to dominate the long-run outcome (a) the more alike are the population profiles between the two 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. By an analogous argument, one can also show that ρ could sometimes dominate the policy of enforced procedure guidelines.

Proposition 4. *A policy of enforced procedure guidelines can be dominated by the long-run outcome ρ.*

The proof is immediate from inspection of the proof of Proposition 3, and hence omitted.

3 Empirical analysis

For elderly patients, the outcomes of PTCA (percutaneous transluminal coronary angioplasty) are currently less successful than for younger patients, due in part to comorbidities and medical conditions that are correlated with aging (Smith et al. 2001). Thus, where PTCA might be the optimal treatment choice for a younger patient, other things the same, it may not be optimal for an elderly one. Moreover, often the age distribution of patients admitted to hospitals for coronary care can vary considerable among hospitals across localities. Florida, for example, has a large elderly and retired population, concentrated more in some communities than others. In some areas, hospitals treat a relatively higher proportion of younger patients than in other areas. The consequence of treating a relatively young patient pool at the hospital is that PTCA is performed

[6] The policy alternative of moving patients to regions based on their characteristics is considered infeasible.

[7] The requirement that all patients be better off, in every state, is too stringent a standard, and quite removed from public policy debates.

more frequently, since it (as well as other other types of surgery) are often the optimal choice for younger patients. Likewise, in hospitals facing relatively older patients, PTCA is approached with greater caution, and this may reduce the frequency of such surgery.

Our theory suggests that, whether it is a consequence of knowledge spillovers or the desire for conformity, the medical staff may be more likely, at the margin, to make surgery the preferred choice of interventions in settings dominated by younger patients, relative to those where there is a greater predominance of elderly patients. The interesting question is whether the demographic effects can be shown in real data. We collected all patient discharge records of Florida hospital patients for the years 1995 to 2001. The Florida patient discharge data come from a legally mandated and audited census of inpatient stays, reported quarterly by hospitals in the state. From this population, we extracted records for a sample of patients who were admitted with a diagnosis of coronary artery disease in the form of atherosclerosis or acute myocardial infarction (AMI). [8] We only used patients treated at a hospital having the authority to perform heart surgery, i.e. a certificate of need license, with facilities to perform heart operations, and for which we had records spanning at least 5 quarters. The 62 included hospitals accounted for a high proportion of all coronary patients given hospital care in the state.

We focus on variations across hospitals as a means to assess geographical variations in the state. The hospitals in our sample treat patients from all of the state's 11 planning districts, Florida Administrative Health Care Districts. Each record gives the patient's age, race, sex, principal diagnosis and (where applicable) secondary diagnoses, treatments received, the hospital name and county location, the length of stay, and related information.[9] We eliminated cases of patients aged younger than 25, and focused on patients who receive one of these alternative procedures: (a) angioplasty, (b) bypass surgery, (c) angiography, or (d) no invasive surgical or diagnostic procedures.[10] Presumably the no-surgery category catches patients who received medical observation or medications and a medical decision was made not to conduct any surgical interventions. The total sample was 572,316 observations, spanning the four treatment categories. Summary statistics are presented in Table 1. Of these patients, 233,505 were treated with angioplasty. The mean age of patients given this treatment is 65.5 years old, with a standard deviation of 11.9 and the ages of these patients range from 25 years to 100 years old. The youngest one-third of patients in the sample are 62 years or less, while the oldest one-third are 73 or older. We calculate the proportions of all coronary patients admitted to each hospital in the bottom-third and top-third of the age distribution to examine the effect that the relative frequency by age has on the treatment given to patients in the other.

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

[9] A limitation of the data is that each observation is a single hospital stay rather than a longitudinal patient record. Identifiers for persons are masked, so a patient's repeat hospitalizations and longer term treatment records are censored, while long term outcomes, such as 30 day survival, are not available.

[10] Thus, among other thing, we exclude patients who receive heart transplants, heart valve surgery, implanted defibrillator devices or pacemakers.

3.1 Testable hypotheses

The basic effect predicted by the model in section 2 suggests that, where patient demographics varies substantially across localities, the treatment given a patient may reflect the choice best suited to the dominant patient type in the locality. Local interaction among the physicians who are used to treating patients with given demographic characteristics creates knowledge spillovers that raise the expected payoff to a particular treatment choice relative to other treatments that might be optimal in a different setting. In particular, 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 placed in hospitals with a relatively younger pool of patients. For coronary care, given that surgery rates decline on average with age, that would imply that the probability that a younger (under age 62) patient receives heart surgery is lower in those localities in Florida with a relatively high proportion of coronary care patients aged 73 or older. Conversely the surgery rates for older patients are higher when they are treated in hospitals facing a relatively young patient pool than elsewhere.

While our empirical analysis is focused on age effects, there may be other characteristics that lead to treatment variations in a similar manner. Nichols (2006) reports differences in the treatment and outcome patterns of African-American patients with AMI admitted to hospitals with disproportionately black patient populations. He notes that, consistent with Chandra and Staiger (2004), providers with greater numbers of black patients are predicted to adopt treatment practices that are particularly effective in treating conditions common among African-Americans. For example, blacks tend to have a greater aversion to invasive heart treatments and enjoy lower rates of these procedures at predominantly black hospitals. While Nichols finds that such treatment patterns lead to better outcomes for black patients, he finds that non-blacks treated in these hospitals receive inferior care and have worse outcomes. Within our model, this result could come about if treatments best-suited to African-American patients become "the norm" among a group of practitioners and are then applied broadly to all patients treated by that group, even if those treatments may be less suitable for other patients. Thus, we suspect our hypothesis may apply to a range of treatment-relevant demographic characteristics and not just to patient age.

3.2 Panel Regression Model

Our econometric model considers the characteristics of two age groups. First, we look at the rates of angioplasty for patients over 73 years of age. This is followed by an identical study of a broader class of surgeries including coronary artery bypass graft surgery (or "bypass"), in addition to angioplasty. The model is as follows:

$$treatment(73)_{ht} = \alpha_h + c_t + \gamma Age(62)_{ht} + \beta X_{ht} + \delta V_{ht} + \epsilon_{ht} \quad (1)$$

The dependent variable in (1), treatment rate, is measured as rate (per thousand patients) of angioplasty (alternatively, surgery) performed in the hospital for coronary patients aged 73 or older in the given period. The model in (1) implies that the treatment rate depends on fixed properties of the hospital(s) at which the patient is treated (one dummy, α_h, for each relevant hospital is included), the current calendar date c_t (a specific quarter), the average age, race, income and insurance status of the hospitals's current patients, X_{ht}, the hospital's overall volume of angioplasty (surgery) procedures, V_{ht}, and the proportion of younger patients being treated at the hospital, $Age(62)_{ht}$.

Since the hypothesized influence should work with the age groups reversed, we can establish the transmission of older treatment modalities to younger patients by analyzing the angioplasty (surgery) rates of patients younger than 63, and testing whether the proportion of older patients, $Age(73)_{st}$, has a significant influence:

$$treatment(62)_{ht} = \alpha_h + c_t + \gamma Age(73)_{ht} + \beta X_{ht} + \delta V_{ht} + \epsilon_{ht} \tag{2}$$

While the variables for hospital-specific effect, time and demographics help to remove the correlated or contextual effects of the hospital setting and treatment decisions, we focus on the treatment of patients in a given age group, and how well that treatment can be explained by the proportional presence at the hospital of heart patients in a different age group, i.e. the effect of $Age(73)_{ht}$ on $treatment(62)_{ht}$ and of $Age(62)_{ht}$ on $treatment(73)_{st}$.

3.3 Results

Table 2. reports the results of our panel regression where the unit of observation is measured at the hospital-quarter level. The model has 1448 observations over 25 quarters and 62 hospitals. Notably, older patients are significantly more likely to receive angioplasty or other surgery when the proportion of younger patients treated at the hospital is relatively high, other things the same. Likewise, in hospitals treating more older patients, where such surgeries are less often indicated, younger patients too are less often treated by surgery. Thus, the idea that treatment choices may be affected by local demographic influences has some support in the data.

Least squares estimates reveal a number of additional, significant effects. Treatment choices are responsive to volume effects. For example it is known that hospitals that perform relatively few invasive procedures tend to have lower success rates.[11] Moreover, there is some evidence of effects due to race: surgery is less likely to be given to older or younger patients, regardless of race, if there is a relatively high proportion of blacks treated at the hospital. The same is also true for the effect of having large numbers of hispanic patients at the hospital, the angioplasty equations shown in table 2.

[11] See, e.g. Birkmeyer (2000).

3.4 Welfare Implications

The results of econometric tests using the treatment rates of the two age groups reported above are informative regarding the hypothesis that demographic characteristics of the patient pool may skew patient treatment choice in the direction of treatments that are optimal for the dominant demographic group.

We believe that the mechanism reflected in this result is consistent with a model in which local interactions among physicians contribute to medical practice variations. The more difficult question, however, is to assess the normative implications. One might be tempted to assume that the patient should be given the treatment that is optimal for her, but the data show that the treatment choice may be altered by the presence of other patient types. One possibility is that, if older patients get more surgery because they are treated along with a younger pool of patients, their health outcomes are worse. Yet, it is also possible that the decision to give older patients surgery relatively more often may *not* affect health outcomes because the greater surgical risks of aging are offset by the quality gains hospitals achieve through additional knowledge spillovers and other benefits of high volume in hospitals with large pools of young patients.

One way to examine the welfare effects would be to see whether outcomes of treatment are related to the dominant demographics. To test this hypothesis we turn to Tables 3 and 4. The results of our panel regressions on the length of hospital stay are reported at the top of table 3, while the mortality equation is reported below. These results reveal, as predicted, that there is a small and significantly beneficial effect (negative coefficient) of the hospital's volume on length of stay and mortality. There are also somewhat longer hospital stays for patients in hospitals with relatively more black and hispanic patients, other things the same. There does not, however, appear to be any effect of young patients on older ones, or vise versa when we use length of stay as a measure of outcomes.

Nevertheless, there is a significant effect on mortality among younger patients associated with hospitals treating large numbers of elderly patients. As shown at the bottom of table 3, the mortality rate of younger patients following angioplasty has significant coefficient associated with older patients. The estimated effect is small, however. Holding other things constant, a one standard deviation increase (+0.1) above the sample mean in the proportion of patients age 73 or older is predicted to add only 2.8 deaths per thousand. Thus, while more evidence would be needed to substantiate this one result, it provides some tentative indication that the lower rate of angioplasties among younger patients placed in these settings may have some adverse health effects for them.[12] In the other three models, there seems to be no evidence of adverse health outcomes attributed to the age distribution despite the regional variation in treatment rates found in table 2.

[12]The data only captures mortality if it occurs during the recorded hospital stay. Thus, mortalities over a longer period following angioplasty are not observed.

4 Discussion

Our study addresses the puzzle of variations in the rates of treatment choices for patients across regions. These variations tend to be sustained even after controlling for demographic and hospital characteristics in some detail. Our theoretical model develops an explanation of the phenomenon in terms of social influence. We show how, starting from almost any initial conditions, simple adaptive behavior leads to region-specific treatment norms. The theory makes sharp predictions about the relationship between average patient characteristics in the local population and procedure use, predictions large confirmed by our empirical study. In particular, we find that the treatment that younger patients in a hospital receive depends upon the prevalence of older patients in the hospital. Analogously, the treatment that older patients receive depends upon the prevalence of younger patients in the hospital. In each case, treatment choices for all patients are skewed toward the choice that is optimal for the dominant demographic group in the area. Our results improve in significant ways upon previous theoretical explanations of the phenomenon (such as Phelps and Mooney, 1993; Chandra and Staiger, 2004; and others): (1) We provide an explanation for *how* regions may arrive at varying treatment patterns. (2) Our model is *flexible* enough to allow for both productivity spillovers and pressures to conform. Both hypotheses are plausible and both give rise to geographical variations. But welfare implications could be very different – if pressures to conform predominate, physicians may be led to over-prescribe or over-utilize health care, fueling the growth of unwarranted health care costs. Consequently, there is a need for further research on distinguishing the two hypotheses empirically. (3) We obtain sharp *welfare results* with implications for proposed policy remedies for treatment variations. (4) Our model of evolution of treatment norms establishes the *stability* of regional variation patterns. This is critical, given that productivity spillovers and pressures to conform so often give rise to models with multiple equilibria.

Our study focused on the treatment of cardiac ailments, where we obtain strong results. Since geographic variations have been observed in treatment rates pertaining to a wide range of health conditions, however, a more complete test of the model would look for the predicted demographic patterns in the application of other medical procedures such as hip replacement surgery and births by cesarian section. The available data permit such tests as well as a more refined model of procedure choice involving a longer list of patient and physician characteristics.

The phenomenon under study is extremely complex, and we have made several simplifying assumptions. For example, we have not allowed patients to respond to the emergence of treatment norms by choosing hospitals that best match their preferences and characteristics. In practice, patients (and their health care providers) exert some choice over the hospitals in which they are treated, and may even select residential locations based in part on proximity to a particular hospital. Such sorting would mitigate the welfare losses, identified in the current model, experienced by minority-type patients in a region. We estimate, however, that there are likely to be considerable constraints on optimal hospital-patient matching, so that our welfare analysis should be robust.

The theoretical welfare analysis demonstrates that, in the presence of knowledge spillovers, patients may be better off when physicians choose treatments in conformity with local norms. The effects can be significant enough to offset the benefits of standardized treatment guidelines based on patient conditions alone with no consideration of returns to local experience. Thus, in contrast to received wisdom, our theoretical results suggest that regional variations do not necessarily imply inferior care. Using two limited measures of quality, short-term mortality and the length of hospital stay for patients given angioplasty and the sample of those given surgery, we find support for the view that regional variations induced by social influence may not be so bad from a welfare perspective. Patient outcomes are not systematically affected by the greater presence of the other age group. Only in one equation, mortality rate of younger patients following angioplasty, do we find a significant outcome effect and it is small in magnitude. So on balance, it would appear that local spillovers, rather than conformity, induce geographical variations. However, the outcome results are presented somewhat tentatively because the data do not reveal longer-term patient outcomes. Further study of the question, with better data, is certainly warranted.

Appendix

Proof of Proposition 1

Proof. Since the process restricted to S is irreducible and aperiodic, it has a 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. The conditions $p_W > 1/2$ and $p_E < 1/2$ ensure that K is finite in the definition of ρ, and the balance equations are satisfied for non-zero $\rho(\cdot)$. 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. □

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:

$$R_t \rightarrow \begin{cases} R_t + 1 & \text{at rate } \lambda \\ \\ R_t - 1 & \text{at rate } 1 \end{cases} \tag{3}$$

$$L_t \rightarrow \begin{cases} L_t - 1 & \text{at rate } \lambda \\ \\ L_t + 1 & \text{at rate } 1 \end{cases} \tag{4}$$

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 (1) $x \in A^0 \Rightarrow \xi(x) = A$, (2) $A^0 \cap (\text{West} \cup \{0\}) \neq \emptyset$ and (3) $[i > \max A^0 \ \& \ i < 0] \Rightarrow \xi(i) = B$. Similarly B^0 denotes the set of contiguous sites with (1) $x \in B^0 \Rightarrow \xi(x) = B$, (2) $B^0 \cap$ East $\neq \emptyset$ and (3) $[i < \min B^0 \ \& \ i \geq 0] \Rightarrow \xi(i) = A$. 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 relabeled. As $t \to \infty$, $|A^0| \to \infty$ and $|B^0| \to \infty$ and their extinction probability becomes zero. B-regions in the West and A-regions in the East tend to become extinct. As $t \to \infty$ the probability, for some location $x \in$ 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. Since a physician's expected utility at a location has been defined as the likelihood of success for the population profile at that location, we can speak of patient welfare in terms of these same payoffs. 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:

$$\begin{aligned}
U_1 &\equiv p_W \pi_A(\alpha, A, A) + (1 - p_W)\pi_A(\beta, A, A) \\
U_2 &\equiv p_W \pi_B(\alpha, B, B) + (1 - p_W)\pi_B(\beta, B, B) \\
U_3 &\equiv p_W \pi_A(\alpha, A, B) + (1 - p_W)\pi_B(\beta, A, B)
\end{aligned}$$

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

$$\begin{aligned}
V_1 &\equiv p_W \pi_A(\alpha, A, A) + (1 - p_W)\pi_B(\beta, A, A) \\
V_2 &\equiv p_W \pi_A(\alpha, B, B) + (1 - p_W)\pi_B(\beta, B, B) \\
V_3 &\equiv p_W \pi_A(\alpha, A, B) + (1 - p_W)\pi_B(\beta, A, B)
\end{aligned}$$

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 both 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.

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

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 $1/2$.[13] 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 $1/2$ (specifically, $\rho(m) \to 0$ as $p_E, p_W \to 1/2$). 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. □

[13] In contrast, for the technology given in section 2.1, the long-run outcome is always superior to enforced procedure guidelines.

References

[1] Bernheim, D. (1994) "A Theory of Conformity," *Journal of Political Economy* 102(5): 841-877.

[2] Birkmeyer, J.D. (2000), "High-risk surgery–follow the crowd," *Journal of the American Medical Association*, 283(9): 1191-1193.

[3] Bramson, M. and D. Griffeath (1981), "On the Williams-Bjerknes Tumour Growth Model I," *The Annals of Probability*, 9: 173-185.

[4] Brock, W. and S. Durlauf (2001) "Discrete Choice with Social Interactions," *Review of Economic Studies,* 68 (2), 235-260.

[5] Burke, M.A., Fournier, G.M. and K. Prasad (2007), The Diffusion of a Medical Innovation: Is Success in the Stars? *Southern Economic Journal,* 73, 588–603.

[6] Burke, M.A., Fournier, G.M. and K. Prasad (2006), The Emergence of Local Norms in Networks, *Complexity,* 11, 65–83.

[7] Chandra, A. and D. Staiger (2004), "Testing a Roy Model with Productivity Spillovers: Evidence from the Treatment of Heart Attacks," NBER Working Paper No. W10811.

[8] Durrett, R. (1988), Lecture Notes on Particle Systems and Percolation, Wadsworth.

[9] Eagle, K.A., *et al.* (1999), "ACC/AHA guidelines for coronary artery bypass graft surgery: A report of the American College of Cardiology/American Heart Association Task Force on Practice Guidelines (Committee to Revise the 1991 Guidelines for Coronary Artery Bypass Graft Surgery)," *Journal of the American College of Cardiology* 34(4): 1262-1347.

[10] Ellison, G. (1993), "Learning, local interaction, and coordination," *Econometrica* 61: 1047-1071.

[11] Folland, S., and M. Stano (1989), "Sources of Small Area Variations in the Use of Medical Care," *Journal of Health Economics* 8: 85-107.

[12] Glover, J.A. (1938), "The Incidence of Tonsillectomy in School Children," *Proceedings of the Royal Society of Medicine* 31: 95-112.

[13] Grytten, J., and R. Sorensen (2003), "Practice Variation and Physician-Specific Effects," *Journal of Health Economics* 22: 403-18.

[14] Gunnar, R.M., P.D. Bourdillon, D.W. Dixon, et al. (1990), "ACC/AHA guidelines for the early management of patients with acute myocardial infarction: A report for the American College of Cardiology/American Heart Association Task Force on Assessment of Diagnostic and Therapeutic Cardiovascular Procedures (subcommittee to develop guidelines for the early management of patients with acute myocardial infarction)," *Circulation* 82: 664-707.

[15] Liggett, T. M. (1999), *Stochastic Interacting Systems: Contact, Voter and Exclusion Processes*. Heidelberg: Springer-Verlag.

[16] Morris, S. (2000), "Contagion," *Review of Economic Studies* 67(1): 57-78.

[17] Nichols, Donald. (2006). "The Impact of Hospital Racialization on Racial Differences in Medical Treatment," *Unpublished Working paper, Department of Economics, Washington University, St. Louis.*

[18] Norris, J.R. (1998), Markov Chains, Cambridge: Cambridge University Press.

[19] O'Connor, G., *et al.* (1999), "Geographic variation in the treatment of acute myocardial infarction: The Cooperative Cardiovascular Project," *Journal of the American Medical Association* 281(7):627–633.

[20] Phelps, C.E., and C. Mooney (1993), "Variations in medical practice use: causes and consequences," in R.J. Arnould, R.F. Rich, and W. White, eds., *Competitive Approaches to Health Care Reform*, Washington, DC: The Urban Institute Press.

[21] Pilote, L., *et al.* (1995), "Regional variation across the United States in the management of acute myocardial infarction," *The New England Journal of Medicine* 333(9): 565-572.

[22] Smith, S.C., Dove, J.T., Jacobs, A.K., et al. (2001), "ACC/AHA guidelines for percutaneous coronary intervention (revision of the 1993 PTCA guidelines)," *Journal of the American College of Cardiology*, 37(8): 2239i-lxvi.

[23] Wennberg, J., and J.D. Birkmeyer, eds. (1999), *The Dartmouth Atlas of Cardiovascular Health Care 1999*, Chicago: Dartmouth Medical School and American Hospital Association.

[24] Wennberg, J., and M. Cooper, eds. (1999), *The Dartmouth Atlas of Health Care 1999*, Chicago: Dartmouth Medical School and American Hospital Association.

[25] Wennberg, J., and A. Gittelsohn (1973), "Small area variations in health care delivery," *Science* 182: 1102-1108.

[26] Wennberg, J., and A. Gittelsohn (1982), "Variations in Medical Care Among Small Areas," *Scientific American* 182: 1102-1108.

[27] Young, H.P., and M.A. Burke (2001), "Competition and custom in economic contracts: a case study of Illinois agriculture," *American Economic Review* 91(3): 559-573.

[28] Young, H. P. (1998), *Individual Strategy and Social Structure: An Evolutionary Theory of Institutions*, Princeton, NJ: Princeton University Press.

[29] Young, H.P. (1996), "The economics of convention," *Journal of Economic Perspectives* 10: 105-122.

[30] Young, H.P. (1993), "The evolution of conventions," *Econometrica* 61: 57-84.

Table 1: *Summary statistics on the panel data set from Florida, 1995 to 2001*

Variable	***Mean***	***Std. Dev.***	***Min***	***Max***
Dependent variables				
Angioplasty Rate per thousand, younger patients	450.25	109.41	25.00	780.95
Angioplasty Rate per thousand, older patients	330.27	124.42	0.00	1000.00
Surgery Rate per thousand, younger patients	671.48	134.39	25.00	1000.00
Surgery Rate per thousand, older patients	555.25	150.14	0.00	1000.00
Mortality Rate per thousand, younger patients given angioplasty	6.08	14.30	0.00	250.00
Mortality Rate per thousand, older patients given angioplasty	25.47	35.36	0.00	400.00
Length of hospital stay, younger patients given angioplasty	3.13	0.88	1.00	10.76
Length of hospital stay, older patients given angioplasty	3.99	1.26	1.00	12.67
Mortality Rate per thousand, younger patients given surgery	8.90	13.87	0.00	250.00
Mortality Rate per thousand, older patients given surgery	36.71	32.03	0.00	333.33
Length of hospital stay, younger patients given surgery	4.68	1.106	1.00	11.01
Length of hospital stay, older patients given surgery	6.44	1.69	1.00	18.80
Explanatory Variables				
Hospital Volume in quarter				
Total number of heart patients in quarter	395.25	227.12	58.00	1647.00
Total volume of angioplasties in quarter	161.10	113.16	11.00	807.00
Total volume of surgeries in quarter	258.90	175.38	11.00	1225.00
Hospital Demographics				
Proportion of Heart Patients in younger group	0.35	0.10	0.10	0.72
Proportion of Heart Patients in older group	0.46	0.10	0.09	0.75
Proportions of patients by Patient Race				
Black	0.07	0.06	0.00	0.36
Hispanic	0.09	0.19	0.00	0.96
Other	0.01	0.04	0.00	0.49
Income, 1999	38615	4423	28053	50513
Proportion of Patients with managed care plan	0.36	0.16	0.00	0.76

Note: There are 1488 hospital-quarter observations, based on 572,316 patient records. Younger patients are defined as the group including youngest one-third of the sample, patients with age<63, while older patients are the oldest one-third in the sample, patients with age >72. Proportions are calculated relative to the full sample of all patients admitted to the hospital for coronary care.

Table 2: *Treatment rates by patient age and the effect of hospital demographics; panel regressions*

Dep. Variable: Angioplasty Rate per thousand	Age> 72 coef.		st. error	Age $\leq$ 62 coef.		st. error
Hospital Volume, number of angioplasties	0.775	**	0.036	0.829	**	0.037
Hospital Demographics						
Proportion of all Patients Aged 62 or younger	179.587	**	69.469			
Proportion of all Patients Aged 73 or older				-170.349	**	51.927
Proportion Patient Race						
Black	-226.590	**	111.540	-302.083	**	86.240
Hispanic	-88.335	*	48.548	-105.609	**	52.578
Other	31.918		64.534	45.419		38.978
Income, 1999	0.005	**	0.002	0.003	*	0.002
Proportion Patients with HMO or PPO insurance	48.223		30.871	22.634		26.155
Intercept	85.983		99.763	311.441	**	84.136

Dep. Variable: Surgery Rate per thousand	Age> 72 coef.		st. error	Age $\leq$ 62 coef.		st. error
Hospital Volume, number of surgeries	0.721	**	0.038	0.584	**	0.038
Hospital Demographics						
Proportion of all Patients Aged 62 or younger	61.318		59.429			
Proportion of all Patients Aged 73 or older				-216.112	**	55.422
Proportion Patient Race						
Black	-530.797	**	120.448	-500.674	**	97.595
Hispanic	-95.639	*	56.477	28.369		53.322
Other	25.764		64.371	47.005		36.091
Income, 1999	0.005	*	0.003	0.003		0.002
Proportion Patients with HMO or PPO insurance	38.588		32.512	-3.901		28.838
Intercept	345.795	**	104.882	565.340	**	90.046

Note: **Significant at $\alpha = 0.05$ level. *Significant at $\alpha = 0.10$. Standard errors are robust. The model includes fixed effects for hospitals and time, not reported here.

Table 3: *Health outcomes following Angioplasty; panel regressions*

Dep. Variable: Length of Stay for patients given Angioplasty	Age> 72 coef.		st. error	Age $\leq$ 62 coef.		st. error
Hospital Volume, number of patients	-0.002	**	0.000	-0.002	**	0.000
Hospital Demographics						
Proportion of all Patients Aged 62 or younger	0.285		0.753			
Proportion of all Patients Aged 73 or older				0.262		0.516
Proportion Patient Race						
Black	3.408	**	1.606	2.894	**	0.976
Hispanic	2.746	**	0.892	1.203	**	0.516
Other	-0.320		1.507	-0.976	**	0.474
Income, 1999	0.000		0.000	0.000		0.000
Proportion Patients with HMO or PPO insurance	-1.132	**	0.462	-0.097		0.245
Intercept	4.882	**	1.464	3.257	**	0.888

Dep. Variable: Mortality Rate per thousand for patients given Angioplasty	Age> 72 coef.		st. error	Age $\leq$ 62 coef.		st. error
Hospital Volume, number of patients	-0.027		0.011	-0.005		0.007
Hospital Demographics						
Proportion of all Patients Aged 62 or younger	-17.129		30.879			
Proportion of all Patients Aged 73 or older				28.959	**	13.482
Proportion Patient Race						
Black	156.814	**	65.496	26.848		21.881
Hispanic	10.286		38.863	-34.668	**	13.791
Other	65.403		43.403	-2.430		8.518
Income, 1999	0.000	*	0.001	0.000		0.000
Proportion Patients with man	14.232		16.969	-4.848		5.901
Intercept	33.437		53.765	-8.978		20.045

Note: **Significant at $\alpha = 0.05$ level. *Significant at $\alpha = 0.10$. Standard errors are robust. The model includes fixed effects for hospitals and time, not reported here.

Table 4: *Health outcomes following Surgery; panel regressions*

Dep. Variable: Length of Stay for patients given Surgery	Age> 72 coef.		st. error	Age $\leq$ 62 coef.		st. error
Hospital Volume, number of patients	-0.002	**	0.000	-0.001	**	0.000
Hospital Demographics						
Proportion of all Patients Aged 62 or younger	1.365		0.991			
Proportion of all Patients Aged 73 or older				-0.383		0.564
Proportion Patient Race						
Black	2.593		1.946	2.840	**	1.044
Hispanic	3.724	**	1.132	1.715	**	0.699
Other	-0.226		1.457	-0.785		0.782
Income, 1999	0.000		0.000	0.000		0.000
Proportion Patients with HMO or PPO insurance	-0.833		0.516	-0.489	*	0.295
Intercept	6.525	**	1.745	4.965	**	1.050

Dep. Variable: Mortality Rate per thousand for patients given Surgery	Age> 72 coef.		st. error	Age $\leq$ 62 coef.		st. error
Hospital Volume, number of patients	-0.023	**	0.010	-0.004		0.007
Hospital Demographics						
Proportion of all Patients Aged 62 or younger	-7.883		27.240			
Proportion of all Patients Aged 73 or older				16.246		13.313
Proportion Patient Race						
Black	97.637	*	57.620	14.483		22.068
Hispanic	6.922		34.287	-29.689	**	13.456
Other	88.776	**	34.851	-5.001		9.800
Income, 1999	0.000		0.001	0.000		0.000
Proportion Patients with man	16.824		14.141	-3.762		5.721
Intercept	53.039		48.870	8.049		19.510

Note: **Significant at $\alpha = 0.05$ level. *Significant at $\alpha = 0.10$. Standard errors are robust. The model includes fixed effects for hospitals and time, not reported here.

Figure(s)

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