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Abstract

Efforts to regionalize cardiac services can increase access costs for patients. This study quantifies this trade off by estimating the effects of changes in the regulation of hospital services on treatments and outcomes. A demand model for surgery services is specified in which heart attack victims form expectations of the need for and productivity of surgery in their choice of hospital and treatment. The results indicate that mortality is relatively insensitive to moderate changes in policy: changes in travel costs and volume offset one another. Despite similar health outcomes, the competing policies have different implications for taxpayers.

KEYWORDS: heart attack, Medicare, dynamic discrete choice estimation

JEL CLASSIFICATION: I12, I18, C35

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1 Introduction

Many states regulate the number and location of hospital services in markets. For example, certificate-of-need (CON) regulations require a hospital to show the medical need of additional services, such as a cardiac surgery facility, in any given market before states permit entry or expansion (Conover and Sloan 1998; Vaughan-Sarrazin et al. 2002). In the case of cardiac facilities, regulators face a trade off between proximity and intensity of use.

Prompt treatment of heart attacks can improve health outcomes dramatically. Allowing additional cardiac surgery services, either in a market or in new markets, could reduce the distance many patients would need to travel to receive treatment, especially in rural areas. The majority of empirical studies of hospital choice have found that distance/travel time is the primary factor in choice of hospital (Porell and Adams 1995). While distance is important, there is also evidence that patients are willing to travel a little farther in order to take advantage of facilities at higher quality hospitals (Hodgkin 1996; Tay 2002). The willingness to trade distance for quality is likely a nonlinear function of health status: patients with extremely mild or severe attacks might not find the additional services worth the cost of travel. Thus, one important issue in the regulation of services is the effect it will have on access costs for patients, costs that might be more likely to be borne for higher quality services and costs that vary by health status (Adams et al. 1991).

A drawback of geographically diffuse cardiac facilities is the lower volume of surgeries performed at each facility. If learning-by-doing is important for physicians and/or economies of scale exist in the production of cardiac surgeries, then regulators have an incentive to concentrate the provision of services in a few centers. A large medical literature has found that higher volume surgery providers have better health outcomes from surgery (e.g., see Dudley et al. 2000; Halm et al. 2002, for reviews of the literature). The volume literature has suggested policies based on these findings, often that hospitals offering surgery services should perform a minimum number of procedures per year. The Leapfrog group, a consortium of insurers and providers, have recommended minimum volume thresholds (e.g., 500 coronary artery bypass grafts (CABGs) per year) to be met by surgery providers (Shahian and Normand 2003). These recommendations are the result of a literature that deals almost exclusively with estimating a type of health production function with provider volume as an input. The volume literature does not model the decision-maker's optimization problem and therefore can say little about predicted behavior in the face of changing regulation.

This model extends the volume literature by allowing hospital and treatment choices to respond to changes in regulation policy. It does this by estimating a structural model of demand that accounts for the trade offs between distance and volume at the individual level along with estimating the health outcome production function. The model's key feature is that decision-makers form expectations of the need for and effectiveness of surgery when making treatment decisions. Thus, they respond to changes in the effectiveness of treatment in all stages of the treatment process: admitting hospital, diagnostic procedures, and curative treatment. For example, lower hospital surgery volume makes surgery less effective in reducing mortality and, therefore, surgery services less attractive for an individual in the choice of hospital.

The treatments this study focuses on are catheterization, percutaneous transluminal coronary angioplasty (PTCA), and CABG. Catheterization is used to visualize the blood flow in coronary arteries and serves as a diagnostic tool to determine the necessity of revascularization surgeries such as angioplasty and bypass surgery. Angioplasty uses a small balloon to open up blood flow in a blocked artery. Bypass surgery uses veins from other parts of the body to create an alternate path for blood flow around the blocked artery. In what follows, "surgery" refers to angioplasty or bypass surgery.

The model is used to conduct two policy experiments. The first asks the following question: what would happen if the average heart attack victim had a surgery hospital that was closer but with lower volume? It provides simulations of the effect of decentralization of cardiac surgery services on hospital choice and transfer, catheterization, surgery, and mortality rates. The second policy experiment simulates the enforcement of minimum volume thresholds for surgery services. Using the estimated structural parameters, low-volume surgery services, defined by different threshold levels, are eliminated and treatment choices and outcomes are predicted.

Overall, the results indicate that one-year mortality is relatively insensitive to moderate changes in policy, either in the direction of decentralization of cardiac services or toward centralization of services. However, this is not the result of travel costs and volume being unimportant; it is the result of these two crucial factors offsetting one another. Decentralization lowers the utility costs of surgery at the same time that surgery becomes less effective due to lower volumes. Centralization leads to fewer, but more effective, surgeries.

Despite similar health outcomes, the competing policies have different implications for taxpayers. Medicare reimbursements for cardiac surgery would be lower under the centralization policy. It is important to note that this is a partial equilibrium result: the demand model in this study does not capture supply-side changes in the market induced by alternative policies.

The study proceeds as follows. The next section reviews the hospital choice and volume-outcome literature with an emphasis on the contribution of the current research. Section 3 describes the data and sample used to estimate the structural model. Section 4 presents the dynamic discrete choice model and empirical specification. Section 5 discusses the estimation strategy and identification. Section 6 provides estimation and simulation results. Section 7 concludes.

2 The Trade Off between Distance and Volume

The primary focus of this study is the trade off many patients and physicians face between choosing a hospital that is close and choosing a hospital that is of high quality. Despite the urgent nature of heart attacks, there are reasons to believe that a trade off between distance and quality could still occur. First, ambulance protocols allow discretion in the choice of hospital based on the health status of the patient (e.g., see the example protocol in Athey and Stern 2000). Furthermore, paramedics can begin basic treatment before arrival at the hospital, which might provide incentives to seek better quality hospitals when available (Meischke et al. 1995). Second, many individuals do not use emergency medical services (EMS). Studies have found that only 42 to 45% of heart attack patients use ambulatory services to get to the hospital (Meischke et al. 1995; Gurwitz et al. 1997). Couple this with the fact that most individuals significantly delay seeking care at all (Dracup et al. 1995), and it is possible that once they decide to go to the hospital, they might use discretion. Third, heart attack has been used as the primary diagnosis before in the literature (Hodgkin 1996; Tay 2002, 2003). Evidence concerning the trade off between distance and service offerings is given below.

The primary quality measure considered in this study is hospital surgery volume. A large medical literature has found that larger volume is associated with better health outcomes (Luft et al. 1990; Hannan et al. 1997; Jollis et al. 1997; Dudley et al. 2000; Canto et al. 2000). (Hamilton and Hamilton (1997) is an exception looking at hip surgery.) There are three primary explanations for the observed relationship between volume and outcomes (Luft et al. 1990). The first explanation posits a direct causal pathway: physicians and hospitals learn how to treat a patient or master a procedure by seeing more patients with the same diagnosis or repeating a procedure (i.e., learning-by-doing). The second explanation is reverse causation: providers with good outcomes attract more patients (i.e., selective referral). The third explanation is that the correlation between outcomes and provider volume is spurious, the result of omitted variable bias. Thus, some other provider attribute, which is correlated with volume, directly affects patient outcomes.

This study limits the influence of selective referral by using patient-level data and focusing on a category of bypass surgeries that are likely non-elective. First, the use of patient-level data will make endogeneity less of a problem; an individual's outcome or complication has a small effect on the overall volume of the provider (Norton et al. 1998). Second, selective referral is more likely for elective procedures. The surgeries observed in this study's sample are less likely to be elective in nature (see section 3). Showstack et al. (1987) finds that the largest effects of CABG volume are for unscheduled treatments.

Hospitals are distinguished in the dynamic model based on their distance from the patients and their offerings of specialized services. In order to check for omitted variable bias, other hospital characteristics such as ownership and teaching status were included in the health transitions. These variables were insignificant conditional on health status.

Despite caveats raised by the empirical issues above, most researchers agree that a relationship exists between volume and outcomes. Given that volume relates to better outcomes, many types of policy recommendations have been issued to promote regionalization (or centralization) of services. If increased volume truly causes better health outcomes (and perhaps lower costs), then patients (and tax payers) would benefit from shifting procedures from low-volume providers to high-volume providers. Even if volume is simply correlated with the true mechanism improving outcomes, there is still room for policies based on provider volume. Volume is an easily measurable proxy of quality in this case, especially given the difficulty in collecting and disseminating more direct, risk-adjusted data on quality and process mechanisms. Groups such as the Leapfrog group, a consortium of insurers and providers, have recommended minimum volume thresholds (e.g., 500 CABGs per year) to be met by surgery providers (Shahian and Normand 2003).

A cost to regionalization is the effect it has on access to surgery for patients (Norton et al. 1998; Shahian and Normand 2003). Centralization of surgery services has the potential of increasing travel times for many patients, especially in rural areas. This implies that proponents of regionalization should consider the distributional effects for patients.

Recent studies in the volume literature have begun to address the trade off by examining the effects of simulated closures of low-volume providers on travel distances to remaining providers (Grumbach et al. 1995; Dudley et al. 2000; Chang and Klitzner 2002; Birkmeyer et al. 2003; Trogdon 2004). These studies provide a starting place for assessing the effects of regionalization as a policy goal on patient access to services. Trogdon (2004) is the first study to model how treatment choices respond to the removal of low-volume services. This study extends the volume literature to predict not only how access to services would change under such a policy, but also how treatment choices *and outcomes* would change.

3 The Cooperative Cardiovascular Project

Regulation changes that alter the number and location of cardiac services within a market will lead to changes in the demand for those services, and hospitals with those services, as well as potentially affect health outcomes. Cardiac services located closer to a larger number of potential patients provide benefits through easier access to care, but at the cost of less effective treatment if procedure volumes are lower. The data used in this study are excellent for studying the changes in demand that result from such policy changes.

First, the data used in this study is a large, nation-wide sample of individuals, which provides power to help identify parameters associated with rare health events and outcomes. The data also contain geographic identifiers that make it possible to trace the effects of changes in the effectiveness of treatment (e.g., changes in hospital surgery volumes) back to the choice of hospital; individuals face a trade off between travel time to a hospital and the presence and effectiveness of cardiac surgery at the hospital and will respond to changes in either dimension.

Second, the data provide extremely detailed information concerning health status at each stage of the treatment process: existing comorbidities at the time of the heart attack, initial severity of the heart attack at admission to the hospital, and the results of diagnostic tests that provide information about the need for curative treatment. The availability of information concerning comorbidities at the time of the choice of hospital allows preferences for hospitals to vary by health status in a more detailed way than in previous hospital choice studies. The information about severity of the heart attack is unique to clinical data and not available in administrative discharge records. It provides important information to identify treatment choices. The data also include records of treatments received in the case of transfer to another hospital, allowing the researcher to observe the full set of treatment choices for each individual.

Finally, in the estimation of the effect of hospital surgery volumes on outcomes, clinical data are important for conditioning on patient health status (e.g., see Sowden et al. 1995). In the volume literature using hospital-level data, a major concern is that the volume-outcome relationship could be due to high-volume hospitals operating on healthier patients. This study uses patient-level data and extensive information about severity to control for patient health while measuring the effect of volume on one-year mortality.

The primary data for the individuals in the study come from the Cooperative Cardiovascular Project (CCP). The CCP was initiated by the Medicare program with the goal of improving quality of treatment received by Medicare patients experiencing heart attack (Jencks and Wilensky 1992; Ellerbeck et al. 1995). The CCP collected patient data through medical record review for a nationally representative random sample of Medicare patients.

The original CCP sample consisted of randomly selected patient records for patients admitted to nonfederal acute care hospitals between February 1994 to July 1995 with a primary diagnosis of acute myocardial infarction (AMI) (ICD-9-CM 410, excluding a fifth digit of 2). Some patients in the CCP sample were transferred to other hospitals. The CCP sample is merged with the respective Medicare Part A claims data for these and subsequent admissions. The data are merged by including in an episode of care all of the admissions that occurred consecutively, or within one day of each other. This definition of an episode of care minimizes the number of elective surgeries, for which selective referral is more likely. The claims data allow me to construct the remaining treatments received by individuals originally admitted to hospitals participating in the CCP. The claims data are also used to calculate the Medicare surgery volume for each hospital in the sample.

Hospital data come from the American Hospital Association's (AHA) Annual Survey of Hospitals 1994 and 1995. Distances between individuals and hospitals are calculated using zip code data from MapInfo 5.0. Using the latitude and longitude for the centroid of each zip code, straight-line distances in miles are calculated using standard great circle trigonometric formulas. [1]

The sample used in estimation meet the following criteria. First, since the CCP is a sample of Medicare beneficiaries, each admission should have Part A claims data available; individuals who have admissions without such data, or admissions to other specialized types of hospitals, are dropped (N = 8,565).

[1] Birkmeyer et al. (2002) uses ArcView to classify roads, which are assigned average speeds, to calculate travel time. However, Phibbs and Luft (1995) show that use of straight-line distance rather than road distance often does not significantly impact hospital choice estimates.

Second, in order to make sure that the complete episode, or sequence of admissions, for a particular heart attack is available, all individuals are dropped who have previous episodes in the data or are first admitted from somewhere other than home (N = 47,432). This sample cut is made for two reasons. First, patients initially transferred from another hospital have had previous and unknown care. Second, the distance calculations are made based on zip code of residence. For patients admitted from other locales (e.g., nursing homes), these calculations would be incorrect.

Third, individuals who choose hospitals outside of the designated choice set are dropped (N = 45,191). [2] The choice set is the nearest hospital in each of three service categories: no specialized services, catheterization only, and open heart surgery. Each of these service categories, if chosen by an individual, provides a unique set of treatment choices. At the same time, heart attack victims are not expected to bypass several hospitals for treatment. In addition, this definition of the choice set keeps the size of the state and parameter spaces manageable. The remaining sample of patients is more likely to have had their heart attacks close to home, minimizing the error in the distance calculations.

Finally, patients who have unexplained sequences of procedures are dropped from the sample (N = 3,764). For example, these include patients with procedures at hospitals that do not have a record for those facilities, patients who have surgery recorded without a diagnostic procedure, patients who have multiple procedures recorded, and a small set of patients who transfer to hospitals that do not offer heart surgery. This leaves a sample of 82,055 patients for the analysis. For computational reasons (see section 5), portions of the model are estimated on a random 5% sub-sample (N = 4,103).

The sub-sample used for estimation closely matches the demographic and health characteristics of the full sample (Table 1). The mean age in both samples is 77. Both samples are evenly divided between men and women, contain similar shares of minorities (9%), and are mostly urban.

The samples exhibit substantial variation in health status and heart attack severity. Initial health status is measured using the Charlson score, a weighted sum of comorbidities, where the weights are proportional to the risk of death from each comorbidity (Charlson et al. 1987). Higher values indicate worse health. Nearly half of the samples have important comorbidities as measured by the Charlson index.

Killip class, a measure of severity at admission, is used as the initial assessment of the severity of the heart attack. Using a method developed by Killip and Kimbal (1967), heart attack patients are

[2] Individuals who live in Alaska are also dropped from the analysis set. The distances in the state are non-representative of the rest of the sample.

classified into one of three classes: those with no evidence of congestive heart failure (CHF) (1), those with mild to moderate CHF (2), and those with overt pulmonary edema and/or cardiogenic shock (3). Thus, a higher classification indicates a more severe heart attack. Killip class has been shown in the medical literature to provide a concise representation of the severity of heart attacks (Rott et al. 1997; DeGeare et al. 2001). Approximately half of the samples have evidence of at least moderate congestive heart failure (CHF) at presentation to the hospital (i.e., Killip class greater than I). Finally, the vast majority of those patients who receive information concerning systolic function by having catheterization show a moderate reduction; approximately 10% of individuals have severe reduction.

Most patients choose no-service hospitals for the initial admission. These are the most common type of hospital in the sample and, on average, are closest to the individual (Table 2). Catheterization-only hospitals are the rarest type of hospital in the sample. Hospitals providing catheterization and surgery are slightly over-represented in the estimation sample. Medicare patients make up one fourth to one half of total procedures in hospitals (Jollis et al. 1997); the Medicare surgery volumes in the estimation sample correspond to average overall hospital surgery volumes between 70 and 105 in 1994 and between 115 and 170 in 1995.

Treatment choices are combinations of a choice for procedure and transfer to another hospital. One third of the sample have catheterization and half of those patients go on to have surgery (Table 1). Approximately 16% of patients are transferred during the treatment process. One year after admission, one third of the individuals in the sample have died.

4 Dynamic Model of Hospital and Treatment Decisions

The goal of the structural dynamic discrete choice model is to fully incorporate 1) the sequential nature of the decision-making process, 2) the information revealed along the decision path, and 3) the constraints current choices place on future options. The resulting estimates of the structural parameters are then used to provide information about how changes in service offerings affect the allocation of patients into hospitals, treatments, and outcomes.

It is assumed that individuals and their providers have identical preferences over hospitals and treatments. Equivalently, the provider's role is that of a perfect agent, providing information to the individual, who then has the final decision concerning care. This is a strong assumption, especially in a situation with such large asymmetries of information (see McGuire 2000, for a review of the agency literature in health economics). It is made for two reasons. First, data limitations preclude consistent linking of patients with their physicians, which would be necessary to model more complex agency relationships. Second, this assumption simplifies the modeling of uncertainty. Physicians and health care providers have repeated interaction with hospitals and are likely to be well informed as to the characteristics of the hospital and the technology of treatment. Therefore, uncertainty enters the model through the uncertainty about future health status. In what follows, "individual" refers both to the patient and to the collection of decision-makers working on behalf of the patient.

4.1 Timing

There are four periods in the dynamic model; individuals make decisions in the first three of these periods. In the first period, the individual has a heart attack. He has information about his initial health status and his preferences for types of hospitals. The component of preferences unobserved to the econometrician is modeled as a draw from the distribution of tastes for types of hospitals. Based on this information he subsequently chooses a hospital. In the second period, individuals receive initial information about the severity of the heart attack. They next receive a draw from the distribution of tastes for catheterization and choose whether or not to undergo catheterization, which could include transfer to another hospital. In the third period, conditional on choosing catheterization, individuals receive information about the systolic functioning of their heart. Then they receive a draw from the distribution of tastes for surgery and choose a surgery option, which again could include a transfer. Mortality outcomes are determined in the fourth period. Individuals do not make a decision in the last period but form expectations about the outcomes that factor into decisions made earlier.

4.2 Choices

In this model, individuals make choices over the type of hospital for admission and the treatments of catheterization and surgery, including the possibility of transfer. Each period represents one of these choices. In the first period, individuals choose a type of hospital. Hospitals are characterized by the specialized services they offer and distance from the individual. Let $j = 1, 2, \ldots, J$ represent each hospital type. Define the decision dummy for these mutually exclusive choices as

$$d_1^j = \begin{cases} 1 & \text{if alternative } j \text{ chosen in period 1} \\ 0 & \text{otherwise} \end{cases}$$

where

$$\sum_{j=1}^{J} d_1^j = 1$$

The vector representing the decision at time one is $d_1 = (d_1^1, d_1^2, \ldots, d_1^J)$. Empirically, the choice set includes the nearest hospital in each of three service categories: no specialized services, catheterization only, and open heart surgery ($J = 3$).

In the second period, individuals choose whether or not to undergo catheterization, which could include transfer to another hospital. Using the same notation as above, denote the diagnosis choices in the second period by $c = 1, \ldots, C$ and define a vector of decision dummies representing the period two choices as $d_2 = (d_2^1, d_2^2, \ldots, d_2^C)$. Empirically, the choices include no transfer/no catheterization, no transfer/catheterization, transfer/no catheterization, and transfer/catheterization, respectively ($C =$ 4). One and only one of the components of d_2 must equal one, but the choice set in the second period is restricted in some cases by the choice made in period one. For example, if a no-service hospital is chosen in the first period, then the second period choices are limited to c =1, 3, or 4; no transfer/catheterization is not an option.

Finally, the surgery options $s = 1, \ldots, S$ available to individuals in the third period are no transfer/no surgery, no transfer/surgery, transfer/no surgery, and transfer/surgery: $d_3 = (d_3^1, \ldots, d_3^4)$. Part of the importance of the dynamic decision process is that the surgery choice set is also conditional on previous decisions. Specifically, surgery is only available to individuals who received catheterization in the second period. Table 3 shows the decision tree facing an individual in the model.

4.3 State Variables

The hospital and treatment decisions are made using the information available at the time of the decision. This information set is defined by a collection of state variables. The state variables describing individuals as they enter the model include demographic characteristics—age; gender (male, female); race (white, minority); and residence in a Metropolitan Statistical Area (MSA)—as well as an index of health status. The Charlson index, $h \in H = \{1, 2, 3\}$, summarizes individuals' health status at the time of the heart attack.

Each individual has a unique hospital choice set. Hospital characteristics include specialized services (no specialized services, catheterization only, and surgery capabilities); distance from the individual in miles; and Medicare surgery volume. Let D represent the individual's demographic characteristics, X

represent the hospital characteristics in the choice set, and Z represent all of the individual's stationary characteristics: $Z = (D, h, X)$.

The next set of state variables drive the dynamic trade offs individuals face in making hospital and treatment decisions. In order to solve the model using backward recursion, all dynamic state variables are discretized. It is also necessary to specify the distributions of all dynamic state variables included in the model (see Section 4.4). After the hospital choice, information is revealed concerning the severity of the heart attack. At admission the individual receives an initial severity diagnosis by categorization into a Killip class, $k \in K = \{1, 2, 3\}$. In the third period, the catheterization reveals information about the extent of blockage $b \in B = \{1, 2, 3\}$, where the categories correspond to normal, mild to moderate reduction, and severe reduction in left ventricular ejection fraction.

The information set at time t, I_t, grows each period as individuals learn more about the nature of the heart attack:

$$I_1 = (Z) \tag{4.1}$$

$$I_2 = (d_1, k; Z) \tag{4.2}$$

$$I_3 = (d_1, k, d_2, b; Z) \tag{4.3}$$

$$I_4 = (d_1, k, d_2, b, d_3; Z) \tag{4.4}$$

4.4 Transition Probabilities

Individuals are forward-looking and form expectations about the possible health states they will be in conditional on the decisions they make. In forming these expectations the individuals use the following transition probabilities.

The probability of Killip class k is a function of the information set in period one and the hospital decision and takes a multinomial logit form:

$$P(K = k) \equiv \pi_K^k(d_1, Z; \delta_k), \quad k = 1, 2, 3 \tag{4.5}$$

where δ_k is a vector of parameters. Age, gender, and race are included to account for differences in the severity of heart attacks across demographic groups. The probability of a particular Killip class is also determined by initial health status: sicker patients initially (e.g., patients with hypertension or previous heart attack) are likely to have a higher probability of a more severe heart attack. Distance traveled and its interaction with residence in a MSA allows the severity status at admission to depend on the travel time to the hospital. This allows for one type of travel cost, namely that the heart attack itself might worsen with delay.

The probability of a particular blockage category b depends the characteristics of the individual, including realized health status from the first period, and takes a multinomial logit form:

$$P(B = b) \equiv \pi_B^b(k, h, D; \beta_b), \quad b = 1, 2, 3 \tag{4.6}$$

where β_b is a vector of blockage parameters. The motivation for demographic characteristics and initial health status is the same as in the Killip transition. Here, not only does initial health affect the severity of the heart attack, but also the initial severity assessment.

In the final period, nature determines whether the individual lives or dies. This study focuses on mortality at one year post admission. In doing so, the model is able to trace the impact of patient characteristics, including health status, on the demand for hospitals, the treatment process, and the ultimate outcome. The probability of mortality in period four is given by the logit probability

$$P(m = 1) \equiv \pi_m(d_3, b, k, h, D, X; \eta) \tag{4.7}$$

where η is a vector of parameters. Similar to the other health transitions, mortality rates are allowed to differ across demographic groups. Previous health status (b, k, h) are also an important determinant of mortality. The coefficient on the surgery decision, d_3, measures the effect of the treatment on mortality outcomes. This effect is also allowed to vary by surgery volume. This is where the benefit of high hospital surgery volume enters the patient's decision-making process.

4.5 Utility

Individuals receive utility in each period based on the choices they make. Period one utility from choosing hospital j is

$$U_1^j(Z, \epsilon_1^j) = \alpha_{10}^j + \alpha_{11h}^j + \alpha_{12} dist + \alpha_{13} dist \cdot MSA + \alpha_{14h} dist + \epsilon_1^j \tag{4.8}$$

α_{10}^j captures the baseline utility from a hospital of service type j. Flow utility in period one is also a function of health status (α_{11h}^j), the distance to the type of hospital chosen (α_{12}), and interactions of the two (α_{14h}). This specification allows travel cost to vary by individual health status. Distance is interacted with a urban/rural indicator to make distance a better proxy for true travel costs (α_{13}); distance in a metropolitan area will have a longer actual travel time than the same distance in a rural area. ϵ_1^j is the utility from hospital choice j unobserved by the econometrician.

In period two, utility from choosing catheterization choice c varies by health status:

$$U_2^c(h, k, \epsilon_2^c) = \alpha_{20}^c + \alpha_{21h}^c + \alpha_{22k}^c + \epsilon_2^c \tag{4.9}$$

The utility from surgery choice s in period 3 is similar, but individuals now have more information about severity (b):

$$U_3^s(h, k, b, \epsilon_3^s) = \alpha_{30}^s + \alpha_{31h}^s + \alpha_{32k}^s + \alpha_{33b}^s + \epsilon_3^s \tag{4.10}$$

Catheterization and surgery impact the flow utility directly for two reasons. First, both of these invasive procedures involve pain and discomfort, especially in the recovery process. This is captured in the choice-specific intercepts α_{20}^c and α_{30}^s. Second, these procedures involve risks for side effects and these risks differ by health status. The same is true for transfer; transfer to another hospital is stressful and disorienting. Thus, there exist utility costs for the treatment choices in the model that are balanced by the decision-maker against the benefits of information gathering and improved outcomes through treatment. ϵ_2^c and ϵ_3^s are the unobserved components of flow utility for catheterization and surgery, respectively.

The model only focuses on one measure of health outcome, one-year mortality. However, the medical literature has shown that heart surgery can also improve quality of life (Allen et al. 1990; McKenna et al. 1994; Papadantonaki et al. 1994; Hlatky et al. 1997). In order to capture this type of utility gain from surgery, utility in period four, terminal utility, is specified as

$$U_4(h, b, d_3) = \begin{cases} \alpha_{40} + \alpha_{41h} + \alpha_{42b}(1 - (d_3^2 + d_3^4)) + \alpha_{43}(d_3^2 + d_3^4) & \text{if } m = 0 \\ 0 & \text{if } m = 1 \end{cases} \tag{4.11}$$

Terminal utility is normalized to zero for death; α_{40} captures the utility from surviving the episode. Utility at the end of the heart attack episode is a deterministic function of health status; some individuals will have a lower valuation of surviving the heart attack and consequently not be as willing to pursue invasive treatments. The model assumes Killip class status has no long term effects. However, blockage, if not treated by surgery, does have long term consequences (α_{42b}). Finally, surgery in the third period provides utility through its effect on quality of life (α_{43}).

4.6 Dynamic Optimization

In each period, individuals choose an option from the relevant choice set to maximize expected lifetime utility. In this model, the information available at the time the individual makes his decisions depends on his past decisions. The dynamic model can be solved recursively, working backwards from the last period. The maximal expected utility in period 4 conditional on the individual knowing his blockage status is

$$V_4\big(I_4\big) = \big(1 - \pi_m(\cdot)\big)U_4(h, b, d_3) \tag{4.12}$$

In period three, individuals choose a surgery option to maximize the current utility from surgery and the expected value of utility next period. Let $\overline{U}$ denote the deterministic part of flow utility. Then the expected lifetime utility when choosing s in period three conditional on choosing catheterization in period two is

$$V_3^s\big(I_3, \epsilon_3^s|(d_2^2 + d_2^4) = 1\big) = \overline{U_3^s}(h, k, b) + \epsilon_3^s + \beta V_4\big(I_4\big) \tag{4.13}$$

where β is the discount factor. The expected lifetime utility when choosing s in period three conditional on not choosing catheterization in period two, and thus not knowing the blockage level, is

$$V_3^s\big(I_3, \epsilon_3^s|(d_2^1 + d_2^3) = 1\big) = \sum_{b=1}^{3} \pi_B^b(\cdot)\left[\overline{U_3^s}(h, k, b) + \epsilon_3^s + \beta V_4\big(I_4\big)\right] \tag{4.14}$$

Thus, if patients do not have catheterization, they form an expected value of utility as a function of their blockage status.

In order to clearly show the effect of past choices on current and future choice sets, let $j = 1, 2, 3$ represent hospitals with no specialized services, catheterization only, and surgery services, respectively. The expected maximized lifetime utility from choosing c in period two is

$$\begin{aligned} V_2^c(I_2, \epsilon_2^c) = {} & \overline{U_2^c}(k, h) + \epsilon_2^c + \\ & \beta\Big\{\sum_{b=1}^{3} \pi_B^b(\cdot) \cdot \{E[max_{s\in\{1,3,4\}} V_3^s(I_3, \epsilon_3^s)] \cdot d_2^2 \cdot d_1^2 + \\ & E[max_{s\in\{1,2\}} V_3^s(I_3, \epsilon_3^s)] \cdot (d_2^4 + d_2^2 \cdot d_1^3) + \\ & E[V_3^1(I_3, \epsilon_3^1)] \cdot (d_2^1 + d_2^3)\}\Big\} \end{aligned} \tag{4.15}$$

The first two components of (4.15) are just the flow utility from choice c. The expected maximized utility in period three has three components. The first is the expected utility next period when choosing no transfer/catheterization at a catheterization-only hospital in period two. The expectations are with respect to ϵ_3. In this situation, the surgery options are no transfer/no surgery, transfer/no surgery, and transfer/surgery. The second component is the expected utility next period when catheterization is chosen at a surgery hospital, either by transferring to a surgery hospital (d_2^4) or by choosing a surgery hospital in the first period ($d_2^2 \cdot d_1^3$). In this situation, transfer is not necessary. The final component is the expected utility next period when choosing no catheterization, which leaves only the no transfer/no surgery option. [3]

The expected maximized lifetime utility from choosing hospital j in period one is

$$
\begin{aligned}
V_1^j(I_1, \epsilon_1^j) = \overline{U_1^j}(Z) + \epsilon_1^j + & \\
& \beta\Big\{\sum_{k=1}^{3} \pi_K^k(\cdot) \cdot \{E[max_{c\in\{1,3,4\}} V_2^c(I_2, \epsilon_2^c)] \cdot d_1^1 + \\
& E[max_{c\in\{1,2,3,4\}} V_2^c(I_2, \epsilon_2^c)] \cdot d_1^2 + \\
& E[max_{c\in\{1,2\}} V_2^c(I_2, \epsilon_2^c)] \cdot d_1^3\}\Big\}
\end{aligned}
\tag{4.16}
$$

Again, each choice of hospital corresponds to a different choice set available next period. Individuals that choose a hospital without specialized services (d_1^1) cannot choose to have catheterization without transfer in the next period. Individuals that choose a surgery hospital (d_1^3) do not have to transfer to another hospital in future periods.

5 Estimation

The unobserved taste parameters, ϵ_t, are assumed to be i.i.d. Type I Extreme Value $\left(\rho_t\gamma, \frac{\pi^2\rho_t^2}{6}\right)$, where γ is the Euler constant and ρ_t is the scale parameter for period t. This distributional assumption allows for estimation of the dynamic model by yielding a closed-form solution for the expected value of the future value functions and choice probabilities. Specifically, let $\overline{V_t^l}$ represent the deterministic portion of the value function for choice l in period t. Then the probability of observing an individual making choice l in time t is

$$
Pr(d_t^l | I_t) = \frac{exp\left(\overline{V_t^l}(I_t)/\rho_t\right)}{\sum_{l'=1}^{M} exp\left(\overline{V_t^{l'}}(I_t)/\rho_t\right)}
\tag{5.1}
$$

If an individual does not choose catheterization, neither he nor the econometrician know the blockage status. If an individual chooses catheterization after transferring to a non-CCP hospital, then he, but not the econometrician, knows the blockage status. In all cases, individuals provide information

[3] Some patients in the sample are observed to have transferred hospitals but not to have received either catheterization or surgery at either hospital. For these cases it is assumed that the transfer was in period two; no transfer/no catheterization and transfer/no surgery is not observed in the data.

for the surgery and mortality probabilities. The likelihood of observing an individual's choices and health transitions when blockage is observed in the data is

$$\begin{aligned}(5.2)\qquad L_i^b = &\prod_{j=1}^{J} Pr(d_1^j|I_1)^{d_1^j} \cdot \prod_{k=1}^{K} \pi_K^k(\cdot)^{1(k=K)} \cdot \prod_{c=1}^{C} Pr(d_2^c|I_2)^{d_2^c} \cdot \\ &\prod_{b=1}^{B} \pi_B^b(\cdot)^{1(b=B)} \cdot \prod_{s=1}^{S} Pr(d_3^s|I_3)^{d_3^s} \cdot \pi_m(\cdot)^{1(m=1)} \left(1-\pi_m(\cdot)\right)^{1(m=0)}\end{aligned}$$

To take advantage of the information concerning the surgery decision and mortality outcomes from all observations, the likelihood for individuals whose blockage was unobserved in the data integrates over the unobserved blockage status:

$$\begin{aligned}(5.3)\qquad L_i^{\text{no } b} = &\prod_{j=1}^{J} Pr(d_1^j|I_1)^{d_1^j} \cdot \prod_{k=1}^{K} \pi_K^k(\cdot)^{1(k=K)} \cdot \prod_{c=1}^{C} Pr(d_2^c|I_2)^{d_2^c} \cdot \\ &\Big\{\sum_{b=1}^{B} \pi_B^b(\cdot)^{1(b=B)} \cdot \Big(\prod_{s=1}^{S} Pr(d_3^s|I_3)^{d_3^s} \cdot \pi_m(\cdot)^{1(m=1)} \left(1-\pi_m(\cdot)\right)^{1(m=0)}\Big)\Big\}\end{aligned}$$

5.1 Estimation in Stages

The assumption of conditional independence of the unobserved taste parameters leads to a log likelihood function that is additively separable across time (or decisions). This assumption precludes correlation of the unobserved taste parameters across choices. It also assumes that there is no unobserved heterogeneity that affects assignments into health classes (i.e., conditional on observed health status, all hospitals assign Killip class in the same way). Allowing for unobserved heterogeneity of the Heckman and Singer (1984) type removes the additive separability of the likelihood function, but estimation can still proceed in stages using the EM algorithm (Arcidiacono and Jones 2003). However, a substantial amount of heterogeneity in preferences and health transitions is captured in the health status state variables provided by the CCP. For this reason, and in order to reduce computation time, unobserved heterogeneity of this type is not allowed.

The model is estimated in stages (Rust and Phelan 1997). First, the Killip and blockage transitions are estimated as standard multinomial logits. [4] The estimation of the utility parameters requires a nested algorithm which solves the dynamic model for each iteration of the parameter values. Since each individual has a unique hospital choice set as defined by the distances to each of the hospitals and the surgery volumes at the surgery hospitals, the dynamic model has to be solved for each person at each parameter iteration. For this reason, a 5% random sample of the data (N = 4,103) is used to

[4]The blockage parameters are estimated on the sub-sample of patients with observed blockage data (N = 17,163).

estimate the mortality transition and utility parameters in stages. Using estimates for the blockage transition (β_b), consistent estimates of the mortality and period three and four utility parameters (η, α_3, and α_4) are obtained simultaneously. Using these estimates, utility parameters for period two (α_2) are recovered from a multinomial logit for the catheterization decision. Finally, these estimates together with consistent estimates of the Killip transition (δ) allow recovery of the period one utility parameters (α_1) using a conditional logit model for hospital choice. Consistent standard errors are obtained by taking one Newton step on the full likelihood function at the consistent estimates from the multi-stage estimation.

5.2 Identification

Each period in the model represents a different choice. Therefore, the estimation is essentially a series of multinomial logits with a different dependent variable in each period. Identification of the parameters for each choice is given by variation in treatment choices across health states (and distances for the hospital choice). This differs from other applications of dynamic discrete choice models that rely on variation over time in state variables to identify repeated choices (for examples in health economics see Gilleskie 1998; Khwaja 2003).

As in standard multinomial logit models, parameter normalizations are required for identification of the model. The parameters for the first category in each health transition (i.e., δ_1 and β_1) and each period's utility (i.e., α_{t1}) are normalized to zero. Utility parameters in the first period are relative to choosing a hospital with no specialized services and in the second and third periods are relative to choosing no transfer/no procedure.

The variance for the unobserved taste parameters is allowed to differ for each period. Each period's utility parameters are relative to the scale parameter for that period. The discount factor (β) is not separately identified from the scale parameters; the estimates are a function of the discount factor and the relative variance of the unobserved tastes between periods (i.e., $\beta\left(\rho_{t+1}/\rho_t\right)$).

Finally, the parameters in the terminal utility function are identified partially by functional form assumptions. All of the variables included in the terminal utility are also included in the mortality transition and are expected to affect both equations similarly. For instance, worse health status will lower both the probability of survival and the utility of survival. Variation in surgery decisions across health states in the data not fully explained by the impact of health and surgery on mortality will identify the terminal utility parameters.

6 Results and Policy Simulations

The parameters of the Killip transition are generally significant and most variables affect the probability of a particular Killip class in expected ways (Table 4). In particular, older individuals have a higher probability of transitioning to a higher Killip class. Higher Charlson categories relative to the lowest category lead to a higher probability of a more severe Killip class. The distance traveled to the hospital and its interaction with residence in a MSA are included in the Killip class transition to allow the time traveled to the hospital to affect health status at arrival. However, these variables do not have a large effect on Killip class at admission; the distance parameters are significant only for the highest Killip class and the odds ratios are 0.99 and 1.00, respectively.

Similar patterns appear in the results for the transition to blockage categories. Older individuals have a higher probability of transitioning into the moderate reduction category relative to the normal category. Age was not significant for the transition to severe reduction. As with Killip class, worse health status in earlier periods leads to a higher probability of worse systolic function. For instance, patients in Killip class III or IV have significantly higher probabilities of also having severe reduction (relative to normal function).

Health status, in every period of the model, is important in determining one-year mortality. Patients admitted with a Charlson greater than 3 are 85% more like to die within a year of admission than patients in the lowest Charlson category; patients in Killip class III or IV are twice as likely to die than patients with Killip class I; and patients with severe reduction are over four times more likely to die than patients with normal systolic function. Older patients have higher probabilities of mortality but there does not appear to be any signficant differences between males and females and across races.

Surgery, especially at higher surgery volume hospitals, is beneficial in reducing the probability of mortality at one year post admission. This estimate controls for detailed health status, which controls for selection at surgery hospitals. This substantial benefit to surgery provides an incentive for individuals to pay the utility costs for the procedure and to choose surgery hospitals in order to avoid the cost of transfer. The cost of providing geographically diverse, lower volume surgery hospitals is that surgery at these hospitals will not be as effective at reducing one-year mortality.

The second set of estimates in the dynamic model are the utility parameters. Hospitals with catheterization and surgery services are preferred to no service hospitals, all else constant (Table 5). Individuals with worse initial health status, as measured by the index of comorbidities, have higher preferences for surgery hospitals relative to no service hospitals. This provides evidence that hospital choice is responsive to health status. Increased distance to the hospital lowers the probability of choosing that hospital. In addition, the disutility from distance is higher for individuals living in urban areas due to the fact that travel time is higher in urban areas for a given distance. There is no evidence of the disutility from distance varying by health status.

The utility parameter estimates for catheterization indicate that there are significant utility costs to this procedure. The choice intercepts measure the utility from each choice relative to choosing no transfer and no catheterization. All three of the intercepts are negative and significant, which indicates that transfer and catheterization have utility costs to the patients, most likely in terms of the pain and suffering associated with the procedure itself and the subsequent recovery. There is little evidence that the costs from transfer and catheterization vary by health status.

The results for the utility parameters associated with the surgery decision are similar to those for the catheterization decision. Again, the parameters are relative to choosing no transfer/no surgery. The intercept for transfer/no surgery is negative and significant, indicating the transfer itself is costly in utility terms to the individual. Transfer/surgery also has significant disutility. However, these costs do not vary significantly by health status.

Finally, the positive and significant intercept coefficient in the terminal utility function indicates that surviving the heart attack episode provides utility. There is some evidence that utility is lower with worse health (i.e., the negative coefficients on the Charlson and blockage variables) and that surgery has long term benefits (i.e., the positive coefficient on surgery), but these parameters are not measured with precision.

6.1 Decentralization of Cardiac Services

Before proceeding to the policy simulations, it is important to check that the empirical model can predict observed behavior well. The first two rows of Table 6 show the fit of the model. The first row shows the mean distance in miles to the nearest surgery hospital, the mean Medicare surgery volume, and the frequencies of choices in the estimation sample. The second row shows the predicted choice frequencies from the structural model. The model fits the data well. The choice of surgery hospital, transfer, and catheterization predictions are very close to the frequencies in the data. The model over predicts surgery rates by six percentage points. This is most likely due to the relative lack of significant utility costs to surgery as a function of health.

Using the estimates of the dynamic model, an experiment is simulated in which cardiac services are decentralized. The simulation tests the following thought experiment: what would happen if the average heart attack victim has surgery hospitals that are closer but with lower volume? The simulation is run with a variety of distance/volume trade offs: for each person in the sample, the distance to the nearest surgery hospital is reduced by 0, 10, 50, and 100% and the surgery volume in that hospital is reduced by 0, 10, 50, and 100%, in all combinations. Each person in the estimation sample is simulated 100 times for each combination of changes in distance and volume by using draws from the distribution of unobserved tastes to solve for the optimal choice paths. The frequencies of choosing a surgery hospital, transfer, catheterization, and surgery and mortality rates are calculated.

The bottom rows of Table 6 show the percent changes in the predicted choice and mortality outcome frequencies for different combinations of changes in distance to the nearest surgery hospital and surgery volume. In general, as distance to the nearest surgery hospital decreases, holding surgery volume constant, the fraction of people that choose a surgery hospital increases; the distance elasticity is -0.6 for small changes in distance and -1.2 for large changes in distance. Since more people are already at a surgery hospital, transfers decrease as distance decreases.

Holding surgery volume constant, catheterization rates and surgery rates increase as distance to the nearest surgery hospital decreases: a 10% decrease in the distance to the nearest surgery hospital increases catheterization rates by 1.6% and surgery rates by 2.8%. The increases in procedure rates occur because as more patients are already at surgery hospitals, they do not have to pay the utility cost of transfer in order to have the procedure. The increases in surgery rates lead to a decrease in one-year mortality of 0.4%.

The effect of decreases in surgery volume holding distance to the hospital constant is the opposite of that of decreases in distance. Since higher surgery volume is advantageous in the treatment of heart attack, individuals respond to lower surgery volumes by choosing surgery hospitals, catheterization, and surgery less often. This is evidence that individuals are forward-looking in their hospital decision. In addition, one-year mortality increases as volume decreases: a 10% decrease in surgery volume leads to a 0.7% increase in mortality, holding distance constant.

Improvements in health outcomes resulting from decentralization are weakened when the associated decrease in volume is taken into account. If a decentralization policy lowers hospital surgery volume by 10%, then the distance to the nearest surgery hospital has to decrease by at least 10% in order for mortality rates not to increase. In the extreme scenario in which each individual has a surgery hospital located in the same zip code but that surgery hospital has yet to perform any surgeries (i.e., 100% decreases in both distance and volume), both surgery and mortality rates increase by 7.6% and 4.7% respectively. This is due to the fact that surgery is less costly in utility terms because more patients do not have to pay the utility cost of transfer at the same time that surgery is less effective in reducing mortality.

Decentralization policies are likely to be targeted to rural populations that are much farther from surgery hospitals. Table 7 reports the same decentralization policy simulated for the individuals in the estimation sample in non-metropolitan zip codes. Holding distance constant, the results for decreases in surgery volume are similar to the entire estimation sample. However, individuals in non-metropolitan areas are twice as sensitive to decreases in the distance to the nearest surgery hospital. Thus, decentralization leads to better mortality outcomes and higher surgery rates relative to the full sample for a given reduction in volume.

6.2 Elimination of Low-Volume Services

The policy recommendations that have resulted from the medical literature have largely focused around the setting of volume thresholds below which hospitals providing the surgery services should reconsider their provision. Grumbach et al. (1995) and Birkmeyer et al. (2003) were the first to address the trade off between distance and volume in the presence of existing thresholds. They simulate elimination of low-volume surgery services and re-calculate the travel times to the remaining high-volume surgery hospitals. Using the estimates from the model presented above, it is possible not only to replicate their policy experiments, but to extend the results to predict what would happen to the choice of hospital, surgery rates, and health outcomes.

The following policy simulations use the dynamic estimation results to eliminate low-volume surgery services from the choice set and predict the optimal choices for individuals in the estimation sample. The simulations use threshold levels of 50, 100, and 200 procedures per year. If Medicare patients make up one fourth to one half of total procedures, then this corresponds to thresholds from 100 to 800 angioplasties and bypass surgeries per year. The Leapfrog group recommends 500 per year. In 1995, 50 procedures was roughly the 60th percentile, 100 procedures was roughly the 80th percentile, and 200 procedures was roughly the 95th percentile of surgery hospitals.

Table 8 shows how elimination of low-volume surgery services affects distance to the nearest surgery hospital. It shows the share of patients from the estimation sample that live within given distances of a surgery hospital. There are rather dramatic changes in distance to surgery providers when low-volume services are removed. When surgery services with less than 50 procedures a year are eliminated, the share of patients living within 5 miles of a surgery hospital falls from 36% to 23%. In addition, the share of patients at least 50 miles from a surgery hospital more than doubles from 7% to 17%. Under the policy with the highest threshold (200 procedures per year), 70% of individuals would have to travel over 50 miles to reach the nearest surgery hospital.

Where previous studies of centralization end here, the model estimated in this study allows analysis of the effect of enforcement of volume thresholds on treatment decisions and outcomes. Table 9 shows the results of removing the low-volume services and predicting forward choices and one-year mortality. The first two rows are the same as before for the estimation sample (i.e., observed distance to the nearest surgery hospital, surgery volume at those hospitals, and observed frequencies for choices and outcome). The last three rows give the same means and frequencies under the different volume thresholds with percentage changes from the baseline predictions in parentheses.

When surgery services with less than 50 procedures per year are eliminated, the fraction of individuals choosing surgery hospitals falls from 36% to 25%. Thus, in order to receive surgery, more patients have to transfer (17% vs. 15%). The net effect of the large decrease in admissions to surgery hospitals and the smaller increase in transfers is that surgery rates fall slightly (21% vs. 22%). One-year mortality falls by less than one percent.

Eliminating surgery services with less than 100 procedures per year decreases the fraction of patients admitted initially to surgery hospitals to 16%. Consequently, transfers increase by 24%. Interestingly, although surgery rates fall, one-year mortality rates are not different than in the baseline predictions. The more stringent threshold of 200 procedures per year shows the same patterns as above except that under this simulation one-year mortality increases by 2.5%. This policy effectively eliminates almost all existing surgery services and leaves the average heart attack victim hundreds of miles from a surgery hospital.

In general, enforcement of threshold volume levels leads to a decrease in the share of individuals choosing surgery hospitals initially, an increase in transfer rates, leading to a net decrease in surgery rates. One-year mortality falls slightly under a low threshold and increases under the highest threshold level. This provides empirical evidence for the trade off between distance and volume: concentrating surgeries in only the highest volume hospitals will not improve mortality outcomes due to the increased costs of accessing surgery services. However, the trade off only appears at high levels of centralization.

For instance, eliminating surgery services with less than 100 procedures per year reduces surgery rates while leaving one-year mortality unchanged.

7 Conclusion

State regulators face a trade off between increasing surgery volumes at hospitals and reducing the access to cardiac services. A large literature, including this study, has shown that increased surgery volume at a hospital reduces patient mortality. Thus, as patients and physicians weigh the costs and benefits of surgery, promoting large, regional centers may increase or decrease both surgery rates and mortality. This study models the hospital and treatment decisions of heart attack victims. It accounts for detailed health status of the patient and the ability of patients to transfer to surgery hospitals during their treatment episode. The model provides predictions of the changes in hospital choices, procedure rates, and mortality outcomes resulting from changes in the distance to the nearest surgery hospital and surgery volume at those hospitals.

The results indicate that heart attack patients are forward-looking in their hospital decisions: reductions in hospital surgery volume, which reduce the benefit to surgery, reduce not only surgery rates, but also catheterization rates and the probability of choosing a surgery hospital for treatment. [5] At the same time, reductions in the distance to the nearest surgery hospital have the opposite effect—they increase procedure rates and the likelihood of choosing a surgery hospital. Thus, the model quantifies the trade off faced by regulators considering changes in the supply of cardiac services in a market.

Overall, the results indicate that mortality is relatively insensitive to moderate changes in policy. However, this is not the result of travel costs and volume being unimportant; it is the result of these two crucial factors offsetting one another. Decentralization increases the number of surgeries but lowers their effectiveness. Centralization leads to fewer, but more effective, surgeries. Therefore, despite similar health outcomes, the competing policies have different implications for taxpayers. Medicare reimbursements for cardiac surgery would be lower under the centralization policy.

This study has limitations. The estimation of a structural dynamic discrete choice model is computationally more costly than alternative models. This restricts the breadth of the data used in the model. For instance, the restriction in the choice set of hospitals reduced the size of the state space

[5] This is not a formal test of dynamic versus myopic behavior.

for which the dynamic programming problem had to be solved at the cost of mis-specifying the relevant choice set (Tay 2003, used a larger choice set of hospitals for heart attack victims). There is also much more information concerning health status and the severity of the heart attack in the CCP that were not utilized in the dynamic model (e.g., see Sloan et al. 2003). Each measure of severity ascertained after admission would require specification of a health transition equation in order for the decision-maker to form expectations about health outcomes.

The limitations of the structural approach are offset by several benefits. Most importantly, in formalizing the decision-maker's optimization problem, the model allows patients and their providers to respond to proposed changes in volume in their treatment decisions. The dynamic aspect provides an avenue for changes in volumes to affect all treatment decisions through expectations of health outcomes. Under the assumptions of the model, the technology and utility parameters can be used to assess a variety of policy simulations beyond those observed in the data. In addition, advances in computing power and estimation strategies can reduce the computational cost of expanding the state space within these types of models (Keane and Wolpin 1994; Ackerberg 2001).

Second, this study only captures the effect on one health outcome: mortality. The medical literature has found that heart surgery can improve other facets of health and quality of life (Allen et al. 1990; McKenna et al. 1994; Papadantonaki et al. 1994; Hlatky et al. 1997). The model allows utility after the heart attack episode to vary by health status and whether or not the individual had surgery, but the parameters are not significant. If surgery provides health benefits beyond reductions in mortality, then the benefits of the decentralization policies considered above are underestimated.

Third, up to 50% of all heart attack deaths occur before the individual reaches the hospital (Dracup et al. 1995). Thus, the CCP sample suffers from a form of selection; the patients with reported health status and hospital choices are systematically different than those heart attack victims not observed. In order to implement corrections for selection, some information about the selected sample would be necessary. This information is not available for hospital-based samples. If the sample of heart attack victims that were not admitted to a hospital had (ex ante) higher preferences for service offerings (e.g., if they died in transit to surgery hospitals), then the policy simulations above underestimate the costs of centralization, which would place surgery hospitals farther from these patients and perhaps increase mortality.

Finally, these results capture only the demand-side response to changes in the market for cardiac services. Other drawbacks to regionalization include effects on competition in the hospital market (including the financial impact on low-volume providers and increases in bargaining power of high-volume providers), congestion at high-volume hospitals, and questions about physician supply under selective referral (Dudley et al. 2000). Due to substantial deviations from the competitive model in the hospital industry, [6] the theoretical implications of increased competition are often ambiguous in this context (see Dranove and White 1994; Dranove and Satterthwaite 2000, for reviews of this literature). Under cost-based reimbursement, the presence of insurance can lead hospitals to compete on the basis of quality, which can lead to increases in costs. However, since Medicare converted to a prospective payment system, there is some evidence that competition lowers costs (Kessler and McClellan 2000). If this was indeed the case, the effects of centralization of cardiac services described above (decreased surgery rates and associated costs) would be partially offset by the decrease in competition. A full analysis of the welfare gains from decentralization would have to take this into consideration.

[6] These include the importance of insurance, imperfect information, and the role of non-profit institutions (Arrow 1963).

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Table 1: Individual Characteristics

Variable	Full Freq.	Full %	Estimation[1] Freq.	Estimation[1] %
Period One: Hospital Choice				
Age (mean, sd)	76.89	7.32	76.76	7.12
Female	40,670	49.56	1,980	48.26
Minority race	7,270	8.86	358	8.73
MSA	58,122	70.83	2,943	71.73
Charlson index = 0 or 1	41,693	50.81	2,124	51.77
Charlson index = 2 or 3	29,070	35.43	1,452	35.39
Charlson index > 3	11,292	13.76	527	12.84
No-service hospital	31,236	38.07	1,574	38.36
Cath-only hospital	21,622	26.35	1,069	26.05
Surgery hospital	29,197	35.58	1,460	35.58
Period Two: Cath choice				
Killip I	40,264	49.07	2,054	50.06
Killip II	9,647	11.76	511	12.45
Killip III or IV	32,144	39.17	1,538	37.48
No transfer/no cath	53,396	65.07	2,644	64.44
No transfer/cath	17,163	20.92	900	21.94
Transfer/no cath	1,381	1.68	68	1.66
Transfer/cath	10,115	12.33	491	11.97
Period Three: Surgery choice				
Systolic: normal[2]	3,295	19.20	172	19.11
Systolic: moderate reduction	12,269	71.49	655	72.78
Systolic: severe reduction	1,599	9.32	73	8.11
No transfer/no surgery	67,921	82.77	3,382	82.43
No transfer/surgery	11,766	14.34	614	14.96
Transfer/no surgery	1,006	1.23	50	1.22
Transfer/surgery	1,362	1.66	57	1.39
Period Four				
Dead at one year	28,091	34.23	1,369	33.37
Sample size	82,055		4,103	

[1] A 5% random sample of individuals is used for estimation.

[2] 17,163 individuals have information on blockage status in the full sample and 900 in the estimation sample.

Table 2: Hospital Characteristics

	Full		Estimation	
Variable	Freq.	%	Freq.	%
<u>1994</u>				
No service hospital	1,672	56.32	619	43.44
Catheterization hospital	523	17.62	357	25.05
Surgery hospital	774	26.07	449	31.51
Surgery volume (mean, sd)[1]	28.52	37.90	35.48	42.81
Sample size	2,969		1,425	
<u>1995</u>				
No service hospital	2,429	61.76	1,192	49.20
Catheterization hospital	576	14.65	528	21.79
Surgery hospital	928	23.60	703	29.01
Surgery volume (mean, sd)[1]	53.49	64.95	57.72	68.12
Sample size	3,933		2,423	

[1] The surgery volume statistics are for surgery hospitals only.

Table 3: Decision Tree

Period 1	Period 2	Period 3
No-service hospital	No tran/no cath	No tran/no surgery
	Tran/no cath	No tran/no surgery
	Tran/cath	No tran/no surgery
		No tran/surgery
Cath-only hospital	No tran/no cath	No tran/no surgery
	No tran/cath	No tran/no surgery
		Tran/no surgery
		Tran/surgery
	Tran/no cath	No tran/no surgery
	Tran/cath	No tran/no surgery
		No tran/surgery
Surgery hospital	No tran/no cath	No tran/no surgery
	No tran/cath	No tran/no surgery
		No tran/surgery

Table 4: Health Transitions: Multinomial Logits[1]

Variable	Killip Class Coeff.	SE	OR	Blockage Coeff.	SE	OR	Mortality Coeff.	SE	OR
	Killip II			Moderate Reduction			Dead at 1 year		
Intercept	-3.932*	0.123		0.593*	0.263		-5.698*	0.486	
Age	0.030*	0.002	1.03	0.008*	0.004	1.01	0.055*	0.005	1.06
Female	0.064*	0.023	1.07	-0.275*	0.040	0.76	-0.014	0.076	0.99
Minority	0.049	0.041	1.05	0.034	0.073	1.03	0.123	0.125	1.13
Charlson 2-3	0.295*	0.025	1.34	0.256*	0.045	1.29	0.354*	0.082	1.43
Charlson >3	0.577*	0.036	1.78	0.347*	0.082	1.41	0.614*	0.114	1.85
Killip II				0.151*	0.062	1.16	0.479*	0.117	1.61
Killip III or IV				0.585*	0.055	1.80	0.732*	0.087	2.08
Moderate reduction							0.191	0.302	1.21
Severe reduction							1.467*	0.368	4.34
Distance	2.2E-4	0.002	1.00						
Dist*MSA	0.002	0.003	1.00						
Surgery							-0.560*	0.189	0.57
Surgery*volume							-0.072*	0.015	0.93
	Killip III or IV			Severe Reduction					
Intercept	-4.367*	0.085		-2.198*	0.418				
Age	0.047*	0.001	1.05	0.009	0.006	1.01			
Female	0.173*	0.016	1.19	-0.533*	0.065	0.59			
Minority	0.182*	0.027	1.20	0.236*	0.109	1.27			
Charlson 2-3	0.742*	0.017	2.10	0.751*	0.070	2.12			
Charlson >3	1.210*	0.024	3.35	1.034*	0.108	2.81			
Killip II				0.603*	0.104	1.83			
Killip III or IV				1.903*	0.075	6.70			
Distance	-0.008*	0.001	0.99						
Dist*MSA	0.004*	0.002	1.00						
N	82,055			17,163			4,103		
ln L	-76,515.80			-12,799.87			-3291.21[2]		

Asymptotic standard errors (SE) and odds ratios (OR) are reported.
* indicates significance at the 95% confidence level.
[1] The reference group for each transition is the healthiest category: Killip I, normal systolic function, and alive at one year.
[2] The mortality equation is estimated jointly with the surgery decision.

Table 5: Utility Parameters[1]

Variable	Hospital Coeff.	Hospital SE	Cath Coeff.	Cath SE	Surgery Coeff.	Surgery SE	Terminal Coeff.	Terminal SE
	Cath only		No Tran/Cath		No Tran/Surgery		Alive at 1 year	
Intercept	0.392*	0.091	-3.727*	0.157	-2.298	1.957	4.511*	1.449
Charlson 2-3	0.265	0.139	0.010	0.100	0.139	0.329	-0.605	1.723
Charlson >3	0.238	0.190	-0.207	0.170	0.209	0.742	-2.924	2.850
Killip II			-0.103	0.146	0.003	0.219		
Killip III or IV			0.031	0.109	-0.313	0.227		
Moderate reduction					-2.569	1.622	-3.011	1.738
Severe reduction					-0.837	1.779	-0.473	3.110
Surgery							2.709	2.928
	Surgery		Tran/No Cath		Tran/No Surgery			
Intercept	0.420*	0.108	-3.329*	0.208	-0.880*	0.382		
Charlson 2-3	0.334*	0.131	0.224	0.280	-0.081	0.367		
Charlson >3	0.412*	0.188	-0.344	0.437	-0.235	0.700		
Killip II			-0.833	0.566	0.151	0.535		
Killip III or IV			0.066	0.267	0.143	0.398		
Moderate reduction					-0.385	0.392		
Severe reduction					-0.396	0.901		
			Tran/Cath		Tran/Surgery			
Intercept			-5.174*	0.198	-4.502*	2.047		
Charlson 2-3			-0.264	0.153	-0.105	0.489		
Charlson >3			0.229	0.247	0.875	0.904		
Killip II			0.550*	0.216	-1.877	1.167		
Killip III or IV			1.242*	0.171	-0.046	0.485		
Moderate reduction					-1.176	1.746		
Severe reduction					0.622	2.204		
Distance	-0.148*	0.004						
Dist*MSA	-0.174*	0.009						
Dist*Charlson 2-3	0.004	0.009						
Dist*Charlson >3	0.018	0.012						
$\beta\,(\rho_{t+1}/\rho_t)$	0.548*	0.089	5.399*	0.187	0.948*	0.378		
N	4,103		4,103		4,103		4,103	
ln L	-2163.99		-2531.89		-3291.21[2]		-3291.21	

Asymptotic standard errors (SE) and odds ratios (OR) are reported.
* indicates significance at the 95% confidence level.
[1] Utility parameters in the first period are relative to choosing a hospital with no specialized services and in the second and third periods are relative to choosing no transfer/no procedure.
[2] The mortality equation, surgery and terminal utility parameters are estimated jointly.

Table 6: Effects of Decentralization

Dist.	Vol.	Surgery Hospital	Transfer	Cath.	Surgery	Mortality
Observed						
17.44	49.48	35.58	16.24	33.91	16.35	33.37
Predicted						
		35.59	15.40	31.68	22.23	33.90
Percent Changes						
-10	0	6.29	-3.12	1.61	2.79	-0.41
-50	0	42.57	-22.40	10.70	18.76	-2.51
-100	0	121.83	-67.60	32.73	54.39	-6.31
0	-10	-0.90	0.58	-2.18	-2.25	0.65
-10	-10	5.28	-2.53	-0.73	0.45	0.27
-50	-10	41.42	-21.62	7.64	15.65	-1.59
-100	-10	120.76	-66.82	28.50	50.20	-5.07
0	-50	-4.55	2.79	-10.89	-11.56	3.01
-10	-50	1.46	-0.26	-10.01	-9.45	2.80
-50	-50	36.58	-18.38	-4.73	2.56	1.77
-100	-50	116.35	-63.44	10.35	32.30	-0.29
0	-100	-8.29	4.94	-20.74	-22.76	5.25
-10	-100	-2.56	2.27	-20.39	-21.28	5.19
-50	-100	31.50	-14.94	-18.88	-13.36	4.99
-100	-100	111.07	-59.16	-12.91	7.56	4.72

Table 7: Effects of Decentralization–Non-Metropolitan Sample

Dist.	Vol.	Surgery Hospital	Transfer	Cath.	Surgery	Mortality
Observed						
38.20	42.99	14.31	24.05	30.86	12.67	33.19
Predicted						
		15.11	20.22	25.52	16.83	34.66
Percent Changes						
-10	0	13.63	-2.18	1.33	2.85	-0.35
-50	0	112.11	-18.00	12.30	23.89	-2.60
-100	0	407.61	-71.46	54.04	93.58	-7.67
0	-10	-0.99	0.15	-0.98	-1.19	0.23
-10	-10	12.44	-1.93	0.27	1.60	-0.09
-50	-10	110.06	-17.61	10.19	21.33	-2.04
-100	-10	405.16	-70.77	49.69	88.71	-6.61
0	-50	-4.43	0.99	-4.31	-5.05	1.01
-10	-50	8.07	-0.89	-3.64	-3.15	0.84
-50	-50	101.39	-15.63	1.92	11.65	-0.14
-100	-50	395.04	-68.00	30.64	68.81	-2.65
0	-100	-7.48	1.63	-7.60	-9.15	1.62
-10	-100	4.10	0.00	-7.41	-7.78	1.56
-50	-100	92.65	-13.35	-5.92	1.54	1.44
-100	-100	383.65	-64.34	6.90	41.95	1.33

Table 8: Share of Patients Within Given Radius of Surgery Hospital

		Eliminate surgery services with <:		
Distance	Observed	50 proc/yr	100 proc/yr	200 proc/yr
0 to 5 miles	36.22	22.54	13.19	3.46
5 to 25 miles	39.00	38.65	31.78	15.57
25 to 50 miles	17.52	21.37	19.38	10.46
50 to 100 miles	6.14	12.60	18.84	17.23
100+ miles	1.12	4.83	16.82	53.28
N	4,103			

Table 9: Elimination of Low Volume Hospitals–frequency (% change)

Dist.	Vol.	Surgery Hospital	Transfer	Cath.	Surgery	Mortality
Observed						
17.44	49.48	35.58	16.24	33.91	16.35	33.37
Predicted						
		35.59	15.40	31.68	22.23	33.90
No surgery hospitals < 50 proc/yr						
32.09	106.45	25.37	17.36	31.87	21.25	33.60
		(-28.72)	(12.73)	(0.60)	(-4.41)	(-0.88)
No surgery hospitals < 100 proc/yr						
68.79	151.57	15.96	19.15	30.15	18.86	33.90
		(-55.16)	(24.35)	(-4.83)	(-15.16)	(0.00)
No surgery hospitals < 200 proc/yr						
204.80	262.92	5.80	21.11	26.69	15.10	34.74
		(-83.70)	(37.08)	(-15.75)	(-32.07)	(2.48)