Measuring Welfare from Ambulatory Surgery Centers: A Spatial Analysis of Demand for Healthcare Facilities

Ellerie Weber*

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Abstract

The purpose of this study is to estimate structural elements of consumers' demand functions for healthcare facilities, particularly hospitals and ambulatory surgery centers (ASCs), towards the goal of answering questions about welfare gains earned from the introduction of ASCs. For identification I use spatial variation across patients and facilities. In line with the existing literature, I show that there is a strong spatial component to demand. Developing a discrete choice model of demand for healthcare facilities, I estimate structural parameters from consumers' demand functions from nested logit and mixed logit (also called random coefficient) specifications. Travel costs are found to be the best predictor of consumers' healthcare facility purchase. Insurance variables are found to be a significant choice in the nest decision of ASC or hospital. The estimation methodology enables calculation of a cross-time substitution matrix to explain how consumers substitute between facilities over space. Finally, I measure how consumer welfare would change if a subset of facilities (ASCs) were removed from consumers' choice sets. All of this is done without explicitly including a price variable, but instead using time and travel costs to give meaning to welfare numbers. Welfare loss from the elimination of ASCs is found to be small, less than five minutes of welfare loss per patient for a given procedure.

1 Introduction

The purpose of this study is to estimate structural elements of consumers' demand functions for healthcare facilities, particularly for hospitals and ambulatory surgery centers (ASCs),

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towards the goal of answering questions about the magnitude and existence of welfare gains earned from the existence of ASCs. Hospitals are healthcare facilities that perform both inpatient and outpatient procedures, while ASCs are healthcare facilities that concentrate exclusively on outpatient procedures. Hospitals and ASCs compete in the outpatient procedure product space. Consumers decide which facility to frequent based on a number of factors, including travel distance. By estimating the importance of these factors relative to the importance of travel costs, I predict welfare losses from removing certain facilities from patients' choice sets.

The study of competition between hospitals has become a popular topic in the fields of industrial organization and healthcare research, but only recently have researchers incorporated ASCs into their work; the literature on them is still nascent. The studies that do exist on ASCs mostly offer unstructured models that address the supply-side of the market[1], or are structure-conduct-performance organized papers, driven by the quest to understand the effects of recent high entry rates by ASCs into the healthcare facility industry.[2]

There has been no study of which I am aware that structurally analyzes patients' demand for all healthcare facilities for outpatient procedures. Gaynor and Vogt [8] analyze demand for hospitals (in California) for inpatient surgeries, and use similar techniques to those used here. Capps, Dranove and Lindrooth [5] also estimate demand for hospitals (in five mid-sized US cities) for inpatient procedures. Both papers perform demand estimates with an eye towards policy recommendations: Gaynor and Vogt want to measure potential welfare losses from mergers, while Capps, Dranove and Lindrooth are interested in welfare losses from hospital closures. Both papers also incorporate travel time or distance measures into their estimates. As I do, Capps, Dranove and Lindrooth use the estimate on time cost as a marginal utility of income to convert welfare numbers from utils. Where comparable, my results support their findings. Moreover, my welfare analysis augments theirs: Welfare estimates from both Gaynor and Vogt and Capps, Dranove and Lindrooth are limited to inpatient procedures only and therefore underestimate the true cost of mergers or closures to patients, who also value hospitals for their provision of outpatient services.

By estimating the patient's demand-side of the market for outpatient surgery, this paper provides some insight into how ASCs and hospitals compete by looking at how consumers

[1]For example, Morrisey and Bian [17] and Plotzke [24] both show that entry by ASCs is associated with a decline in a hospitals outpatient surgeries and no significant change in impatient surgeries. Lynk and Longley [12] use a case study to frame a similar result: that hospital-based outpatient surgical volume falls when the hospitals' physicians open an ASC. Plotzke [24] also finds that there is no significant effect of ASC entry on hospital profit margins for either outpatient or inpatient departments. Housman [11] looks at the dynamics of ASC and hospital entry and exit, and finds that ASCs benefit most from a nearby hospital, while hospitals are hurt by ASC entry.

[2]Just as the hospital literature grew in response to the heavy merger activity of the late 1990s.

substitute between them, and at how consumers' welfares change when some facilities are removed from their choice set.

I think about the problem in the following way: After being recommended by their physician to have surgery, and perhaps to use a particular facility, patients make a two-part decision. First they decide whether to have surgery, then they decide at which facility to have the procedure performed. This paper focuses on the last part of the decision tree [3]: conditional on needing to undergo an outpatient procedure, which facility does the consumer choose? In particular, I look at how a bundle of facility characteristics including geographic location impact consumers' purchase choices. The farther away a facility is from patients' homes, the higher are patients' travel costs. Travel costs are measured with a time-to-travel variable that specifies the distance (in minutes) from each patient to each and every facility.

I model this decision as one of discrete choice, where the consumer picks one facility from among her choice set. I use both nested and mixed (also called random coefficients) logit models.

In choosing to measure demand as a discrete choice where travel time is a significant predictor of facility purchase, my paper follows sizable literatures in the fields of recreation demand, transportation and environmental economics. As with many of the papers in those literatures, travel costs serve to identify the marginal utility of income, thereby enabling authors to recover values for goods not traded in traditional markets. This is a useful extension to make to the health economics field. Although prices exist in health markets, insurance and other complicating factors make price data noisy, mis-measured, or irrelevant.[4] Luckily, we can substitute price with another (non-monetary) cost to consumers, namely travel time costs. While such a substitute cost is not needed per se, it is useful if we want to interpret magnitudes about how much consumers value individual product characteristics. Usually, coefficients on price variables enable us to make the conversion into dollar-denominated marginal effects and welfare effects. I use travel time as the relevant cost, and measure elasticities and welfare with respect to time. See references in the recent survey by Maler and Vincent [22] for a discussion on how the aforementioned literatures use time costs as a significant input to purchase decisions (either in lieu of, or in addition to, price).

This paper also follows and extends the structural IO and discrete choice literatures

[3]Note that in some cases, consumers may need to make an intermediate decision about whether to have the procedure performed on an inpatient or outpatient basis. By omitting that decision step from the model, I am implicitly assuming that conditional on a particular procedure, consumers do not substitute between inpatient and outpatient settings. This is a valid assumption for the top outpatient procedures in my data, for which the vast majority of patients have their surgery done in outpatient facilities exclusively.

[4]Like for Medicare patients, who pay the same amount (the co-pay) regardless of facility choice and who compose a large share of total market purchases for outpatient procedures. In general, insurance coverage dampens price variation considerably, making price much less important than it might otherwise have been.

that address issues of unobserved heterogeneity in differentiated products, and that allow patient characteristics to influence demand. Many papers in the IO literature (Berry [1], Berry, Levinsohn and Pakes [25], Petrin [21], Nevo [20]) deal with unobserved heterogeneity on demand and supply-side equations by using complicated estimation algorithms to find product fixed effects that absorb omitted variables causing endogenity. Their estimation strategies must be complex to compensate for the fact that they only have market level data so they do not actually observe consumer choices, and therefore cannot link consumers to particular products except through matching moments. Once fixed effects are estimated, additional nuance is needed to recover coefficients on price, which is needed for welfare calculations.

In contrast, the identification strategy and analyses used in this paper are simpler than many of the structural IO papers. Partly, this is a result of better data: we can control for unobserved heterogeneity because there exist micro data about patients making health care facility choices. The micro data contain demographic variables that describe patient characteristics, which allows one to explain variation in choice with actual, observed patient indiosyncracies. Moreover, there are a lot of data. Given that we can observe many observations (that is, purchase choices) for each facility, it is straightforward though computationally intense to include product-level (facility-level) fixed effects to absorb unobserved variables, like quality, which we know influence consumers' choices. Berry, Levinsohn and Pakes [2], and Gaynor and Vogt [8], discuss the benefits of having micro data within an IO framework. The discrete choice literature with respect to micro data is voluminous; see McFadden [15] for a starting point. Note that my paper also differs from BLP and other structural IO models in that there is no supply-side estimation done here.

Specifically, I estimate a nested logit specification that posits that consumers make a decision about which type of facility – an ASC or a hospital – in addition to deciding a particular preferred facility. The nested logit specification allows us to test whether there exist within-nest correlations, or whether the traditional assumption of the independence of irrelevant alternatives (IIA) holds. I find that for many procedures there are significant within-nest correlations, even after controlling for observed patient characteristics that can explain nest choice.

I then specify a mixed (also called random coefficients) logit model. The mixed logit allows parameters to contain a random component distributed over the observed population, so that estimation returns the mean and standard deviation of the distribution of the parameter, instead of just the mean parameter as is done in the traditional multinomial logit model. For variables like travel costs, for example, our prior is that different consumers value time differently, and therefore coefficients should differ between consumers. Some variation can be explained by observed patient characteristics, but much about consumers is unobserved, such as income. Using random coefficients, therefore, should increase the fit of the model and and provide better welfare estimates. This is the traditional random coefficients logit model as described by Train [28] and McFadden [13].

I also show a link between the nested and mixed logit specifications. In particular, the nested logit presumes that within-nest correlation is homogeneous across unobservable patient characteristics, while the mixed logit allows for structure in the distribution of correlations across patients.

All specifications of the demand model allow for easy calculation of a cross-time substitution matrix, which describes how patient demand shifts over geographic space, given a proposed change in any facilities' location. As the travel time from all patients to any one facility increases to infinity, that facility can be thought to disappear from the choice set, and we can estimate how patients substitute to other facilities accordingly. This is a useful policy tool.

Finally, I calculate welfare estimates. The main this paper considers is: How much would consumers lose if all ASCs in their market were closed? This question is of particular interest to policy makers because of recent, heavy entry by ASCs into the healthcare facility industry. Hospitals have decried this phenomenon, arguing that doctors are "cherry-picking" the best, least costly patients to send to ASCs, and sending the unprofitable patients to hospitals (see Plotzke [23] and Winter [30]). Moreover, hospitals perceive that ASC entry is coming disproportionately into high-profit procedural areas, thereby also cherry-picking the best, most profitable product-lines. Hospitals are therefore claiming that their survival is in danger, as their profits are falling into the red because they are receiving less profitable patients and facing competition in more profitable product-lines.[5] In some cases, they are lobbying for stricter entry laws (Certificate of Need laws) to limit ASC entry. Given that hospitals indisputably provide indispensable services to local communities (emergency care, for instance), threat to hospital survival is a serious policy matter. On the other hand, if ASCs are not allowed to enter, patients stand to lose surplus. Using demand model estimates, I can measure the potential for lost surplus.

There is the additional policy matter of how safe ASCs are relative to hospitals. Even though outpatient surgery performed in either an ASC or hospital setting is generally quite safe (Fleisher et al [7]), it is still possible to measure in money terms the cost of any potential risk of an ASC by using probabilities of adverse outcomes and estimates for the value of a statistical life (see Murphy and Topel [19]). By itself, however, such a cost lacks context. The welfare numbers calculated in this paper provide a benefit against which costs can be

[5] Their claims have been disputed by some economists. See Plotzke [24].

compared.

The next section briefly defines ambulatory surgery and outlines how the healthcare facility industry is organized. Section 3 proposes the structural model of demand and section 4 lays out the estimation strategy. In section 5, I describe the data. Section 6 presents results. Section 7 discussed identification. Finally, welfare calculations are made in section 8.

2 Overview of Product & Industry

Product

Also known as day surgery or ambulatory surgery, outpatient surgeries are defined as those procedures not requiring overnight stay in a healthcare facility. This is the sole defining characteristic of an outpatient surgery; outpatient procedures may be short or long, may require general or local anesthetic, and may be minimally invasive or require serious incision.

There are many different types of outpatient surgeries. According to my data, the five most common ambulatory procedures performed in 2006 were endoscopy of the large intestine, endoscopy of the small intestine, extraction of (cataract) lens, injection of agent into the spinal canal, and insertion of prosthetic lens. In 1996, the five most common procedures were cataract removal, endoscopy of large intestine, removal of skin lesion, arthroscopy of knee, and repair of inguinal hernia.

Healthcare Facility Industry

Both hospitals and ASCs compete to perform outpatient procedures. Hospitals also perform inpatient procedures; ASCs do not. Besides offering only outpatient procedures, ASCs differ from hospitals in at least four other dimensions. First, they do not have emergency rooms, but rather accept elective surgeries only. Second, they tend to be privately owned, with multiple owners. It is typical for physicians who perform surgery in the facility to have an ownership stake as well. Large healthcare companies, and development and management companies are other common shareholders in ASCs. Third, ASCs tend to be more specialized than hospitals, focusing on select body regions, or on categories of procedures, like pain management, or diagnostic procedures, like colonoscopies. Finally, ASCs are smaller than hospitals on average, doing fewer total procedures, and having fewer operating rooms available for use.

The advent of the ASC into the surgery provision arena is quite recent. Since their inception in the 1970s, entry by ASCs has been rampant. According to data collected by the Center for Medicare Services, in the decade between 1995-2005, the number of ASCs in the

United States grew by 10 percent annually; more than 4,500 freestanding facilities existed by 2006. Evidence of high growth is echoed by other large-scale surveys: the National Survey of Ambulatory Surgery, done by the National Center for Health Statistics, show that total ASC market share grew from less than 20 percent to almost 50 percent of all ambulatory surgeries between 1996-2006, and is expected to continue to grow. In 2006, that implied that ASCs performed more than 15 million procedures. Moreover, my data show that ASCs gained market share relative to hospitals in the majority of major ambulatory surgeries.

The general revenue model for healthcare facilities – be they hospitals or ASCs – charges patients, or their insurance companies, fees related to capital and labor costs incurred by the facility during the surgery. This may include charges for the operating room, recovery room, diagnostic services, lab services, and anesthesia services, among other incidentals. Insurance companies pay some fraction of these charges, usually at rate negotiated in periodic bargaining sessions. Uninsured patients may pay charges in full, or in large part, as they are rarely in a strong position to negotiate with facilities. Medicare does not negotiate with facilities on an individual basis, but rather pays facilities a prospectively set reimbursement rate. Note that the facility fee is distinct from the physician's fee; physicians bill patients separately.

3 Demand Model

I model consumer demand for healthcare facilities as a discrete choice problem. The person making the choice is called *the consumer*. Consumer utility can be thought of as some weighted mix of patient utility and physician utility, since physicians also have some preference over the facility-patient match, and presumably some influence over patients' choices through means of recommendation, or restriction on where they themselves operate. Section 7 discusses identification of utility components that are uniquely physician-genereated versus uniquely patient-generated.

The consumer's choice set is some set of facility alternatives in the state of Florida. There is no ex-ante restriction on what this set can be; even the set of all facilities is acceptable. While actual choice sets are likely small and geographically constrained, the flexibility allows the data to naturally determine consumer's market boundaries, instead of imposing a constraint exogenously ex-ante. Getting a perfect snapshot of consumer's choice sets is complicated slightly because of border issues with the two neighboring states of Louisiana and Georgia. This is discussed further in section 7.

I specify two different discrete choice logit models to elucidate different aspects of the consumer's choice problem. First, I write down a mixed logit (also called random coefficients) model. Random coefficients allow the parameters of the utility functions to vary over consumers based on observed and unobserved consumer characteristics. In contrast, the standard multinomial logit model assumes that utility function parameters are fixed over all decision makers. A logit specification with random coefficients is often referred to as a mixed logit model; this is the nomenclature I use here. The term "mixed" refers to the mixing distribution from which random parameters are assumed to be drawn. Second, I specify a nested logit model, by showing how the nested logit is a special case. The nested logit presumes that consumers first choose the type of facility (ASC or hospital) and then elect a particular facility from the subset of options yielded by their higher-level choice.[6] I show how the nested logit model can be written as a special case of the mixed logit, where the within-nest correlation is assumed to be homogeneous across consumers.

Both the nested and mixed logit models adequatly circumvent the well-known restrictive substitution patterns (the IIA problem) imposed by the standard multinomial logit model (see Train [28]). They are also appropriate because our null hypothesis is that coefficients vary over the population.

Healthcare facility choices depend on the interaction between patient characteristics and facility characteristics; this is equivalent to saying that tastes vary across patients. For instance, sicker patients may prefer facilities with emergency rooms — that is, hospitals — as insurance against a negative outcome, while healthier patients may be more willing to visit ASCs, which don't have emergency rooms. In another example, older patients may be less willing than younger patients to travel far for a given procedure. Making explicit the interaction between patient and facility characteristics naturally allows coefficients to differ across consumers. These interactions are one component of the random coefficeint. Some of the variation in coefficients across patients, however, may result from differences in unobserved patient characteristics. This variation is captured with a pure error term and is the second component of the random variation. Gaynor and Vogt [8] and Ho [10] use similar approaches.

3.1 Mixed Logit

Formally, suppose there are I consumers. The elements of the choice set for consumer i are: $A_i = \left\{ j_1, j_2, \ldots, j_{J_i} \right\}$, where J_i is the cardinality of the choice set for consumer i. From each potential alternative in her choice set, the consumer receives utility U_{ij} and she chooses the facility that maximizes her utility. That is, consumer i chooses facility j if and only if

[6] Note that the model does not require the nest-facility decision to be in fact sequential. It is just a useful construct for thinking about the problem.

$U_{ij} > U_{il}\ \forall j \neq l$, where j and $l \in A_i$.[7]

Since there are aspects of consumers' decision-making processes that the econometrician does not observe, we write utility for consumer i from facility j as the sum of explained and random parts.

$$U_{ij}\left(\mathbf{X_j}, \mathbf{Z_i}, T_{ij}, \xi_\mathbf{j}, \upsilon_\mathbf{i}; \theta\right) = V_{ij}\left(\mathbf{X_j}, \mathbf{Z_i}, T_{ij}, \xi_\mathbf{j}, \upsilon_\mathbf{i}; \theta\right) + \epsilon_{ij} \tag{1}$$

The explained part, V_{ij}, is a function of observed facility characteristics, $\mathbf{X_j}$; observed patient characteristics, $\mathbf{Z_i}$; unobserved facility characteristics, $\xi_\mathbf{j}$; unobserved patient characteristics, $\upsilon_\mathbf{i}$; and the time-to-travel between the patient and the facility, T_{ij}. The random part of utility, ϵ_{ij} will be assumed to be distributed type I extreme value, from which the final logit specification will emerge. Put together, the vectors of observed and unobserved facility characteristics contain all elements of the facility that could influence a patient's decision choice. Utility is parameterized by the vector of parameters θ.

For simplicity, I specify the explained portion of utility to be linear-in-parameters:

$$V_{ij} = T_{ij}\alpha_i + \mathbf{X_j}\beta_\mathbf{i} + \xi_\mathbf{j} \tag{2}$$

where $\beta_\mathbf{i}$ is defined as the vector of random coefficients on observed facility characteristics and α_i is the (scalar) random coefficient on the time-to-travel variable. To derive the random coefficients, I interact patient and facility characteristics in the following way: Let α_i and $\beta_\mathbf{i}$ be functions of patient characteristics, so that

$$\alpha_i = \tilde{\alpha} + \kappa\mathbf{Z_i} + \upsilon_i^1, \text{ and} \tag{3}$$

$$\beta_\mathbf{i} = \tilde{\beta} + \gamma\mathbf{Z_i} + \upsilon_\mathbf{i}^\mathbf{2}, \tag{4}$$

where υ_i^1 and $\upsilon_\mathbf{i}^\mathbf{2}$ are random variables[8], which may be correlated[9] (see Train and Sonnier [29] and Train [27]). In this paper, I presume that υ_i^1 and $\upsilon_\mathbf{i}^\mathbf{2}$ are not correlated. For ease of notation, write $\upsilon_\mathbf{i} = [\upsilon_i^1, \upsilon_\mathbf{i}^\mathbf{2}]$. Assume $\upsilon_\mathbf{i}$ is independent across i and drawn from distribution $F(\upsilon)$[10], with moments $[\mu, \Sigma]$.

Note that $\beta_\mathbf{i}$ is a Cx1 vector of coefficients, where C is the number of observed facility

[7] All variables should be superscripted with an additional variable: namely, p, to denote the fact that a patient's choice of facility is procedure-specific. I abstract from this dimensions here to keep the notation simple, but discuss them in section 5.1.

[8] $\upsilon_\mathbf{i}^\mathbf{2}$ is actually a random vector of dimension C, such that $\upsilon_\mathbf{i}^\mathbf{2} = [\upsilon_{i1}^2, ..., \upsilon_{iC}^2]$

[9] Correlation is induced if υ_i^1 and $\upsilon_\mathbf{i}^\mathbf{2}$ are draws from some distribution, $F(\mu, \Omega)$, such that Ω is a non-diagonal variance-covariance matrix.

[10] Where $\Sigma = \begin{pmatrix} \sigma^1 & \mathbf{0} \\ \mathbf{0} & \sigma^\mathbf{2} \end{pmatrix}$, which has dimension $(C+1)$x$(C+1)$ since σ^1 =Var(υ_i^1) is a scalar while $\sigma^\mathbf{2}$ is a CxC diagonal matrix equal to Var$(\upsilon_\mathbf{i}^\mathbf{2})$

characteristics, that is, the dimension of X_j. The cth element of $\beta_{\mathbf{i}}$ is:

$$\begin{aligned} \beta_{ic} &= \tilde{\beta}_c + \gamma_{\mathbf{c}} \mathbf{Z_i} + \upsilon^2_{ic} \\ &= \tilde{\beta}_c + \sum_{m=1}^{M} z_{im} \gamma_{mc} + \upsilon^2_{ic} \end{aligned} \tag{5}$$

where M is the dimension of the Mx1 vector of observed patient characteristics $\mathbf{Z_i}$; $\gamma_{\mathbf{c}}$ is a 1xM vector of coefficients that is the cth row of the CxM matrix, γ; and υ^2_{ic} is the random error term on the cth characteristic. Stack the elements, β_{ic}, to create $\beta_{\mathbf{i}}$ and plug $\beta_{\mathbf{i}}$ into (2) and then (1) to get:

$$\begin{aligned} U_{ij} &= T_{ij}\alpha_i + \mathbf{X_j}\beta_{\mathbf{i}} + \xi_{\mathbf{j}} + \epsilon_{ij} \\ &= T_{ij}\tilde{\alpha} + \mathbf{X_j}\tilde{\beta} + T_{ij}\sum_{m=1}^{M} z_{im}\kappa_m + \mathbf{X_j}\sum_{m=1}^{M} z_{im}\gamma_{\mathbf{m}} + T_{ij}\upsilon^1_i + \mathbf{X_j}\upsilon_{\mathbf{i}}{}^2 + \xi_j + \epsilon_{ij} \end{aligned} \tag{6}$$

The parameters to estimate from this model are $\theta = \left[\tilde{\alpha}, \tilde{\beta}, \kappa, \gamma, \mu, \Sigma\right]$, where $\tilde{\beta}$ is the vector of mean coefficients on facility characteristics, $\tilde{\alpha}$ is the mean coefficients on time-to-travel, γ is the CxM matrix of coefficients on patient-facility characteristic interactions, κ is the vector of coefficients on the interaction between patient characteristics and time-to-travel, and (μ, Σ) are the moments of $F(\upsilon)$, the distribution of υ. Once these underlying parameters are estimated, it is a straightforward exercise to find the random coefficients α_i and $\beta_{\mathbf{i}}$ using equations (3) and (4).

It should now be clear how random coefficients are derived through interactions between patient and facility characteristics. Across all patients, the average impact of the cth facility characteristic on utility is $\tilde{\beta}_c$, but for any particular patient i, the actual impact of the cth facility characteristic is specific to that consumer, and depends on their personal characteristics, Z_i, as well as the population estimate of γ, and the patient's draw from υ.

To gain insight about the implications of the random coefficients specification, we can write utility in another way: As the sum of a mean component that does not vary over consumers, and a deviation from that mean that explains variation in utility across consumers. The mean component includes all the elements of utility that are exclusively facility-specific. The deviation from this mean depends on patient characteristics, Z_i, and the patient draw from $F(\upsilon)$. Denote mean utility from facility j as:

$$\delta_j = \mathbf{X_j}\tilde{\beta} + \xi_j \tag{7}$$

and re-write equation (6) as

$$\begin{aligned} U_{ij} &= \delta_j + T_{ij}\tilde{\alpha} + T_{ij}\sum_{m=1}^{M} z_{im}\kappa_m + \mathbf{X_j}\sum_{m=1}^{M} z_{im}\gamma_{\mathbf{m}} + T_{ij}\upsilon_i^1 + \mathbf{X_j}\upsilon_{\mathbf{i}}{}^2 + \epsilon_{ij} \\ &= \delta_j + T_{ij}\tilde{\alpha} + T_{ij}\sum_{m=1}^{M} z_{im}\kappa_m + \sum_{c=1}^{C}\sum_{m=1}^{M} x_{jc}z_{imc}\gamma_{mc} + T_{ij}\upsilon_i^1 + \sum_{c=1}^{C} x_{jc}\upsilon_{ic}^2 + \epsilon_{ij} \end{aligned} \tag{8}$$

The last line expands out all vectors, and presents utility as a sum of scalars. Ultimately, this is what I take to the data.

The convention of using δ to denote mean utility began with Berry [1] and Berry, Levinsohn and Pakes [25]. Writing utility in this way is useful because it shows that, even with unobserved facility characteristics, given δ_j, it is straightforward to estimate the coefficients that interact with patient characteristics (that is, γ), as the ξ_j's can be themselves estimated with facility fixed effets. BLP could not directly include facility fixed effects, and instead needed complication techniques to recover δ, which was itself needed to identify the coefficient on price. Because we have travel costs, we have no need for a coefficient on price, and can rest with the direct inclusion of facility dummies.

Note that T_{ij} is not included in δ_j in equation (7). This is because the time-to-travel is not facility-specific, but depends on the location of the facility relative to each patient. Because time-to-travel varies among patients all choosing the same facility, $T_{ij}\tilde{\alpha}$ is not subsumed by δ_j.

For notational convenience for the next section, I re-write equation (8) as:

$$U_{ij} = \delta_j + T_{ij}\tilde{\alpha} + \mathbf{W_{ij}}\mathbf{\Gamma_i} + \mathbf{W_{ij}}\upsilon_{\mathbf{i}} + \epsilon_{ij} \tag{8'}$$

where $\mathbf{W_{ij}} = [T_{ij}, \mathbf{X_j}]$, $\mathbf{\Gamma_i} = \left[\sum_{m=1}^{M} z_{im}\kappa_m, \sum_{m=1}^{M} z_{im}\gamma_{\mathbf{m}}\right]'$, and $\upsilon_{\mathbf{i}} = [\upsilon_i^1, \upsilon_{\mathbf{i}}^{\mathbf{2}}]'$.

3.1.1 Choice Probabilities

For a logit model without random coefficients the unconditional probability, P_{ij}, that consumer i chooses facility j is a simple function of the model primatives: $P_{ij} = Pr(U_{ij} > U_{il}\ \forall j \neq l|\ \theta)$. Introducing υ, however, adds a layer of complexity; the simple formula now only applies to the conditional choice probability, $\hat{P}_{ij}$, which is the probability that consumer i chooses facility j *conditional* on i's random draw from $F(\upsilon)$.

$$\begin{aligned} \hat{P}_{ij}\Big(\mathbf{X_j}, \mathbf{Z_i}, T_{ij}, \xi_j; F(\upsilon), \theta\Big) &= Pr\Big(U_{ij} > U_{il}\ \forall j \neq l|\ F(\upsilon), \theta\Big) \\ &= \int_{\epsilon} I\Big(\epsilon_{il} < \epsilon_{ij} + V_{ij} - V_{il}\ |\ F(\upsilon), \theta\Big) dF(\epsilon) \end{aligned} \tag{9}$$

Because we do not know patients' random draws, we need to integrate the conditional choice probabilities over the distribution of draws, $F(\upsilon)$, to regain the unconditional choice probabilities.

$$P_{ij}\big(\mathbf{X_j}, \mathbf{Z_i}, T_{ij}, \xi_j; F(\upsilon), \theta\big) = \int \hat{P}_{ij} dF(\upsilon) \tag{10}$$

Assuming that each component of the 1xJ random vector, ϵ_i, is distributed independently and identically extreme value, the conditional choice probability becomes the standard logit probability. That is, when $f(\epsilon_{ij}) = e^{-\epsilon_{ij}} e^{-e^{-\epsilon_{ij}}}$, equation (9) has the closed form:

$$\hat{P}_{ij} = \frac{\exp\big(\delta_j + T_{ij}\tilde{\alpha} + \mathbf{W_{ij}}\mathbf{\Gamma_i} + \mathbf{W_{ij}}\upsilon_\mathbf{i}\big)}{\sum_{l=1}^{J} \exp\big(\delta_l + T_{il}\tilde{\alpha} + \mathbf{W_{il}}\mathbf{\Gamma_i} + \mathbf{W_{il}}\upsilon_\mathbf{i}\big)} \tag{11}$$

and equation (10) becomes:

$$P_{ij} = \int \frac{\exp\big(\delta_j + T_{ij}\tilde{\alpha} + \mathbf{W_{ij}}\mathbf{\Gamma_i} + \mathbf{W_{ij}}\upsilon_\mathbf{i}\big)}{\sum_{l=1}^{J} \exp\big(\delta_l + T_{il}\tilde{\alpha} + \mathbf{W_{il}}\mathbf{\Gamma_i} + \mathbf{W_{il}}\upsilon_\mathbf{i}\big)} dF(\upsilon) \tag{12}$$

Finally, to get the ex-ante probability, P_j, that any patient in the population chooses facility j, we also need to integrate over the joint density of patient types and (the spatial density of) patient locations, $F(\mathbf{Z}, T)$.

$$P_j = \int_{T,Z} \int_{\upsilon} \frac{\exp\big(\delta_j + T_{ij}\tilde{\alpha} + \mathbf{W_{ij}}\mathbf{\Gamma_i} + \mathbf{W_{ij}}\upsilon_\mathbf{i}\big)}{\sum_{l=1}^{J} \exp\big(\delta_l + T_{il}\tilde{\alpha} + \mathbf{W_{il}}\mathbf{\Gamma_i} + \mathbf{W_{il}}\upsilon_\mathbf{i}\big)} dF(\upsilon) dF(\mathbf{Z}, T) \tag{13}$$

Recall, $\mathbf{Z}$ is embedded in $\mathbf{\Gamma_i}$.

3.1.2 Market Shares & Elasticities

The probability in equation (13) can also be interpreted as the market share of product j, $s_j(X_j, Z_i, T_{ij}, \xi_j; F(\upsilon), F(\mathbf{Z}, T), \theta) = P_j$, which can in turn be used to compute demand elasticities.[11] Traditionally, the interest is in calculating demand elasticities with respect to price. In this paper, however, I instead derive demand time elasticities.

There are good reasons to avoid calculating price-elasticities when working with demand curves for healthcare products. First, health related data sets are notorious for their lack of valid price variables. The FACHA data set I use is no exception: It contains only bad measures of price, which is why price is subsumed by the fixed effect instead of being put into the regression explicitly. Second, trying to tease out price elasticities to describe how patient's substitute between facilities based on price seems futile when price is only one, and

[11] Analogously, the probability from equation (11) can be interpreted as the market share of product j purchased by type i, conditional on their random draw from $F(\upsilon)$: $\hat{s}_{ij}$.

perhaps not even the most important, product characteristic that consumers consider when making their purchase decisions. Finally, since location is measured in travel time, the units lend themselves to a natural interpretation of the magnitude of the elasticity. Therefore, I calculate the magnitude of substitution when all characteristics are held constant, and only the location changes.

Given heterogeneity among patients, each individual i will have an idiosyncratic sensitivity to changes in product characteristics, depending on their own type and their random draw from $F(\upsilon)$. To get the elasticity of demand in the general population, individual elasticities are averaged, where the weights used in the average come from the joint distribution of patient types and locations, $F(\mathbf{Z}, T)$. This mean elasticity of demand for facility j with respect to a change in the location of facility l is:

$$\eta_{jl} = \frac{\partial s_j}{\partial T_l}\frac{T_l}{s_j} = \begin{cases} \frac{1}{s_j}\int\int T_{ij}\beta_i \hat{s}_{ij}(1-\hat{s}_{ij})dF(\upsilon)dF(\mathbf{Z},T) & \text{if } j = l, \\ \frac{1}{s_j}\int\int -T_{il}\beta_i \hat{s}_{ij}\hat{s}_{il}dF(\upsilon)dF(\mathbf{Z},T) & \text{otherwise,} \end{cases} \tag{14}$$

This is identical to the elasticity of demand for any generic product characteristic (such as price, see Nevo [20]), except that T_{ij} is part of the integrand, and not outside of it. Time-to-travel is not a fixed product characteristic, but depends on the patient-facility pair and therefore I must integrate over its distribution.

3.2 Nested Logit

I now extend the model derived in section 3.1 to show how a nested logit can be interpreted as a special case of a mixed logit. The concept of a nested-mixed logit analogue is discussed Train [28] and Munizaga and Alvarez-Daziano [18].

I induce coefficients that yield nest correlations without resorting to the traditional nested logit choice probability,[12] by augmenting the mixed logit model with dummy variables. I introduce nest-specific dummy variables, D_{jn}, where $D_{jn} = 1$ if facility j is in nest B_n and equals zero otherwise, and then associate an error component, $\upsilon_{\mathbf{i}}^{\mathbf{3}}$, with the dummies. Let $\mathbf{D_j}$ denote the (length-n) vector of these dummies.

[12] For alternative j in nest B_n (where $n \in [1, K]$ labels the nest), the nested logit choice probability for person i would be:

$$P_{ij} = \frac{e^{\frac{V_{ij}}{\lambda_n}}\left(\sum_{j\in B_n} e^{\frac{V_{ij}}{\lambda_n}}\right)^{\lambda_n - 1}}{\sum_{l=1}^{K}\left(\sum_{j\in B_l} e^{\frac{V_{ij}}{\lambda_l}}\right)^{\lambda_l}} \tag{15}$$

where the parameter, λ^k, called the *log-sum coefficient*, describes the degree of correlation within nest k. See McFadden (1978) [14] for a derivation of this choice probability.

Formally, I re-write equation (8) as:

$$U_{ij} = \delta_j + T_{ij}\tilde{\alpha} + T_{ij}\sum_{m=1}^{M} z_{im}\kappa_m + \mathbf{X_j}\sum_{m=1}^{M} z_{im}\gamma_{\mathbf{m}} + \mathbf{D_j}\sum_{m=1}^{M} z_{im}\psi_{\mathbf{m}} + T_{ij}\upsilon_i^1 + \mathbf{X_j}\upsilon_{\mathbf{i}}^{\mathbf{2}} + \mathbf{D_j}\upsilon_{\mathbf{i}}^{\mathbf{3}} + \epsilon_{ij} \quad (16)$$

where now we have introduced a new parameter, $\psi_{\mathbf{m}}$, which is a CxM matrix of coefficients on the patient-facility dummy. Suppose the error component, $\upsilon_{\mathbf{i}}^{\mathbf{3}} = [\upsilon_i^{31}, \upsilon_i^{32}]$, associated with the dummy variables, is a vector of random terms with zero mean, and a variance-covariance matrix $\Lambda = diag(\lambda^1, \lambda^2)$.

Then the unobserved (random) part of utility can be written as: $\eta_{ij} = T_{ij}\upsilon_i^1 + \mathbf{X_j}\upsilon_{\mathbf{i}}^{\mathbf{2}} + \mathbf{D_j}\upsilon_{\mathbf{i}}^{\mathbf{3}} + \epsilon_{ij}$. To see explicitly how utility is correlated between nests, we look at:

$$\begin{aligned}
\text{Cov}(\eta_{ij}, \eta_{ij'}) &= E(T_{ij}\upsilon_i^1 + \mathbf{X_j}\upsilon_{\mathbf{i}}^{\mathbf{2}} + \mathbf{D_j}\upsilon_{\mathbf{i}}^{\mathbf{3}} + \epsilon_{ij})(T_{ij'}\upsilon_i^1 + \mathbf{X_{j'}}\upsilon_{\mathbf{i}}^{\mathbf{2}} + \mathbf{D_{j'}}\upsilon_{\mathbf{i}}^{\mathbf{3}} + \epsilon_{ij'}) \\
&= T_{ij}T_{ij'}\sigma_1 + \mathbf{X_j}'\sigma^{\mathbf{2}}\mathbf{X_{j'}} + \mathbf{D_j}'\Lambda\mathbf{D_{j'}} \\
&= \begin{cases} T_{ij}T_{ij'}\sigma_1 + \mathbf{X_j}'\sigma^{\mathbf{2}}\mathbf{X_{j'}} + \lambda^n & \text{if } j, j' \in B_n, \\ T_{ij}T_{ij'}\sigma_1 + \mathbf{X_j}'\sigma^{\mathbf{2}}\mathbf{X_{j'}} & \text{otherwise} \end{cases} \qquad (17)
\end{aligned}$$

Therefore, if facilities j and j' are in the same nest, then covariance between the utilities for consumer i for the two facilities have an additional covariance term, λ^n. This term describes the correlation between facility choices that arises exclusively because facilities belong to the same nest, and it exists regardless of consumer characteristics.

Although we derived it from the mixed logit model, the λ^n term is the analogue to the log-sum coefficient in the traditional nested logit. That is they represent pure within-nest correlation. In fact, if we assume no random coefficients on T_{ij} and $\mathbf{X_j}$, such that $\sigma_1 = 0$ and $\sigma^{\mathbf{2}} = (0)$, then equation 17 simplifies to $\text{Cov}(\eta_{ij}, \eta_{ij'}) = \lambda^n$, which is exactly the within-nest correlation parameter in nested logit. Therefore, conversely, the nested logit log-sum parameters can be interpreted as the variance estimate of a error-components mixing distribution on a nest dummy variable. Given that nest dummies are constant across i, this implies a implicit assumption by the nested logit that the within-nest correlation is also constant across i. On the other hand, the mixed logit puts a richer structure on the cross-substitution patterns and allows within-nest correlation to vary over the population, as represented by the term $T_{ij}T_{ij'}\sigma_1$. Note that a random coefficient on any individual-specific variable would create a similar result. Bhat [3] discusses the concept of homogenous and heterogenous log-sum parameters in much greater detail.

As the reader should also note, fundamentally there is no difference between equations (8) and (16) – the change is only in notation. In equation (8), $\mathbf{D_j}$ was notationally subsumed by $\mathbf{X_j}$, $\upsilon_\mathbf{i}^\mathbf{3}$ was subsumed by $\upsilon_\mathbf{i}^\mathbf{2}$, ψ was subsumed by γ, and Λ was subsumed by Σ. To see this in another way, we could re-write equation (8′) as

$$U_{ij} = \delta_j + T_{ij}\tilde{\alpha} + \mathbf{W_{ij}\Gamma_i} + \mathbf{W_{ij}}\upsilon_\mathbf{i} + \epsilon_{ij} \tag{16'}$$

where now $\mathbf{W_{ij}} = [T_{ij}, \mathbf{X_j}, \mathbf{D_j}]$, $\mathbf{\Gamma_i} = \left[\sum_{m=1}^{M} z_{im}\kappa_m, \sum_{m=1}^{M} z_{im}\gamma_\mathbf{m}, \sum_{m=1}^{M} z_{im}\psi_\mathbf{m}\right]'$, and $\upsilon_\mathbf{i} = [\upsilon_i^1, \upsilon_\mathbf{i}^\mathbf{2}, \upsilon_\mathbf{i}^\mathbf{3}]'$. This implies that all results and derivations (see sections 3.1.1 and 3.1.2) hold without loss of generality.

However, by making explicit the distinction between true facility-specific variables, $\mathbf{X_j}$, and nest-specific variables, $\mathbf{D_j}$, as well as between the coefficients on these variables, we now understand more clearly the analogue relationship between the mixed and nested logit models. This is useful when trying to interpret coefficients, as we do later in the paper.

In this section, I introduced a new variable, $\mathbf{D_j}$, and a new error component, $\upsilon_\mathbf{i}^\mathbf{3}$. The distribution of new error component required us to introduce two new parameters: ψ, which is the vector of coefficients on the interaction between the facility dummies and patient characteristics, and Λ, the variance of the distribution of the error component. I therefore update the vector of parameters we want to estimate to be $\theta = [\tilde{\alpha}, \tilde{\beta}, \kappa, \gamma, \psi, \mu, \Sigma, \Lambda]$.

4 Estimation Strategy

Simulation is the traditional way to estimate parameters of a mixed logit model. I use simulated maximum likelihood (SML) for reasons of efficiency.

The algorithm for SML proceeds as follows: Choose initial values for the coefficients $\theta_0 = (\tilde{\alpha}_0, \tilde{\beta}_\mathbf{0}, \gamma_\mathbf{0}, \kappa_0, \psi_\mathbf{0}, \mu_0, \Sigma_0, \Lambda_0)$, and sample a large number of draws of $\upsilon \sim f(\mu_0, \Sigma_0)$ for each observation. Using the initial values, the data, and the random draws, calculate the conditional choice probability from equation (11) for each observation, for each draw of υ. Let R be the total number of draws. Approximate the integral in equation (12) by summing over the R draws for each person. Then the simulated unconditional choice probability is:

$$\bar{P}_{ij} = \frac{1}{R}\sum_{r=1}^{R} \hat{P}_{ij}(\alpha_i^r, \beta_i^r) \tag{18}$$

Recall that α_i and β_i are the random coefficients from equations (3) and (4); they are comprised of components contained in the vector θ. Note also that $\bar{P}_{ijk}$ is strictly positive, so lnP_{ij} is always defined. Therefore we can construct the simulated log likelihood function, as:

$$SLL = \sum_{i=1}^{I} \sum_{j=1}^{J} d_{ij} ln \bar{P}_{ij} \tag{19}$$

where $d_{ij} = 1$ if i chose j, and zero otherwise. The argument maximizer of the simulated log-likelihood function is the vector of estimated coefficients: $\hat{\theta} = (\hat{\alpha}, \hat{\bar{\beta}}, \hat{\gamma}, \hat{\kappa}, \hat{\psi}, \hat{\mu}, \hat{\Sigma}, \hat{\Lambda})$ See Train [28] for more details.

4.0.1 Substitution Matrix

Simulation is also required to get an estimate for the substitution matrix, η_{jl}. Using the estimated coefficients just described, I simulate the integrand in (14). Let S_{ijl} represent the integrand, so that

$$S_{ijl}(\hat{\alpha}_i, \hat{\beta}_i; T_{il}, \mathbf{Z_i}) = \begin{cases} \beta_i \hat{s}_{ij}(1 - \hat{s}_{ij}) & \text{if } j = l, \\ \beta_i \hat{s}_{ij} \hat{s}_{il} & \text{otherwise}, \end{cases} \tag{20}$$

Using the data, the estimated coefficients, and the random draws from the estimated distribution, the simulated integrand is:

$$\bar{S}_{ijl}(\hat{\alpha}_i, \hat{\beta}_i; T_{il}, \mathbf{Z_i}) = \frac{1}{R} \sum_{r=1}^{R} S_{ijl}(\hat{\alpha}_i^r, \hat{\beta}_i^r; T_{il}, \mathbf{Z_i}) \tag{21}$$

And therefore the simulated entries for the substitution matrix are:

$$\bar{\eta}_{jl} = \frac{1}{\bar{s}_j} \sum_{i=1}^{I} T_{il} \bar{S}_{ijl}(\hat{\alpha}_i, \hat{\beta}_i; T_{il}, \mathbf{Z_i}) p(\widehat{T_{il}, Z_i}) \tag{22}$$

where $p(\widehat{T_{il}, Z_i})$ is the weight, estimated from the data, on person i. It is the probability that the individual has demographic profile $\mathbf{Z_i}$, and lives a distance of T_{il} from facility l.

5 Data Description

I use micro-level administrative data collected by the Florida Agency for Health Care Administration (FAHCA) that contain the universe of outpatient procedures performed in the state between 2000 and 2001. FAHCA is a state government agency that licenses and regulates health care facilities and health maintenance organizations. The unit of observation is at the procedure or surgery level. The data are quarterly. There were more than 5.5 million ambulatory procedures performed in Florida healthcare facilities between 2003-2004.

As there are only a few hundred facilities in the state, this rich data set provides multiple observations of each facility as a product choice.

In theory, the data record every interaction between a patient and a health care facility for an ambulatory surgery incident. Given this level of detail, I can calculate precise demand information and market shares at the quarter, institution, and procedure level for a variety of geographic-market definitions. This is in comparison to other event-level data sets, such as Medicare data, which only captures interactions between Medicare patients and the health care system, instead of between all patients regardless of insurance.

Separately, I obtained facility characteristics from FAHCA, such as facility street address and licensing status, that is, whether the facility is active, closed, or expired.

Finally, I compute distance and time-to-travel variables between patients and facilities. Computing distance and travel time requires that I observe patient location. Unlike for facilities, where we know exact street address, the smallest geographic identifier that the data provide for patients is zip code; for facilities, exact addresses are available.[13] Using the geographic software, GIS, I map patient zip codes and facility addresses and using a database of road-networks, compute the distance from each zip to each and every facility in the state of Florida, as the patient would have to drive (or walk) it. Then, using additional data on the Florida road network, I compute the distance from each zip to each and every facility, measured in minutes of time. The latter calculation relies on GIS's built-in network analysis capacity. Given road network data, which contains road-loactions, road-types, and standard assumptions about road speed limits, GIS solves for the quickest route between two points.[14] Figure 1 gives a pictorial view of the locations of ASCs and hospitals. The boundary lines within the state demarcate zip codes.

To get the final data set used for analysis, I subsample the raw data in two ways. First, I use only data from quarter one in both years 2003 and 2004. This is done because of computational constraints; estimation takes too long if all the data is used. There are over one million observed procedures performed in the first quarters of 2003 and 2004, and over 400 competing ASCs and hospitals. All results are robust to using different time subsamples of the data. Second, I subsample the data in terms of procedures, which I describe in greater

[13]It is a potential problem that patient location data is not exact. All of the distance variables that I create use as their starting point the zip centroid associated with the patient's zip code and not the patient's specific street address. The zip centroid is the latitude and longitude coordinates associated with a given zip code; it is often a post-office address. The centroid is supposed to be the geographic midpoint of the zip code, but it may not be the midpoint of the zip code's population density function. If the differences in these two midpoints is serially correlated over many zips, then estimates of the time-to-travel coefficient will be biased because of spatial autocorrelation. I assume that the mean error over all zips is zero. This issue is discussed further in the Identification section.

[14]Many thanks to Todd Schuble for his help in computing and learning how to compute these variables.

detail in the following subsection.

5.1 Procedural Codes

Until now, the demand model has been presented and discussed in terms of two subscripts: consumer i choosing facility j. In reality, however, there should be another subscript integrated into the model – namely, one to denote the procedure, p (see footnote 7). The omission of subscript p was purely for notational simplicity; the true model posits consumer i choosing facility j for a specific procedure p. Now we must choose the set of p to study.

Ideally, for the most accurate welfare estimates, one would measure demand for each and every procedural group. By casting the widest possible net, we would obtain the clearest picture of how consumers would lose if ASCs were eliminated. Unfortunately, there are too many different outpatient procedures (and too few observations for the more infrequent procedural codes) to do the comprehensive analysis. There are over 4,000 procedural codes in the data. Figure 6 shows the distribution of procedures, which are highly right skewed in terms of frequency. Procedures are labeled by Current Procedural Terminology, or CPT, codes.

Therefore, I truncate the choice of procedural codes based on rank. For the final welfare analysis in this paper, I use the top X number of procedural codes that account for the top 70 percent of total eligible surgeries. An 'eligible' surgery is one for which ASCs and hospitals are the main competing providers of service. More precisely, an eligible procedural code is one for which the ASC and hospital share is both strictly greater than zero, and for which the sum of the ASC and hospital shares is greater or equal to .95. An example of an ineligible (but otherwise very common) outpatient procedure would be renal dialysis. ASCs are not significant competitors in the renal dialysis market (the ASC market share is zero). Hospitals and dialysis centers mainly compete to provide this service, and therefore renal dialysis codes, while accounting for a large fraction of total outpatient surgeries, are not relevant for the purposes of this paper and are omitted.

Of the more than 4,000 procedural codes in the raw data from quarters one of years 2000 and 2001, more than 2,700 procedures are deemed eligible, which corresponds with just under one million observations. The top 69 procedural codes account for the 70 percent of all surgeries (that is, X=69). Table 1 gives the number of observations, the ASC and hospital shares, and the percent of all (eligible) surgeries for the top-10 procedural codes. As can be seen, the facility-type (ASC versus hospital) market share varies quite considerably over procedures. The sharp fall-off in column 2 echoes the skewed distribution shown in figure 6. A general descriptive procedural group is also provided in the last column of table 1. A more detailed description of the top-10 procedures can be found in table 3.

So as not to clutter the tables, results will be shown only for the top-10 procedures. Regression results for the other procedures are available from the author by request.

5.2 Discussion of Variables

Included in the observed facility characteristics vector, $\mathbf{X_j}$ is the *scope* variable, which measures the number of different procedures a facility performs each year. The variable included in the nest-specific vector, $\mathbf{D_j}$ is the *facility type* variable, which is a dummy variable that denotes whether the facility is an ASC. Variables included in the observed patient characteristics vector, $\mathbf{Z_i}$, are *age*, *sex*, *race*, *insurance type*, and *additional procedures*. The latter variable is a dummy that equals one if the patient has an additional procedure performed besides the principal procedure.[15] *Time-to-travel*, T_{ij}, gives the number of minutes (in fractions of hours) between the centroid of patients' zip codes and the facility. Quality is the quintessential example of an unobserved facility characteristic, ξ_j. Health status is the primary example of an unobserved patient characteristic, υ_i; income would be another. Suffice it to say, if any unobserved variables are correlated with included variables, then estimated coefficients will be biased and inconsistent.

With regards to interactions, I allow all patient characteristics, $\mathbf{Z_i}$, to interact with two variables: time-to-travel and the dummy for facility type. Only the dummy for whether the patient has additional procedures performed is permitted to interact with scope. Time-to-travel (T_{ij}) interacts with the dummy for facility type (D_{jn}).

Following the discussion of the nested-mixed logit analogue, the dummy for facility type is also interacted with zero-mean random draws ($\upsilon_{\mathbf{i}}^{\mathbf{3}}$) on top of the interactions with $\mathbf{Z_i}$ just described.

I assume the coefficient on travel-time (α_i) to be distributed lognormally, so that $\ln(\upsilon_i^1) \sim N(\mu_1, \sigma^1)$. The coefficient on the facility type dummy (ψ_{i1}) is assumed to be independently and normally distributed with zero means[16]. Thus, $[\upsilon_i^2] \sim N(0, \sigma^2)$, and $[\upsilon_i^{3n}] \sim N(0, \lambda^n) \;\; \forall \;\; n = 1, 2$.

As mentioned in the introduction, the data do not contain useful price information; only total charges are included. Total charges list what the facility charges the third-party payer (or the patient directly, if the patient is self-insured); they are not necessarily correlated with the final price paid by the patient, which is the quantity of interest to the econometrician, and therefore are omitted from the analysis.

[15]A little over half of the records in that data are for patients having multiple (at least two) procedures. All analysis is done on the primary procedure only.

[16]This is the error components model.

5.3 Summary Statistics

The final data set includes 239 ASCs and 196 hospitals, and just under one million observed facility choices by consumers. Table 2 shows the basic summary statistics for the included variables discussed in the previous subsection. The summary statistics are broken down by facility type – ASC statistics are listed in the first two columns and hospital statistics in the last two columns. As expected, ASCs are smaller in scope (offering on average 91.7 different types of procedures versus hospitals' 298.6).

In terms of characteristics of patients who frequent each type of facility, ASC patients are older on average (61.8 years versus 53.9 years), less likely to have additional procedures performed (27.2 percent versus 61.2 percent), and more likely to have insurance from Medicare (47.4 percent versus 30.2 percent), or private commercial insurance (20.4 percent versus 9.5 percent), but less likely to have an HMO. Moreover, patients travel further on average to ASCs than to hospitals (19.1 minutes versus 17.6 minutes).

The striking disparity between ASC and hospital patients' characteristics underline the need for a model with interactions between patient and facilities variables. Note that the summary statistics in table 2 describe the data when all procedures are aggregated together, rather than considered separately. When looking across procedures, the composition and number of patients that each type of facility receives do vary, but similar differences in patient characteristics persist.

Note that while it is clear that there are significant differences between patients who frequent ASCs versus those who frequent hospitals, it is not clear whether this is a demand or supply-driven phenomenon. This is discussed further in the identification section.

6 Estimation Results

To reiterate, the objective is to estimate the coefficients $\theta = [\tilde{\beta}, \tilde{\alpha}, \gamma, \kappa, \psi\mu, \Sigma, \Lambda]$ from (16) by maximizing log-likelihoods from equations (**??**) or (19). Note that none of the results shown in this section represent marginal effects, unless denoted otherwise.

6.1 Nested Logit Results

Tables 4 through 7 display results from the nested logit regressions for the top-10 procedures. Tables 4 and 5 give results for consumers with any type of Medicare insurance, while tables 6 and 7 give results for consumers with private commercial insurance, or who are self-insured. The decision to run regressions separately for consumers with different insurance carriers is discussed further in the identification section.

I discuss the lower level nest – the particular facility choice – first. As can be seen, across all columns of tables 4 - 7, the time-to-travel variable is always significant and negative, ranging from -4.920 to -2.274, which suggests that longer distances between facilities and consumers decrease choice probabilities, as expected. Similarly, the dummy for whether travel time is greater than 75 minutes[17] is also always negative and significant, suggesting that consumers display an added dislike of extreme distances. These results echo repeated findings in the healthcare literature (see for example Gaynor and Vogt [8], David and Neuman [6] and Capps, Dranove and Lindrooth [5]) that distance matters.

The distaste for traveling increases slightly with age, as shown by the unanimous negative and significant, though small, coefficients on the interaction between travel time and age. Being male, on the other hand, reduces the dislike for traveling, and by a magnitude larger than age. This holds true across procedures for Medicare consumers, however for private and self-insured consumers the coefficient on the interaction between travel time and the dummy for gender is not consistently significant across procedures.

The coefficient on scope is small but significant and mostly positive, which implies that consumers prefer facilities that do a wide range of procedures. The only time the scope coefficient is negative is for eye (cataract) procedures, that is, codes 66821 and 66984. Recall from table 1 that the production of these two procedures is heavily dominated by ASCs. Most of the ASCs performing cataract procedures are dedicated eye-surgery centers, so it is not surprising that the scope coefficient is negative for the cataract regressions. The general preference for facilities with broader scopes may be slightly bigger or smaller depending on whether the consumer is having an additional procedure done, as indicated by the coefficient on the interaction between scope and the dummy for additional procedures. Across procedures, this coefficient changes sign and is of mixed significance.

Looking now at the determinants of upper level nest choices, we see that the dummy variable for whether the consumer will have additional procedures performed and insurance variables are the largest predictors of nest choice (ASC versus hospital). Personal demographics are also significant predictors of nest choice, but are of a magnitude smaller than insurance and additional procedure variables.

I discuss the insurance variables first. In general, having a managed care plan, or being self-insured, decreases the probability of choosing an ASC relative to a hospital (and relative to indemnity plans). For Medicare patients, the coefficient on the dummy for HMO is significant and large across all procedures. Having an HMO decreases Medicare consumers' probabilities of choosing an ASC (the coefficient is negative), except for eye procedures,

[17]This cutoff value is based on the distribution of travel times in the population, and all results are robust to variation in the precise number.

where having an HMO increases the probability of choosing an ASC (positive coefficient). The results are similar for private and self-insured patients, where having an HMO or PPO or being self-insured decreases consumers' likelihood of choosing an ASC.

The insurance results can be explained in two ways: First, to the extent that the dummies for HMO, PPO and self-insurance proxy for price, this result could imply that ASCs are relatively more expensive than hospitals for managed care and self-insured patients, and therefore these patients are actively deciding against choosing ASCs. Second, it may be that managed care plans have lower physician reimbursement rates and therefore that doctors are actively discriminating against performing procedures on HMO and PPO patients at ASCs. This is an area for further research, and is discussed in greater detail in the identification section.

Having an additional procedure increases the likelihood of choosing a hospital over an ASC, as indicated by the negative, significant and large coefficients on the dummy variable for additional procedure. Again, eye procedures are the exception to the rule here – those coefficients are positive.

With regards to consumer demographics, the coefficient on age is consistently significant and positive but small, except again for the eye procedures, where it is negative. This implies that older consumers are more likely to ASCs relative to hospitals, except for consumers of eye procedures. This result was predicted in the raw data, too. When significant, being non-white for the most part increases private and self-insured consumers' likelihoods of choosing an ASC, but decreases Medicare consumers' likelihood of doing the same. Being male also tends to increase privately and self-insured patients likelihood of choosing an ASC, but has mixed results for Medicare patients.

Finally, we turn to the log-sum (λ_n) parameters, which indicate the degree of correlation within a nest, where higher values of λ imply more independence between nest alternatives. At the extreme, $\lambda_n = 1$ implies a complete lack of correlation, and suggests that the common independence of irrelevant alternative (IIA) fear is obviated. In such a case, nested logit is not needed and a simpler multinomial logit would suffice.

Among Medicare patients, t-tests reject (computing the statistic as $\frac{\lambda_n - 1}{s.e.(\lambda_n)}$) the hypothesis that the nested logit specification is valid for procedure 29881. They cannot however reject the null hypothesis ($H_0 : \lambda_{ASC} = 1$) that there is no significant correlation between ASCs in three of the remaining nine procedural groups (CPTs 45384, 45380 and 62331), nor can we reject the null hypothesis ($H_0 : \lambda_{Hosp} = 1$) of no significant correlation between hospitals in two of the remaining nine groups (CPTs 66821 and 66984).

Among private and self-insured patients, t-tests fail to reject the hypothesis that there is no significant correlation among alternatives for any nests, for any procedures.

Note that in none of regressions are the log-sum coefficients constrained to be weakly less than one. Therefore when t-tests reject the null hypothesis and when the log-sum coefficients are greater than one (as happens for λ_{ASC} for procedure 66984 for Medicare patients and for λ_{ASC} and λ_{Hosp} for procedures 66821 and 66984 for private and self-insured patients), there may be an inconsistency with utility maximization [28].

6.2 Mixed Logit Results

Estimates from the mixed logit model provide additional insight into consumers' facility choice decisions that the nested logit did not. In particular, the mixed logit presumes that within-nest correlation varies across consumers because of unobserved patient characteristics characterized by the parameters from the mixing distribution. In contrast, nested logit postulates that this quantity, which it measures with the log-sum parameters, is typically assumed constant over the population. Bhat [3] shows another way to characterize the heterogeneity in log-sum parameters.

Parts (b) of tables 8 and 9 give a general description of the coefficients on the non-random variables for Medicare and private and self-insured consumers, respectively. Coefficients on the interactions between travel time and patient characteristics, and on the scope variable, correspond to coefficients in the *lower level nest* of tables 4-7. These are the independent variables that vary at the facility level. Similarly, coefficients on interactions between the dummy for ASC and patient characteristics correspond to coefficients in the *lower level nest* of tables 4-7. These are the independent variables that vary at the patient level.

As can be seen, the signs, magnitudes, and prevalence of significance of estimates from the mixed logit results are similar to those for the nested logit results. Precise numbers are available on request from the author, and were omitted for simplicity of presentation.

Parts (a) of tables 8 and 9 give coefficient estimates on the two random variables, travel time and the dummy for ASC. As can be seen, the mean (μ) of the mixing distribution for travel time, $F(\upsilon^1)$, which is assumed to be lognormal, roughly corresponds to the nested logit coefficient estimates for travel time. However, the addition of the variance term (σ), plus the lognormality assumption implies the average (of the absolute value of the) coefficient on time-to-travel actually found in the population is higher than the nested logit coefficient. This finding shrinks when a dummy for extreme travel-times (greater than 75 minutes) is included.

Part (a) in tables 8 and 9 also show the mean and standard deviation of the mixing distribution for the ASC dummy. The average coefficient column under the ASC dummy closely corresponds to λ^n in the nested logit model, except that the nested logit estimate was absorbing some of what is now being attributed to variation in preference for travel time. As can be seen, mean preference for ASCs is constrained to be zero (as in an error-components model), but there is variation (σ) around that mean. Looking at the column which shows share of individuals whose draw implies a coefficient less than zero, we see that the share is correlated with the actual ASC market, implying that the random coefficient on the ASC dummy is indeed picking up some unobserved attributes of consumers.

6.3 Substitution Matrix Results

Using the logit estimates, I create cross-time substitution matrices (one for each procedural code) that describe how patients substitute between competing facilities, given a change in any one facility's location. The matrices are constructed from equation (14). For a given procedure, the full matrix is very large – its dimension is the number of facilities offering that procedure, which is on the order of $400x400$..

In this section, as an example, I show a subset of the substitution matrix for an orthopedic procedure (CPT code 29881), for facilities in a sparsely populated area of inland Florida. This area was chosen purely for convenience, as it had a small enough number of facilities that they could be easily shown in a table, or graphically. A similar matrix could be constructed between any subset of facilities in the state of Florida, even those not in the same city.

Figure 2 highlights the geographic area of interest that corresponds to the subset of the matrix in which we are interested. Figures 3 and 4 incrementally zoom into this area, and figure5 zooms in even further and lists the corresponding distance between the relevant subset of facilities. Figure 4 also points out which facilities are hospitals, which facilities are ASCs, and if they are ASCs, labels their specialty if one exists.

Table 10 displays the matrix results. The upper table (part (a)) gives the own and cross-time substitution patterns and the lower table part (b) shows the corresponding distance in minutes between facilities. The diagonal of the substitution matrix gives the own-time elasticity. For instance, if ASC2 increasesd its distance from all consumers by one percent, then its share of the market would fall by 2.2 percent. The off-diagonal elements describe cross-time elasticities, which is the degree to which consumers substitute to other facilities, given a location change of the primary facility. For instance, if ASC2 increases its distance from all patients by one percent, then demand for HospitalB would increase 0.34 percent.

Not that the matrix is asymmetric, which tells us that a location change of firm J impacts demand for firm L differently than a location change of firm L would impact demand for firm J. This makes sense, as the degree to which firm J is a substitute for firm L depends on the location of firm L's patients, and vice-versa. Unless firms J and L have exactly overlapping consumer bases, their cross-time elasticities will not be identical.

Admittedly, this may be a strange thought experiment, as it is hard to think about a situation where a facility increases its distance from all consumers simultaneously. However, the matrix is of interest because it meets the expectation that two facilities that are closer together in space are indeed closer substitutes. Comparing table 10 with table **??**, it is possible to eyeball this relationship; the formal statistic for the correlation between the two matrices is -0.21, and is significant. The negative sign confirms the intuition that larger distances between facilities implies less substitutability.

7 Identification

Identification comes from variation in consumer types who choose the same facility. To obtain consistent estimates in the logit models, ϵ_{ij} must be independent from the decision variables in consumers' utility functions (equation 8). This condition is not met if there are any omitted variables that are correlated with included characteristics, which is a concern here: the ξ_k term was introduced precisely to represent omitted facility characteristics that are observed by consumers and influence their decisions, but are unobserved by the econometrician. In estimation, the fixed effect, δ_j, is included to alleviate this problem; it captures all omitted facility-specific variables represented by ξ.

Fixed effects absorb all unobserved facility characteristics, such as quality and price, as well as all observed facility characteristics that do not vary over time, such as capacity, and the dummy for facility type. As a result, some elements of the vector $\tilde{\beta}$ are not identified from this approach for time invariant facility characteristics; it is for this reason that $\tilde{\beta}$ does not appear in table **??**. Including facility fixed effects buys us simple and consistent estimation of the c x m matrix γ.

As there is no formal supply-side model included in this paper, we cannot identify whether these are demand or supply-side effects. For instance, it may be that facilities are locating in areas based on patient characteristics. This is an area for further research.

7.0.1 Identifying Physician Versus Patient Utility

Whose utility function do estimates identify? The term 'consumer' is very specific in the model (section 3), and is based on a notion of consumer preferences as the weighted sum of patient preferences and the preferences of her physician. Facility choice is often a joint decision between a patient and her doctor, as both parties have preferences over the surgery location and may be able to exert control during the decision-making process. Unfortunately, unless there are theoretical reasons to believe that certain observable characteristics of the patient do not influence physicians' recommendations for surgery location, it will be impossible to identify each parties' separate contribution to the final decision. On the other hand, unless there are reasons to believe that patient preferences are influenced by physician characteristics, coefficients on physician-specific variables are identified, and interpretable.

The data however, do not contain any physician-specific variables. To the extent that physicians' choices are based on observable patient characteristics, patient demographics will proxy for physician demand. But we cannot interpret which portion of these coefficients come only from patient preferences and which from physician preferences.

Any variable that is uniquely a decision factor for the patient and does not enter the utility function of the physician will be identified during estimation. The only variable meeting this criteria is travel-time, and it is met only under the assumption that physicians do not consider patients' locations when recommending a locale for surgery, but rather assume the patient-physician match has already aligned the geographic preferences of the two parties. To obtain consistent welfare estimates therefore, it must be true that physicians do not consider patient location in their recommendation.

Identifying physician-specific preferences for ASCs would require incorporating physician-specific characteristics, like physician time-to-travel, into the regression. How much physicians prefer ASCs because of higher profits they provide to physicians is currently absorbed in the fixed effects, but could be identified by interacting the ASC dummy with physician characteristics. The identification of physician demand separate and apart from patient demand is thus theoretically possible, since physician specific codes are included in the data. In theory, I could interact physician specific dummies with the ASC dummy. In practice however, the number of physicians operating in most markets is large enough to strain the size of the data.

A recent paper by David and Neuman ([6]) do something similar. They analyze physicians' *choice of setting* decisions – that is, when they choose to perform procedures at ASCs versus hospitals. They find that 94 percent of doctors split their time between ASCs and hospitals, performing on average 68 percent of cases in the ASC and 32 percent in the hospital. David and Neuman concentrate on patient risk profiles and distance from an ASC to the nearest hospitals as the main predictors of the choice of setting decision, and abstract from the patient contribution to the choice of setting decision. In essence, they are doing the complement to my paper, looking at physician-specific variables instead of patient specific variables.

8 Welfare Analysis

Both the reduced form and structural estimates imply that consumers significantly prefer facilities that are located closer to their homes in the geographic plane. Using this fact enables me to quantify welfare counterfactuals. I consider: What would happen if ASCs were removed entirely from one market's choice set? As discussed in the introduction, these welfare calculations are germane to current policy debates about whether business stealing by ASCs harms hospitals (and by extension their local communities) and therefore whether there is a case for shutting them down, or limiting entry.

Usually we need price elasticities to construct welfare measures, because they allow us to convert the util units from indirect utility into dollar units. Having a time elasticity however is almost as good. After removing ASCs from the choice set, we can let the model tell us where consumers choose to go instead. There will be a utility loss from this forced second-choice pick of facility, which is measurable in time-units of minutes. Estimating the value of time to different consumers is straightforward. With that one extra step, we can find the monetary value of the utility loss by translating it to a time-cost.

Formally, I denote the subset of hospitals by H, and the subset of ASCs by A, and write the change in consumer surplus for patient i from removing A from the choice set as:

$$\Delta E(CS_{ij}) = \frac{1}{\alpha_i}\Big(E_\epsilon[\max_{j\in A\cap H}(V_{ij}+\epsilon_{ij})] - E_\epsilon[\max_{j\in H}(V_{ij}+\epsilon_{ij})]\Big) \tag{23}$$

where α_i is the coefficient on time-to-travel from the demand equation estimated before. The term inside the brackets describes the change in utility caused by removing A from the choice set. Multiplying it by $\frac{1}{\alpha_i}$ translates the util change into a welfare number that is measured in minutes. The final steps are to translate minutes into money terms, and aggregate (23) over all patients.

In that consumers are heterogenous and differentiated by their observable characteristics, aggregating will require integrating over the distribution of patient characteristics, $\hat{F}(Z)$, and, if unobserved patient characteristics are included (as done in the mixed logit model), over the distribution, $F(\upsilon)$. Estimation is made simpler by the result from Small and Rosen [26], who show that if ϵ is distributed type-I extreme value, then

$$E_\epsilon[\max_{ij}(V_{ij}+\epsilon_{ij})] = ln\Big(\sum_{j}^{J} e^{V_{ij}}\Big) + C \tag{24}$$

where C is an unknown constant that is irrelevant from a policy perspective. Therefore, (23) becomes

$$\Delta E(CS_{ij}) = \frac{1}{\alpha_i}\Big(\ln \sum_{j \in A \cup H} e^{V_{ij}} - \ln \sum_{j \in H} e^{V_{ij}}\Big) \tag{25}$$

which is what I take to the data, after integrating over the distribution of patient types.

A similar exercise was done by Petrin [21] for the introduction of minivans, and by Gentzkow [9] for the introduction of online newspapers as new products. Note that the welfare numbers are *not* only the welfare loss from a change in location, rather they reflect the loss from all characteristics that consumers value about ASCs.

Results

The results from the welfare calculation are shown in Tables 11 (**??**) and 12 (**??**), and give the welfare gain (in minutes) to Medicare patients from having ASCs in their choice sets. The counterfactual is a world with no ASCs. Patients lose welfare because they must travel further to reach a healthcare facility, and because ASCs have product characteristics that patients prefer. Looking at the first row of table 11 (**??**), for instance, we see that patients having procedure 66984 (cataract surgery) lose on average 9.63 minutes of surplus each were ASCs to be removed. Welfare numbers are based on results from the mixed logit regressions.

Attributing an average hourly wage of $15.70[18], therefore, would imply that total surplus lost from the elimination of ASCs, for Medicare, private and self-insured patients having the top-10 procedures during the first quarters of 2003 and 2004, is approximately $1,127,859 (the sum of the two totals from tables **??** and **??**). This is the amount consumers would be willing to pay not to close all ASCs for those two quarters. The hours-denominated unit for welfare loss (column 3) may be preferred to the dollar-denominated one as it does not require any assumption for how patients value their time. These estimates are negligibly different from zero.

Note that these results are of a slightly smaller magnitude than estimates from other papers. Capps, Dranove and Lindrooth [5] find the net welfare loss to consumers from a closure of a general hospital in Tampa in 1996 to be between $680,000 and $920,000, which is slightly less than half the annual net welfare loss as we find for *all* ASCs. This may be because relative to ASCs, hospitals perform more critical procedures, which consumers value at a much higher level.

To the extent that we are not accounting for physicians' utility losses from ASC closure, our estimates may be a lower bound on the true welfare numbers.

[18]Source: Occupational Employment Statistics and Wages Florida Agency for Workforce Innovation, 2004

9 Conclusions

This paper explores demand for healthcare facilities, particularly for ASCs and hospital. Running nested and mixed logit specifications for demand, I find that travel time is a significant predictor of demand for facilities, and that insurance variables are significant predictors of nest choice. The degree to which travel-time matters, however, depends on the type of procedure under consideration, and on demographic characteristics of the patient. Using the logit results, I calculate a cross-time substitution matrix to show how consumers substitute to other facilities over geographic space, given a change in location of one facility, and find asymmetric substitution patterns between facilities.

This paper also calculates welfare estimates from the elimination of ASCs. Using the coefficient on travel time as the marginal utility of income, I convert welfare results from utils to minutes and find that if ASCs were removed from patients choice sets, the welfare losses would be small. The welfare numbers seem slightly out of line with estimates from other papers.

Further work is needed to incorporate the supply-side of this market. A separate interesting area of research would be a joint model of physician and patient demand for facilities.

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Figure 1: Map of ASCs and Hospitals

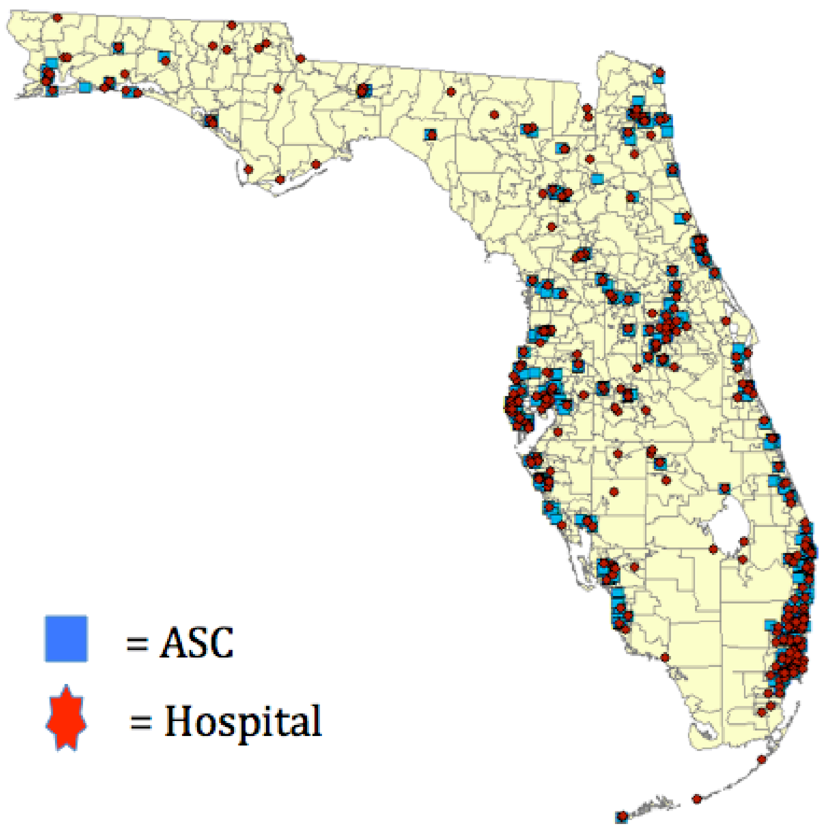

Figure 1 shows the geographic distribution of the set of ASCs and hospitals present in Florida in 2003 and 2004.

Table 1: Summary of Market Shares and Market Sizes for Top-10 Outpatient Procedures

Procedure Rank	% of Total (Eligible) Surgeries	ASC Share	Hospital Share	N (Obs)	Procedure Code	Group
1	10%	0.81	0.185	99,400	66984	Eye
2	8.5%	0.476	0.522	84,033	45378	Colon
3	7%	0.433	0.564	69,860	43239	Gastro
4	4.6%	0.557	0.442	45,602	62311	Pain
5	4.1%	0.933	0.064	41,113	66821	Eye
6	3.3%	0.51	0.487	33,000	45385	Colon
7	3.2%	0.489	0.509	31,865	45380	Colon
8	2.9%	0.491	0.505	28,342	45384	Colon
9	1.5%	0.387	0.608	15,270	43235	Gastro
10	1.3%	0.498	0.499	12,531	29881	Ortho
Total # of (eligible) Procedures :						2734
Total # of (eligible) outpatient surgeries:						991,417

Table 1 gives the market shares of ASCs and hospitals for each of the top-10 procedural codes, as well as the number of each type of procedures (N) performed (in 2003-2004, q1), and the % of total surgeries each procedure accounts for. Note that "eligible" here means those CPTs where ASCs and hospitals account for 95% of the total market, and where both ASCs and hospitals have strictly positive market shares.

Figure 2: Area of Interest for Substitution Matrix

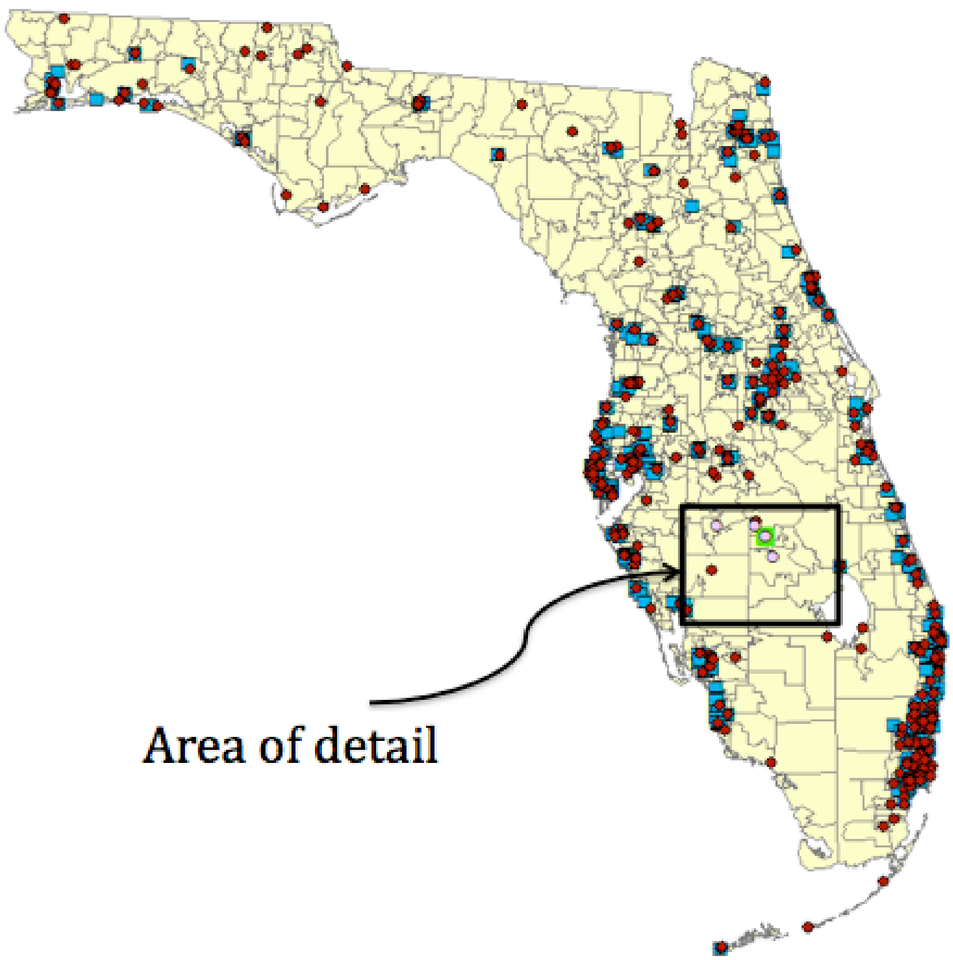

Figure 2 highlights the area of interest in the presentation of the cross-time substitution matrix results.

Figure 3: Zoom 1 of Area of Interest for Substitution Matrix

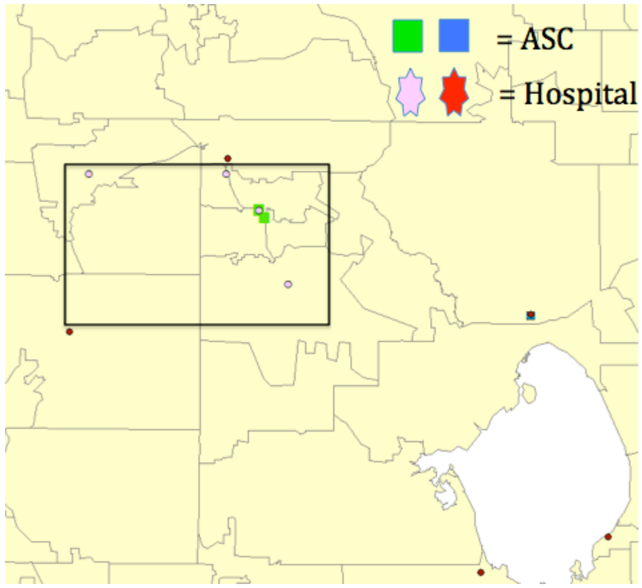

Figure 4: Zoom 2 of Area of Interest for Substitution Matrix

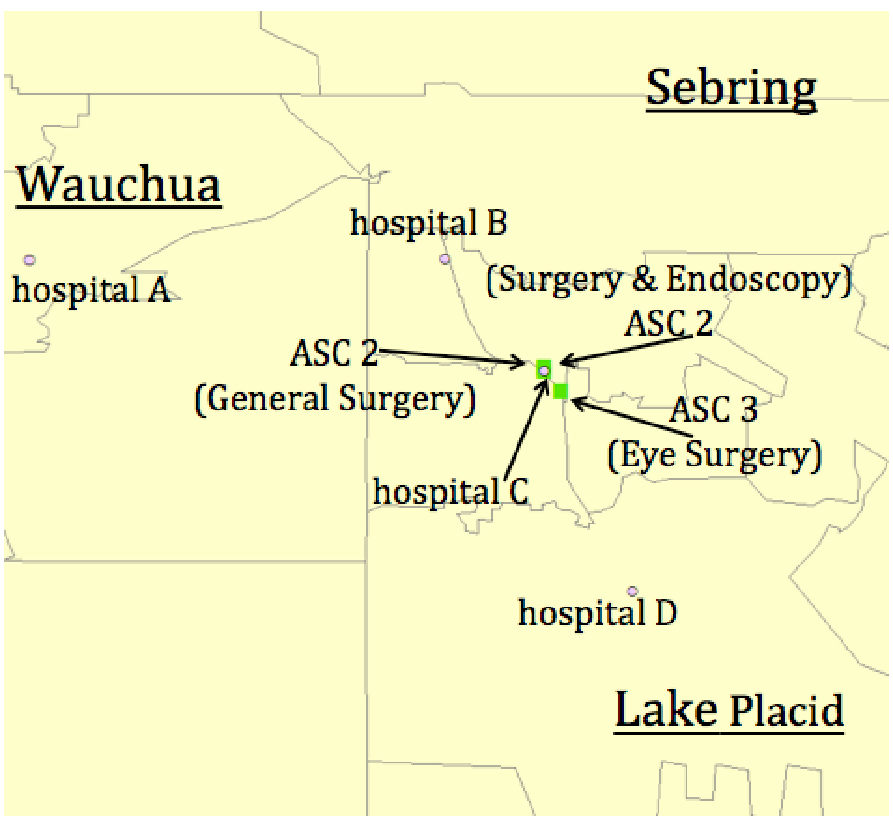

Figure 5: Distance Between Facilities in the Area of Interest for Substitution Matrix

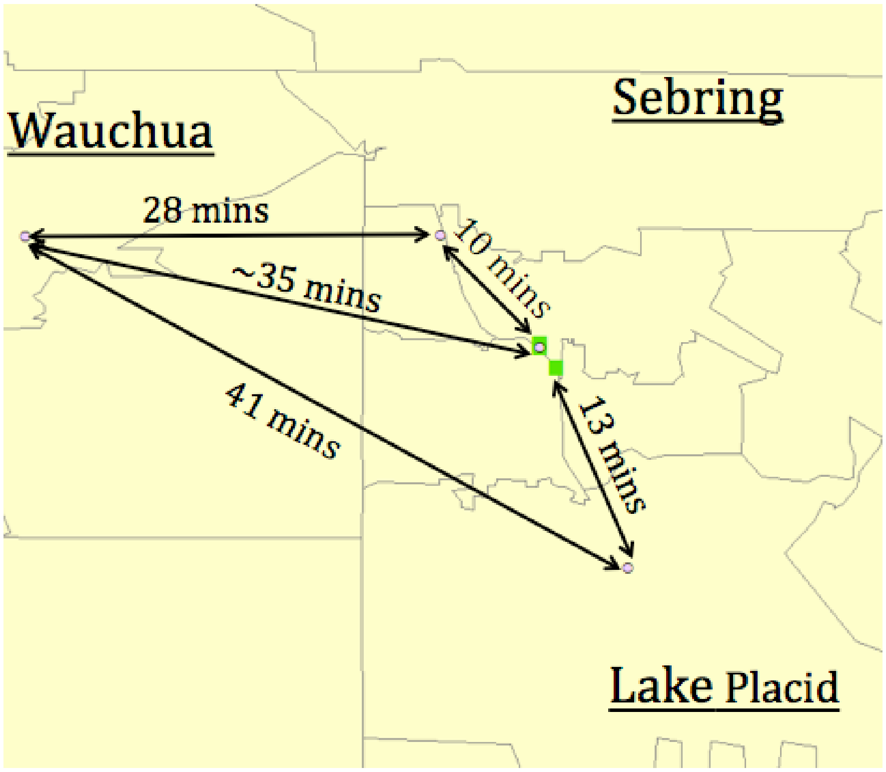

Figure 6: Distribution of CPT Codes

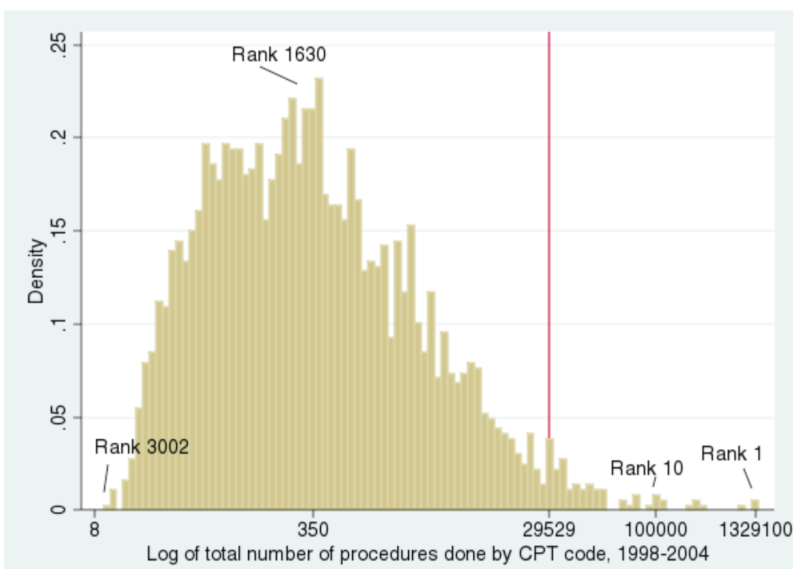

Table 2: Summary of Patients and Facilities, by Facility Type, Across All Procedures

	ASCs		Hospitals	
	Mean	Std Dev	Mean	Std Dev
Description of Patients	(N=447,650)		(N=555,926)	
Age (yrs)	61.78	18.81	53.93	21.46
Travel time (mins)	19.09	24.90	17.60	24.22
Having add'l procedures (%)	27.2	44.5	61.2	48.7
Non-white (%)	10.3	30.5	18.5	38.8
Male (%)	44.0	49.6	43.3	49.5
Medicare (%)	47.4	49.9	30.3	46.0
Medicare, HMO (%)	2.8	16.4	6.0	23.7
Medicaid (%)	1.8	13.2	4.0	19.7
Medicaid, HMO (%)	0.3	5.7	1.7	12.8
Private (%)	20.4	40.3	9.5	29.3
Private, HMO (%)	12.6	33.2	21.6	41.2
Private, PPO (%)	7.2	25.9	17.6	38.1
Governent Ins. (%)	4.3	20.3	4.9	21.6
Self Ins (%)	2.8	16.5	3.2	17.5
Description of Facilities	(N=239)		(N=196)	
Scope	91.66	84.44	298.57	169.66

Table 2 gives summary statistics for patients and facilities separately by facility type, but pooled across procedures. Note that the numbers of observations for travel time is N=420,547 and N=518,271 for ASCs and hospitals, respectively. This is because map imperfections prevent GIS from mapping roads from every consumers to each and every facility.

Table 3: Current Procedural Terminology (CPT) Codes Used in Analysis for Top-10 Procedures

Rank	Grouping	Description	CPT CODE
1	EYE	Extracapsular cataract removal with insertion of intraocular lens prosthesis (one stage procedure), manual or mechanical technique (eg, irrigation and aspiration or phacoemulsification)	66984
2	COLON	Colonoscopy, flexible, proximal to splenic flexure; diagnostic, with or without collection of specimen(s) by brushing or washing, with or without colon decompression (separate procedure)	45378
3	GASTRO	Upper gastrointestinal endoscopy including esophagus, stomach, and either the duodenum and/or jejunum as appropriate; with biopsy, single or multiple	43239
4	PAIN	Injection, single (not via indwelling catheter), not including neurolytic substances, with or without contrast (for either localization or epidurography), of diagnostic or therapeutic substance(s) (including anesthetic, antispasmodic, opioid, steroid, other solution), epidural or subarachnoid; lumbar, sacral (caudal)	62311
5	EYE	Discission of secondary membranous cataract (opacified posterior lens capsule and/or anterior hyaloid); laser surgery (eg, YAG laser) (one or more stages)	66821
6	COLON	Colonoscopy, flexible, proximal to splenic flexure; with removal of tumor(s), polyp(s), or other lesion(s) by snare technique	45385
7	COLON	Colonoscopy, flexible, proximal to splenic flexure; with biopsy, single or multiple	45380
8	COLON	Colonoscopy, flexible, proximal to splenic flexure; with removal of tumor(s), polyp(s), or other lesion(s) by hot biopsy forceps or bipolar cautery	45384
9	GASTRO	Upper gastrointestinal endoscopy including esophagus, stomach, and either the duodenum and/or jejunum as appropriate; diagnostic, with or without collection of specimen(s) by brushing or washing (separate procedure)	43235
10	ORTHO	Arthroscopy, knee, surgical; with meniscectomy (medial OR lateral, including any meniscal shaving)	29881

Table 3 describes the top-10 procedural codes and lists their CPT code and their broad categorical group, as defined by the author.

Table 4: Nested Logit for Medicare Patients for 6th-10th ranked procedures

Rank	10	9	8	7	6
CPT Group	Ortho	Gastro	Colon	Colon	Colon
CPT Code	29881	43235	45384	45380	45385
Lower Level Nest					
Total T2T	-4.651	-3.014	-4.920	-4.414	-3.378
	(0.933)	(0.387)	(0.582)	(0.417)	(0.463)
T2T > 75 mins	-2.430	-2.599	-3.308	-2.924	-2.665
	(0.295)	(0.183)	(0.157)	(0.150)	(0.136)
Scope	0.026	0.014	0.012	0.014	0.016
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
T2T x Age	-0.039	-0.053	-0.050	-0.051	-0.055
	(0.012)	(0.005)	(0.008)	(0.006)	(0.006)
T2T x Male	0.530	0.277	0.575	0.396	0.561
	(0.244)	(0.119)	(0.122)	(0.114)	(0.103)
T2T x Medicare HMO	-1.616	-1.280	-1.056	-1.516	-0.867
	(0.501)	(0.269)	(0.234)	(0.253)	(0.183)
T2T x Add'l proc	-0.196	0.949	-0.119	0.577	0.220
	(0.253)	(0.128)	(0.127)	(0.119)	(0.101)
Scope x Add'l proc.	-0.005	-0.004	0.010	0.006	0.000
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Upper Level Nest (Base=Hospital)					
age	0.028	0.011	0.019	0.018	0.017
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Add'l proc.	-1.322	-1.162	-1.438	-1.626	-1.043
	(0.125)	(0.070)	(0.053)	(0.055)	(0.045)
Non-white	-0.482	-0.267	-0.111	-0.080	0.150
	(0.219)	(0.097)	(0.080)	(0.089)	(0.072)
Male	-0.198	-0.039	0.066	0.111	0.095
	(0.095)	(0.056)	(0.040)	(0.043)	(0.035)
Medicare HMO	-1.051	-1.275	-0.973	-0.522	-1.086
	(0.159)	(0.109)	(0.068)	(0.072)	(0.058)
Log-sum parameters					
λ_{ASC}	0.943	0.797	1.007	0.967	0.786
	(0.064)	(0.042)	(0.032)	(0.033)	(0.025)
λ_{Hosp}	0.947	0.733	0.874	0.860	0.715
	(0.065)	(0.040)	(0.030)	(0.030)	(0.024)
N Obs	292,801	822,496	1,713,537	1,678,407	2,079,940
N Consumers	2,478	6,475	13,580	12,451	15,695
Number of choices per person					
Min	11	13	8	12	10
Avg	118.2	127	126.2	134.8	132.5
Max	179	204	201	216	216

Table 4 gives the results for Medicare patients for the 6th-10th most common procedures from the nested logit, including the upper level nest coefficients, the lower level nest coefficient, the log-sum parameters. Standard errors are in parentheses. Facility fixed effects are included in all regressions.

Table 5: Nested Logit for Medicare Patients for 1st-5th ranked procedures

Procedure Rank	5	4	3	2	1
Procedure Group	Eye	Pain	Gastro	Colon	Eye
CPT Code	66821	62311	43239	45378	66984
Lower Level Nest					
Total Time (T2T)	-2.274	-3.114	-2.815	-3.126	-2.320
	(0.277)	(0.277)	(0.175)	(0.226)	(0.188)
T2T > 75 mins	-1.302	-2.582	-2.159	-2.716	-1.843
	(0.071)	(0.118)	(0.083)	(0.089)	(0.047)
Scope	-0.036	0.023	0.010	0.013	-0.009
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
T2T x Age	-0.040	-0.056	-0.039	-0.047	-0.061
	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)
T2T x Male	0.351	0.328	0.195	0.154	0.313
	(0.058)	(0.092)	(0.050)	(0.058)	(0.039)
T2T x Medicare HMO	-0.923	-0.881	-0.856	-1.023	-0.761
	(0.158)	(0.180)	(0.103)	(0.120)	(0.091)
T2T x Add'l proc	0.835	-0.323	0.675	0.687	0.518
	(0.095)	(0.104)	(0.055)	(0.061)	(0.049)
Scope x Add'l proc.	-0.009	-0.002	0.002	0.002	0.005
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Upper Level Nest (Base=Hospital)					
Age	-0.016	0.012	0.015	0.010	-0.014
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Add'l proc.	1.072	-1.590	-1.736	-0.803	1.177
	(0.110)	(0.051)	(0.032)	(0.032)	(0.034)
Non-white	-0.259	0.545	-0.181	-0.201	0.719
	(0.094)	(0.084)	(0.045)	(0.044)	(0.032)
Male	-0.213	0.006	0.050	-0.011	-0.110
	(0.058)	(0.038)	(0.028)	(0.024)	(0.022)
Medicare HMO	0.359	-0.787	-0.780	-1.027	1.101
	(0.109)	(0.065)	(0.046)	(0.040)	(0.033)
Log-sum parameters					
λ_{ASC}	0.849	1.029	0.662	0.753	1.218
	(0.026)	(0.032)	(0.020)	(0.018)	(0.017)
λ_{Hosp}	1.091	0.851	0.530	0.656	0.989
	(0.048)	(0.024)	(0.017)	(0.017)	(0.015)
N Obs	1,995,530	1,901,574	3,689,801	4,362,464	9,206,123
N Consumers	25,274	15,642	28,044	32,286	76,037
Number of choices per person					
Min	4	4	12	13	11
Avg	79	121.6	131.6	135.1	121.1
Max	122	195	221	223	192

Table 5 gives the results for Medicare patients for the 1st-5th most common proceduresfrom the nested logit, including the upper level nest coefficients, the lower level nest coefficient, the log-sum parameters. Standard errors are in parentheses. Facility fixed effects are included in all regressions.

Table 6: Nested Logit for Privately and Self-Insured Patients for 6th-10th ranked procedures

Rank	10	9	8	7	6
CPT Group	Ortho	Gastro	Colon	Colon	Colon
CPT Code	29881	43235	45384	45380	45385
Lower Level Nest					
Total T2T	-2.742	-2.300	-3.107	-2.744	-3.325
	(0.231)	(0.258)	(0.271)	(0.166)	(0.251)
T2T > 75 mins	-1.145	-0.960	-1.590	-1.512	-1.750
	(0.107)	(0.113)	(0.122)	(0.096)	(0.118)
Scope	0.021	0.008	0.015	0.013	0.012
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T2T x Age	-0.016	-0.006	-0.020	-0.038	-0.028
	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)
T2T x Male	0.030	0.175	0.184	0.124	0.104
	(0.076)	(0.052)	(0.073)	(0.063)	(0.076)
T2T x Private HMO	-0.458	-0.549	-0.820	-0.913	-0.412
	(0.101)	(0.090)	(0.108)	(0.094)	(0.097)
T2T x Private PPO	-0.194	-0.097	-0.371	-0.019	0.012
	(0.090)	(0.065)	(0.095)	(0.074)	(0.097)
T2T x Self Ins.	0.032	0.387	0.675	0.032	0.501
	(0.232)	(0.094)	(0.162)	(0.173)	(0.196)
T2T x Add'l proc	0.026	0.268	0.109	0.242	0.075
	(0.077)	(0.057)	(0.076)	(0.066)	(0.077)
Scope x Add'l proc.	-0.005	-0.003	-0.002	0.001	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Upper Level Nest (Base=Hospital)					
Age	0.032	0.024	0.035	0.032	0.035
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Add'l proc.	-1.066	-1.198	-1.591	-1.832	-1.314
	(0.056)	(0.064)	(0.050)	(0.046)	(0.045)
Non-white	-0.225	0.108	0.264	0.130	0.311
	(0.079)	(0.072)	(0.064)	(0.057)	(0.058)
Male	0.205	0.010	-0.011	0.144	0.066
	(0.049)	(0.057)	(0.044)	(0.038)	(0.039)
Private HMO	-0.421	-1.235	-1.149	-0.743	-1.066
	(0.061)	(0.063)	(0.053)	(0.043)	(0.046)
Private PPO	-0.815	-1.682	-1.518	-1.146	-1.659
	(0.064)	(0.074)	(0.057)	(0.047)	(0.052)
Self Ins.	-0.512	-1.873	-1.694	-0.694	-1.838
	(0.158)	(0.160)	(0.146)	(0.118)	(0.129)
Log-sum parameters					
λ_{ASC}	0.502	0.356	0.552	0.655	0.618
	(0.035)	(0.038)	(0.034)	(0.030)	(0.030)
λ_{Hosp}	0.504	0.361	0.502	0.611	0.575
	(0.034)	(0.038)	(0.031)	(0.027)	(0.028)
N Obs	886,447	843,813	1,348,460	2,031,971	1,723,469
N Consumers	7,351	6,673	11,170	15,366	13,611
Number of choices per person					
Min	8	11	7	12	11
Avg	120.6	126.5	120.7	132.2	126.6
Max	203	206	204	224	220

Table 6 gives the results for private and self-insured patients for the 6th-10th most common procedures from the nested logit, including the upper level nest coefficients, the lower level nest coefficient, the log-sum parameters. Standard errors are in parentheses. Facility fixed effects are included in all regressions.

Table 7: Nested Logit for Privately and Self-Insured Patients for 1st-5th ranked procedures

Rank	5	4	3	2	1
CPT Group	Eye	Pain	Gastro	Colon	Eye
CPT Code	66821	62311	43239	45378	66984
Lower Level Nest					
Total T2T	-3.586	-2.670	-2.658	-2.877	-2.976
	(0.485)	(0.189)	(0.113)	(0.126)	(0.247)
T2T > 75 mins	-1.344	-1.137	-1.585	-1.433	-1.937
	(0.202)	(0.087)	(0.068)	(0.063)	(0.111)
Scope	-0.070	0.015	0.011	0.012	-0.019
	(0.004)	(0.001)	(0.000)	(0.000)	(0.001)
T2T x Age	-0.044	-0.017	-0.038	-0.020	-0.068
	(0.007)	(0.002)	(0.002)	(0.002)	(0.004)
T2T x Male	0.382	-0.006	0.061	0.075	0.083
	(0.170)	(0.058)	(0.038)	(0.036)	(0.087)
T2T x Private HMO	-2.029	-0.726	-0.416	-0.475	-1.575
	(0.262)	(0.080)	(0.054)	(0.050)	(0.117)
T2T x Private PPO	-2.612	-0.411	0.171	0.067	-1.954
	(0.430)	(0.078)	(0.049)	(0.045)	(0.182)
T2T x Self Ins.	-0.476	0.197	0.542	0.582	0.295
	(0.250)	(0.137)	(0.090)	(0.089)	(0.128)
T2T x Add'l proc	1.488	0.118	0.301	0.244	0.243
	(0.305)	(0.061)	(0.041)	(0.040)	(0.119)
Scope x Add'l proc.	0.010	-0.008	0.000	-0.005	0.022
	(0.009)	(0.001)	(0.000)	(0.000)	(0.002)
Upper Level Nest (Base=Hospital)					
Age	-0.035	0.026	0.036	0.029	-0.028
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Add'l proc.	2.293	-1.411	-1.863	-1.084	0.643
	(0.304)	(0.047)	(0.030)	(0.031)	(0.071)
Non-white	0.071	0.275	0.270	0.122	0.291
	(0.163)	(0.065)	(0.033)	(0.031)	(0.052)
Male	-0.148	0.320	0.137	-0.003	-0.054
	(0.128)	(0.039)	(0.026)	(0.023)	(0.040)
Private HMO	2.050	-0.708	-1.217	-1.382	1.242
	(0.160)	(0.047)	(0.030)	(0.027)	(0.050)
Private PPO	2.942	-1.311	-1.685	-1.764	1.913
	(0.195)	(0.052)	(0.034)	(0.030)	(0.061)
Self Ins.	0.475	-1.287	-1.540	-1.800	0.895
	(0.241)	(0.101)	(0.080)	(0.077)	(0.076)
Log-sum parameters					
λ_{ASC}	1.147	0.605	0.613	0.519	1.456
	(0.062)	(0.036)	(0.022)	(0.018)	(0.039)
λ_{Hosp}	1.776	0.526	0.524	0.447	1.246
	(0.114)	(0.028)	(0.018)	(0.015)	(0.033)
N Obs	398,674	1,443,218	4,382,164	4,893,172	2,653,734
N Consumers	5,558	12,659	33,847	37,772	22,655
Number of choices per person					
Min	4	5	12	13	10
Avg	71.7	114.0	129.5	129.5	117.1
Max	114	198	226	223	194

Table 7 gives the results for private and self-insured patients for the 1st-5th most common procedures from the nested logit, including the upper level nest coefficients, the lower level nest coefficient, the log-sum parameters. Standard errors are in parentheses. Facility fixed effects are included in all regressions.

Table 8: Mixed Logit Results for Medicare Patients for 1st-10th Ranked Procedures

(a) Random Coefficients

CPT Rank	Travel time (T2T)			Dummy, ASC			
	Avg. Coeff.	μ	σ	Avg. Coeff.	μ	σ	Share< 0
1	-6.22	1.53	0.78	0.078	0	0.006	0.110
2	-7.55	1.12	0.45	0.045	0	0.002	0.537
3	-8.61	2.45	0.39	-0.039	0	0.006	0.621
4	-7.49	2.78	0.51	-0.051	0	0.003	0.568
5	-7.86	2.52	0.14	-0.014	0	0.001	0.523
6	-9.40	3.16	0.60	-0.060	0	0.005	0.597
7	-10.58	2.55	0.42	0.042	0	0.008	0.130
8	-12.07	3.03	0.93	-0.093	0	0.010	0.700
9	-11.91	4.33	0.09	-0.009	0	0.006	0.616
10	-10.28	3.80	0.72	-0.072	0	0.010	0.693

Table 8 (a) shows the random coefficients, μ and σ, on travel time and the dummy for ASC for the top-10 CPT codes for Medicare patients. For T2T, the mixing distribution is assumed to be lognormal; for the dummy for ASC, it is assumed to be normal with zero mean, hence μ is constrained to be 0. The "Average Coefficient" column gives the average coefficient in the population implied by the estimates for μ and σ. The "Share $<$ 0" column gives the fraction of consumers who have a negative coefficient on the dummy for ASC, which is also implied by the estimates. Interactions and non-random facility variables are included in these regression; those results are presented below in part (b). Facility fixed effects are also included. All coefficient estimates presented in this table are significant at the 95% confidence level.

(b) Interaction and Control Coefficients

Dummy, ASC X	Age	+, small, significant.
	Dummy, Male	mixed
	Dummy, Medicare HMO	-, large, mostly significant
	Dummy, Add'l Proc	-, large, significant
T2T X	Age	+, small, significant
	Dummy, Male	mostly -, large, mixed sig.
	Dummy, Medicare HMO	+, large, significant
	Dummy, Add'l Proc	mostly -, large, significant
Scope		mostly +, small, significant
Scope X	Dummy, Add'l Procs	mixed +/-, small, mixed sig

Table 8 (b) gives a general description of the coefficients on the fixed variables (the interactions between patient characteristics with travel time and the dummy for ASC, as well as the scope variable) across the mixed logit regressions for the top-10 CPT codes for Medicare patients.

Table 9: Mixed Logit Results for Private and Self-Insured Patients for 1st-10th Ranked Procedures

(a) Random Coefficients

	Travel time (T2T)			Dummy, ASC			
CPT Rank	Avg. Coeff.	μ	σ	Avg. Coeff.	μ	σ	Share< 0
1	-8.73	2.13	0.27	0.027	0	0.001	0.090
2	-5.26	3.78	0.74	-0.074	0	0.003	0.557
3	-8.73	2.04	0.27	-0.027	0	0.001	0.520
4	-7.60	1.54	0.40	-0.040	0	0.008	0.669
5	-5.31	3.78	0.69	-0.069	0	0.010	0.692
6	-10.05	1.58	0.95	-0.095	0	0.006	0.617
7	-10.30	2.59	0.70	0.070	0	0.007	0.120
8	-7.54	1.24	0.46	-0.046	0	0.009	0.673
9	-6.68	3.05	0.32	-0.032	0	0.005	0.604
10	-8.41	0.51	0.59	-0.059	0	0.004	0.574

Table 9 (a) shows the random coefficients, μ and σ, on travel time and the dummy for ASC for the top-10 CPT codes for private and self-insured patients. For T2T, the mixing distribution is assumed to be lognormal; for the dummy for ASC, it is assumed to be normal with zero mean, hence μ is constrained to be 0. The "Average Coefficient" column gives the average coefficient in the population implied by the estimates for μ and σ. The "Share $<$ 0" column gives the fraction of consumers who have a negative coefficient on the dummy for ASC, which is also implied by the estimates. Interactions and non-random facility variables are included in these regression; those results are presented below in part (b). Facility fixed effects are also included. All coefficient estimates presented in this table are significant at the 95% confidence level.

(b) Interaction and Control Coefficients

Dummy, ASC X	Age	mostly +, small, significant
	Dummy, Male	mostly +, mixed sig.
	Dummy, Non-white	mixed +/-, mostly sig.
	Dummy, Private HMO	mostly -, large, significant
	Dummy, Private PPO	mostly -, large, significant
	Dummy, Add'l Proc	mixed +/-, large, significant
T2T X	Age	-, small, significant
	Dummy, Male	mostly -, mixed sig.
	Dummy, Private HMO	-, mixed size, significant
	Dummy, Private PPO	mostly -, mixed size, mixed sig.
	Dummy, Add'l Proc	+, mixed size, mixed sig.
Scope		mostly +, small, significant
Scope X	Dummy, Add'l Procs	mostly -, small, mixed sig.

Table 9 (b) gives a general description of the coefficients on the fixed variables (the interactions between patient characteristics with travel time and the dummy for ASC, as well as the scope variable) across the mixed logit regressions for the top-10 CPT codes for private and self-insured patients.

Table 10: Corresponding Matrices of Substitution & Distance Between Facilities

(a) Substitution Matrix (Cross-Time Elasticities)

Facility	**Wauchua**	**Sebring**					**Lake Placid**
	Hospital A	Hospital B	ASC 1 (Srgry & Endscpy)	ASC 2 (Srgry)	Hospital C	ASC 3 (Eye Srgry & Laser)	Hospital D
Hospital A	-	-	-	-	-	-	-
Hospital B	-	-0.029	-	0.0034	0.0093	-	0.0008
ASC 1	-	-	-	-	-	-	-
ASC 2	-	0.0058	-	-0.022	0.0013	-	0.0006
Hospital C	-	0.0032	-	0.0044	-0.071	-	0.0016
ASC 3	-	-	-	-	-	-	-
Hospital D	-	0.0092	-	0.0051	0.0025	-	-0.087

(a) Distance Between Facilities Matrix (Minutes)

Facility	**Wauchua**	**Sebring**					**Lake Placid**
	Hospital A	Hospital B	ASC 1 (Srgry & Endscpy)	ASC 2 (Srgry)	Hospital C	ASC 3 (Eye Srgry & Laser)	Hospital D
Hospital A	-	-	-	-	-	-	-
Hospital B	-	0	-	10	10	-	23
ASC 1	-	-	-	-	-	-	-
ASC 2	-	10	-	0	0	-	13
Hospital C	-	10	-	0	0	-	13
ASC 3	-	-	-	-	-	-	-
Hospital D	-	23	-	13	13	-	0

This table gives the cross-time substitution (part (a)) and corresponding distance matrix (part (b)) between facilities in the area of interest as highlighted in previous figures. These are the results for a single orthopedic procedure CPT code 22981. The matrix is sparse as not all facilities compete in this procedural market.

Table 11: Welfare Change From the Elimination of ASCs for the Top-10 Procedures: Medicare Patients

CPT	Rank	Total Expected Change in CS (hours)	Expected per capita change in CS (mins)	N (Consumers)	Expected Change in CS ($)
66984	1	12,204	9.63	76,037	183,059
45378	2	5,257	9.77	32,286	78,859
43239	3	6,086	13.02	28,044	91,283
62311	4	1,940	7.44	15,642	29,094
66821	5	5,223	12.40	25,274	78,349
45385	6	2,713	10.37	15,695	40,689
45380	7	1,772	8.30	12,451	25,836
45384	8	2,467	10.90	13,580	37,006
43235	9	1,468	13.60	6,475	22,015
29881	10	477	11.55	2,478	7,155
				Total:	593,345

Table 12: Welfare Change From the Elimination of ASCs: Private and Self-Insured Patients

CPT	Rank	Total Expected Change in CS (hours)	Expected per capita change in CS (mins)	N (Consumers)	Expected Change in CS ($)
66984	1	3,564	9.44	22,655	53,466
45378	2	9,525	15.13	37,772	142,873
43239	3	8,473	15.02	33,847	127,095
62311	4	2,783	13.19	12,659	41,743
66821	5	1,042	9.92	5,558	15,632
45385	6	2,046	11.25	13,661	30,693
45380	7	2,541	9.02	15,366	38,108
45384	8	2,716	14.59	11,170	40,742
43235	9	1,495	13.44	6,673	22,421
29881	10	1,449	11.83	7,351	21,741
				Total:	534,514