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

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Abstract

The purpose of this study is to estimate structural elements of patients' 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. Spatial variation across patients and facilities, among other variables, is used for identification. Using data that contain the universe of outpatient surgeries in Florida from 1998 through 2004, I estimate by reduced-form quantile regressions of facilities' actual demand curves as functions of travel-cost between patient and facility. I show that there is a strong spatial component to demand. Then, developing a discrete choice model of demand for healthcare facilities, I estimate structural parameters from patients' demand functions from multinomial logit and mixed logit (random coefficient) specifications. Time-to-travel is found to be a significant factor in patients' choice of healthcare facility. I construct a cross-time substitution matrix to explain how patients substitute between facilities when facilities change their location. Finally, I measure how patient welfare would change if a subset of facilities (ASCs) were removed from patients' choice sets. All of this is done without explicitly including a price variable, but instead using facility fixed effects that absorb price and quality, among other unobserved product characteristics.

1 Introduction

The purpose of this study is to estimate structural elements of patients' demand functions for healthcare facilities, particularly for hospitals and ambulatory surgery centers (ASCs), towards the goal of answering questions about the magnitude and existence of welfare gains

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earned from the introduction of ASCs. Hospitals are healthcare facilities that perform both inpatient and outpatient procedures, while ASCs are healthcare facilities that concentrate exclusively on outpatient procedures. Spatial variation across patients and facilities, among other variables, is used as identification.

There are many reasons to study the healthcare facility industry, the least of which is its size and ubiquity. According to Census statistics, hospitals and ASCs employ 40 percent of all workers in the healthcare industry, approximately 5.44 million people. In 2003, hospital earned $536 billion in revenues. Given the significance and relevance of healthcare facilities to the overall economy, it is especially interesting to consider the nature of demand for and supply of its products, as well as the competition landscape between industry participants.

Largely for these reasons, the study of competition between hospitals has become a popular topic in the fields of industrial organization and healthcare research. However few authors have written about ASCs; the literature on them is still nascent. The studies that do exist on ASCs are mostly about the supply-side of the market, 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.[1] For example, Morrisey and Bian [10] and Plotzke [15] 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 [8] use a case study to frame a similar result: that hospital-based outpatient surgical volume falls when the hospitals' physicians open an ASC. Plotzke [15] also finds that there is no significant effect of ASC entry on hospital profit margins for either outpatient or inpatient departments.

There has been no study of which I am aware that analyzes the demand-side for all healthcare facilities for outpatient procedures. Gaynor and Vogt [5] do analyze demand for hospitals (in California) for inpatient surgeries, and use similar techniques as those used here. Where comparable, my estimates support their findings.

Without understanding demand for healthcare facilities, we cannot understand fully how facilities compete. Competition analysis is incomplete if it does not specify how consumers choose between products. This paper provides some insight into how ASCs and hospitals compete by looking at how patients substitute between them, and at how patients' welfare changes when some facilities are removed from patients' choice set.

To do this, I use a model of a discrete choice demand function by patients for healthcare facilities. I think about the problem in the following way: After being recommended by their physician to have surgery, and to use a particular facility, patients make a two-part decision. First they decide whether to have surgery, in some cases, whether to have inpatient or

[1] As the hospital literature grew in response to the heavy merger activity of the late 1990s.

outpatient surgery, and finally at which facility to have the procedure performed. This paper focuses on the last part of this decision tree: conditional on having to have an outpatient procedure performed, which facility does the patient choose? In particular, I look at how facility characteristics including geographic location impact consumers' choices. Location is measured with a time-to-travel variable that specifies the distance (in minutes) from each patient to each and every facility.

In modeling demand, I follow and extend the structural IO and discrete choice literatures that address issues of unobserved heterogeneity in differentiated products, and that allows patient characteristics to influence demand. If there is product heterogeneity not controlled for in the empirical specification, estimates will be biased as they erroneously attribute variation in choices to observed variables only. Most of the papers in the literature (Berry [1], Berry, Levinsohn and Pakes [16], Petrin [13], Nevo [12]) deal with unobserved heterogeneity by using complicated estimation algorithms to find facility fixed effects that can absorb omitted variables. Their estimation strategies also must be complex enough to compensate for the fact that they do not actually observe consumer choices, and therefore cannot link consumer characteristics with product characteristics except through matching moments.

I can control for unobserved heterogeneity because I have micro-data. The micro data contains demographic variables that describe patient characteristics, which allows me to explain variation in choice with actual, observed patient indiosyncracies. Moreover, there is a lot of data; I observe many observations (that is, purchase choices) for each facility, and therefore in a straightforward manner can include product-level (facility-level) fixed effects to absorb unobserved variables, like quality, that we know influence patients' choices. Berry, Levinsohn and Pakes (Micro) [2], and Gaynor and Vogt[5], also discuss the benefits of having micro-data.

The dearth of research about healthcare facility demand is largely a constraint imposed by data availability. Few agencies make available micro-level about consumers' health care choices. I use data collected by the Florida Agency for Health Care Administration (AHCA) that contain the universe of outpatient procedures performed in the state between 1998 and 2004. Over this period, there are over seven million observed facility choices made by patients needing one of the top-100 procedures.

Using GIS software, I construct the time-to-travel variable by measuring a time-cost for the distance between each facility and each patient. The time-to-travel variable is a natural, and rich source of exogenous variation in consumer choices; it gives some measure of protection against endogeneity bias in the results.

Finally, understanding and estimating the demand curve is important as the results enable us to do welfare analyses based on various counterfactuals. The main one I consider 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 [14] and Winter [19]). Moreover, hospitals perceive that ASC entry is coming disproportionately into high-profit procedural areas, thereby also cherry-picking the best, most profitable product-lines. In receiving less profitable patients and facing competition in more profitable products, hospitals are claiming that their survival is in danger as profits are falling into the red.[2] 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. This paper weighs in on the policy debate by measuring this latter quantity.

There is an additional policy matter regarding the potential safety of ASCs relative to hospitals. Even though outpatient surgery performed in either an ASC or hospital setting is generally quite safe (Fleisher et al [4]), it is still possible to measure in money terms the cost of any additional risk by using probabilities of adverse outcomes and estimates for the value of a statistical life (see Murphy and Topel [11]). By itself, however, such a cost lacks context. The welfare numbers calculated in this paper provide a benefit against which costs can be compared.

The next section offers a brief definition of ambulatory surgery and an overview of the healthcare facility industry. Section 3 describes the data. In section 4, I do a reduced form spatial analysis, which motivates the demand model and provides some insight into the geography of healthcare facility markets. Section 5 brings us to the structural model of demand, section 6 lays out the estimation strategy, and section 7 discusses the results and identification. 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

[2]Their claims have been disputed by some economists. See Plotzke [15]

require general or local anesthetic, and may be minimally invasive or require more serious incision.

There are many different types of outpatient surgeries. 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, there was 10 percent annual growth in the number of ASCs in the United States. 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. 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, who bills the patient separately.

Few trustworthy national statistics about outpatient surgeries are available. According to the National Survey of Ambulatory Surgery, as of 2006, there are there are more than 4,500 freestanding ASCs performing more than 15 million procedures annually. Visits to hospital-based ASCs account for another 20 million ambulatory procedures, at approximately another 4,500 short-term, acute care hospitals. Ambulatory surgeries as a fraction of all surgeries grew from 44 to 56 percent in the decade between 1996 and 2006. However, a study by the Lewin Group[3], states that ambulatory surgery represented only 15 percent of national healthcare spending in 1999.

3 Data Description

The major data used are the universe of patient level ambulatory surgery events for the years 1998-2004 and come from the Florida Agency for Health Care Administration (AHCA), which 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 is quarterly. There were 18.8 million ambulatory procedures performed in Florida healthcare facilities between 1998-2004.

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 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 AHCA, such as facility street address, and capacity in terms of number of beds, and current licensing status, that is, wether the facility is active, closed, or expired. Unlike the procedure level data set just described, the facility information set is current at the date of receipt, which was early 2008. If any information changed between 1998 and 2008, it will not be captured by the facility data set. This is most problematic for the capacity variable, which may indeed change over time. However, according to conversations with AHCA employees, ASC capacities at least tend to stay fixed after entry, even though this is not true for hospitals.

[3]Study of Outpatient Healthcare Cost Drivers

Finally, I compute distance and time-to-travel variables between patients and facilities. The smallest geographic identifier that the data contains for patients is zip code; for facilities, exact addresses are available.[4] 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.[5]

4 Spatial Analysis

All else equal, demand for a facility should be higher for patients located near the facility as compared with patients farther away. While the *level* of demand will be affected by many variables (quality, price, competition, demographic and geographic characteristics, etcetera), the spatial pattern of relatively higher demand for nearby facilities should hold across all observed firms. The exact shape of the spatial pattern will be driven by the opportunity cost of time spent traveling, and the inconvenience cost of traveling after undergoing an outpatient procedure. Because of these demand drivers, the pattern will hold even if facility location is an endogenous choice by facilities.

Figures 1 and 2 confirm this expectation. On them, I graph percent of facility j's output that comes from zip code k (y-axis) against the travel-time between zip code k and facility j (x-axis). The x-axis units are minutes. The y-axis variable is calculated as:

$$s_{kjt} = \frac{N_{kjt}}{N_{jt}} \tag{1}$$

where N_{kjt} equals the number of procedures facility j performs on patients from zip code k in period t and N_{jt} equals the total number of surgeries performed by facility j during that same time. Time periods are quarters between 2001-2003.

[4]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 it 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.

[5]Many thanks to Todd Schuble for his help in computing these variables.

These figures are identical except the top one is for ASCs only (s_{kjt}^{ASC}) and the bottom one for hospitals only (s_{kjt}^{Hosp}). The y-axis variable was calculated separately for each facility, which is why a box-plot is used – the box-plot represents the pdf (over facilities) of facilities' fractions of total outputs, conditional on location. The view from which we see the pdf is a bird's-eye view.

Another interpretation of figures 1 and 2 is as pdfs of producer demand over space. The curves shown are averages of vertical slices of facilities' three-dimensional demand bell-curves hanging in space, with the facility at the center of the bell. The average throws away location-specific information and reduces the picture to a single dimension: the distance between patients and facilities. As can be seen, the median facility procures a larger share of its total output from nearby zip codes relative to zip codes farther away. More important, a comparison of the two figures indicates that the strength of this relationship differs by facility type: hospital demand is more spatially concentrated than ASC demand, but has a longer tail.

This finding is reinforced by a quantile regression in which the (log) fraction of the median facility's total output (in period t) from a particular zip code is regressed on the (log) time-to-travel between zip code and facility, and year dummies. Results are shown in Table 1. The last column, "All", corresponds to the figures just described. The other columns show results of the same regression for specific procedures. Standard errors are bootstrapped.

Identification comes from variation in location of facilities' patients, which of course generates variation in time-to-travel. If patient location is correlated with omitted facility characteristics, like price or quality, then one would worry about bias in the estimates. This is precisely the appeal of using time-to-travel in the demand function: it is likely to be independent from any omitted variables.

Looking at the last column, the estimate for the constant term says that the median ASC gets 26.7 percent of its sales from those zip codes located immediately next door, while the median hospital gets 22.8 percent from its nearest zips (converting the coefficient from logs). The estimate for the coefficient on (log) time-to-travel reads that the fraction of sales coming from zip codes further away tapers off at a rate of 1.26 percent for every one percent increase in the minutes of travel time for the median hospital, but only at a rate of 1.13 percent for the median ASC.

Graphically, the coefficients on the constant compare the y-intercepts of the median facilities (darkened line in the middle of the left-most boxes) in figures 1 and 2, which are not markedly different, as the regression confirms.[6] The coefficients on time-to-travel compare

[6]The difference in the vertical axis scale in the figures and the scale of the constant in the quantile regression results from the fact that discrete bins are used the figures, while a continuous time-to-travel

the slopes of curve for the median facilities, which is steeper for the median hospital relative to the median ASC, and suggest that demand is more spatially concentrated for hospitals than for ASCs.

I run the same quantile regression for the 85th percentile facilities (no table). The coefficient for the constant of the 85th percentile ASC implies they get 83 percent from zips nearby, versus 100 percent for the 85th percentile hospital, while the coefficients on the time-to-travel variable are -1.11 versus -1.32 for ASCs and hospitals respectively. Translating into picture terms, these estimates tell us the y-intercepts and slopes from figures 1 and 2, but this time do so for the upper whisker, instead of for the middle of the box.

It is also interesting to contrast across columns of Table 1. Doing so illustrates two points: First, that the shape of the demand density is different across procedures. This can be seen by comparing the levels of the (constant) estimates across columns. Demand for colonoscopy, eye and urology procedures, for instance, is more spatially concentrated than demand for foot or OB/Gyn procedures; both ASCs and hospitals get a larger fraction of their patients from nearby zip codes relative to other procedures.

Second, compare the R-squareds across columns. It is apparent that the extant to which travel-time influences facility purchase decisions (vis-a-vis other variables) also varies across procedures. For example, the high R-squared in the urology procedure regression compared to the low statistic in the ENT procedure regression imply that travel-time explains more variation in the spatial concentration of demand for facilities doing urology procedures than for facilities do ENT procedures. It cannot be determined from these regressions whether the variation in R-squareds is because, ceteris paribus, the cost of travel is higher for some procedures, or because there is *less* variation in facilities' other differentiating characteristics across procedures. If there was little variance in facility quality, or any other dimension of product heterogeneity, then one would expect demand to be more spatially concentrated, as time would matter more vis-a-vis other factors.

Given this explanation, the results are consistent with a story that says there is less observed or unobserved facility heterogeneity among facilities who perform eye (mostly cataract), colonoscopy and gastroenterology procedures. From an industry perspective, this result makes sense: These procedures are among the safest, and the scale on which they are produced is much larger than other types of outpatient procedures, so most facilities are already likely farther out on any learning curve. Among health procedures, one can think of cataract surgeries, colonoscopies and gastroenterological endoscopies as being the most commoditized, therefore it is not surprising that geographic location plays a larger role in the decision choice.

variable is used in the regression.

I now formalize a model of demand with a goal of reproducing the spatial stylized facts of demand just discussed.

5 Demand Model

Consumer demand for healthcare facilities is modeled as a discrete choice. The consumer is the patient, and her choice set is the set of all facility alternatives in the state. In reality, consumers' actual choice sets are likely much smaller, but the flexibility allows for the data to naturally determine consumer's market boundaries, instead of imposing a constraint exogenously.

I specify the discrete choice model to be logit, and the coefficients to be random, in that the parameters of the utility functions very over consumers based on observed and unobserved consumer characteristics. In contrast, the standard logit model assumes utility function parameters to be fixed over all decision makers. A logit specification with random coefficients is sometimes referred to as a mixed logit model; this is the nomenclature I use here.

I choose to use the more flexible mixed logit model both to circumvent the well-known restrictive substitution patterns imposed by the standard logit model (see Train [18]), and also because the appropriate null hypothesis is that coefficients are random in 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. Gaynor and Vogt [5] and Ho [7] use similar approaches.

Formally, suppose there are K markets, $k = 1, 2, \ldots, K$. In market k, there lives I_k consumers. The elements of the choice sets for all consumers are the same: $A = \left\{ j_1, j_2, \ldots, J \right\}$. The constancy of choice sets over all consumers reflects the fact that all facilities are potential choices for all consumers. From each potential alternative in her choice set, the consumer receives utility U_{ij} and she chooses the facility that maximizes her utility. Consumer i chooses facility j if and only if $U_{ij} > U_{il} \; \forall j \neq l$, where j and $l \in A$.[7]

[7] All variables should be superscripted with an additional three variables: (1) t to denote time, (2) k, to denote the market (zip code) where the patient lives, and (3) p, to denote the fact that a patient's choice of facility is procedure-specific. I abstract from these dimensions here to keep the notation simple, but discuss them in the Identification Section with respect to the added variation they provide.

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.

$$U_{ij}\big(X_j, Z_i, T_{ij}, \xi_j, \upsilon_i; \theta\big) = V_{ij}\big(X_j, Z_i, T_{ij}, \xi_j, \upsilon_i; \theta\big) + \epsilon_{ij} \tag{2}$$

The explained part, V_{ij}, is a function of observed facility characteristics, X_j, observed patient characteristics, Z_i, unobserved facility characteristics, ξ_j, unobserved patient characteristics, υ_i, and the time-to-travel between the patient and the facility, T_{ij}; V is parameterized by θ. 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 influence a patient's decision choice.

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

$$V_{ij} = T_{ij}\alpha_i + X_j\beta_i + \xi_j \tag{3}$$

where β_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 β_i be functions of patient characteristics, so that

$$\begin{aligned} \alpha_i &= \tilde{\alpha} + \kappa Z_i + \upsilon_i^1, \text{ and} \\ \beta_i &= \tilde{\beta} + \gamma Z_i + \upsilon_i^2, \end{aligned}$$

where υ_i^1 and υ_i^2 are draws from (two potentially different) iid random variables. Note that β_i is a Cx1 vector of coefficients, where C is the dimension of X_{jk}. The cth element of β_i is:

$$\begin{aligned} \beta_{ic} &= \tilde{\beta}_c + \gamma_c Z_i + \upsilon_{ic}^2 \\ &= \tilde{\beta}_c + \sum_{m=1}^{M} z_{im}\gamma_{mc} + \upsilon_{ic}^2 \end{aligned} \tag{4}$$

where M is the dimension of the Mx1 vector Z_i, υ_{ic}^2 is the random error term on the cth characteristic (assumed to be distributed iid across patients), and γ_{mc} is a 1xc vector that is the mth row of the Mxc matrix, γ . Stack the elements, $\beta_{ic}\forall c$, to create β_i and plug into

(3) and then (2) to get:

$$\begin{aligned} U_{ij} &= T_{ij}\alpha_i + X_j\beta_i + \xi_j + \epsilon_{ij} \\ &= T_{ij}\tilde{\alpha} + X_j\tilde{\beta} + T_{ij}\sum_{m=1}^{M} z_{im}\kappa_m + X_j\sum_{m=1}^{M} z_{im}\gamma_m + T_{ij}\upsilon_i^1 + X_j\upsilon_i^2 + \xi_j + \epsilon_{ij} \end{aligned} \tag{5}$$

The parameters to estimate from this model are $\theta = \left[\tilde{\alpha}, \tilde{\beta}, \kappa, \gamma, \Pi\right]$, 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 c x m 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 Π are the moments of $F(\upsilon)$, the distribution of υ. It should now be clear how random coefficients are equivalent to 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 magnitude of γ, and the distribution of υ (parametrized by Π) over the population.

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:

$$\delta_j = X_j\tilde{\beta} + \xi_j \tag{6}$$

and re-write equation (5) as

$$U_{ij} = \delta_j + T_{ij}\tilde{\alpha} + T_{ij}\sum_{m=1}^{M} z_{im}\kappa_m + X_j\sum_{m=1}^{M} z_{im}\gamma_m + T_{ij}\upsilon_i^1 + X_j\upsilon_i^2 + \epsilon_{ij} \tag{7}$$

The convention of using δ to denote mean utility began with Berry [1] and Berry, Levinsohn and Pakes [16]. Writing utility in this way is useful because it shows that, given δ_j, it will be a straightforward exercise to estimate the coefficients that interact with patient characteristics, that is, γ. I discuss this in more detail in the Estimation Strategy section below.

Note that T_{ij} is not included in δ_j in equation (6). 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, I re-write equation (7) as:

$$U_{ij} = \delta_j + T_{ij}\tilde{\alpha} + X_{ij}\Gamma + X_{ij}\upsilon_i + \epsilon_{ij} \tag{6$'$}$$

where $X_{ij} = [X_j, T_{ij}]$, $\Gamma = \big[\sum_{m=1}^{M} z_{im}\gamma_{m1}, \sum_{m=1}^{M} z_{im}\gamma_{m2}, \ldots, \sum_{m=1}^{M} z_{im}\gamma_{mc}, \sum_{m=1}^{M} z_{im}\kappa_m\big]'$, and $\upsilon_i = [\upsilon_i^1, \upsilon_i^2]'$.

Choice Probabilities

Without the random term, υ, the probability 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 $F(\upsilon)$.

$$\begin{aligned} \hat{P}_{ij}\big(X_j, Z_i, T_{ij}, \xi_j; F(\upsilon), \theta\big) &= Pr\Big(U_{ij} > U_{il}\ \forall j \neq l|\ F(\upsilon), \theta\Big) \\ &= \int_{\epsilon} I\Big(\epsilon_{il} < \epsilon_{ij} + V_{ij} - V_{il} \mid F(\upsilon), \theta\Big) dF(\epsilon) \end{aligned} \tag{8}$$

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.

$$P_{ij}\big(X_j, Z_i, T_{ij}, \xi_j; F(\upsilon), \theta\big) = \int \hat{P}_{ij} dF(\upsilon) \tag{9}$$

Assuming that each component of the 1xJ random vector, ϵ, 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 (8) has the closed form:

$$\hat{P}_{ij} = \frac{\exp\big(\delta_j + T_{ij}\tilde{\alpha} + X_{ij}\Gamma + X_{ij}\upsilon_i\big)}{1 + \sum_{l=1}^{J} \exp\big(\delta_l + T_{il}\tilde{\alpha} + X_{il}\Gamma + X_{il}\upsilon_i\big)} \tag{10}$$

and equation (9) becomes:

$$P_{ij} = \int \frac{\exp\big(\delta_j + T_{ij}\tilde{\alpha} + X_{ij}\Gamma + X_{ij}\upsilon_i\big)}{1 + \sum_{l=1}^{J} \exp\big(\delta_l + T_{il}\tilde{\alpha} + X_{il}\Gamma + X_{il}\upsilon_i\big)} dF(\upsilon) \tag{11}$$

Finally, to get the ex-ante probability, P_j, that any randomly selected patient in the population chooses facility j, we also need to integrate over the density of patient types, $F(Z)$.

$$P_j = \int_Z \int_\upsilon \frac{\exp\left(\delta_j + T_{ij}\tilde{\alpha} + X_{ij}\Gamma + X_{ij}\upsilon_i\right)}{1 + \sum_{l=1}^{J} \exp\left(\delta_l + T_{il}\tilde{\alpha} + X_{il}\Gamma + X_{il}\upsilon_i\right)} dF(\upsilon) d\hat{F}(Z) \tag{12}$$

where $\hat{F}(Z)$ makes explicit that the distribution of types is taken from the data, and Z is imbedded in Γ.

Market Shares & Elasticities

The probability in equation (12) can also be interpreted as the market share of product j: $s_j(X_j, Z_i, T_{ij}, \xi_j; F(\upsilon), \hat{F}(Z), \theta) = P_j$, which can in turn be used to compute demand elasticities. (Analogously, the probability from equation (10) can be interpreted as the market share of product j purchased by type i, conditional on their random draw from $F(\upsilon)$: $\hat{s}_{ij}$.) Economists are traditionally interested in demand elasticities with respect to price, as price is the most convenient and usually the most logical product characteristic to use. Theoretically, however, there is nothing stopping us from measuring demand elasticities with respect to any product characteristic.

This is what I now derive: Demand elasticities with respect to non-price characteristics, particularly location. There are good reasons to avoid calculating a price-elasticity. First, as has been mentioned already, there are only bad measures of price in the data set. 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 perhaps not even the most important, product characteristic that consumers consider. Instead, I try to 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 using the individual specific probabilities of purchase as weights. This mean elasticity of demand with respect to change in the location of facility j is:

$$\eta_{jl} = \frac{\partial s_j}{\partial T_l}\frac{T_l}{s_j} = \begin{cases} \frac{1}{s_j} \int\int\int T_{ij}\beta_i \hat{s}_{ij}(1-\hat{s}_{ij}) dF(\upsilon) d\hat{F}(Z)\hat{F}(T) & \text{if } j = l, \\ \frac{1}{s_j} \int\int\int -T_{il}\beta_i \hat{s}_{ij}\hat{s}_{il} dF(\upsilon) d\hat{F}(Z)\hat{F}(T) & \text{otherwise,} \end{cases} \tag{13}$$

where s_{ij} is the market share just computed. This is identical to the elasticity of demand for any generic product characteristic (such as price, see Nevo [12]), 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 must be integrated over.

6 Estimation Strategy

Logit with Interactions

If the term with the υ_i interaction is discarded from indirect utility in equation (7), then estimation is straightforward. Such an omission could be created by letting the variance of the distribution of υ degenerate to zero around a zero mean. In that case, I can run a simple logit regression of the binary (facility j chosen) purchase decision on facility fixed effects (δ_j) and on facility characteristics (X_j) interacted with patient characteristics (Z_i). The log likelihood equation is:

$$\begin{aligned} \ln L(\theta) &= \sum_i^I \sum_j^J \ln\big(Pr(i \text{ chooses } j)\big) \\ &= \sum_i^I \sum_j^J d_{ij} \ln \hat{P}_{ij} \end{aligned} \tag{14}$$

where d_{ij} is the binary dependent variable that equals one if patient i chose facility j and $\hat{P}_{ij}$ is as written equation (10) except that the term $X_{ij}\upsilon_i$ is omitted.

Mixed Logit

If the υ_i term is not discarded, then a different estimation approach is needed. Simulation is the traditional way to estimate parameters of a mixed logit model. Simulated maximum likelihood (SML) and the method of simulation moments (MSM) are two such simulation-based methods. I use the former for reasons of efficiency; SML tends to be much faster than MSM.

The algorithm for SML proceeds as follows. Choose initial values for the coefficients $(\tilde{\alpha}_0, \tilde{\beta}_0, \gamma_0)$, and sample a large number of draws from the assumed density $f(\upsilon)$ for each observation. Using the initial values and random draws, calculate the conditional choice probability from equation (10) for each observation, for each draw from $f(\upsilon)$. Approximate the integral in equation (11) by summing over the υ draws for each observation. Let R be the total number of draws from $f(\upsilon)$. Then the simulated unconditional choice probability is:

$$\bar{P}_{ij} = \frac{1}{R} \sum_{r=1}^{R} \hat{P}_{ij}(\alpha^r, \beta^r, \gamma^r, \kappa^r) \tag{15}$$

Note that $\bar{P}_{ijk}$ is strictly positive, so lnP_{ij} is always defined. Therefore we can construct the simulated log likelihood function, as:

$$SLL = \sum_{i=1}^{I} \sum_{j=1}^{J} d_{ij} ln \bar{P}_{ij} \tag{16}$$

where $d_{ij} = 1$ if i chose j, and zero otherwise. See Train [18] for more details.

7 Estimation Results & Identification

To reiterate, the objective is to estimate the coefficients $\theta = [\tilde{\beta}, \tilde{\alpha}, \gamma, \kappa, \pi]$ from (7) by maximizing log-likelihoods from equations (14) or (16). Estimating (14) yields the first four parameters of θ; π is only relevant to the mixed logit model that culminated in equation (16). I now describe the variables included in the regressions, then show results and discuss identification.

7.1 Discussion of Variables & Summary Statistics

Variables contained in the data that are included in the observed facility characteristics vector, X_j are: Capacity, measured in number of beds; scope, measured in the number of different procedures a facility performs each year; and type, which is a binary variable that equals one if the facility is an ASC. Variables included in the observed patient characteristics vector, Z_i are age, insurance type, and a dummy variable that equals one if the patient has an additional procedure performed besides the principal procedure.[8] Time-to-travel, T_{ij}, gives the number of minutes 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. Suffice it to say, if any unobserved variables are correlated with included variables, then estimated coefficients will be biased.

Note what is not included in the observed facility characteristic vector: Price. The omission of price is partly a strategic decision, and partly an imposed constraint of the data set. Strategically, the relevant issue is how greatly price factors into demand. If price was the major decision variable, then its omission would almost render useless the demand estimation exercise. I argue that it is not. That said, if a price variable was available, I would use it. The price that would theoretically pertinent to consumers' choices is the final price

[8] 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.

patients pay, after co-pays, deductibles and insurance factor in. Unfortunately, the data do not include such information, but rather only the total charge (list price) for the service, therefore I am constrained.

Estimation is further constrained computationally, given the way that I constructed the dataset. What appears in the data are patients' choices. But to run a logit estimation specification, I must know patients' non-choices. Non-choices are the facilities in patients' choice sets that are not frequented. To generate non-choices, I use the counterfactual notion that a patients' choice set includes all facilities in the entire state; I rectangularize the data set, and create an observation for each facility for each patient. In theory, a patient could live in Miami, but choose a facility on the opposite side of the state, say in Jacksonville. A rich counterfactual like this is possible partly because of the time-to-travel variable, which I have for every potential patient-facility match. Generating counterfactual prices for patients' no-choices would be next to impossible, given the tremendous price discrimination in the market and therefore the tremendous patient-price-specifity. For this additional reason, I choose to omit price. As will be discussed in the identification section below, the omission should not bias estimates when fixed effects are included.

In terms of interactions, I allow all patient characteristics to interact with two variables: the time-to-travel variable and the dummy for facility type (ASC, or hospital). Only the dummy for whether has additional procedures is permitted to interact with scope. No patient characteristic is interacted with capacity, making the implicit assumption that capacity is not a valued characteristic for any other reason then it provides immediate availability. I do interact time-to-travel with the dummy for facility type, just to connect to the findings of the reduced form spatial regressions from section 4.

Table 2 shows the basic summary statistics for the included variables. The summary statistics are broken down by facility type – ASC statistics are listed in column one and hospital statistics in column two. As expected, ASCs are smaller in scope and capacity relative to hospitals, and perform fewer procedures on average per period. In terms of characteristics of patients who frequent each type of facility, ASC patients are older on average (60.8 years versus 54 years), less likely to have additional procedures performed (66 percent versus 27 percent), and more likely to be Medicare patients (46.8 percent versus 36.8 percent). The striking disparity between ASC and hospital patients' characteristics underline the need for a model with interactions between patient and facilities variables.

These summary statistics describe the data when all procedures are aggregated together, rather than considered separately. However, the composition and number of patients that each type of facility receives may differ greatly between procedures. To account for these differences, all econometric specifications stemming from the theoretical model are run on ten different procedural groups, classified primarily by body part. The groups are: breast procedures, colon procedures, ear, nose & throat procedures, eye procedures, foot procedures, gastroenterological procedures, hernia procedures, gynecological procedures, orthopedic procedures, and urological procedures.

I create another table of summary statistics, table 3, identical to the first except that it compares summary statistics for three of the ten procedural groups only. The rest of the groups' summary statistics can be found at (www.uchicago.edu/home/˜eweber). Note the main differences between the procedural groups: Eye procedural patients (mostly cataracts) tend to be older, Medicare patients compared with the privately insured and slightly younger patients who are having colon (mostly colonoscopies) and foot (bunion or hammertoe) procedures. Patients having foot procedures are very likely to have an additional procedure done concurrently. The characteristics of the facilities performing these procedures also vary slightly.

Groups are used to simply the analysis. More than 4,000 unique procedures appear in the data, and as can be seen in Figure 3, the distribution of the (log) number of each procedure performed is highly right-skewed – a few procedures account for the bulk of demand. Groups were also created because competition happens on a procedural level, since that is corresponding level at which choices are made (see footnote 7, and therefore it is the level at which estimates are structurally interpretable.

I construct and choose which procedural groups to use in the following way: First, for each year, I rank each procedural code (also known as common procedural terminology codes, or CPT codes) based on the raw counts.[9] Second, I identify annual top-100 ranked procedures. There are 126 distinct procedures that fall into the top-100 category between 1998 and 2004. Of these, I keep only 42 procedures, which are the ones continuously ranked in the top-100 for all seven years. Finally, I eliminate procedures for which facility-types other than hospitals and ASCs – like radiation facilities and lithiotropsy centers – have large market shares. The precise rule is to keep procedures for which hospitals and ASCs together account for more than 95 percent of the total market, and for which both ASCs and hospitals have strictly positive market shares.

The 42 retained procedures are listed in table 4, along with their frequencies. As can be seen there, many of the procedure codes are only nominally different, and can be classified into approximately ten broad groups, mostly based on body area. Each group contains between two and six unique procedural codes. These are the groups used for analysis. In

[9] $\frac{N_{pt}}{N_t}$ = Fraction of statewide procedures performed in year-t that are of type-p. Ordering the fractions over all p procedural codes yields rank. Ranks are computed over the entire year instead of quarterly to reduce variance in the ranks of rarer procedures and to account for seasonality.

total, the procedures kept account for about 45 percent (7.4 million) of the total data sample, echoing the right-skewed distribution from Figure 3.

7.2 Results: Logit with Interactions

Table 5 shows results from the simple logit with interactions between facility and patient statistics. To avoid cluttering the table, I show the results only for five of the ten procedural groups. However, statements made in following discussion apply to all ten groups, no exceptions. Results from regressions that do not appear in the table can be found at (www.uchicago.edu/home/˜eweber).

The time-to-travel variable is significant and negative in all regressions, ranging from -0.074 to -0.133, which suggests that longer distances between facilities and patients decrease choice probabilities, as expected. Taking the eye regression as an example, it reads that increasing the distance between a patient and a facility by one percent decreases the probability the patient chooses that facility by -0.0003. In addition, the impact that travel time has on patients varies across procedures, supporting the hypothesis that procedures are distinct products. The impact of time-to-travel changes with patient age, as indicated by the negative and significant coefficients on the interaction between those two variables. Finally, having additional procedures done implies that patients are likely to travel further.

Also as expected, the coefficients on scope are all positive (and significant), varying between 0.001 and 0.0028; the interaction between scope and the dummy variable for whether the patient has additional procedures performed is positive, too, further strengthening the likelihood of choosing a facility that offers more services.

Coefficients on the interaction between insurance dummies and the dummy denoting whether the facility is an ASC are generally negative, though the magnitude and significance of these coefficients can vary a lot depending on the procedure being done. Comparing across procedures, however, it is apparent that choosing an ASC is least likely for patients with Medicaid (largest negative impact), or those who self-pay, relative to patients with Medicare or Private insurance (smallest negative impact). As insurance is correlated with both income and total facility charges, it may be proxying for the final price that consumers pay, which would explain both the sign and relative magnitudes of the estimates.

Interpreting coefficients on the interaction between travel time and insurance is similarly difficult. In general, these coefficients are small and positive, though not always significant. They imply that a patients with insurance are more inelastic with respect to travel time. This seems logical if the price of the procedure without insurance outweighs the cost of traveling to a facility that honors the patient's insurance. Moreover, the interaction coefficients are largest for Medicaid and self-insured patients, implying this effect is largest for them. Again, this makes sense if we believe those customers are most price sensitive.

Finally, comparing across columns, it is interesting to note the pattern of significances on the interacted coefficients: It is correlated with procedure type. This harkens back to the discussion in section 4 about R-squareds, where it was hypothesized that the extent to which travel-time influences facility purchase decisions (vis-a-vis other variables) depends on the variance of product heterogeneity. The more product heterogeneity apart from facility location, the less of impact travel-time should have. The significance pattern found in these regression suggests another possibility: a greater variation in patient characteristics across procedure groups also reduces the relevance of travel-time relative to other product characteristics. Again, this adopts particular significance if we believe insurance is correlated with the final price patients pay, or with income.

Identification

To obtain consistent estimates for either the logit with interactions or the mixed logit models, it is necessary that ϵ_{ij} be independent from the decision variables included in the utility function in equation (7). This will not happen 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 facility characteristics that are observed by consumers and influence their decisions, but are unobserved by the econometrician. In estimation, the fixed effect, δ_j, was included to alleviate this problem; it captures all omitted facility-specific variables represented by ξ. Omitted patient characteristics would similarly be a problem if they were correlated with included variables. In the mixed logit specification, the υ error term accounts for unobserved patient characteristics.

Assuming all patient characteristics are observed, including facility fixed effects in both the simple logit with interactions model and the mixed logit model buys simple and consistent estimation of the c x m matrix γ. Identification comes off variation in consumer types who choose the same facility. If there is unobserved patient heterogeneity, then estimates of γ will be biased despite the inclusion of fixed effects.

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, $\tilde{\beta}$ is not identified from this approach for time invariant facility characteristics, and does not appear in table 5.

This approach is in the spirit of Berry, Levinsohn and Pakes [16], Petrin [13], Nevo [12], among others. They, however, obtain $\hat{\delta}_j$ using a method of moments that picks $\hat{\delta}$ to minimize the distance between predicted shares, $\hat{s}_j$ and actual shares, s_j. They embed this routine in the likelihood iteration – for every parameter estimate that solves the maximum likelihood problem, they re-estimate $\hat{\delta}_j$ – a very slow and cumbersome process. Given that I have micro-data, and a lot of it, I can use the simpler fixed effects approach, effectively adding a dummy for each facility in my data. More important, I can shun complicated techniques because I am not trying to recover estimates from $\tilde{\beta}$, which is a typical goal of papers in the literature. Here, the variable of interest is time-to-travel, which is identified because there is exogenous variation in patient location vis-a-vis facilities.

The other important element of identification concerns whose utility function the estimates indentify. In the model described above, healthcare facilities' consumers are assumed to be only patients, even though physicians also have some preference over the facility-patient match (and presumably some influence over patients' choices). Therefore, the model omits some variables that belong to the physician. It does not entirely omit physicians' decision variables because some of physicians' decisions are based on patient characteristics (health, insurance, etc.) that are included in the data.[10] In that way, too, patient demographics proxy for physician demand. But we cannot interpret coefficients on these variables as coming only from patient preferences, because they are a mix of patient utilities and physician utilities.

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. Moreover, the criteria 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 identify physician-specific preferences for ASCs would require incorporating physician-specific characteristics, such as physician location, or practice-type, into the regression. For instance, 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.

7.3 Substitution Matrix

Using the logit estimates, I create substitution matrices (one for each procedure group) that describe how patients substitute between facilities, given changes in one facility's location. The matrix is constructed from equation (13). A subset of the matrix for foot procedures is shown in the top panel of table 6. The bottom panel of the table lists the distance

[10] Insurance is included, and health is proxied for with age.

between facilities for the same subset. The diagonal of the substitution matrix gives the own-time elasticity. For instance, if facility eight increases its distance from all consumers by one percent, then demand for its product would fall 0.0028 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 facility two increases its distance from all patients by one percent, then demand for facility six would increase 0.000013 percent.

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 for two reasons: First, it meets the expectation that two facilities that are closer together in space are indeed closer substitutes. Comparing the upper and lower panels of table 6, it is possible to eyeball this correlation; the formal statistic for the correlation between the two matrices is -0.277, and is significant. Second, 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.

Gaynor and Vogt [5] do this, too, except their matrix is based on price-elasticities instead of time-elasticites. As a price variable, they use the list-price, or charge, that hospitals cite payers. List-prices are inflated; they are not the final prices that patients face. If list-prices are proportional to final-prices across all patients, then their method is valid. Otherwise, their results will not reflect substitution patterns accurately.

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 the 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. 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:

$$\Delta E(CS_{ij}) = \frac{1}{\alpha_i}\Big(E_\epsilon[\max_{j\in A\cap H}(V_{ij}+\epsilon_{ij})] - E_\epsilon[\max_{j\in H}(V_{ij}+\epsilon_{ij})]\Big) \tag{17}$$

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, albeit one measured in minutes. The final steps are to translate minutes into money terms, and aggregate (17) 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 [17], who show that if ϵ is distributed type-I extreme value, then

$$E_\epsilon[\max_{ij}(V_{ij}+\epsilon_{ij})] = ln\Big(\sum_{j}^{J} e^{V_{ij}}\Big) + C \tag{18}$$

where C is an unknown constant that is irrelevant from a policy perspective. Therefore, (17) becomes

$$\Delta E(CS_{ij}) = \frac{1}{\alpha_i}\Big(\ln\sum_{j\in A\cap H} e^{V_{ij}} - \ln\sum_{j\in H} e^{V_{ij}}\Big) \tag{19}$$

which is what I take to the data.

A similar exercise was done by Petrin [13] for the introduction of minivans, and by Gentzkow [6] for the introduction of online newspapers as new products.

Results

The results from the welfare calculation are shown in table 8, and give the welfare gain (in minutes) to 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 column, for instance, we see that eye patients lose 1,902,372 minutes, or 31,706.2 hours of surplus. Attributing an average hourly wage of \$15.70[11], therefore, would imply that total surplus lost from the elimination of ASCs is \$497,787 . This is the amount consumers would be willing to pay not to close all ASCs.

9 Conclusions

This paper explores the shape and structure of the demand function for healthcare facilities. I find differences in the spatial concentration of demand around ASCs versus the spatial concentration of demand around hospitals. Quantile regressions suggest that the median (upper-percentile) hospital gets more of its business from its immediate surroundings as compared with the median (upper-percentile) ASCs.

Structural estimates also find that time-to-travel between a facility and a patient is a significant variable in demand. The degree to which travel-time matters, however, depends on the type of procedure under consideration, and on demographic characteristics of the patient. These conclusions are based on a discrete choice multi-nomial logit model of demand with interactions between facility and patient characteristics. Using the logit results, I estimate a substitution matrix based on the cross-time elasticity, and find asymmetric substitution patterns between facilities. Also with the logit results, I calculate the welfare effects of a hypothesized counterfactual in which all ASCs are removed from the choice sets. Welfare effects are measured in time-cost units, and converted to money-units using estimates of patients' values of time.

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10 Appendix 1: Figures & Tables

Figure 1: Spatial Demand Function, ASCs, All Procedures

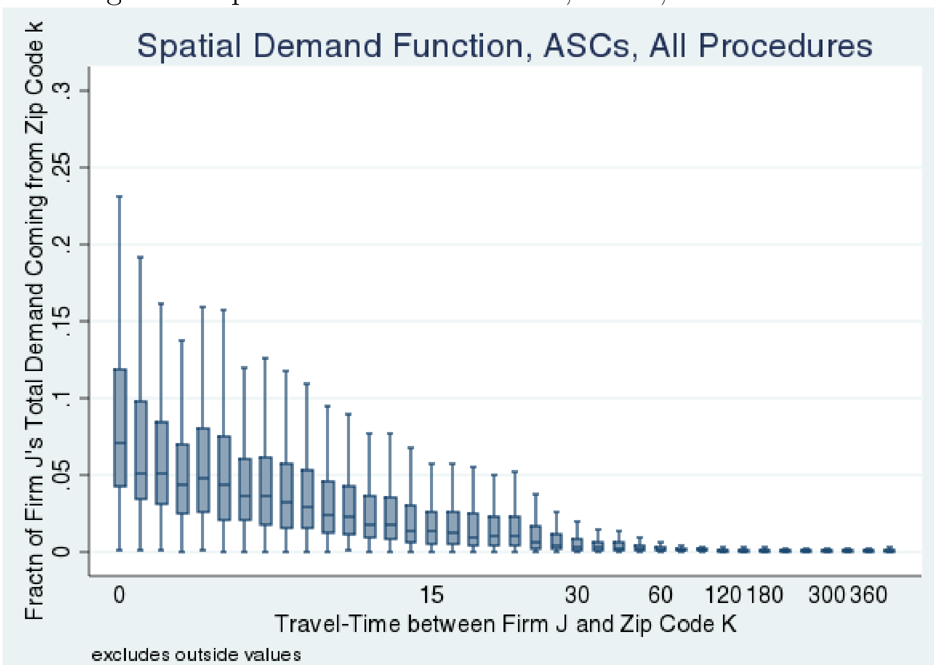

Figure 2: Spatial Demand Function, Hospitals, All Procedures

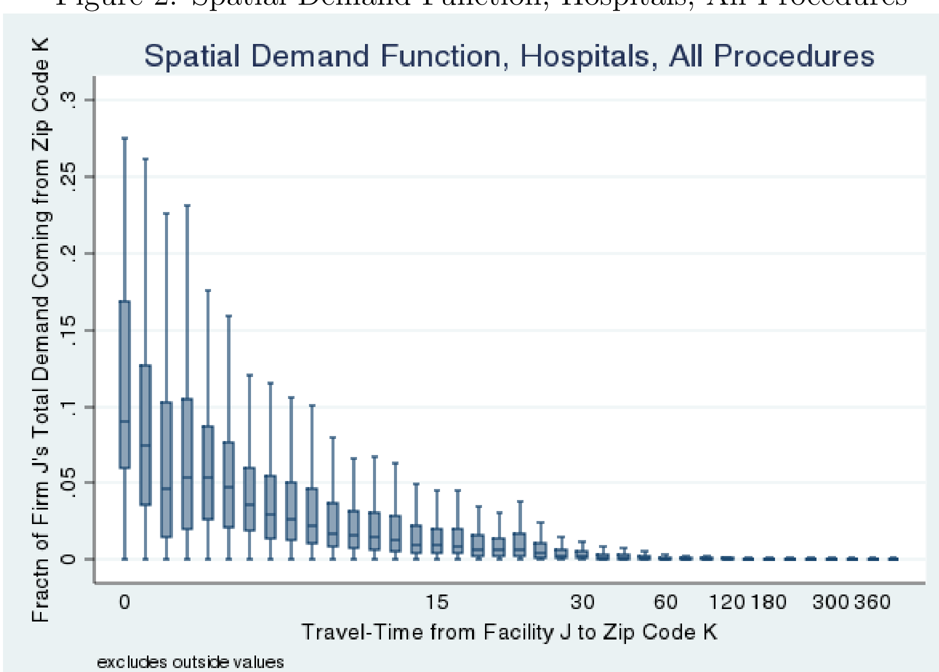

Table 1: Quantile Regression: Dependent Var = (Median) Fraction of Facility j's Total Procedures that Come from Zip Code k

	ASC										
	Breast	Colon	ENT	Eye	Foot	Gastro	General	OB/Gyn	Orthopedic	Urological	All
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Indep. Var.	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)
Log, Time-to-Travel	-0.359	-1.064	-0.351	-1.013	-0.326	-0.904	-0.310	-0.201	-0.627	-0.900	-1.131
	(-29.61)	(-362.85)	(-41.32)	(-233.74)	(-35.00)	(-334.63)	(-30.33)	(-17.45)	(-123.47)	(-87.74)	(-495.68)
Constant	-1.942	-1.111	-1.825	-1.3744	-1.741	-1.285	-1.757	-1.948	-1.779	-0.695	-1.322
	(-50.36)	(-81.17)	(-49.96)	(-91.24)	(-53.55)	(-87.00)	(-49.58)	(-52.48)	(-105.26)	(-19.51)	(-129.07)
N	18,983	125,048	22,471	138,542	25,982	93,553	20,626	13,408	71,785	29,146	400,329
R-squared	0.05	0.30	0.04	0.24	0.05	0.27	0.05	0.02	0.15	0.19	0.3
	Hospital										
	Breast	Colon	ENT	Eye	Foot	Gastro	General	OB/Gyn	Orthopedic	Urological	All
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Indep. Var.	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)
Log, Time-to-Travel	-0.486	-0.913	-0.427	-0.703	-0.24	-0.694	-0.363	-0.276	-0.494	-0.559	-1.260
	(-105.44)	(-231.80)	(-54.13)	(-115.19)	(-23.70)	(-220.22)	(-75.23)	(-45.04)	(-134.55)	(-113.56)	(-508.87)
Constant	-1.931	-1.625	-1.557	-1.938	-1.678	-1.979	-2.100	-2.188	-2.092	-1.706	-1.477
	(-120.67)	(-99.00)	(-54.95)	(-81.38)	(-53.29)	(-168.96)	(-131.59)	(-107.51)	(-136.57)	(-99.74)	(-121.87)
N	67,547	156,478	38,286	57,429	20,752	132,274	62,831	44,836	88,019	72,625	434,710
R-squared	0.10	0.21	0.07	0.14	0.02	0.17	0.07	0.03	0.11	0.12	0.34

Note: Standard Errors bootstrapped.

Note: Time Fixed Effects included in all regressions.

Table 2: Summary Statistics

	ASCs (Number of facilities = 354) (Number of obs = 6,507,403)			Hospitals (Number of facilities=211) (Number of obs=10,681,119)		
Variable	**Mean**	**Std Dev**	**N**	**Mean**	**Std Dev**	**N**
Facility Characteristics						
Scope[a]	165.8	162.6	1,785	561.4	298.5	1,383
Capacity (beds) [b]	2.8	1.6	354	261.2	212.23	211
Number of primary procs performed[c]	963.6	671	6,753	1956.6	1778.2	5,459
Patient Characteristics						
Age	60.8	18.7	6,507,403	54.0	21.4	10,681,119
Add'l Procs	N=1,760,703 (%=27.1)			N=7,112,152 (%=66.6)		
Medicare	N=3,044,606 (%=46.8)			N=3,934,321(%=36.8)		
Medicaid	N=149,725 (%=2.3)			N=802,243 (%=7.4)		
Private	N=2,738,130 (%=42.1)			N=4,887,229 (%=45.8)		
Government	N=270,512 (%=4.2)			N=450,871 (%=4.2)		
Self	N= 179,235 (%=2.8)			N=376,234 (%=3.5)		

a: Calculated for each facility, for each year.

b: Collected from AHCA. Only one observation per facility, dated from 2008.

c: Gives the number of procedures a facility performs. Calculated for each facility, for each quarter.

Figure 3: Distribution of CPT Codes

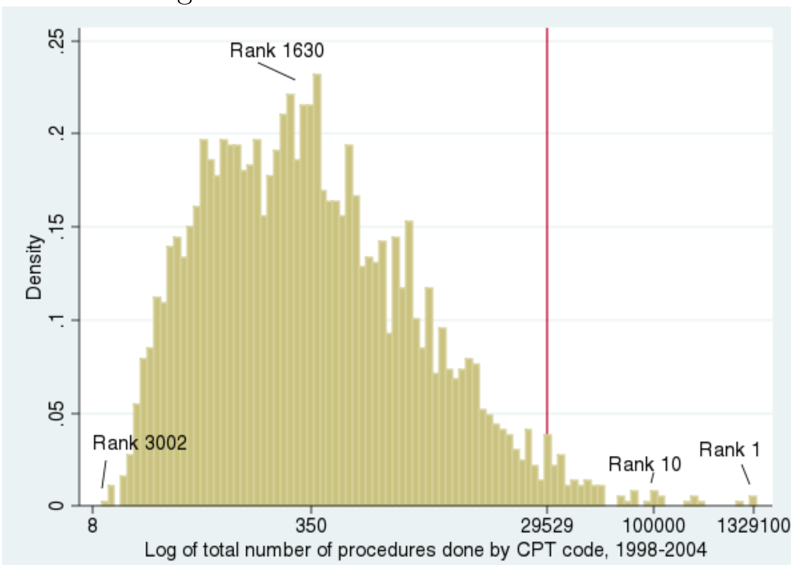

Table 3: Summary Statistics: Colon, Eye and Foot Procedures

	Colon					
	ASCs			Hospitals		
	(Number of fac =200) (Number of obs = 1,432,267)			(Number of fac=204) (Number of obs=1,310,628)		
Variable	**Mean**	**Std Dev**	**N**	**Mean**	**Std Dev**	**N**
Facility Characteristics						
Scope[a]	200.6	173.0	973	572.5	294.3	1,341
Capacity (beds) [b]	3.2	1.84	200	268.6	211.9	204
Number of observations per facility[c]	399.5	370.0	3,595	250.2	245.3	5,238
Patient Characteristics						
Age	62.6	13.6	1,432,267	61.5	14.5	1,310,628
Add'l Procs	N=316,702(%=22.0)			N=637,493(%=48.6)		
Medicare	N=616,347(%=42.9)			N=554,526(%= 42.3)		
Private	N=757,833(%=52.8)			N=666,669(%=50.9)		

	Eye					
	ASCs			Hospitals		
	(Number of fac =203) (Number of obs = 1,561,130)			(Number of fac=158) (Number of obs=282,279)		
Variable	**Mean**	**Std Dev**	**N**	**Mean**	**Std Dev**	**N**
Facility Characteristics						
Scope[a]	208.1	170.0	1,039	635.9	301.9	884
Capacity (beds) [b]	3.3	1.6	203	284.7	203.2	158
Number of observations per facility[c]	399.9	462.4	3,924	88.1	122.7	3,204
Patient Characteristics						
Age	73.5	9.3	1,561,130	72.2	10.5	282,279
Add'l Procs	N=133,419(%=8.5)			N=93,765(%=33.2)		
Medicare	N=1,187,465(%=76.1)			N=206,688(%=73.2)		
Private	N=288,312(%=18.5)			N=54,235(%=19.2)		

	Foot					
	ASCs			Hospitals		
	(Number of fac = 173) (Number of obs = 46,291)			(Number of fac=201) (Number of obs=31,326)		
Variable	**Mean**	**Std Dev**	**N**	**Mean**	**Std Dev**	**N**
Facility Characteristics						
Scope[a]	299.5	140.2	841	608.3	281.2	1,206
Capacity (beds) [b]	3.7	1.7	173	271.4	212.0	201
Number of observations per facility[c]	15.7	16.2	2,956	7.9	12.9	3,942
Patient Characteristics						
Age	55.3	16.3	46,291	53.6	16.4	31,326
Add'l Procs	N=29,657 (%=64.1)			N=24,631 (%=78.6)		
Medicare	N=14,432 (%=31.2)			N=8,689(%=27.7)		
Private	N=28,181 (%=60.9)			N=20,598 (%=65.8)		

a: Calculated for each facility, for each year.

b: Collected from AHCA. Only one observation per facility, dated from 2008.

c: Gives the number of procedures a facility performs. Calculated for each facility, for each quarter.

Table 4: Current Procedural Terminal (CPT) Codes Used in Analysis

Rank	Grouping	Description	CPT CODE	Number
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	1,328,448
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	1,184,276
3	GASTRO	Upper gastrointestinal endoscopy including esophagus, stomach, and either the duodenum and/or jejunum as appropriate; with biopsy, single or multiple	43239	959,438
4	COLON	Colonoscopy, flexible, proximal to splenic flexure; with removal of tumor(s), polyp(s), or other lesion(s) by snare technique	45385	474,950
5	COLON	Colonoscopy, flexible, proximal to splenic flexure; with biopsy, single or multiple	45380	435,543
6	EYE	Discission of secondary membranous cataract (opacified posterior lens capsule and/or anterior hyaloid); laser surgery (eg, YAG laser) (one or more stages)	66821	427,783
7	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	380,230
8	DIABETES	Debridement; skin, and subcutaneous tissue	11042	230,952
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	197,705
10	ORTHO	Arthroscopy, knee, surgical; with meniscectomy (medial OR lateral, including any meniscal shaving)	29881	167,619
11	HERNIA	Repair initial inguinal hernia, age 5 years or older; reducible	49505	135,549
12		Tympanostomy (requiring insertion of ventilating tube), general anesthesia	69436	135,474
13	BREAST	Excision of cyst, fibroadenoma, or other benign or malignant tumor, aberrant breast tissue, duct lesion, nipple or areolar lesion (except 19300), open, male or female, one or more lesions	19120	127,135
14	ORTHO	Neuroplasty and/or transposition; median nerve at carpal tunnel	64721	110,415
15	UROL	Cystourethroscopy (separate procedure)	52000	103,007
16	BREAST	Excision of breast lesion identified by preoperative placement of radiological marker, open; single lesion	19125	79,284
17	ENT	Tonsillectomy and adenoidectomy; younger than age 12	42820	73,700
18	COLON	Sigmoidoscopy, flexible; diagnostic, with or without collection of specimen(s) by brushing or washing (separate procedure)	45330	73,400
19		Biopsy of liver, needle; percutaneous	47000	69,273
20	COLON	Colonoscopy, flexible, proximal to splenic flexure; with ablation of tumor(s), polyp(s), or other lesion(s) not amenable to removal by hot biopsy forceps, bipolar cautery or snare technique	45383	65,905
21	ORTHO	Arthroscopy, knee, surgical; with meniscectomy (medial AND lateral, including any meniscal shaving)	29880	63,988
22		Debridement; skin, partial thickness	11040	59,794
23	GASTRO	Upper gastrointestinal endoscopy including esophagus, stomach, and either the duodenum and/or jejunum as appropriate; with insertion of guide wire followed by dilation of esophagus over guide wire	43248	59,604
24	UROL	Cystourethroscopy, with ureteral catheterization, with or without irrigation, instillation, or ureteropyelography, exclusive of radiologic service;	52005	59,561
25		Debridement; skin, full thickness	11041	57,713
26	UROL	Biopsy, prostate; needle or punch, single or multiple, any approach	55700	57,482
27	GYN	Dilation and curettage, diagnostic and/or therapeutic (nonobstetrical)	58120	54,480
28	ORTHO	Arthroscopy, shoulder, surgical; decompression of subacromial space with partial acromioplasty, with or without coracoacromial release	29826	50,241
29		Removal of implant; deep (eg, buried wire, pin, screw, metal band, nail, rod or plate)	20680	49,611
30	GYN	Treatment of missed abortion, completed surgically; first trimester	59820	47,488
31		Introduction of needle or intracatheter, vein	36000	46,005
32		Septoplasty or submucous resection, with or without cartilage scoring, contouring or replacement with graft	30520	45,096
33	ORTHO	Arthroscopy, knee, surgical; debridement/shaving of articular cartilage (chondroplasty)	29877	44,079
34	UROL	Circumcision, surgical excision other than clamp, device, or dorsal slit; older than 28 days of age	54161	38,969
35	FOOT	Correction, hallux valgus (bunion), with or without sesamoidectomy; with metatarsal osteotomy (eg, Mitchell, Chevron, or concentric type procedures)	28296	38,116
36	ENT	Tonsillectomy, primary or secondary; age 12 or over	42826	37,343
37	FOOT	Correction, hammertoe (eg, interphalangeal fusion, partial or total phalangectomy)	28285	36,099
38	ORTHO	Tendon sheath incision (eg, for trigger finger)	26055	35,699
39		Debridement; skin, subcutaneous tissue, and muscle	11043	35,319
40	UROL	Cystourethroscopy, with insertion of indwelling ureteral stent (eg, Gibbons or double-J type)	52332	34,588
41	UROL	Cystourethroscopy, with calibration and/or dilation of urethral stricture or stenosis, with or without meatotomy, with or without injection procedure for cystography, male or female	52281	33,361
42	HERNIA	Repair umbilical hernia, age 5 years or older; reducible	49585	29,529

Table 5: Logit with Interactions Regression: Dependent Var (0/1) = Choice of facility k

Indep. Var.	Colon Coeff. (Std. Error)	Eye Coeff. (Std. Error)	Foot Coeff. (Std. Error)	Orthopedic Coeff. (Std. Error)	Urology Coeff. (Std. Error)
(Log) Time-to-Travel ($\tilde{\alpha}$)	-1.824**	-1.666**	-2.105**	-2.061**	-1.806**
	(0.013)	(0.129)	(0.098)	(0.107)	(0.227)
Scope ($\tilde{\beta}_1$)	0.001**	0.002**	0.003**	0.003**	0.003**
	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.001)
Time-to-travel X Dummy, ASC ($\tilde{\beta}_3$)	0.068	0.116	0.017*	0.010	-0.301*
	(0.088)	(0.049)	(0.086)	(0.077)	(0.140)
Interactions: Scope					
Dummy, Add'l Procs (γ_{11})	0.0005**	0.001**	0.0003	0.0005**	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0003)
Interactions: Dummy, ASC					
Medicare (γ_{12})	0.024	-0.621	-1.346**	-1.547**	0.039
	(0.397)	(0.397)	(0.346)	(0.308)	(0.744)
Medicaid (γ_{22})	-0.441	-0.737	-1.940**	-1.948**	-0.933
	(0.447)	(0.476)	(0.419)	(0.387)	(0.700)
Private (γ_{32})	0.194	-0.499	-1.417**	-1.323**	-0.241
	(0.404)	(0.411)	(0.327)	(0.304)	(0.711)
Government (γ_{42})	-0.077	-1.016	-1.390**	-1.429**	-0.683
	(0.449)	(0.615)	(0.411)	(0.328)	(0.740)
Self (γ_{52})	-.609	-0.343	-1.564**	-1.497**	-0.783
	(0.476)	(0.471)	(0.388)	(0.392)	(0.834)
Dummy, Add'l Procs(γ_{62})	-1.080**	-1.144**	-0.636**	-0.946**	-2.032**
	(0.126)	(0.285)	(0.153)	(0.109)	(0.287)
Age (γ_{72})	0.012**	0.011**	0.005*	0.007**	0.010
	(0.003)	(0.003)	(0.002)	(0.002)	(0.007)
Interactions: (log) Time-to-Travel					
Medicare (κ_1)	-0.068	0.224*	0.288**	0.327**	0.021
	(0.114)	(0.090)	(0.066)	(0.086)	(0.214)
Medicaid (κ_2)	0.170	0.225*	0.355**	0.401**	0.056
	(0.112)	(0.096)	(0.081)	(0.085)	(0.196)
Private (κ_3)	-0.036	0.177	0.294**	0.288**	0.009
	(0.117)	(0.093)	(0.065)	(0.087)	(0.211)
Government (κ_4)	0.126	0.302*	0.282**	0.330**	0.072
	(0.120)	(0.0131)	(0.072)	(0.088)	(0.204)
Self (κ_5)	0.157	0.182	0.305**	0.335**	0.084
	(0.119)	(0.102)	(0.092)	(0.099)	(0.226)
Dummy, Add'l Procs (κ_6)	0.091**	0.133**	0.104**	0.066**	0.214**
	(0.032)	(0.050)	(0.036)	(0.023)	(0.055)
Age (κ_7)	-0.002**	-0.004**	-0.001**	-0.001**	0.002
	(0.0005)	(0.0007)	(0.0003)	(0.0004)	(0.001)
N	2,913,509	2,870,619	2,852,797	2,888,488	2,756,813

Note: Standard errors clustered at facility level
Note: Facility and time fixed effects included in all specificiations.
**, Significant at 1%
*, Significant at 5%

Table 6: Corresponding Subsets of Substitution & Distance Between Facilities Matrices: Foot Surgery

Substitution Matrix (Cross-Time Elasticities)

Facility	1	2	3	4	5	6	7	8
1	-0.2803	0.0001	0	0	0	0	0.0001	0
2	0	-0.2634	0	0	0	0.0001	0.0046	0
3	0	0	-0.2449	0	0	0	0	0
4	0	0	0	-0.1603	0.0001	0	0	0
5	0	0	0	0	-0.1502	0	0	0
6	0	0.0013	0	0	0	-0.2875	0.0012	0
7	0	0.0023	0	0	0	0.0001	-0.3266	0
8	0	0	0	0	0	0	0	-0.3115

Distance Between Facilities Matrix (Minutes)

Facility	1	2	3	4	5	6	7	8
1	0	106	125	533	610	158	81	217
2	106	0	228	578	655	57	25	304
3	125	228	0	420	497	198	203	104
4	533	578	420	0	142	525	590	330
5	610	655	497	142	0	602	667	415
6	158	57	198	525	602	0	76	251
7	81	25	203	590	667	76	0	292
8	217	304	104	330	415	251	292	0

Table 7: Summary: Substitution Matrix

Group	**Colon**	**Eye**	**Foot**	**Ortho**	**Urol**
Correlation	-0.254	-0.139	-0.246	-0.293	-0.267
(btw. distance and cross-elasticity)					
Avg. Own-Elasticity					
ASCs	-0.025	-0.0283	-0.0271	-0.0193	-0.0223
hospitals	-0.645	-0.821	-0.919	-0.679	-0.176
Avg. Cross-Elasticity (conditional on facilities 25-30 minutes apart)					
Between hospitals	0.000189	0.0000199	0.000122	0.000345	0.0105
Between ASCs	0.0000123	0.0000188	0.0000184	0.0000228	0.000282
Between ASC & hospital	0.0000104	0.0000126	0.0000185	0.0000198	0.0105

Table 8: Welfare Calculation (by procedural group)

	Colon	Eye	Foot	Orthopedic	Urological
Welfare (in minutes)	689,755.6	1,902,847.3	699,722.5	550,054.4	384,195.6