Physician Market Power and Medical-Care Expenditures*

Abe Dunn and Adam Hale Shapiro†

January 13, 2012

Abstract

Physicians play a critical role in determining medical-care expenditures. In this study, we empirically assess the degree to which physicians exploit their bargaining leverage over insurance carriers as a means to raise service prices. We also examine the degree to which these potentially higher payments may translate into different levels of service utilization. We find that physicians are able to translate bargaining leverage into both higher fees and higher service utilization. *Ceteris paribus*, a cardiologist with high market power (concentration in the 90th percentile) will charge 26 percent higher prices and perform 24 percent more services than a cardiologist with low market power (concentration in the 10th percentile). The corresponding orthopedist will charge 29 percent higher prices and perform 6 percent more services. We provide evidence that the effect of bargaining leverage on service utilization may be explained by physicians responding to the negotiated service prices.

*We thank Seidu Dauda and Eli Liebman for excellent research assistance.

†Bureau of Economic Analysis

1 Introduction

Physicians play a critical role in determining medical-care expenditures. By acting as the patient's health-care consultant, as well as the medical service provider, they can control the quantity of services provided to the patient.[1] Additionally, by flexing their bargaining muscle, they can also potentially raise the fees they charge to insurance carriers. This puts physicians in a unique position of potentially being able to control both the price and the utilization of services—the two components of medical-care expenditures. This control over expenditures is compounded by the possibility that the fee-for-service arrangement between physicians and health insurance carriers may alter the physician's incentives to provide services. Specifically, all else equal, a higher service price (that is, fees) may incentivize the physician to increase service utilization (Hickson et. al. (1987), Hemenway Et. al. (1990), Gruber, Kim, and Mayzlin (1999), Grant (2008), Decker (2009)). In this study, we empirically assess the degree to which physicians exploit their bargaining leverage over insurance carriers as a means to raise service prices. We also examine the degree to which these potentially higher payments may translate into different levels of service utilization. These effects are identified through the large variation in expenditures and prices observed across markets (Dunn, Shapiro, and Liebman (2011)).

Examining how physicians' market power affects prices and utilization may be an important step in assessing the cause of overall medical-care spending variation. Numerous studies have documented large increases in overall medical-care expenditures over the last few decades, which now account for more than 17 percent of GDP.[2] Growth in medical expenditures has been accompanied by a trend toward consolidation across health care providers.[3] Thus, it is conceivable that long-run trends in consolidation have contributed to the growth in medical-care expenditures. Furthermore, potential concerns have been raised by some industry experts and antitrust authorities that the recent health care reforms enacted in 2010 may accelerate consolidation because they encourage greater cooperation among providers.[4] Understanding how physician market power affects medical-care

[1]See, for example, Sirovich, Gallagher, Wennberg, Fisher (2008).

[2]See Aizcorbe and Nestoriak (2011), Chernew, Hirth, and Cutler (2009), Chernew, Baiker, and Hsu (2010), Cutler and Ly (2011), Dunn, Liebman, Pack and Shapiro (2010).

[3]Gaynor and Haas-Wilson (1999), Smart (2006) and Liebhaber (2007).

[4]Both the Federal Trade Commission (FTC) and Department of Justice (DOJ) have taken different views on the potential impact of recent health care reform. The FTC see consolidation resulting from these reforms as a potential risk that could lead to higher prices, while the DOJ is seen as more receptive to the potential consumer benefits from the proposed reforms (Thomas Catan (2011) "This Takeover Battle Pits Bureaucrat vs. Bureaucrat." *The Wall Street Journal*). Other health economists, interest groups,

spending may give important insights about the potential outcome of this policy reform.

While there has been an extensive line of research regarding hospitals' ability to leverage their market power into higher fees,[5] there has been very little empirical research regarding physicians' bargaining power.[6] Physicians are distinct from hospitals on important dimensions relating to medical-care expenditures. Specifically, the incentives of physicians to affect their own revenue by shifting services provided to patients is distinct from hospitals because hospitals are usually paid on a disease basis.[7] As physicians are usually paid on a fee-for-service basis, earning additional revenue for every procedure performed, their incentives may be aligned to respond to price changes by shifting the utilization of services.

A major reason for the lack of research regarding physician bargaining has been the dearth of historical granular data covering physician firms. To add fuel to the fire, one must also be able to accurately link physician-firm data to detailed medical-care expenditure information. This study is unique in this regard as we are able to link together a wealth of historical data on physician firms with a comprehensive data set on commercial payments. The physician data is from the SK&A© physician database and includes information on the firm size, specialty, and specific geographic coordinates of over 95 percent of physician firms in the United States. This highly detailed data enables us to construct precise physician concentration measures, specific to a particular geographic area. We link these concentration measures with commercial health insurance claims from the MarketScan® Research Database from Thomson Reuters. The data includes individual patient health claims for several million privately covered individuals covering thousands of procedures and hundreds of diseases and types of health plans across the entire U.S. The sheer size of this data is a bit daunting, but proves to be important for identification purposes because there is an enormous degree of heterogeneity in types of health service providers, proce-

and politicians have raised some concerns that the new health care law may spur additional consolidation and harm consumers (America's Health Insurance Plans (AHIP) (2011), Berenson, Ginsburg, and Kemper (2010), and "Hearing on Health Care Industry Consolidation" September 2011).

[5]See Noether (1988), Dranove, Shanley, and White (1993), Lynk (1995), and Keeler, Melnick, and Zwanziger(1999), Town and Vistnes (2001), Capps, Dranove, and Satterthwaite (2003).

[6]Research regarding physician market competition has primarily focused on identifying whether or not physicians actually possess monopoly power. As explained by Gaynor (1995), most of these studies have aimed to infer the presence of market power by searching for monopoly rents and supra-normal returns on investment to education (Sloan 1970, Leffler and Lindsay 1980, Burstein and Cromwell 1985).

[7]It appears that different incentives are at work in hospital markets. Indeed, Dafny (2005) finds that hospitals respond to price changes (diagnosis-specific prices) by "upcoding" patients to diagnosis codes associated with large reimbursement increases.

dures, patient ages, diseases, stages of illness, co-morbidities and plan types.[8] Finally, we link together data from HealthLeaders-Interstudy©, which provides comprehensive information on enrollment for health insurance firms. This allows us to create concentration measures of insurance firms. To simplify our analysis and computation burden, we limit our analysis to cardiologists and orthopedists. We believe these two specialties provide a comprehensive look at the physician market since these are two of the largest specialities and cover a wide spectrum of physicians.[9] Cardiologists represent the broad category of internists treating chronic conditions, while orthopedists represent the broad category of surgeons treating more acute conditions.

This paper employs a unique methodology to study competition that is customized to the features of the physician marketplace and the rich data sources available in this study. First, this paper exploits the detailed micro level data to look at the effects of competition on both service price and utilization at the highly granular patient level. Second, the precise geographic coordinates of physicians are used to build a consistently defined concentration measure that takes into account the distance and travel time of patients to competing doctors in surrounding areas. We refer to this measure as the "Fixed-Travel-Time Herfindahl-Hirshman Index" (FTHHI). Third, using individual patient claims and a program provided by Thomson Reuters that categorizes claims into "episodes" of treatment (called the Medstat Episode Grouper®), we are able to build a uniform measure of the quantity of physician services per episode of treatment. This allows us to study the effects of competition on a consistently defined measure of service utilization, which has not previously been studied. Fourth, a novel instrumental variable strategy is used to address endogeneity concerns. The identification strategy relies on how physician firms and insurance carriers respond to different aggregate demographic variables. Namely, physician firms enter markets with large numbers of elders (especially people over the age of 65) because these are areas with highest demand for medical care. By contrast, commercial insurance firms will not be affected to such a large degree by the size of this population because elder citizens have lower demand for commercial insurance. Instead, insurance carriers enter markets with low unemployment rates because employed people are more likely to purchase commercial insurance. Physician entry is less affected by employment condi-

[8] The payment information used to construct prices in this database are the actual negotiated amounts paid to providers and not the "charges"or list price that have been the basis of many prior studies of health care competition.

[9] The Major Practice Categories of "Cardiology" and "Orthopedics & Rheumatology" are the two highest for the commercially insured population (See Aizcorbe and Nestoriak (2011) and Dunn, Liebman, Pack and Shapiro (2010)).

tions because the unemployment rate is positively correlated with COBRA and Medicaid coverage (Cromwell, Hurdle, and Wedig (1986) and Holahan and Garrett (2009)).

To simplify the exposition of the paper, we divide the components of medical-care expenditures between those variables decided before the patient has sought care and those variables decided after. For example, physician's fees are usually negotiated on an annual basis, and can therefore be considered set before the patient is treated by the physician. In terms of our analysis, we first assess the effect of physician bargaining leverage on service prices, and subsequently assess the effects of service prices on the utilization of services. For completeness, we also incorporate the first stage impact of insurance carrier market power on both the negotiated service prices and benefits, and the second stage impact of these variables on utilization. Although we put structure on the timing of the expenditure decisions, we treat the key explanatory variables as being determined endogenously.

We find that physician concentration is positively and significantly correlated with service price levels. Specifically, our instrumental variables specification shows that a cardiologist with the 90th percentile FTHHI will charge 26 percent higher prices than a cardiologist with the 10th percentile FTHHI. The corresponding specification for orthopedists shows that a physician with the 90th percentile FTHHI would charge 29 percent higher prices than one in the 10th percentile. We also find that health-plan concentration is inversely correlated with service price fees. That is, insurance carriers in more concentrated health insurance markets pay lower fees to physicians.

Having estimated the determination of the first-period variables, we estimate the effects of variation in service prices and out-of-pocket prices on the utilization decision. A key to our identification is that patients and physicians likely respond to different price variables. While physicians respond to the service price paid to them by the insurance carriers, patients, by contrast, will respond to the out-of-pocket price. We find a price elasticity of supply of 1.01 for cardiologists and 0.29 for orthopedists. While in most markets an upward sloping supply curve would be unsurprising, in the health service market, this means that physicians treat patients according to service price levels. In other words, a physician with a higher price-cost margin will perform more services. On the demand side, we find an out-of-pocket price elasticity of -0.40 for cardiology patients and -0.20 for orthopedic patients. This finding supports prior research which suggest that patients are price sensitive (Manning et al. (1987) and Keeler and Rolph (1988)).

These estimates imply that physician bargaining leverage may translate into net shifts in utilization. We show that higher physician bargaining leverage (and lower insurance carrier bargaining leverage) is likely associated with higher utilization through its effect on service prices and out-of-pocket prices. More precisely, a cardiologist with the 90th percentile FTHHI will provide 24 percent more services than a cardiologist with the 10th percentile FTHHI. The corresponding orthopedists would provide 6 percent more services. The effects are reversed and much larger for insurance carrier concentration. Therefore, unlike most markets where consolidation leads to a reduction in purchases, the unique incentives of physicians lead to the counter-intuitive result of an expansion of services.

This paper is organized as follows. Section 2 provides an overview of the physician and insurance carrier industry. We provide a basic framework of physician-insurance carrier bargaining, intended to illustrate how bargaining leverage can affect service prices as well as service utilization. In Section 3, we give a comprehensive overview of the data used in this study. We provide quite a bit of detail as to the construction of our variables as this study includes a battery of new measures not discussed in prior research. In Section 4 we estimate the determination of service prices and benefits and in Section 5 we estimate the determination of service utilization. In Section 6, we quantify the effect of bargaining leverage on service utilization. We conclude in Section 7.

2 Physician and Health Insurance Carrier Organizations

2.1 Physician Organization

The study of physician consolidation has historically been a relatively uninteresting topic due to the fact that a vast majority of physicians worked in solo-practices. However, the market for physicians has shifted dramatically over the past few decades. In 1965 only about 10 percent of physicians were in group practices with three or more physicians, but by 1991 group practice physicians accounted for more than 30 percent of all physicians (Smart (2006)). This trend continued through the 1990s and early 2000s. Based on physician surveys, in 1996-1997 the proportion of physicians in solo and two-physician practices decreased significantly from 40.7 percent to 32.5 percent in 2004-2005 (Liebhaber (2007)). There is concern that the recent passage of the health care reforms in 2010 may accelerate the pace of consolidation because the law encourages greater cooperation among providers through the formation of Accountable Care Organizations (ACOs).[10] For

[10] An ACO is a network of providers that share the provision of care to patients. An ACO would normally include both physicians and hospitals and would encourage greater coordination of care among providers through financial incentives.

instance, a 2011 *New York Times* article by Robert Pear ("Trade Commission Challenges a Hospital Merger") reports that federal officials are seeing a wave of mergers, in part because of the incentives built into the new health law.

As physician consolidation grew there emerged wider variation in the type of physician practices. Physician group practices vary in size as well as the degree of specialization. Most group practices consist of physicians of the same specialty (that is, single-specialty groups) but there also exist groups with differing specialties (that is, multi-specialty groups). There also exist physician groups that are part of a larger health system that contain other group practices, as well as hospitals (i.e. Physician-Hospital Organization (PHO)). More complex forms of horizontal structures may involve group practices clustering with one another for bargaining purposes.[11]

Although there are a variety of organizational structures, this paper focuses on the horizontal aspects of these organizations where physicians with the same type of specialization are part of the same group or system. This type of horizontal consolidation has clear implications for bargaining and leverage with health insurance plans.[12] The source of the bargaining power rests on the ability of physicians to threaten to exclude its group from an insurance carrier's network, which may cause significant harm to the profitability of the health insurer. For example, an insurance carrier may find it challenging to attract and adequately treat enrollees if it has only a limited number of cardiologists or orthopedists.

2.2 Insurance Carrier Organization

Similar to the physician market, the health insurance market includes a wide variety of types and sizes of firms (that is, health insurance carriers). They can range in size from small local firms to large firms that are national in scope.[13] Insurance carriers compete

[11]For example, two physician groups may have distinct offices and administrative services, but may contract with insurance carriers for legal bargaining purposes as an independent practice association (IPA). In most states, IPAs represent physicians who only compete for *capitated* HMO contracts. For non-capitated contracts, the physicians must negotiate individually unless the FTC rules that they are "clinically integrated" for efficiency reasons (Berenson, Ginsburg, and Kemper (2009)). (Here we focus on specialists that are less often subject to capitated payments where the IPA market stucture is less applicable.) In another example, two physician groups may join forces to share administrative services (e.g. a group practice without walls (GPWW)) as well as contracting.

[12]There have been fewer studies of the effects of consolidation in health care markets along the vertical dimension where the theoretical impact of this type of consolidation is ambiguous (See Cuellar and Gertler (2006) and Ciliberto and Dranove (2006)).

[13]Dranove, Gron, and Mazzeo (2003) show that this type of differentiation can be important in how insurance firms compete.

with one another to attract enrollees. Three important characteristics that differentiate plans in the eyes of the patient are (1) the size of its provider network, (2) restrictions on the patients' choices and (3) the overall price of its insurance contract. Generally, it is assumed that consumers prefer a large choice of providers, less restrictions, and lower prices.

The overall size of the insurance carrier's network is determined according to the bargaining outcome with providers, which we will discuss in the next subsection. Although most commercial health insurance plans have a network of providers, these network insurance plans differ in the restrictiveness of their network.[14] There is a spectrum of types of plans ranging from the least restrictive PPO plans that often contain a broad network of providers and include out-of-network coverage, to the most restrictive type of plans, health maintenance organizations (HMO). Generally, but not always, HMOs will not cover out-of-network providers and will also require a primary-care physician to act as a gatekeeper for seeing a specialist. Finally, the overall price of the insurance contract usually includes the price of the premium, as well as out-of-pocket payments such as a deductible, a coinsurance payment or a fixed co-payment.

Of course, the insurance carrier would like to increase market share, but it will also like to lower its overall costs, which includes the expenditure of treating an episode of care. There are two primary ways in which an insurance carrier can attempt to control the expenditure of an episode of care. It can (1) attempt to lower payments (that is, fees) made to providers or it can (2) attempt to lower the amount of services per episode of care (that is, service utilization). Like the size of the provider network, fees will be bargained over with providers, which we will discuss below. There are a few ways in which an insurance carrier can lower the utilization of services per episode of care. One way is by persuading *patients* in the form of lower benefits. That is, the insurance carrier can pass on some price sensitivity to patients by sharing the cost of the services. A second way is by including more restrictions in the plan, such as monitoring the physicians actions. For instance, before implementing a procedure, an insurance carrier may require the patient to verify that this procedure is appropriate according to the insurance carrier's medical director. A third, and a bit less intuitive way, is for the insurance carrier to dissuade the *physician* via fee schedules, which works in tandem with how physicians and health insurance carriers bargain over fee payments.[15] We discuss physician-insurance carrier bargaining below.

[14]According to the Kaiser Health Benefit Survey less than 3 percent of enrollees in the U.S. had a conventional indemnity insurance plan.

[15]Duggan and Morton (2010) assess the impact of Medicare Part D on the insurers ability move demand

2.3 Physician-Insurance Carrier Bargaining

Both an insurance carrier's and a physician group's bargaining power resides in the ability to credibly exclude the other side from its patient base.[16] Through a simple framework, we show how each side can use this leverage to affect the expenditure of an episode of care. Specifically, the framework shows how the relative level of concentration on each side of the bargaining table can transmit into variations in service prices (that is, physician fees) as well as service utilization (that is, the quantity of services per episode)—the two components of episode expenditures. To keep the theory parsimonious, we assume symmetric information between patients and these two players.[17]

Assume that each patient, indexed by n, pays a fixed premium for an insurance contract that guarantees a minimum number of health "services," $\underline{Q}$, in the occurrence of an episode of illness. Physicians face marginal cost $\psi(Q)$, where the physician's marginal cost will be an increasing function of the number of services provided (that is, $\psi'(Q) > 0$).[18] The total expenditure of treating an episode of care, TE_n, is thus the service price, P_n, times the total number of services, Q_n (that is, $TE_n = P_n \cdot Q_n$). Letting α_n represent the proportion of expenditures paid by the patient (a measure of the generosity of benefits), the patient's demand for services can be represented as $D(P_n^{pock})$, where $P_n^{pock} = \alpha_n P_n$ is the out-of-pocket price.

The determination of these variables is easier to understand if one thinks of them occurring in two distinct periods.[19] This can be thought of as a dichotomy between those variables determined before the patient seeks care versus those variables determined after the patient seeks care. In the "first period," a service price, P_n^*, and a benefits schedule, α_n^*,

lower priced pharmaceuticals.

[16]Staten, Umbeck, and Dunkelberg (1987, 1988) as well as Sorenson (2003) are studies showing that an insurance carrier's bargaining leverage resides in its credibility of exclusion.

[17]Full information is an overly strong assumption in the market for healthcare, however, it allows us to isolate the effects of the competitive bargaining game between the insurance carrier and the physician.

[18]There are several factors that may cause physician firms to have increasing marginal costs for the treatment of patients. Perhaps the most important factor is the opportunity cost of the physician's time. The physicians limited amount of time in a day will make it necessary to hire additional units of labor or capital as they expand the number of services provided per patient (e.g. assistants or other physicians may be added to the physician firm) which may be costly. It is also possible that physicians perceive that the probability of malpractice lawsuits or damage to their reputation are higher as more services are done that may be less beneficial to the patient. In any case, the empirical model in this paper will test this assumption. Note that if the marginal cost curve is flat, we should not expect to find an empirical relationship between the physicians price and utilization.

[19]TE_n is sometimes referred to as the "episode price" in the literature.

are determined. Specifically, the physician and the insurance carrier bargain over service prices, defined as the price per service paid to the physician by the insurance carrier, and the insurance carrier and the patient determine a benefits package for the patient. In the "second period," an optimal service utilization decision, Q_n^*, is made.

2.3.1 First-Period

A major determinant of the level of benefits, α_n^*, will be the level of concentration in the insurance carrier market (for example, Dafny et al (2011) and Dunn (2010)). Specifically, if an insurance carrier has a larger degree of market power, it will be in its interest to offer less generous benefits (that is, a larger α_n). For simplicity, we assume that in the first period physicians expect that all patients have chosen the same benefit structure, such that $\alpha_n^* = \bar{\alpha}$.

The service price (that is, fee schedule) will depend on negotiations between the physician group and the insurance carrier. Specifically, the service price will depend on the relative degree of bargaining power, we label Z, of the physician and the insurance carrier in the market. One possible measurement of Z is the logarithm of the ratio of concentration measures: $Z = \ln\left(\frac{HHI_{phys}}{HHI_{plan}}\right)$, where HHI_{phys} and HHI_{ins} are the degrees of concentration in the physician and insurance carrier market, respectively. To examine how service price may depend on Z, we look at two polar market structures:

$$\begin{aligned} Z_1 \approx -\infty \quad &\Rightarrow \quad \text{Competitive Physician, Monopolistic Insurance Carrier.} \\ Z_2 \approx \quad \infty \quad &\Rightarrow \quad \text{Monopolistic Physician, Competitive Insurance Carrier.} \end{aligned}$$

Moving from market structure Z_1 to Z_2, we are shifting market power leverage from insurance carriers to physicians. Under market structure Z_1 the monopolistic insurance carrier can credibly threaten to keep the competitive physician out of its network. This credible threat will subsequently induce physicians to bid the price of services down to to the point where $P = \psi(\underline{Q})$, the physician's marginal cost of providing the minimum amount of services. By contrast, under market structure Z_2, the monopolistic physician can credibly threaten to exclude the insurance carrier's patients from using its services. Specifically, provided that the risk-free rate of return is earned, there will always be at least one insurance carrier willing to accept the profit-maximizing monopoly price.[20] Thus, any insurance carrier who wants to contract with this physician must offer the profit maximizing service price.

[20]That is, the monopoly price will be $P = \frac{\varepsilon}{1-\varepsilon}\psi^{mon}$, where ε is the patient's demand elasticity and ψ^{mon} is the marginal cost at the monopoly quantity of services.

The actual marketplace is rarely perfectly competitive or completely monopolistic. Instead, prices will be pulled towards either of these two extremes by the side with larger bargaining leverage. Thus, bargaining leverage is manifested in price variations by each side's ability to credibly exclude the other from its network. It is also important to note that this type of bargaining is usually implicit, rather than direct, interactive bargaining. That is, a health care plan may not directly discuss or haggle with a physician firm over price, but rather just recognize its relative competitive position and create a payment schedule that would entice the physician firm to participate in the plan.

2.3.2 Second-Period

Under certain simplifications, the physician's profit-maximizing amount of services to provide to the patient is quite intuitive. For example, let us assume that out-of-pocket costs are small (that is, α_n is close to zero) such that patients are not price sensitive. It follows that the physician solves the following:

$$\max_{Q} \; Q_n P_n^* - \int_0^{Q_n} \psi(s) ds \tag{1}$$

where P_n^* is the service price set in the first period. This results in the profit maximizing number of services:

$$Q_n^* = \psi^{-1}(P_n^*) \tag{2}$$

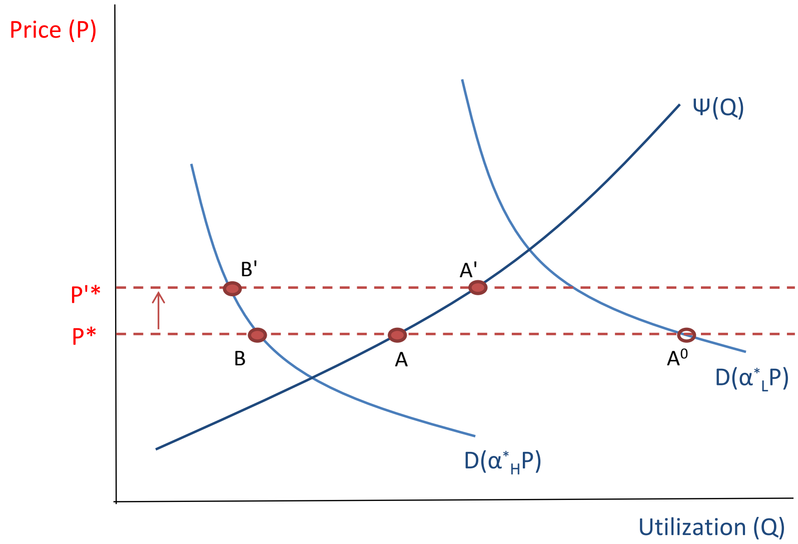
Given a first-period negotiated service price, the physician will provide the quantity of services to the patient up to the point where his marginal revenue equals his marginal cost. It follows that as long as marginal cost is increasing with the number of services, (that is, $\psi'(Q) > 0$), then the physician's optimal utilization is *increasing* in the pre-negotiated service price.[21] In other words, in the second-period the physician acts as a price-taking firm with the traditional, upward-sloping supply curve.

Under more general conditions, there will exist a distribution of patients, each having distinct benefit schedules, α_n^*. In this case, the physician's profit maximization problem is identical to (1), except that it includes the constraint that the patient perceives that each additional service provides a positive net marginal benefit. This constraint implies that the physician cannot force the patient to consume more services than the patient demands.[22] A

[21]This follows since $\frac{d\psi^{-1}}{dQ} = \frac{1}{(d\psi/dR)} > 0$ if $d\psi/dQ > 0$.

[22]This is identical to the assumption in Dranove (1988) where he assumes that "The patient receives treatment if and only if the physician recommends it and he consents."

Figure 1: Second-Period Utilization Decision



lower benefits schedule (that is, a larger α_n) may therefore induce the patient to demand a lower amount of services because it reduces the net marginal benefit of an additional service.

This can be more clearly demonstrated by examining Figure 1 where we have a diagram depicting the second-period service utilization decision. Here, the first-period negotiated price is denoted as the constant dashed line at P^* and the marginal cost curve is denoted by the upward sloping curve, $\psi(Q)$. We have also depicted two different demand curves, corresponding to patients with benefit schedules α_L^* and α_H^* where $\alpha_L^* < \alpha_H^*$.[23]

Under benefit structure α_L, the patient faces a low out-of-pocket price and demands services corresponding to point A^0. At this level of services, the service price does not cover marginal cost, which means the physician can only provide services up to the point A, where service price equals marginal cost. Since the utilization decision resides on the physicians marginal cost curve, the patient's demand curve is not binding and a marginal increase in the first-stage negotiated price to P'^* will increase the utilization of services to A'. This is the outcome shown in equation (2) where we assumed that the patient faced low out-of-pocket costs, $\alpha \approx 0$. By contrast, let us examine the scenario where the patient faces a large out-of-pocket price, $P^{pock} = \alpha_H^* P^*$. Specifically, at a first-period negotiated service price of P^*, the patient faces an out-of-pocket price of $\alpha_H^* P^*$, and will demand

[23]It follows that as $\alpha_n \to 0$, the price paid by the patient falls for any given P^*, and the demand curve shifts to the right.

services at point B. As the service price at this level of utilization covers the physician's marginal cost, the demand curve is binding. In this case, a marginal increase in the first-period negotiated price (from P^* to $P^{'*}$) corresponds to a movement along the demand curve and will consequently lower the utilization of services provided.

The overall effect of a change in service price on service utilization will therefore depend on the amount of benefits provided to the patient. When benefits are low, such that the out-of-pocket price is relatively high, utilization is likely to be negatively correlated with service prices. However, when benefits are high, such that out-of-pocket costs are low, a higher service price may ultimately raise the quantity of services provided. Thus, insurance carriers can thwart any effect of a positive supply elasticity by raising the amount of cost sharing, α_n, to the patient. Overall, this framework is intended to show how market power can dictate physician episode expenditures, TE_n. First, larger physician bargaining leverage can translate into higher fees P_n. Second, if patients are receiving high benefits, such that they do not face the full service price, these higher prices may result in more services provided to the patient.[24] The point is that physician bargaining leverage can ultimately alter service prices as well as service utilization, the two components of medical-care expenditures.

Discussion The ability of physicians to affect the utilization of services has been modeled theoretically by a number of researchers studying supplier induced demand (for example, Evans (1974), Fuchs (1978), Dranove (1988), and McGuire and Pauly (1991)), but much of the literature relies on the assumption that physicians may recommend treatment that the patient would not have desired under symmetric information. This is a controversial assumption in both the economic and medical fields. One advantage of the framework presented here is that it adheres to a more neoclassical theory where prices and quantity are determined by market forces. Just like in a typical market, firms are profit maximizing and all services purchased by the consumer provide a perceived net benefit. In fact, in the framework presented here, it is often the case that physicians are actually constraining the

[24]We should also note that one should not be too quick to make any consumer welfare predictions under this example. The overall welfare implication to the patient in this example is that she is unambiguously better off in market structure Z_2 compared to market structure Z_1. For example, in market structure Z_2, the patient receives more services in exchange for her fixed payment to the insurance firm. In market structure Z_1, for the same fixed payment, the patient receives fewer services and the insurance carrier reaps all of the benefits of the lower episode costs to itself. This welfare result, however, is just an artifact of the simplification of the example: it hinges on (1) information symmetry between the patient and the physician (Arrow (1963, 1986), Dranove and White (1987), Mooney and Ryan (1993), Gaynor (1995)) as well as (2) that the insurance carrier holds its premiums and benefits fixed.

number of services used by the patient (that is, the patient would be willing to undergo additional treatment upon recommendation).[25] Another advantage of this model is that it combines the price responses of both the physician *and* the patient into a unified framework. Specifically, the model allows for both a positive supply response from physicians as well as a negative demand response by patients. In previous literature, these effects have been modeled separately. It is important to highlight that our empirical specification will not constrain the relationship between service prices and utilization in any direction. Thus, we allow for a possible negative relationship as suggested by the theories of Evans (1974), Fuchs (1978), and Dranove (1988).[26]

3 Data

In this section, we give a comprehensive overview of the datasets used in this study. First, we describe the MarketScan® health claims data which is a database that tracks claims from all providers using a nationwide convenience sample of patients. We also provide an overview of how we calculated our service price and service utilization variables, which we show are components of total physician expenditures. Second, we describe the SK&A© physician database which includes information on location, specialty, unique physician identifiers, medical practice group, and health system of physicians in the United States. We then give an overview of the HealthLeaders-InterStudy© as well as the Area Resource File data which provides information used to make concentration measures of health insurance firms as well as demographic information.

[25]It is not clear that restraining the number of services is actually harmful to the patient in the first period. Due to the classic moral hazard issues, the additional service utilization in the second period may lead to a welfare loss from higher premiums that are necessary to cover greater expected medical expenditures.

[26]It is also possible that the alternative inducement theory of McGuire and Pauly (1991) may be the true underlying mechanism through which service prices affect utilization, which also suggests that higher prices can lead to greater utilization in some cases. Consistent with the supplier induced demand hypothesis, their model also suggests that possibility that higher service prices may lead to less utilization if higher service prices increase income by a sufficient amount, so that income effects dominate the substitution effect. Here we do not consider physician "income effects" in our model, since we treat physicians as firms that are not constrained by diminishing marginal utility from leisure. Although income effects are possible and could potentially be incorporated in our model, the consolidation of the physician markets over the past several decades suggests that in today's market viewing physicians as firms may be the more plausible economic assumption.

3.1 MarketScan® Data

The MarketScan® database tracks claims from all providers using a nationwide convenience sample of patients. Our collected data spans 2005 through 2008. The data includes health claims from employers and insurance carriers throughout the entire United States; all claims have been paid and adjudicated. Each enrollee and provider has a unique identifier and can be identified at the county level. This paper uses the Commercial Claims and Encounters Database portion of the MarketScan® Databases, which includes healthcare utilization and cost records at the encounter level. This portion of the database provides patient identifiers that may be used to sum expenditures to the patient-episode level.

The Commercial Claims and Encounters Database contains data from employer and insurance carrier sources concerning medical and drug data for several million employer-sponsored insurance (ESI)-covered individuals, including employees, their spouses, and dependents. Each observation in the data corresponds to a line item in an "explanation of benefits" form; therefore each claim can consist of many services and each encounter can consist of many claims.

Importantly we can differentiate between payments made to physicians from those paid to other providers (for example, hospitals and pharmacies). For instance, suppose a patient is being treated for congestive heart failure in a hospital. The claims data differentiates between types of providers such that payments made to the physician for performing a coronary artery bypass are distinct from those made for hospital operating room expenses. We use MarketScan's "payment" variable which is defined as the total gross payment to a provider for a specific service. Specifically, this is the amount of dollars eligible for payment after applying pricing guidelines such as fee schedules and discounts, and before applying deductibles and co-payments. MarketScan® also indicates the type of plan the claim was made under, which allows us to ignore episodes in which a capitation payment was made.[27]

3.1.1 Physician Expenditure of an Episode of Care

To obtain the physician expenditure for a particular episode of care we apply the Medstat Episode Grouper® (MEG). This algorithm, provided by Thomson Reuters, assigns a procedure to an episode using information on claims as well as the patient's medical history. Spending is allocated to a patient between a beginning and an end date by

[27]Approximately 3 percent of our sample are capitated episodes. These observations are likely to include closed HMO systems such as Kaiser-Permanente patients.

assigning an "episode ID", n, to each claim in the data.[28] Let Γ_n be the set of procedures used for treating episode n identified by the MEG. The total expenditures made to the physician for treating episode n is:

$$TE_n = \sum_{j \in \Gamma_n} p_{jn} \tag{3}$$

where p_{jn} is the full payment (including the patient's out-of-pocket costs) to the physician for procedure j in episode n.[29] Pricing information for a specific procedure is the payment attached to the specific health claim line in the MarketScan® data. We identify procedures j at the most granular level possible, based on a specific CPT code, modifier, and "place of service."[30] Note that each episode uniquely identifies an individual patient, k, with disease d, treated by a physician p, in county c, that begins in time period t.[31] The large advantage of the MEG algorithm is that it allows us to isolate the service mix and total price for treating a particular patient's illness. However, these algorithms are also considered a "black box" in the sense that they rely entirely on the expertise of those that developed the grouper software.

3.1.2 Decomposing the Expenditure of an Episode of Care

As outlined in the Section 2, the outcome of a bargaining game between physicians and insurance carriers will result in variation in both service prices (that is, the fee schedule) as well as the utilization mix of services in a given episode of care. Thus, embedded in the expenditure of an episode of care is a "service-price component" and a "service-utilization component."

The service-utilization component is the number of services provided to the patient over the course of the episode of care. We measure this variable by the following:

$$Q_n = \sum_{j \in \Gamma_n} r_j \tag{4}$$

[28]We isolated episodes where the patient sees the same physician for the entire episode of care, however, results were not sensitive to this exclusion.

[29]Note that each episode occurs only once in the data, thus we do not have a panel of episodes.

[30]We chose to differentiate procedures by place of service based on the fact that Medicare provides higher fees for physicians who have their own office-based facility.

[31]An episode of care may span several time periods (half-years in our analysis) for chronic diseases. We assign the episode to the date at which the episode begins. For our analysis, we isolated episodes treated by only one physician.

where r_j is the average price of procedure j in the entire sample. Here, r_j serves as a proxy for the number of services rendered for each given procedure, and thus one can think of r_j as being comparable to each procedure's relative value units (RVUs) assigned by Medicare. Any variation in the utilization component between two episodes of care will be attributable to differences in the number of services used as opposed to differences in the prices charged for the same service. The remaining component of the expenditure of an episode of care is the service price:

$$P_n = \frac{\sum_{j \in \Gamma_n} p_{jn}}{\sum_{j \in \Gamma_n} r_j} \tag{5}$$

which is the price of the episode of care in terms of its total price per service. In our empirical analysis, we will assess how market power affects each of these components individually. Specifically, we use the fact that in logs our decomposition of total episode cost takes the tractable form:

$$\ln(TE_n) = \ln(Q_n) + \ln(P_n) \tag{6}$$

This equation shows that any percentage change in total physician expenditures, TE_n, will be due to either a percentage change in service utilization or a percentage change in service price.

Table 1 shows summary statistics of P_n, Q_n, and TE_n for our entire MarketScan® sample. On average, cardiologists bill 459 dollars per episode of care while orthopedists bill 463 dollars.[32] Note that due to how we defined services, the mean and median price per service will be approximately equal to one by construction. Overall, the data show a large amount of variation in both prices and utilization. The 90th percentile service price is about twice as large as the 10th percentile service price for both cardiology and orthopedics. There is much wider dispersion in utilization rates, especially for cardiology. The 90th-percentile utilization is 58 times the magnitude of the 20th-percentile utilization for cardiologists and 17 times the magnitude for orthopedics. Although these differences in utilization rates appear large, it is important to note that this variation may partly be explained by the wide variety of different diseases treated by each specialty.

[32] We removed outliers we believe are attributable to clerical data input error by discarding episodes in the bottom first percentile and top 99th percentile based on price per service and utilization.

Table 1: Summary Statistics

	Mean	SD	10th Ptile	90th Ptile
	Cardiology			
$FTHHI_{phys}$	0.119	0.107	0.026	0.241
HHI_{ins}	0.231	0.100	0.130	0.358
P_n	1.012	0.339	0.684	1.338
Q_n	459.6	717.9	23.0	1336.9
TE_n	459.9	755.1	24.3	1298.7
HMO_n	0.106	0.308	0	1
PPO_n	0.660	0.473	0	1
POS_n	0.105	0.306	0	1
$HDHP_n$	0.002	0.041	0	0
$CDHP_n$	0.020	0.141	0	0
$BMCOMP_n$	0.076	0.264	0	0
$EMPLOYER_n$	0.606	0.488	0	1
AGE_n	51	11	36	63
$COMORBID_n$	5.93	3.37	2	10
α_n	0.27	0.31	0	0.85
Stage of Illness	1.23	0.651	1	2
	Orthopedics			
$FTHHI_{phys}$	0.104	0.105	0.022	0.218
HHI_{ins}	0.233	0.101	0.130	0.358
P_n	1.032	0.279	0.742	1.356
Q_n	462.5	729.7	59.3	1176.3
TE_n	463.7	769.4	67.0	1166.7
HMO_n	0.111	0.314	0	1
PPO_n	0.663	0.472	0	1
POS_n	0.120	0.325	0	1
$HDHP_n$	0.002	0.045	0	0
$CDHP_n$	0.025	0.155	0	0
$BMCOMP_n$	0.049	0.216	0	0
$EMPLOYER_n$	0.576	0.494	0	1
AGE_n	40	18	13	61
$COMORBID_n$	5.59	3.20	2	10
α_n	0.30	0.29	0.025	0.83
Stage of Illness	1.01	0.167	1	1

3.2 SK&A© Data

The SK&A© database includes information on location, specialty, name, medical practice group, and health system. The data base is updated every six months, spans 2005 to 2008, and includes 95 percent of office-based physicians practicing in the United States.[33] One major advantage of the SK&A data over other databases is that each physician is verified over the telephone, which increases the accuracy of its physician location and group size information.[34]

Given the different types of physician organizations, assigning each physician to a specific firm is not a straightforward task. One difficulty is how to overcome the complexity in the vertical dimension. For instance, a small portion of our sample (6 percent) of those physicians who belonged to a group medical practice also belonged to a larger health system. Anecdotal evidence from physicians leads us to believe that bargaining in this case would take place at the larger health system level; therefore we make the assumption that physicians use their full market power whenever possible.[35] Thus, for each physician we assign the broadest medical group or system she was assigned in the data. Specifically, if the physician is not associated with a health system we assign her to the group medical practice she is listed with.

Pinpointing the geographic market for provider services is also a challenging task, and has been the subject of many antitrust cases (see Gaynor and Haas-Wilson (1999) and Haas-Wilson (2003)). Neither the Justice Department nor the Federal Trade Commission have a set standard as to how to measure the size of a geographic market for medical services.[36] In creating our measure of the geographic market, we use as much of the granularity of the physician-location information as possible. We define a geographic region as the area surrounding a given patient, as would be done in a standard Hotelling problem. Specifically, for each location in the SK&A data, we create a distinct concentration mea-

[33]SK&A has a research center that verifies every field of every record in its data base. The data also includes the names of DOs, NPs, PAs and office managers.

[34]The six month frequency of their telephone survey may be important, since SK&A reports that on average, 14.2% of physicians move each year. Although all the information in the survey is telephone verified, they gather information for physicians through a variety of sources. This includes company and corporate directories, websites, state licensing information, mergers and acquisitions announcements, trade publications, white and yellow pages directories, professional associations, and government agencies.

[35]This is consistent with the common assumption made in the hospital literature that the hospitals bargain at the system level.

[36]Although many experts agree that the merger guidelines provide an appropriate framework for defining and analyzing geographic markets in the health care sector, there is no consensus for the precise methodology that should be used across all markets (See FTC and DOJ (2004)).

sure based on the physicians in the surrounding geographic region. To do this takes a few steps. First, we define a geographic region by specifying a maximum amount of driving time, $\bar{k}$, a patient would be willing to travel to see a physician.[37] The value of $\bar{k}$ is 80 minutes and is found by searching for the value that resulted in the lowest mean-squared error in our regression analysis. Second, we calculate the probability that a patient located at the center of the geographic coordinate would travel to see a physician. We do so based on the assumption of linear travel costs and uniform taste preferences. Third, using the probabilities of seeing each physician calculated in step two, we calculate expected market shares based on the physician group's size and distance to the specific geographic coordinate. In this fashion, those physicians closer to the patient are given more weight than those physicians farther away. Using these market shares, we construct the concentration measure for each coordinate, representing the competition for that patient in the surrounding area, $HHI^{patient}$. Fourth, we link these measures to the MarketScan® data by averaging $HHI^{patient}$ over the county, so that there is one HHI_c specific to a county. Fifth, to arrive at a HHI specific to a physician (the fixed-travel time HHI, $FTHHI_{phys}$), we weight the aggregate county HHI_c measures using information on the county of the patients for each provider in the MarketScan® data. We treated each specialty as distinct from each other, meaning that cardiologists were not counted in the $FTHHI_{phys}$ created for orthopedists and vice versa. More explicit details of the construction of $FTHHI_{phys}$ are available in Appendix A.

It is important to note that for hospitals it is possible to define the market based on a demand estimate using a discrete-choice framework where patients choose among a discrete set of hospitals (see Town and Vistnes (2001) and Capps, Dranove, and Satterthwaite (2003)). However, this paper takes a more reduced form approach for three reasons. First, the discrete-choice framework applied in the hospital literature is not possible with our data because we do not have granular geographic information in the MarketScan® data (that is, MarketScan® tracks providers and patients at the county level rather than the zip code level). Second, the number of physician firms is magnitudes larger than the number of hospitals, which means the number of possible physician choices becomes quite large. Third, the effects of competition among physicians are not well understood or documented, so as a first step in analyzing this market we focus more directly on the relationship between the competitive environment and its effects on service prices and

[37]Driving times were calculated in Stata using the traveltime command developed by Ozimek and Miles. This command finds the driving time between two latitude and longitude via Google maps. See Appendix A for more details.

outcomes. For these reasons, this paper more closely follows papers that apply more reduced form techniques (for example, Dranove et al. (2008), Duggan (2002), Dranove and Ludwick (1999) and Lynk (1995)).

Table 1 provides summary statistics for the physician concentration measure, $FTHHI_{phys}$, for both our cardiologists and orthopedists sample. The orthopedist market is slightly less concentrated with an average $FTHHI_{phys}$ of 0.104 versus an average of 0.119 for cardiologists. There is also a wide degree of variation in this variable, as, in both samples, the 90th-percentile measure is roughly ten times larger than the 10th-percentile measure. There is not a large degree of time series variation in the physician HHI variables. The mean cardiology $FTHHI_{phys}$ is 0.123 in the first half of 2005 and is 0.108 in the second half of 2008. The corresponding measures for orthopedists are 0.109 and 0.097.

3.3 HealthLeaders-InterStudy© Data

Enrollment information on health insurers is obtained from the HealthLeaders-InterStudy© database of insurance carriers for the years 2005 to 2008. This MSA level enrollment data is collected through a biannual survey of health insurance carriers where they are asked to report enrollment by geographic location. The enrollment information for each insurance carrier is also provided by the type of health insurance plan (that is, PPO, POS and HMO)[38] and also whether the contract is fully-insured or self-insured.[39]

Using this enrollment data, we construct an HHI concentration measure for the health

[38]Prior to 2004 HealthLeaders-Interstudy collected data on only HMOs, but they significantly expanded the coverage of their plan survey in 2004. Prior to 2006 they did not separately report POS, but included this enrollment as part of the HMO category.

[39]A fully-insured health insurance contract is a contract purchased from an insurer where the insurer assumes the full risk of the individual. All other contracts are considered self-insured.

The American Medical Association (AMA) (2010) produces health insurance concentration figures for MSAs across the United States using HealthLeaders-InterStudy©. In general, we follow many of the AMA guidelines for calculating concentration measures using HealthLeaders-InterStudy© data. Specifically, we exclude PPO rental networks (e.g. Beech Street Corporation). These companies provide administrative services only and/or contract with health insurance carriers, which may cause double counting for those enrollees that are enrolled in another insurance plan that also contracts with a PPO rental network. We also exclude markets where HealthLeaders-InterStudy© data does not capture a plausible fraction of the insured population. Specifically, we calculate the ratio of total enrollment to the total eligible enrollment (i.e. population-uninsured-(Medicare+Medicaid-Dual)) estimated fraction of total possible enrollment in the market. Similar to the AMA, we exclude those MSAs where the ratio is less than 30 percent. Unlike the AMA concentration measures that only includes HMO and PPO enrollment we also include POS enrollment.

insurance market. The HHI measure is constructed based on the share of total enrollment for each plan. Specifically, we let S_{ins} be the share of enrollment for an insurance carrier in an MSA, then the concentration measure for the enrollee is $HHI_{ins} = \sum_{ins \in MSA}(S_{ins})^2$.[40]

3.4 Demographic Data - Area Resource File & Census Data

For additional information regarding the demographic information in a county area we use data from the Area Resource File (ARF). The ARF is a database containing extensive information for U.S. counties: information on demographics, health facilities, health professionals, measures of resource scarcity, health status, and economic activity. The data is gathered from various sources, often on an annual basis.[41] The variables constructed from these data that are used in our analysis include median household income, education, population, population over the age of 65, hospital facility characteristics and a number of additional variables.[42]

4 Estimation of First Period: Effects of Market Power on Service Price and Benefits

The goal of this study is to estimate if, and to what extent, physician market power dictates medical-care expenditures. As discussed in the previous section, one can categorize the determination of medical-care expenditures into two distinct periods of decision making. First, fees are negotiated and benefits are chosen, and subsequently a service utilization decision is made. In this section, we estimate the determinants of these first-period decision variables—the negotiated service price, P_n, and the benefit schedule, α_n. In estimating the determinants of the service price, we pay particular attention to the degree of bargaining leverage of physicians relative to insurance carriers. In estimating the determinants of the benefits schedule, we examine the impact of insurance carrier concentration. In the subsequent section, we will estimate the determinants of service utilization. Although we put structure on the timing of these expenditure decisions, we treat these key explanatory variables as being determined endogenously.

[40] As an alternative to the total enrollment, we also constructed an HHI based solely on the fully-insured insurance share information, and we obtain similar results.

[41] Some of the sources included Census, the American Hospital Association database, American Medical Association database.

[42] Some of the additional variables include rental value of property, population over the age of 65 and share of hospitals that are university facilities.

4.1 Determinants of Service Price

4.1.1 Specification

The following estimation routine quantifies the impact of the relative physician-insurance carrier bargaining leverage on the logarithm of service price P_n:

$$\begin{aligned}\ln(P_n) &= \beta_1 \ln(FTHHI_{phys}) + \beta_2 \ln(HHI_{ins}) + \delta' COST \\ &\quad + \kappa' QUAL + \lambda' PAT + \zeta_{at} + \zeta_d + \varepsilon_n. \end{aligned} \tag{7}$$

where each episode, n, is uniquely associated with a patient k, a disease-stage-of-illness d, a physician p, an MSA m in a county c, and state a in time t. This specification essentially splits our measure of bargaining power leverage, Z, into its two components, $FTHHI_{phys}$ and HHI_{ins}.[43] As discussed above, the FTHHI of physicians is constructed at the physician-specialty level (see the Appendix), while the HHI of insurance firms is constructed at the MSA geographic level.

We include state-time fixed effects, ζ_{at}, as well as disease-stage-of-illness fixed-effects,[44] ζ_d, defined by the MEG. Specifically, the MEG algorithm classifies an episode of care into five major stages of illness and is meant to indicate the severity of a particular episode compared with other episodes in that disease group.[45] See Table 1 for summary statistics on this measure. To decrease computational burden, we include only the 100 most common disease groups for each specialty, which represents over 90 percent of the total samples.[46] We control for demographic attributes of the patient with the vector PAT, which includes a polynomial in the patient's age, a dummy variable indicating the patient's gender, as well as a polynomial in the number of co-morbidities of the patient. This latter variable is meant to control for those patients with multiple diseases, who may be sicker or harder to treat than patients with only a single disease. The patient-specific variables also include the patient's type of insurance carrier (for example, HMO, PPO, etc), whether the patient

[43] It would be equivalent to using Z as a covariate if we were to constrain $\beta_1 = -\beta_2$.

[44] For example, stage 3 acute myocardial infarction.

[45] Specifically, MEG assigns a severity score to each patient episode based on the "Disease Staging" disease progression model and does not depend on the utilization of care. Stage 0 represents a history or suspicion of a condition, exposure to a disease, or well visits. Stage 1 represents conditions with no complications or problems with minimal severity. Stage 2 represents problems limited to a single organ or system, significantly increased risk of complication than Stage 1. Stage 3 represents multiple site involvement, generalized systemic involvement, or poor prognosis and Stage 4 represents death.

[46] No results changed when included all diseases on a 30 percent subsample of the data.

works for a larger employer[47], the logarithm of the median income of the patient's county, as well as the logarithm of the fraction of college educated individuals in the patient's county. We also include covariates that control for the physician's cost, $COST$, as well as the physician's quality, $QUAL$. The latter vector includes the percentage of hospitals in the physician's county that are affiliated with a university as well as a weighted average of the patient's county-level median income.[48] The former vector includes the logarithms of the median rent, median home price, median income and average health care facility wage in the physician's county. These cost variables were chosen as controls because fees are usually bargained as a percentage of Medicare prices, which vary by cost-of-living variables such as rent, wages, and house prices. See Appendix B for details on the construction of these variables as well as specifications with additional controls for firm scale and physician supply.[49]

4.1.2 Correcting for Unobserved Physician Quality

The reason for including the controls described above is that they serve as a proxy for variables that affect both the negotiated service price as well as the competitive patterns of physicians and insurers. For instance, we include cost-of-living variables because physicians and insurers often bargain off of Medicare's relative value unit system, but cost-of-living factors may also affect the location choices of physicians and insurance firms. Estimation bias can arise, however, if important "bargaining chips" exist that are unobserved to the econometrician and also affect competition. Of primary concern is unobserved physician quality. Specifically, higher physician quality may result in larger negotiated fees, drawing more physicians into an area and dissuading insurance carriers from entering a market. This would result in upward bias on the insurance HHI coefficient and downward bias on the physician HHI coefficient.

Similar studies in the hospital literature have found it crucial to use instrumental vari-

[47]This is actually based on an indicator of whether the data source for the claims information is from an employer (which is typically a large employer) or from a health insurance firm.

[48]The basic idea is that the higher quality doctors may attract the more wealthy patients. The weighted average is the average income of patients that see a particular doctor (based on county-level income data). This income variable is an average across patients seeing a particular doctor, which is distinct from the patients income variable that enters as a demographic variable.

[49]We chose not to include these variables in our main specification because the are likely endogenous variables. Gaynor and Haas-Wilson (1999) note that "the extant literature on physician groups suggests that scale economies for such practices are also exhausted at relatively small sizes-three to five physicians (Pope and Burge (1996))."

ables to account for unobserved quality.[50] Our instrumental variable estimation strategy is to identify physician and insurer competitive variation solely attributable to long-run entry and exit patterns of physicians and insurers. In particular, we expect there to be a larger number of physician firms and insurance firms in more populated markets. However, given our set of control variables, there is little reason to expect population to be correlated with physician quality.[51]

Another important factor for identification is that we need instruments that are correlated with insurance entry and physician entry *uniquely*. For this reason, we include populations of certain age groups because physicians and insurance carriers may respond differently to age demographics. For instance, a greater number of senior citizens should encourage more entry from physicians relative to insurance carriers since these are generally sicker patients already covered by Medicare. We also include the population of employed individuals (the unemployment rate) for a similar reason. Insurance carriers are more likely to enter geographic areas with more employed individuals where the base of potential customers is higher. Physicians, however, are more indifferent to this factor because unemployed individuals are often covered by Medicaid or COBRA.

In Appendix C we show estimates of the first-stage estimates of the instruments as well as results from two robustness exercises. In all first-stage regressions, F statistics, testing the joint significance of the instruments, were large (ranging from 13 to 69).[52] We also estimated (7) using an entirely different instrument set, which consists of the number and size distribution of business establishments in the physician's county.[53] Point estimates

[50]As a recent example, Dranove et al. (2008) provides an instrumental variable strategy for estimating the effects of concentration on price in hospital markets.

Findings in the physician literature also suggest that price may be endogenous. Frank (1985) finds that psychiatrists respond to price, Schwartz et al. (1980), Newhouse et al. (1982), find that physicians locate in response to effective demand.

[51]Although unlikely, if for some reason higher quality physicians prefer to practice medicine in more populated areas than lower quality physicians, our estimates will be attenuated towards zero statistical significance. In this sense, our estimates will be conservative. One may be concerned that population may be correlated with physicians per capita. However, we show in Appendix C.4.1 that results do not change when we include the number of physicians per capita as a control variable.

[52]As a robustness exercise, we replaced the instrument set with a set that included the population over and under 65 for the MSA and for the county (four total instruments). No qualitative results changed, however standard errors grew a bit.

[53]These variables are meant to affect both physician and insurance entry as more business establishments may encourage more entry from either physician firms or insurance firms. Additionally, insurance carriers may be more affected by the size of firms as larger firms may demand more insurance variety for its employees.

were very similar under this alternative instrument set (see Appendix C.2).[54]

4.1.3 Results

We report results of specification (7) in Table 2. Standard errors are clustered by physician-county. This degree of clustering is meant to control for the fact that physicians bargain with an insurance carrier over an entire fee schedule.[55] In the sample of cardiologists as well as the sample of orthopedics there is a positive and statistically significant effect of physician leverage on price per service. The OLS estimates indicate that a 10 percent increase in physician concentration will cause about a 0.3 percent increase in fees, but they also show that a 10 percent increase in insurance concentration causes a 0.2 percent increase in fees. Using instrumental variables appears to remove the downward bias on $FTHHI_{phys}$ and the upward bias on HHI_{ins} that we believe is attributable to unobserved physician quality. The IV estimates indicate that a 10 percent increase in physician concentration will result in about one percent higher fees for cardiologists and orthopedists, on average. Price effects from a change in the concentration of the insurance carrier are quite large, as a 10 percent increase in the insurance carrier's HHI will reduce prices by about 3.2 percent for cardiologists and 2.4 percent for orthopedists.[56]

[54]As an additional check on the main instrument set, we collected the residuals from (7) under the alternative instrument set, and ran a regression of these residuals on the main instrument set. If the residuals were highly correlated with the main instruments, this would suggest a potential bias. In fact, the residuals were not correlated ($R^2 \approx 0.001$) with the main instrument set (see Appendix C.3). Standard errors were all large, the R^2 of both samples was quite low, around 0.001, and F statistics testing their joint significance were also fairly low (between 3 and 6).

[55]We also estimated a different specification of the episode price, P_n, regression where we used procedure price, p_j, as the dependent variable while including procedure fixed effects. This specification will be identical to specification (7) if physicians bargain with insurance carriers according to a discount on *all* procedures. That is, if $p_{jn} = \theta_n r_j \; \forall \; j$ for some $|\theta_n| < 1$, then it follows that $\ln(P_n) = \ln(\frac{p_{jn}}{r_j})$, which is equivalent to $\ln(\theta_n)$ as the dependent variable. No results changed using this specification indicating that, on average, physicians likely bargain over their entire fee schedule.

[56]As an alternative to the OLS results, we also estimate the fee regression using county fixed-effects and we obtain a similar coefficent on the physician $FTHHI_{phys}$ coefficient, although it is slightly lower. The county fixed-effects will control for all factors unique to a provider in a county that are not captured by other variables. Although the county fixed effects make identification more difficult, we are still able to identify competitive effects from the fact that different providers compete in a different fashion for patients in neighboring counties.

Table 2: Determinants of Service Price

	OLS		IV	
	Cardiology	Orthopedics	Cardiology	Orthopedics
$\ln(HHI_{phys})$	0.038***	0.033***	0.105***	0.111***
	(0.005)	(0.004)	(0.015)	(0.021)
$\ln(HHI_{ins})$	0.019**	0.025***	-0.320***	-0.240**
	(0.010)	(0.008)	(0.095)	(0.096)
$\ln(medval_{phys})$	0.058**	0.068***	0.064***	0.088***
	(0.025)	(0.023)	(0.022)	(0.018)
$\ln(rent_{phys})$	-0.033	-0.089**	-0.050	-0.046
	(0.052)	(0.041)	(0.061)	(0.045)
$\ln(facwage_{phys})$	0.003	0.014**	-0.007	0.004
	(0.006)	(0.006)	(0.007)	(0.008)
$\ln(medinc_{phys})$	-0.012	-0.035	-0.064	-0.130***
	(0.032)	(0.025)	(0.041)	(0.041)
$\ln(medinc_{flow})$	-0.031**	0.048***	-0.017	0.099***
	(0.014)	(0.014)	(0.022)	(0.020)
UNIV	0.022**	0.016*	0.012	-0.002
	(0.009)	(0.009)	(0.014)	(0.014)
$\ln(medinc_{pat})$	0.035***	0.018***	0.037***	0.027***
	(0.007)	(0.007)	(0.008)	(0.009)
$\ln(educ_{pat})$	0.077***	0.155***	0.139***	0.183***
	(0.024)	(0.027)	(0.034)	(0.033)
EPO	-0.034***	-0.037***	-0.031***	-0.021***
	(0.007)	(0.007)	(0.007)	(0.008)
HMO	-0.033***	-0.004	-0.040***	-0.004
	(0.006)	(0.006)	(0.006)	(0.006)
POS	-0.013***	-0.002	-0.018***	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)
PPO	0.005	0.009**	0.001	0.006*
	(0.004)	(0.004)	(0.004)	(0.004)
HDHP	-0.001	0.000	-0.003	0.005
	(0.011)	(0.006)	(0.011)	(0.007)
CDHP	0.033***	0.037***	0.029***	0.038***
	(0.004)	(0.004)	(0.005)	(0.004)
EMPLOYER	-0.004	0.026***	-0.006	0.023***
	(0.009)	(0.005)	(0.008)	(0.007)
Observations	3668928	4135610	3664348	4131612

Notes: The dependent variable is the logarithm of service price, $\ln(P_n)$. All regressions include a dummy variable indicating the patient's gender, a polynomial in the patient's age (i.e. AGE, AGE^2, and AGE^3), a polynomial in the number of co-morbidities, as well as state-halfyear and disease-stage-of-illness fixed effects. The omitted plan types are "basic medical" and "comprehensive," $BMCOMP$. Standard errors are in parentheses and are clustered by provider-county. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.

4.2 Determinants of Benefits

As discussed in Section 2.3, a horizontal theory of competition among health insurers would suggest that markets with higher concentrations of insurance carriers likely offer plans with less generous benefits. To verify the effects of competition in this market, we run the following estimation routine, which quantifies the impact of insurance carrier concentration on our measure of the generosity of benefits, α_n:

$$\ln(\alpha_n) = \beta_3 \ln(\widehat{HHI_{ins}}) + \lambda' PAT + \zeta_{at} + \zeta_d + \varepsilon_n.. \tag{8}$$

where we instrument for HHI_{ins} using the same instrument set as used in specification (7).[57] Here we control for attributes of the patient with the vector PAT and disease-stage-of-illness fixed effects, which are included to control for any characteristic that may affect the patient's insurance carrier decision.[58] We also include state-time fixed effects, ζ_{at}. Since the plan decision is ultimately determined by the patient, we report Huber-White robust standard errors.

Table 3 reports the estimate of β_3 for each sample under OLS and IV. As expected, an increase in health-plan concentration is associated with a larger share of expenditures being paid out-of-pocket. In all specifications, there is a positive and statistically significant effect of insurance concentration on out-of-pocket shares. Specifically, under OLS, a ten percent rise in insurance carrier concentration is associated with a 0.7 percent increase in α_n for cardiology patients and 0.4 percent increase for orthopedic patients. In our IV specification, the corresponding effects 1.4 and 2.1 percent respectively.

The previous literature offers relatively little evidence of the effects of health insurance competition on consumer welfare.[59] The findings in this section provide an important contribution to the literature by showing that insurers in more consolidated markets are able to reduce medical benefits to consumers, which is consistent with the recent work by Dunn (2010) and Dafny et al. (2011) who find that additional consolidation leads to higher premiums and lower benefits.

[57] Results did not significantly change when we limited the instrument set to two variables: the population of the MSA and the unemployment rate of the county. Results under this specification were $\beta_3 = .20$ for orthopedics and $\beta_3 = .11$ for cardiology, both significant at the one percent level.

[58] No results changed when we included the vector $COST$ and the vector $QUAL$.

[59] As far as we are aware, only the recent work of Dafny et al (2011) tests the effects of health insurance competition on benefits in commercial insurance markets.

Table 3: Determinants of Benefit Schedule

	OLS		IV	
	Cardiology	Orthopedics	Cardiology	Orthopedics
$\ln(HHI_{ins})$	0.069***	0.043***	0.140***	0.216***
	(0.003)	(0.002)	(0.008)	(0.006)
$\ln(medinc_{pat})$	-0.041***	-0.064***	-0.025***	-0.024***
	(0.004)	(0.003)	(0.004)	(0.003)
$\ln(educ_{pat})$	-0.486***	-0.305***	-0.484***	-0.285***
	(0.015)	(0.011)	(0.015)	(0.011)
EPO	-0.435***	-0.337***	-0.428***	-0.332***
	(0.007)	(0.006)	(0.007)	(0.006)
HMO	-0.695***	-0.521***	-0.694***	-0.520***
	(0.003)	(0.003)	(0.003)	(0.003)
POS	-0.587***	-0.426***	-0.586***	-0.424***
	(0.003)	(0.003)	(0.003)	(0.003)
PPO	-0.324***	-0.215***	-0.323***	-0.214***
	(0.003)	(0.002)	(0.003)	(0.002)
HDHP	0.112***	0.301***	0.113***	0.303***
	(0.015)	(0.012)	(0.015)	(0.012)
CDHP	-0.080***	0.082***	-0.077***	0.083***
	(0.006)	(0.005)	(0.006)	(0.005)
EMPLOYER	-0.016***	0.027***	-0.017***	0.026***
	(0.002)	(0.001)	(0.002)	(0.001)
Observations	2977876	3826327	2974278	3822689

Notes: The dependent variable is the logarithm of the share of expenditures paid by the patient, $\ln(\alpha_n)$. Both regressions include a dummy variable indicating the patient's gender, a polynomial in the patient's age (i.e. AGE, AGE^2, and AGE^3), a polynomial in the number of co-morbidities, state-halfyear and disease-stage-of-illness fixed effects. The omitted plan types are "basic medical" and "comprehensive," $BMCOMP$. Huber-White robust standard errors are reported. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.

5 Estimation of Second Period: Service Utilization

Having estimated the determinants of the first-period variables—service prices and health-plan benefits—we are now in a position to estimate the determinants of the utilization of services. As delineated in the earlier part of this paper, the utilization of services is decided upon by the physician and the patient, given the first-period negotiated prices and chosen benefit schedule. A key to our identification is that patients and physicians likely respond to different price variables. While physicians respond to the service price paid to them by the insurance carriers, P_n, patients, by contrast, will respond to the out-of-pocket price, P_n^{pock}, which is defined as the price per service paid by the patient such that $P_n^{pock} = \alpha_n P_n$.

5.1 Determinants of Service Utilization

Our baseline specification for estimating the empirical relationship between service price, out-of-pocket price, and service utilization is:

$$\ln(Q_n) = \gamma_1 \widehat{\ln(P_n)} + \gamma_2 \ln\widehat{(P_n^{pock})} + \delta' COST + \kappa' QUAL + \lambda' PAT + \zeta_{at} + \zeta_d + \varepsilon_n, \qquad (9)$$

where we use the same instruments as in the preceding section for P_n and P_n^{pock}. Just to be clear, these instruments will be valid as long as population and the unemployment rate do not depend on individual service utilization rates, given our set of covariates. They will be good instruments insofar as they are correlated with price, P_n, and out-of-pocket price, P_n^{pock}, solely due to competitive patterns of physicians and insurance carriers.

The coefficient γ_1 provides an estimate of the marginal effect of a change in service price on service utilization holding fixed the out-of-pocket price. Thus, γ_1 measures the effect of change in service price, holding fixed the patient's demand response, and can therefore be interpreted as an estimate of the physician's supply elasticity. The coefficient on γ_2 provides an analogous estimate on the patient side. Specifically, γ_2 provides the marginal effect of a change in out-of-pocket price, holding fixed any supply response due to variation in the service price. Thus, it can be interpreted as an estimate of the demand elasticity.

We use the same controls as in specification (7), where we control for the costs and quality of the physician with vectors $COST$ and $QUAL$, as well as the demographics of the patient, PAT. Again ζ_d represents disease-stage-of-illness fixed effects and ζ_{at} represent state-time fixed effects. We cluster standard errors by disease and the provider's county

Table 4: Determinants of Service Utilization

	Cardiology	Orthopedics
$\widehat{\ln(P_n)}$	1.007***	0.286***
	(0.156)	(0.067)
$\widehat{\ln(P_n^{pock})}$	-0.402***	-0.199***
	(0.084)	(0.047)
$\ln(medinc_{pat})$	0.009	0.018***
	(0.011)	(0.005)
$\ln(educ_{pat})$	-0.422***	-0.344***
	(0.043)	(0.024)
EPO	-0.069*	-0.084***
	(0.039)	(0.018)
HMO	-0.176***	-0.148***
	(0.059)	(0.025)
POS	-0.183***	-0.090***
	(0.052)	(0.021)
PPO	-0.126***	-0.048***
	(0.029)	(0.011)
HDHP	0.051**	0.090***
	(0.022)	(0.018)
CDHP	-0.025**	0.079***
	(0.011)	(0.007)
EMPLOYER	0.035***	-0.053***
	(0.007)	(0.004)
$\ln(medval_{phys})$	-0.081***	-0.076***
	(0.011)	(0.008)
$\ln(rent_{phys})$	0.395***	0.161***
	(0.054)	(0.024)
$\ln(facwage_{phys})$	-0.028***	-0.010**
	(0.008)	(0.004)
$\ln(medinc_{phys})$	0.040	0.091***
	(0.028)	(0.016)
$\ln(medinc_{flow})$	-0.078***	-0.049***
	(0.020)	(0.011)
UNIV	-0.007	-0.033***
	(0.013)	(0.006)
Observations	2962896	3798361

Notes: The dependent variable is the logarithm of the utilization of services, $\ln(Q_n)$. All regressions include a dummy variable indicating the patient's gender, a polynomial in the patient's age (i.e. AGE, AGE^2, and AGE^3), a polynomial in the number of co-morbidities, as well as state-halfyear and disease, stage-of-illness fixed effects. The omitted plan types are "basic medical" and "comprehensive," $BMCOMP$. Standard errors are clustered by disease, provider, and county. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.

in order to control for any correlation in ε_n attributable to how distinct physicians treat patients with the same disease.

We report estimates of specification (9) in Table 4. The estimate of the supply elasticity, γ_1, is 1.01 for cardiology and 0.29 for orthopedics. These estimates imply that, holding the patient's demand response fixed, a ten percent increase in service prices will induce a cardiologist to provide 10.1 percent more services and an orthopedist to provide 2.9 percent more services. The estimate on the demand elasticity is -0.40 for cardiology patients and -0.20 for orthopedic patients. Both estimates imply that patients are price sensitive, but relatively inelastic.[60]

It is important to highlight that the empirical relationship estimated from equation (9) does not precisely coincide with the stylized theory proposed in Figure 1. In that framework, either the consumer's net marginal benefit or the physician's marginal cost are binding constraints on additional utilization. In other words, utilization is held back because either the physician decides to stop treatment (perhaps because P_n is low) or the patient chooses not treat her condition further (perhaps because P_n^{pock} is too high). In this case, an estimation procedure consistent with this theory would be a switching regression that would estimate both the physician and consumer decision problems separately and also include a regression that would predict which of the two agents makes the binding decision. However, this approach is not taken for two reasons. First, we would need to estimate a maximum likelihood switching regression model that would account for the endogeneity of P_n and P_n^{pock}, which may be computationally burdensome given the large number of observations. Second, even if the switching model is the ideal specification, the proposed model achieves the primary goal of estimating the average effects of P_n and P_n^{pock} on utilization.[61]

[60] We note that the estimate for orthopedics is close in magnitude to those measured using randomized data from the RAND health insurance experiment (Manning Et. al (1987) and Keeler and Rolph (1988)) who find elasticities in the -0.1 to -0.2 range.

[61] If a switching model is the correct specification, then the absolute values of the elasticities of individuals and physicians may be greater than the values estimated. In particular, the empirical model averages the elasticities of consumers that are responding to P_n^{pock} and those that are constrained by their physician's decision and have a P_n^{pock} elasticity of 0.

Although one may be concerned that the empirical model does not precisely conform to the proposed theory, it is worth noting that specification (9) fits closely to a related theory of physician-induced demand where the profit margin of the physician influences the consumer preferences for different levels of services. That is, a higher profit margin may cause a physician to induce a patient to seek additional services, as in McGuire and Pauly (1991). However, since the key empirical predictions from either of the two theories are the same (that is, negative effect on utilization from P_n^{pock} and positive effect from P_n), empirically

Table 5: Net Effect of Change in Service Price on Utilization

	Cardiology			Orthopedics		
	Full Sample	Low α_n Sample	High α_n Sample	Full Sample	Low α_n Sample	High α_n Sample
$\ln(P_n)$	0.874***	1.149***	0.438**	0.121*	0.351***	-0.267***
	(0.155)	(0.171)	(0.178)	(0.066)	(0.079)	(0.069)
Observations	3669306	1834653	1834653	4133673	2066836	2066836

Notes: The dependent variable is the logarithm of the utilization of services, $\ln(Q_n)$. All regressions include a dummy variable indicating the patient's gender, a polynomial in the patient's age (i.e. AGE, AGE^2, and AGE^3), a polynomial in the number of co-morbidities, state-halfyear and disease/stage-of-illness fixed effects, as well as variables in the vector PAT, $COST$, and DEM. Standard errors are clustered by disease, provider, and county. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.

5.2 Net Effects of a Change in Service Price on Utilization

As an alternative to a formal switching model, we attempt to estimate an improvised switching model that captures the key features of the theory. Intuitively, one may think that the level of coverage of an individual may be a key determinant of whether the binding constraint is from the physician or the patient. In particular, we should expect that for patients with low benefits (high α_n) the patient's demand is more likely to be the binding constraint, relative to physicians (that is, the physician would like to have greater utilization than the patient allows). In contrast, we should expect that for patients with high benefits (low α_n) the physician is more likely to be the binding constraint, relative to the patient (that is, the patient is willing to have more treatments than the physician allows). Therefore, by focusing on the effects of P_n on utilization for different individuals with different levels of coverage, we are able to offer an alternative test of the proposed theory.

As an additional exercise, we examine the net overall effect of a change in the service price on the utilization of services:

$$\ln(Q_n) = \gamma_3 \widehat{\ln(P_n)} + \delta' COST + \kappa' QUAL + \lambda' PAT + \zeta_{at} + \zeta_d + \varepsilon_n, \tag{10}$$

which is identical to specification (9), however, we have removed the out-of-pocket price

distinguishing between these theories may be challenging. More importantly, the policy implications of both theories are very similar, so for many practical purposes it may not matter which of the two theories is the correct one.

as a covariate. It is important to note that γ_3 is an estimate of the *average* effect of a marginal price increase over *all* patients in the full sample. As demonstrated in Figure 1, there will be patients in the full sample with low benefits (high α_n)—where a price increase should likely represent a movement along the patient's demand curve—and there will also be patients with large benefits (low α_n)—where a price increase likely represents a movement along the physician's supply curve. Thus, γ_3 reports an estimate of the average effect of price on utilization for all of these individuals.

As a test of the theoretical predictions of the framework in Section 2.3.2, we divide the sample in half, between those patients with α_n above the median and those patients with α_n below the median.[62] By assessing sub-samples of patients with high and low out-of-pocket costs we are attempting to isolate the two disparate effects delineated in the model. Specifically, the average effect of prices on utilization γ_3 should be larger on those patients with better benefits.

Estimates are shown in Table 5. The net effect of a service price change on the entire sample of cardiologists is 0.87 and is 0.12 for orthopedists. This implies that, on net, a ten percent increase in the service price induces a 9 percent increase in service utilization for cardiology patients and a 1.2 percent increase for orthopedic patients. In line with the theoretical framework, the net effect of a change in service price on utilization is dependent on the generosity of benefits. For example, for orthopedic patients with large benefits (the sample where α_n lies below the median level), the net effect is 0.35, while for patients with low benefits (the sample where α_n lies above the median level) the net effect is -0.27. For cardiology patients with large benefits, the net price effect on the sample with large benefits is 1.15, while for patients with low benefits the net effect is 0.44. Thus, there is evidence that cost-sharing with the patient does in fact dampen the effect of the physician's positive supply elasticity.

[62]Due to the nonlinear structure of benefits attributable to deductables and maximum dollar expenditures, the measure of α_n is inherently dependant on the underlying quantity of services provided. For instance, episodes with a very large quantity of services will inherently have a low α_n, even though the actual benefit structure may be the same as a patient with a larger α_n but a more moderate degree of services provided. To correct for this, we divide the sample based on predicted measures, $\widehat{\alpha_n}$, the fitted values from $\ln(\alpha) = \beta' IV + \theta' COST + \kappa' QUAL + \lambda' PAT + \zeta_{at} + \zeta_d + \varepsilon_n$, where IV is the set of instruments. This is part of reason why using instrumental variables in specifications (8) and (9) was crucial.

6 Market Power and Service Provision

Taken together, the estimates from specifications (7) and (9) imply that an increase in physician bargaining leverage may translate into higher service utilization rates through its effect on service price. That is, specification (7) implies that an increase in physician concentration raises service prices, while specification (9) implies that an increase in service prices raises service utilization. Furthermore, the estimates on the insurance carrier side indicate that an increase in health-plan concentration lowers both prices as well as benefits. Thus, our estimates imply that insurance carriers can lower service utilization through both removing price incentives for physicians (via lowering P_n), as well as inducing patients to become more price sensitive (via raising α_n).

These features can be better understood by decomposing specification (9) into its structural components. Dropping subscripts and control variables for ease of notation, we can write this equation as:

$$\ln(Q_n) = \gamma_1 \ln(P) + \gamma_2 \ln(P^{pock}).$$

Plugging in $P^{pock} = \alpha P$, yields:

$$\ln(Q_n) = \gamma_1 \ln(P) + \gamma_2[\ln(\alpha) + \ln(P)]. \tag{11}$$

Next, note that specification (7) implies that P is function of both $FTHHI_{phys}$ and HHI_{ins}, while specification (8) implies that α is a function of HHI_{ins}. This means we can take the partial derivative of (11) with respect to $\ln(FTHHI_{phys})$:

$$\frac{\partial \ln(Q)}{\partial \ln(FTHHI_{phys})} \approx \beta_1[\gamma_1 + \gamma_2] \tag{12}$$

or we can take the partial derivative of (11) with respect to $\ln(HHI_{ins})$:

$$\frac{\partial \ln(Q)}{\partial \ln(HHI_{ins})} \approx \beta_2[\gamma_1 + \gamma_2] + \gamma_2\beta_3. \tag{13}$$

where β_1 and β_2 represent $\frac{\partial \ln(P)}{\partial \ln(FTHHI_{phys})}$ and $\frac{\partial \ln(P)}{\partial \ln(HHI_{ins})}$, β_3 represents $\frac{\partial \ln(\alpha)}{\partial \ln(HHI_{ins})}$, and γ_1 and γ_2 represent $\frac{\partial \ln(Q)}{\partial \ln(P)}$ and $\frac{\partial \ln(Q)}{\partial \ln(P^{pock})}$. Note that these parameters correspond to the coefficients taken from specifications (7), (8), and (9), respectively. The equations (12) and (13) describe the basic mechanism by which bargaining leverage can translate into shifts in utilization. A larger degree of bargaining leverage enables physicians to raise prices, captured by $\beta_1 > 0$. This price increase will translate into an *increase* in service utilization, on average, if the supply elasticity is larger (in absolute value) than the demand elasticity (that is $\gamma_1 + \gamma_2 > 0$) and a *decrease* in service utilization if the supply elasticity is smaller in absolute value than the demand elasticity. On the insurance side, there is an extra effect by which the insurance firm can shift the benefit schedule, captured by $\beta_3 > 0$. Plugging in our estimated values of β_1, β_2 from (7), β_3 from (8) and γ_1 and γ_2 (9), we calculate the marginal effect of physician concentration on service utilization to be 0.064 for cardiology and 0.010 for orthopedics, and for marginal effect for insurance carriers is -0.238 for cardiology and -0.072 for orthopedics.

To directly estimate the marginal effect of bargaining leverage on service utilization we estimate a reduced-form specification, analogous to (7):

$$\begin{aligned} \ln(Q_n) &= \phi_1 \ln(\widehat{FTHHI}_{phys}) + \phi_2 \ln(\widehat{HHI}_{ins}) + \delta' COST \\ &\quad + \kappa' QUAL + \lambda' PAT + \zeta_{at} + \zeta_d + \varepsilon_n. \end{aligned} \tag{14}$$

where ϕ_1 is an approximation of $\frac{\partial \ln(Q)}{\partial \ln(FTHHI_{phys})}$ and ϕ_2 is an approximation of $\frac{\partial \ln(Q)}{\partial \ln(HHI_{ins})}$. As in our previous specification, we include disease-stage-of-illness fixed effects, ζ_d, state-time fixed effects, ζ_{at}, as well as controls for the physician's cost, $COST$, quality, $QUAL$, and the patient's demographic factors, PAT. Standard errors are clustered by disease and the provider's county to allow for correlation in ε_n specific to how certain physicians care for specific diseases. We instrument using the same set of aggregate demographic variables.

Estimates are depicted in Table 6. The estimate of ϕ_1 is 0.095 for cardiologists and 0.024 for orthopedists. This implies that a 10 percent increase in the physician HHI induces a cardiologist to perform approximately 0.95 percent more services and an orthopedist 0.24 percent more services. The effects are larger for insurance carriers. Increasing an insurance carrier's HHI by 10 percent will induce a 4.4 percent decrease in patient utilization for cardiologists and 1.7 percent drop for orthopedists.

As our estimates indicate that bargaining leverage affects both prices *and* utilization, the effects on medical-care expenditures become magnified relative to the scenario where bargaining power translates only into price effects. This can be seen more clearly by reexamining equation (6), which shows that, by construction, the sum of the coefficients on price and utilization will equal the coefficient on total episode expenditures. This implies that a 10 percent rise in $FTHHI_{phys}$ is associated with roughly a 2 percent increase in expenditures for cardiologists and a 1.4 percent increase for orthopedists.[63] To put this number in better perspective, all else equal, a cardiologist with the 90th-percentile $FTHHI_{phys}$ will have about 56 percent higher expenditures per episode on average than

[63]That is, $0.20 \approx 0.105 + 0.095$ for cardiologists and a $.14 \approx 0.111 + 0..024$

Table 6: Market Structure and Service Utilization

	Cardiology	Orthopedics
$\ln(HHI_{phys})$	0.095***	0.024**
	(0.021)	(0.010)
$\ln(HHI_{ins})$	-0.443***	-0.173***
	(0.114)	(0.043)
$\ln(medval_{phys})$	-0.044***	-0.062***
	(0.013)	(0.009)
$\ln(rent_{phys})$	0.384***	0.120***
	(0.049)	(0.024)
$\ln(facwage_{phys})$	-0.038***	-0.005
	(0.010)	(0.004)
$\ln(medinc_{phys})$	-0.032	0.063***
	(0.036)	(0.020)
$\ln(medinc_{flow})$	-0.124***	-0.032***
	(0.025)	(0.012)
UNIV	0.002	-0.033***
	(0.014)	(0.007)
$\ln(medinc_{pat})$	0.076***	0.026***
	(0.010)	(0.006)
$\ln(educ_{pat})$	-0.190***	-0.306***
	(0.043)	(0.020)
EPO	0.038***	0.012*
	(0.011)	(0.007)
HMO	0.007	-0.024***
	(0.008)	(0.004)
POS	0.017*	0.010***
	(0.010)	(0.004)
PPO	0.015**	-0.008***
	(0.007)	(0.003)
HDHP	0.044**	0.013
	(0.018)	(0.011)
CDHP	0.015*	-0.038***
	(0.009)	(0.004)
EMPLOYER	0.039***	-0.043***
	(0.009)	(0.003)
Observations	3664348	4131612

Notes: The dependent variable is the logarithm of the utilization of services, $\ln(Q_n)$. All regressions include a dummy variable indicating the patient's gender, a polynomial in the patient's age (i.e. AGE, AGE^2, and AGE^3), a polynomial in the number of co-morbidities, as well as state-halfyear and disease/stage-of-illness fixed effects. The omitted plan types are "basic medical" and "comprehensive," $BMCOMP$. Standard errors are clustered by disease, provider, and county. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.

a cardiologist with the 10th-percentile $FTHHI_{phys}$. The corresponding orthopedist will have 36 percent higher expenditures per episode. Splitting this number between the price and utilization component, the 90th-percentile cardiologist will charge 26 percent higher prices and perform 24 percent more services.[64] For orthopedics, a physician with the 90th percentile $FTHHI_{phys}$ will charge 29 percent higher fees and perform 6 percent more services than a physician with the 10th percentile $FTHHI_{phys}$.

7 Conclusion

The effects of physician bargaining power are important given the observed consolidation of physicians over the past few decades, and the potential increase in consolidation due to health care reform. This paper studies the role of physician bargaining leverage in determining service prices and service utilization—the two components of physician medical-care expenditures. Our estimates suggest that those physicians with greater market power relative to insurance carriers are able to receive higher service payments. In addition, we find that those physicians facing higher service prices are willing to provide more services to the patient, compared to those physicians facing lower service prices. Market power of insurance carriers also play an important role. We provide evidence that insurance carriers with greater market power are able to negotiate lower service prices and are also able to reduce the generosity of physician benefits. These results have broad implications for antitrust policy and the designing of payment schedules to physicians.

These findings may explain a portion of the large geographic variation in overall medical expenditures documented in Dunn, Shapiro, and Liebman (2011). In particular, this study shows how bargaining power of physicians and insurers may affect both the service prices and utilization of services. However, Dunn, Shapiro, and Liebman (2011) also document significant variation in many other health services (for example, hospital outpatient, hospital inpatient, and pharmacy services). Given the central role of physicians as the agents selecting health care services for patients, it is possible that the incentives of physicians may impact ancillary health care services used in the treatment of a disease (e.g. inpatient facility payments to a hospital). Expenditures may increase with physician utilization due to complementarities with other services, or physician services may be an alternative substitute for other treatments. Further research would entail analyzing how physician market power manifests itself into different mixes of services (for exam-

[64]For example, $0.26 = \frac{exp(.105*\ln(.241))-exp(.105*\ln(.026))}{exp(.105*\ln(.026))}$ where 0.241 and 0.026 are the 90th and 10th percentile $FTHHI_{phys}$, respectively.

ple, pharmacy services, inpatient services, outpatient services) being administered to the patient.

In sum, we find that the overall effects of physician market power on medical-care spending are enormous. In particular, a cardiologist with the 90th percentile FTHHI will spend 56 percent more dollars per episode of care than a cardiologist with the 10th percentile. However, we do not have information on the health outcome of the patient. Thus, it is not entirely clear whether those patients being treated by physicians with larger market power are receiving higher quality treatment and/or are getting better health outcomes. Future research would therefore also entail measuring how physician market power translates into physician quality and health outcomes. Additional work is also necessary to fully examine the effect of higher physician expenditures on downstream costs. Recent papers have confirmed an ability of health insurers to exercise market power and its affect on premiums and benefits (Dunn (2010) and Dafny et al. (2011)), but more work is necessary to determine if the higher prices and utilization due to physician market power are actually passed on to consumers in the form of higher premiums.

References

[1] Aizcorbe, A. and Nestoriak, N. 2011. "Changing Mix of Medical Care Services: Stylized Facts and Implications for Price Indexes", *Journal of Health Economics*, forethcoming

[2] Capps, C., D. Dranove and Satterthwaite, M. 2003. "Competition and Market Power in Option Demand Markets." *RAND Journal of Economics.* 34(4): 737-763

[3] Cromwell, J., Hurdle, S., and Wedig, G. 1986. "Impacts of Economic and Programmatic Changes on Medicaid Enrollments." *The Review of Economics and Statistics* Vol. 68, No. 2, pp. 232-240

[4] Cutler, D. and Ly, D. 2011. "The (Paper)Work of Medicine: Understanding International Medical Costs." *Journal of Economic Perspectives* 25(2) pp. 3-25.

[5] Chernew, M., Lindsay S., Chandra,A. Gibson, T. and Newhouse,J. 2010. "Geographic Correlation Between Large-Firm Commercial Spending and Medicare Spending", *American Journal of Managed Care*, 16(2) pgs 131-138.

[6] Chernew, M., Hirth, R., Cutler D. 2009 "Increased spending on health care: long-term implications for the nation." *Health Affairs* vol. 28 no. 5 1253-1255

[7] Dafny, L. 2005. "Do Hospitals Respond to Price Changes?" *American Economic Review.*

[8] Dafny, L. 2010. "Are Health Insurance Markets Competive?" *American Economic Review.*

[9] Dafny, L., M. Duggan, and S. Ramanarayanan, 2011. "Paying a Premium on Your Premium? Consolidation in the U.S. Health Insurance Industry." *American Economic Review.*

[10] Decker, S. 2009. "Changes in Medicaid Physician Fees and Patterns of Ambulatory Care." *Inquiry* Vol. 46, No. 3, pp. 291-304.

[11] Dranove, D., 1988. "Demand Inducement and the Physician/Patient Relationship." *Economic Inquiry.* Vol. 26 pgs. 251-298.

[12] Dranove, D., Shanley, M., and White, W. 1993. "Price and Concentration in Hospital Markets: The Switch from Patient Driven to Payer-Driven Competition." *Journal of Law and Economics*, Vol. 36, pp. 179-204.

[13] Dranove, D., R. Lindrooth, W. White, and J. Zwanziger, 2008. "Is the impact of managed care on hospital prices decreasing?", *Journal of Health Economics*, Vol. 27, pp. 362-376.

[14] Dranove, D., A. Gron, and M. Mazzeo, 2003. "Differentiation and Competition in HMO Markets." *Journal of Industrial Economics.*

[15] Duggan, M., F.S. Morton 2010 "The Impact of Medicare Part D on Pharmaceutical Prices and Utilization" (with Fiona Scott Morton), *American Economic Review.*

[16] Dunn, A., A. H. Shapiro, and E. Liebman, 2011. "Geographic Variation in Commercial Medical Care Expenditures: A Decomposition Between Price and Utilization." Working Paper.

[17] Dunn, A., 2010. "The Effect of Health Insurance Competition when Private Insurers Compete with a Public Option." Working Paper.

[18] Evans, R., 1974. "Supplier-induced Demand" in: M. Perlman, ed., The Economics of Health and Medical Care (Macmillan, London) pgs 162-173.

[19] Federal Trade Commision (FTC) and Department of Justice (DOJ), 2004. Improving Health Care: A Dose of Competition. Report.

[20] Fuchs, V.R., 1978. "The Supply of Surgeons and the Demand for Operations", The Journal of Human Resources pgs 35-56.

[21] Liebhaber A, Grossman JM., 2008. "Physicians Moving to Mid-Sized, Single-Specialty Practices." Health Systems Change Tracking Report Report No. 18. www.hschange.org/CONTENT/941.

[22] Gaynor, M., and Haas-Wilson, D. 1999. "Change, consolidation, and competition in health caremarkets." *Journal of Economic Perspectives*, 13(1), 141–164.

[23] Grant, Da. 2009. "Physician Financial Incentives and Cesarean Delivery: New Conclusion from the Healthcare Cost and Utilization Project." *Journal of Health Economics.* Volume 28, Issue 1, Pages 244-250.

[24] Gruber, J., Kim, J., and Mayzlin, D. 1999. "Physician fees and procedure intensity: the case of cesarean delivery." *Journal of Health Economics*. Volume 18, Issue 4, August 1999, Pages 473-490.

[25] Hemenway, D., Killen, A., Cashman, S. Parks, C., Bicknell, W. 1990. "Physicians' responses to financial incentives. Evidence from a for-profit ambulatory care center" *New England Journal of Medicine* Apr 12;322(15):1059-63.

[26] Haas-Wilson, D. 2003. *Managed care and monopoly power: The antitrust challenge.* Cambridge: Harvard University Press.

[27] Holahan, J., and Garrett, B. 2009 "Rising Unemployment, Medicaid and the Uninsured," Urban Institute Policy Brief.

[28] Keeler, E.B., Melnick, G. and Zwanziger, J. 1999. "The Changing Effects of Competition on Non-profit and For-Profit Hospital Pricing Behavior." *Journal of Health Economics*, Vol. 18, pp. 69-86.

[29] Keeler, E. and Rolph, J. 1988. "The Demand for Episodes of Treatment in the Health Insurance Experiement." Journal of Health Econoimcs,

[30] Liebhaber A, Grossman JM. Physicians Moving to Mid-Sized, Single-Specialty Practices. Health Systems Change Tracking Report Report No. 18. www.hschange.org/CONTENT/941. Published August 2007. Accessed September 15, 2008.

[31] McGuire, T.G. and M.V. Pauly, 1991. "Physician Response to Fee Changes with Multiple Players.", *Journal of Health Economics* pp. 385-410.

[32] Noether J. 1988. "Competition Among Hospitals." *Journal of Health Economics*, Vol. 7 , pp. 259-284.

[33] Pauly, M.V., 1980. *Doctors and Their Workshops: Economic Models of Physician Behavior.* University of Chicago Press, Chicago.

[34] Pope, G. C., Burge, R. T., 1996. "Economies of scale in physician practice." *Medical Care Research and Review*, 53(4), 417-440.

[35] Sirovich B, Gallagher PM, Wennberg DE, Fisher ES. 2008. "Discretionary decision making by primary care physicians and the cost of U.S. Health care." *Health Affairs* 2008 May-Jun; 27(3):813-23.

[36] Smart D.R. 2006. *Medical group practices in the US*, 2006 edition. Chicago, IL: American Medical Association.

[37] Sorensen, A. 2003. "Insurer-hospital bargaining: negotiated discounts in post-deregulation Connecticut." *The Journal of Industrial Economics*, 51: 469–490.

[38] Staten, M. Umbeck, J. and Dunkelberg, W., 1987. "Market Share and the Illusion of Power: Can Blue Cross Force Hospitals to Discount?" *Journal of Health Economics* 6(1), 43-58.

[39] Staten, M. Umbeck, J. and Dunkelberg, W., 1988. "Market Share/Market Power Revisited: A New Test for an Old Theory," *Journal of Health Economics* 7(1), 73-83.

[40] Smart DR. Medical group practices in the US, 2006 edition. Chicago, IL: American Medical Association; 2006

[41] Town, R. and Vistnes, G. 2001. "Hospital Competition in HMO Networks," *Journal of Health Economics*, Vol. 20., pp. 733-753.

Appendix

A Construction of Fixed-Travel-Time HHI

We construct fixed-travel-time concentration measures in the following fashion. For each geographic location we define a latitude and longitude location as a vector $x = \{lat, long\}$. Using Google's Maps software we can measure a maximum radial distance based on amount driving time $\bar{k}$. For instance, for any location x we can calculate a radius of $\bar{k} = 80$ minutes of driving time. To do so, for each county, c, we drew a random coordinate and then calculated the average speed, $speed_c$, one could travel 0.1 degrees north, south, east, and west latitude. We use the Stata package, "traveltime," written by Ozimek and Miles. This allows us to define a maximum radial distance for any latitude and longitude coordinate in county c as $\bar{k} * speed_c$.

For each location in the SK&A data, we attach weights to each physician group in the surrounding area. These weights can be thought of as probabilities of whether a patient located at x_0 would be willing to travel to a physician located at x_i. For a consumer located at x_0, we define their driving time to a physician located at x_i as k_{x_i}. It follows that a patient who lives at location x_0 resides k_{x_i} minutes away from the physician located at x_i. We then create a weight variable which represents the probability that a patient located at x_0 would consider traveling to the physician located at x_i. We do this in the most tractable manner possible by assuming that patients' idiosyncratic taste shocks lie on the uniform distribution and that k_{x_i} is directly proportional to travel costs. Specifically, a consumer will choose a physician located at x_i instead of a physician located at x_0 if $V - k_{x_i} + \varepsilon_{i0} > V - k_{x_0}$ where V is the consumer valuation of treatment and ε_{i0} is a patient taste shock of traveling from x_i to x_0 which lies on the uniform distribution between 0 and $\bar{k}$. As $k_{x_0} = 0$ by construction, it follows that a patient located at x_0 would be willing to travel to x_i (that is, travel k_{x_i} minutes) with probability:

$$Pr(\varepsilon_{i0} > k_{x_i}) = \begin{cases} 1 - (1/\bar{k})k_{x_i} & \text{if} \quad k_{x_i} \leq \bar{k} \\ 0 & \text{if} \quad k_{x_i} > \bar{k} \end{cases} \tag{15}$$

We treat these probabilities as physician weights used to calculate the expected market share for a given location. This means the expected market share of a physician located at x_i for patients located x_0 is $E[S_{x_i}(x_0)] = \frac{Pr(\varepsilon_{i0} > k_{x_i})}{\sum_j Pr(\varepsilon_{j0} > k_{x_j})}$ where j indexes each physician in the database. For example, suppose there exist ten physicians all residing exactly at location x_0 while every other physician in the data resides over 80 minutes away. It follows that each of these ten physicians has equal probability of attracting patients from location x_0, resulting in each having an expected market share of 0.1 for patients located at x_0. It follows that the expected market share at location x_0 for physician *group* i that has N_i physicians in the group, located at x_i is $E[S^*_{x_i}(x_0)] = \frac{N_i Pr(\varepsilon_{i0} > k_{x_i})}{\sum_j N_j Pr(\varepsilon_{j0} > k_{x_j})}$.

As we have only county level information about where consumers live in the SK&A data, we calculate an HHI for every geographic coordinate listed. Thus, we are in essence proxying patient location with the physician locations in the SK&A data. For each location, h, in the SK&A data, we calculate a distinct $HHI(x_h) = \sum_i E[S^*_{x_j}(x_h)]^2$ based on the expected market shares at location h. We then created an average concentration for the county as $HHI_c = \frac{1}{M_c}\sum_{h \in c} HHI(x_h)$ where M_c is the number of geographic points, h.

Finally, we merge the county-level HHI_c in the MarketScan® data. Since MarketScan® has information on the county of both the provider as well as the patient, we have information on where each physician's patients reside. For each physician, p, we take a weighted sum of the counties where physician p's patients reside to arrive at our physician level concentration measure $FTHHI^p_{phys} = \sum_c \omega_{cp} HHI_c$ where ω_c is the share of physician p's patients from county c.

B Variable Definitions

- Concentration Measures
  - $FTHHI_{phys}$: The Fixed-Travel-Time Herfindahl-Hirschman concentration measure for physicians. This measure is specific to each physician in the MarketScan® data. See Appendix A for details on construction.
  - HHI_{ins} : The Herfindahl-Hirschman concentration measure for insurance carriers. This measure is specific to each MSA. See Section 3 for details on construction.
- Expenditure Measures
  - P_n : The logarithm of price per service for episode of care n of services performed by the physician. See Section 3 for details on construction.
  - Q_n : The logarithm of service utilization for episode of care n provided by the physician. See Section 3 for details on construction.

- TE_n : The logarithm of total physician expenditures of episode of care n. See Section 3 for details on construction.

- Patient-Specific Controls (PAT)
  - $\ln(medinc_{pat})$ - The logarithm of the median income in the patient's county.
  - $educ_{pat}$ - The fraction of college educated individuals in the patient's county.
  - EPO - A dummy variable indicating if the patient's health plan is an exclusive provider organization.
  - HMO - A dummy variable indicating if the patient's health plan is a health maintenance organization.
  - POS - A dummy variable indicating if the patient's health plan is a point-of-service plan.
  - PPO - A dummy variable indicating if the patient's health plan is a preferred provider organization.
  - $HDHP$ - A dummy variable indicating if the patient's health plan is a high-deductible health plan.
  - $CDHP$ - A dummy variable indicating if the patient's health plan is a consumer-driven health plan.
  - $EMPLOYER$ - A dummy variable indicating if the patient's health plan is employer based
  - AGE - The patient's age
  - AGE^2 - The patient's age squared
  - AGE^3 - The patient's age cubed
  - $COMORBID$ - The number of co-morbidities (that is, concurrent diseases) of the patient.
  - $COMORBID^2$ - The number of co-morbidities squared.
  - $COMORBID^3$ - The number of co-morbidities cubed.
  - $GENDER$ - A dummy variable indicating the patient's gender

- Physician Quality Controls ($QUAL$)

- $\ln(medinc_{flow})$: The logarithm of the patient-weighted median household income. Here, $medinc_{flow} = \sum \omega_{cp} medinc_c$, where $medinc_c$ is the median income in county c and ω_{cp} is the share of physician p's patients from county c. Taken from the Area Resource File.
- $UNIV$: The fraction of hospitals in the physician's county, c, that are affiliated with a medical university. Taken from the Area Resource File.

- Physician Cost Controls ($COST$)
  - $\ln(rent_{phys})$: The logarithm of the median gross rent in the physician's county. Taken from the Area Resource File.
  - $\ln(medval_{phys})$: The logarithm of the median home value in the physician's county. Taken from the Area Resource File.
  - $\ln(medinc_{phys})$: The logarithm of the median household in the physician's county. Taken from the Area Resource File.
  - $\ln(facwage_{phys})$: The logarithm of the total health care facility payrolls divided by the number of facility employees. Taken from the Area Resource File.

- Instruments
  - $\ln(pop_{flow})$ - The logarithm of the patient-weighted total population. Here, $pop_{flow} = \sum \omega_{cp} pop_c$, where pop_c is the total population in county c and ω_{cp} is the share of physician p's patients from county c. Taken from the Area Resource File.
  - $\ln(pop65_{flow})$ - The logarithm of the patient-weighted population over 65 years of age. Here, $pop65_{flow} = \sum \omega_{cp} pop65_c$, where $pop65_c$ is the population over 65 in county c and ω_{cp} is the share of physician p's patients from county c. Taken from the Area Resource File.
  - $\ln(popK_{flow})$ - The logarithm of the patient-weighted population between K-10 and K years of age, where K = 65, 55, 45, and 35. Here, $popK_{flow} = \sum \omega_{cp} popK_c$, where ω_{cp} is the share of physician p's patients from county c and $popK_c$ is the imputed population between K and K - 10 years of age in county c in the Area Resource file. That is, $popK_c = fracK_c * pop_c$, where $fracK$ is the fraction in K to K-10 age-group for county c in the entire MarketScan® database.

– $\ln(pop_{MSA})$ - The logarithm of the population of the MSA. Taken from the Area Resource File.

– $URATE$ - The unemployment rate in the physician's county. Taken from the Area Resource File.

– $URATE^2$ - The unemployment rate in the physician's county squared. Taken from the Area Resource File.

– $URATE^3$ - The unemployment rate in the physician's county cubed. Taken from the Area Resource File.

C Robustness Tables

C.1 Estimates of First-Stage Instrumental Variables

	Cardiology		Orthopedics	
	$\ln(FTHHI_{phys})$	$\ln(HHI_{ins})$	$\ln(FTHHI_{phys})$	$\ln(HHI_{ins})$
$\ln(pop_{flow})$	-0.042	0.331	1.401**	0.260
	(0.470)	(0.257)	(0.597)	(0.223)
$\ln(pop35_{flow})$	0.643**	-0.186	-0.909**	-0.205
	(0.293)	(0.166)	(0.380)	(0.144)
$\ln(pop45_{flow})$	-1.313***	-0.170*	-0.034	-0.068
	(0.284)	(0.095)	(0.255)	(0.087)
$\ln(pop55_{flow})$	0.811***	0.143**	-0.190	0.118**
	(0.169)	(0.065)	(0.167)	(0.056)
$\ln(pop65_{flow})$	-0.422***	-0.117**	-0.454***	-0.112***
	(0.141)	(0.048)	(0.143)	(0.043)
$\ln(pop_{msa})$	-0.196***	-0.050***	-0.195***	-0.052***
	(0.019)	(0.007)	(0.020)	(0.008)
$URATE$	-10.523	11.339*	18.539	17.735***
	(17.703)	(5.836)	(25.114)	(6.014)
$URATE^2$	-317.630	-511.005***	-526.586	-709.270***
	(518.614)	(169.012)	(699.627)	(178.561)
$URATE^3$	6388.340	4719.404***	5304.468	6186.941***
	(4268.752)	(1431.793)	(4874.304)	(1518.631)
F-Stat	69.2	13.1	60.4	22.3
Observations	3664348	3669306	4131612	4133673

Notes: The dependent variable is listed at the column head. Standard errors are clustered by provider-county. Not shown are the estimates on the covariates of specification (7). F-statistics test the null hypothesis that all instruments are jointly equal to zero. For each sample, the total effect of the unemployment rate on $\ln(HHI_{ins})$ (that is, $\widehat{\delta}_1 URATE + \widehat{\delta}_2 URATE^2 + \widehat{\delta}_3 URATE^3$) is positive for all values within the 99th percentile unemployment rate.

C.2 Alternative Instrument Set

We report estimates of specification (7) using the following alternative instrument set constructed from the U.S. Census Bureau's County Business Patterns database.

- $\ln(firms)$ - The logarithm of the number of business establishments in the physician's county c in year y.
- $\ln(firm20)$ - The logarithm of the fraction of business establishments with less than 20 employees in the physician's county c in year y.
- $\ln(firm50)$ - The logarithm of the fraction of business establishments with greater than 20 employees and less than 50 employees in the physician's county c in year y.
- $\ln(firm50)$ - The logarithm of the fraction of business establishments with greater than 50 employees and less than 100 employees in the physician's county c in year y.

	Cardiology	Orthopedics
$\ln(HHI_{phys})$	0.116***	0.164***
	(0.018)	(0.035)
$\ln(HHI_{ins})$	-0.208*	-0.299**
	(0.114)	(0.123)
$\ln(medval_{phys})$	0.075***	0.113***
	(0.022)	(0.019)
$\ln(rent_{phys})$	-0.009	0.004
	(0.061)	(0.053)
$\ln(facwage_{phys})$	-0.004	-0.001
	(0.007)	(0.009)
$\ln(medinc_{phys})$	-0.078*	-0.192***
	(0.040)	(0.049)
$\ln(medinc_{flow})$	0.018	0.160***
	(0.020)	(0.032)
UNIV	0.016	-0.008
	(0.013)	(0.017)
$\ln(medinc_{pat})$	0.042***	0.036***
	(0.008)	(0.011)
$\ln(educ_{pat})$	0.099***	0.172***
	(0.036)	(0.042)
EPO	-0.025***	-0.009
	(0.007)	(0.010)
HMO	-0.039***	-0.005
	(0.006)	(0.007)
POS	-0.017***	-0.008
	(0.006)	(0.006)
PPO	0.003	0.006
	(0.004)	(0.004)
HDHP	-0.001	0.009
	(0.011)	(0.007)
CDHP	0.029***	0.038***
	(0.005)	(0.005)
EMPLOYER	-0.007	0.020**
	(0.007)	(0.008)
Observations	3668928	4135610

Notes: The dependent variable is the logarithm of service price, $\ln(P_n)$. All regressions include a dummy variable indicating the patient's gender, a polynomial in the patient's age (i.e. AGE, AGE^2, and AGE^3), a polynomial in the number of co-morbidities, as well as state-halfyear and disease-stage-of-illness fixed effects. The omitted plan types are "basic medical" and "comprehensive," $BMCOMP$. Standard errors are in parentheses and are clustered by provider-county. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.

C.3 Instrument Validity

	Cardiology	Orthopedics
$\ln(pop_{flow})$	0.063	0.058
	(0.074)	(0.074)
$\ln(pop35_{flow})$	-0.050	0.003
	(0.047)	(0.050)
$\ln(pop45_{flow})$	0.028	-0.071*
	(0.033)	(0.042)
$\ln(pop55_{flow})$	-0.046*	0.014
	(0.024)	(0.026)
$\ln(pop65_{flow})$	0.004	-0.001
	(0.021)	(0.018)
$\ln(pop_{msa})$	0.003	0.002
	(0.003)	(0.003)
$URATE$	0.711	6.701**
	(2.635)	(3.148)
$URATE^2$	29.555	-151.948
	(77.060)	(92.577)
$URATE^3$	-752.531	519.568
	(586.559)	(657.722)
R^2	0.0007	0.0015
F-Stat	3.2	5.4
Observations	3664348	4131612

Notes: Here we report results of an exercise assessing the validity of the main instrument set. First we collect the residuals from specification (7) using the alternative instrument set (estimates shown above in Section C.2). Next, we run an OLS regression of these residuals on the main instrument set used in the study. Standard errors are in parentheses and are clustered by provider-county. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.

C.4 Additional Endogenous Controls

We provide additional estimates where we include controls for the size of the firm and the number of physicians per capita in the county. Specifically, we include a variable $\ln(scale)$ which is the logarithm of the average number of doctors per firm in county c at time t. We also include a variable $\ln(physdens)$ which is measured as the logarithm of the total number of cardiologists (or orthopedists) per capita in county c at time t. The former variable is meant to control for possible economies of scale of larger firms, while the later variable is meant to control for the overall supply of physicians. As these two variables may be endogenous to the extent that physicians chase higher prices, we also include specifications where we include them as endogenous right-hand-side variables.

All regressions include a dummy variable indicating the patient's gender, a polynomial of the patient's age (i.e. AGE, AGE^2, and AGE^3), a polynomial in the number of co-morbidities, as well as state-halfyear and disease/stage-of-illness fixed effects. The omitted plan types are "basic medical" and "comprehensive." Standard errors are in parentheses and are clustered by provider and county in specification with service price as the dependent variable and are clustered by disease, provider, and county in the specification with service utilization as the dependent variable. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.

C.4.1 Additional Endogenous Controls: Market Structure on Price

	Exogenous Controls		Endogenenous Controls	
	Cardiology	Orthopedics	Cardiology	Orthopedics
$\ln(HHI_{phys})$	0.113***	0.097***	0.119***	0.108***
	(0.016)	(0.019)	(0.016)	(0.023)
$\ln(HHI_{ins})$	-0.312***	-0.200**	-0.298***	-0.296**
	(0.094)	(0.087)	(0.103)	(0.132)
$\ln(scale)$	-0.060***	-0.033**	-0.070**	0.069
	(0.013)	(0.014)	(0.033)	(0.082)
$\ln(physdens)$	0.044***	0.040***	0.013	0.014
	(0.009)	(0.011)	(0.030)	(0.036)
$\ln(medval_{phys})$	0.049**	0.067***	0.051**	0.093***
	(0.020)	(0.019)	(0.021)	(0.024)
$\ln(rent_{phys})$	-0.008	-0.059	0.010	-0.071
	(0.058)	(0.044)	(0.066)	(0.058)
$\ln(facwage_{phys})$	-0.005	0.005	0.013	-0.011
	(0.009)	(0.008)	(0.020)	(0.024)
$\ln(medinc_{phys})$	-0.061	-0.097***	-0.063	-0.141***
	(0.039)	(0.035)	(0.039)	(0.047)
$\ln(medinc_{flow})$	0.007	0.099***	0.001	0.100***
	(0.022)	(0.018)	(0.023)	(0.021)
UNIV	0.018	-0.000	0.029*	-0.021
	(0.014)	(0.012)	(0.017)	(0.025)
$\ln(medinc_{pat})$	0.041***	0.027***	0.042***	0.027***
	(0.008)	(0.008)	(0.009)	(0.009)
$\ln(educ_{pat})$	0.112***	0.151***	0.138***	0.157***
	(0.032)	(0.030)	(0.037)	(0.039)
EPO	-0.032***	-0.025***	-0.031***	-0.019**
	(0.007)	(0.008)	(0.007)	(0.009)
HMO	-0.038***	-0.005	-0.038***	-0.005
	(0.006)	(0.006)	(0.006)	(0.007)
POS	-0.018***	-0.004	-0.018***	-0.007
	(0.005)	(0.005)	(0.005)	(0.006)
PPO	0.000	0.007*	-0.000	0.006
	(0.004)	(0.004)	(0.004)	(0.004)
HDHP	-0.003	0.004	-0.002	0.005
	(0.012)	(0.007)	(0.013)	(0.007)
CDHP	0.030***	0.038***	0.030***	0.037***
	(0.005)	(0.004)	(0.005)	(0.005)
EMPLOYER	-0.005	0.024***	-0.004	0.022***
	(0.009)	(0.006)	(0.009)	(0.007)
Observations	3648599	4116786	3648599	4116786

Notes: The dependent variable is the logarithm of service price, $\ln(P_n)$. All regressions include a dummy variable indicating the patient's gender, a polynomial in the patient's age (i.e. AGE, AGE^2, and AGE^3), a polynomial in the number of co-morbidities, as well as state-halfyear and disease-stage-of-illness fixed effects. The omitted plan types are "basic medical" and "comprehensive," $BMCOMP$. Standard errors are in parentheses and are clustered by provider-county. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.

C.4.2 Additional Endogenous Controls: Market Structure on Utilization

	Exogenous Controls		Endogenenous Controls	
	Cardiology	Orthopedics	Cardiology	Orthopedics
$\ln(HHI_{phys})$	0.106***	0.005	0.151***	0.021**
	(0.023)	(0.010)	(0.022)	(0.010)
$\ln(HHI_{ins})$	-0.399***	-0.115***	-0.214*	-0.159***
	(0.114)	(0.043)	(0.128)	(0.053)
$\ln(scale)$	-0.074***	0.016**	-0.236***	0.076**
	(0.013)	(0.008)	(0.031)	(0.037)
$\ln(physdens)$	0.025**	0.011*	-0.148***	-0.047***
	(0.010)	(0.006)	(0.032)	(0.015)
$\ln(medval_{phys})$	-0.058***	-0.065***	-0.065***	-0.033***
	(0.013)	(0.009)	(0.015)	(0.012)
$\ln(rent_{phys})$	0.450***	0.101***	0.653***	0.118***
	(0.052)	(0.024)	(0.062)	(0.028)
$\ln(facwage_{phys})$	-0.024**	-0.011**	0.117***	-0.010
	(0.010)	(0.004)	(0.023)	(0.010)
$\ln(medinc_{phys})$	-0.032	0.084***	-0.036	0.042*
	(0.036)	(0.018)	(0.038)	(0.022)
$\ln(medinc_{flow})$	-0.100***	-0.037***	-0.110***	-0.039***
	(0.024)	(0.012)	(0.024)	(0.012)
UNIV	0.018	-0.034***	0.115***	-0.036***
	(0.015)	(0.007)	(0.020)	(0.012)
$\ln(medinc_{pat})$	0.080***	0.024***	0.092***	0.025***
	(0.010)	(0.006)	(0.010)	(0.006)
$\ln(educ_{pat})$	-0.204***	-0.328***	-0.054	-0.288***
	(0.042)	(0.020)	(0.046)	(0.023)
EPO	0.037***	0.009	0.039***	0.013*
	(0.011)	(0.007)	(0.012)	(0.007)
HMO	0.009	-0.025***	0.013	-0.024***
	(0.008)	(0.004)	(0.008)	(0.004)
POS	0.017*	0.011***	0.012	0.008**
	(0.011)	(0.004)	(0.010)	(0.004)
PPO	0.015**	-0.007**	0.014**	-0.008***
	(0.007)	(0.003)	(0.007)	(0.003)
HDHP	0.046***	0.012	0.055***	0.013
	(0.018)	(0.011)	(0.018)	(0.011)
CDHP	0.016*	-0.038***	0.021**	-0.038***
	(0.009)	(0.004)	(0.009)	(0.004)
EMPLOYER	0.041***	-0.042***	0.048***	-0.044***
	(0.009)	(0.003)	(0.009)	(0.003)
Observations	3648599	4116786	3648599	4116786

Notes: The dependent variable is the logarithm of the utilization of services, $\ln(Q_n)$. All regressions include a dummy variable indicating the patient's gender, a polynomial in the patient's age (i.e. AGE, AGE^2, and AGE^3), a polynomial in the number of co-morbidities, as well as state-halfyear and disease/stage-of-illness fixed effects. The omitted plan types are "basic medical" and "comprehensive," $BMCOMP$. Standard errors are clustered by disease, provider, and county. One, two, and three asterisks indicate significance at the 10-percent, 5-percent, or 1-percent significance level, respectively.