Do Physicians Possess Market Power?

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Abstract

We study the degree to which greater physician concentration leads to higher service prices charged by physicians in the commercially insured medical care market. Using a database of physicians throughout the United States, we construct physician-firm concentration measures based on market boundaries defined by fixed driving times, which we label the fixed-travel-time Herfindahl-Hirschman index. We link these concentration measures to health insurance claims. We find that physicians in more concentrated markets charge higher service prices; a physician in the 90th percentile of market concentration will charge 14–30 percent higher fees than a physician in the 10th percentile. Our estimates imply that physician consolidation has caused about an 8 percent increase in fees on average over the last 20 years and substantially higher increases in concentrated markets.

1. Introduction

Physicians play a critical role in the health care market. Acting as the patient's health care consultant, as well as the medical service provider, they act on the patient's behalf to choose medical services (Sirovich et al. 2008). However, physicians also organize themselves into firms and may therefore act as profit-maximizing agents. By flexing their bargaining muscle, physician firms may be

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able to raise the fees that they charge insurance carriers. In this study, we empirically assess the degree to which greater market concentration of physicians leads to higher service prices for physicians. These effects are mainly identified through the large variation in service prices observed across markets (Dunn, Shapiro, and Liebman 2013).

While there has been an extensive line of research regarding hospitals' ability to leverage their market power into higher fees (Noether 1988; Dranove, Shanley, and White 1993; Lynk 1995; Keeler, Melnick, and Zwanziger 1999; Town and Vistnes 2001; Capps, Dranove, and Satterthwaite 2003), there has been very little research regarding physicians' bargaining power.[1] Examining how physicians' market power affects prices may be an important step in assessing the cause of overall variation in medical care spending. 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 the U.S. gross domestic product (Aizcorbe and Nestoriak 2011; Chernew, Hirth, and Cutler 2009; Chernew, Baiker, and Hsu 2010; Cutler and Ly 2011; Dunn et al. 2013). Growth in medical expenditures has been accompanied by a trend toward consolidation across health care providers (Gaynor and Haas-Wilson 1999; Smart 2006; Liebhaber and Grossman 2007). 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 health care reforms enacted in 2010 may accelerate consolidation because they encourage greater cooperation among providers. The Federal Trade Commission (FTC) and Department of Justice (DOJ) have taken different views on the potential impact of these health care reforms. The FTC sees consolidation resulting from these reforms as a potential risk that could lead to higher prices, while the DOJ appears more receptive to the potential consumer benefits from the reforms (see Catan 2011).[2] Understanding how physician market power affects medical care spending may offer important insights into the potential outcome of this policy reform.

A major reason for the lack of research regarding physician market power has been the dearth of historical granular data covering physician firms. 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 a wealth of historical data on physician firms with a comprehensive data set on commercial payments. The data on physicians are from the SK&A physician

[1] Research regarding physician market competition has primarily focused on identifying whether physicians actually possess monopoly power. As explained by Gaynor (1994), most of these studies aim to infer the presence of market power by searching for monopoly rents and supranormal returns on investment to education (Sloan 1970; Leffler and Lindsay 1981; Burstein and Cromwell 1985). Wong (1996) assesses the nature of competition (that is, monopoly, perfect competition, monopolistic competition) in the physician market.

[2] Other health economists, interest groups, and politicians have raised some concerns that the new health care law may spur additional consolidation and harm consumers (America's Health Insurance Plans 2011; Berenson, Ginsburg, and Kemper 2010; U.S. Senate 2011).

mailing list and include information on firm size, specialty, and specific geographic coordinates. According to SK&A, the data cover over 95 percent of physician firms in the United States. These highly detailed data enable us to construct precise physician concentration measures. We link these concentration measures with commercial health insurance claims from the MarketScan Research Databases from Truven Health Analytics. The data include individual patient health claims for several million privately insured individuals covering thousands of procedures and hundreds of diseases and types of health plans throughout the United States. Though daunting, the sheer size of the data set proves to be important for identification purposes because there is an enormous degree of heterogeneity in types of health service providers, procedures, patient ages, diseases, stages of illness, comorbidities, and plan types.[3] Finally, we link data from HealthLeaders-InterStudy, which provides comprehensive information on enrollment to health insurance firms. These data allow 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 that these two specialties provide a representative look at the physician market since these are two of the largest specialities and cover a wide spectrum of physicians.[4] 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 that is customized to the features of the physician marketplace and the data sources available in this study. This paper exploits the detailed microlevel data to look at the effects of competition on service prices at the patient-disease level. This allows us to control for a multitude of patient characteristics. In addition, 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-Hirschman index (FTHHI). Similar to the measure used in Kessler and McClellan (2000), the FTHHI is based on theoretically predicted market shares. It is important to note that the shares are based solely on information about the size of firms and the distance between the firms and patients. This removes potential contamination attributable to higher quality providers attracting more patients.

An important feature of the physician service market is that the determination of prices depends not only on physician concentration but also on the concentration of the insurance market. That is, service prices are likely determined by

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

[4] The major practice categories (1) cardiology and (2) orthopedics and rheumatology are the two highest expenditure categories for the commercially insured population (see Aizcorbe and Nestoriak 2011; Dunn et al. 2013).

the relative degree of bargaining power between physicians and insurance carriers, not just the level of concentration in the physician market. To control for the insurance side of the market, we include an insurance concentration measure in our regression analysis. As this measure is constructed using actual patient shares, there would likely be endogeneity bias using an ordinary least squares (OLS) approach. We attempt to mitigate this bias by applying an instrumental variables (IV) approach.

We find that physician concentration is positively and significantly correlated with service price levels. In particular, our cross-sectional estimates show that a 10 percent increase in the FTHHI results in a .5–1 percent increase in physician fees. This implies that a physician in a market with the 90th-percentile concentration will charge fees that are approximately 14–30 percent higher than a physician in the 10th-percentile market. This translates into a difference of $70–$138 per treatment. Our estimates also imply that the market size for physician services may be as small as a 20-minute driving-time radius. Even controlling for market-specific fixed effects that account for all market-specific determinants of price that are common among cardiologists and orthopedists, we find that if cardiologists (orthopedists) are relatively more concentrated than orthopedists (cardiologists) in the same market, they are able to command significantly higher prices. Finally, we estimate a panel regression in which we use only variations in concentration for a given market over time. Estimates are larger but not as precisely estimated as the cross-sectional estimates. Linking our estimates to historical survey data discussed in Rebitzer and Votruba (2011) implies that physician consolidation resulted in an increase in fees of about 8 percent over the last 2 decades (1988–2008).[5] We also find some evidence that insurance carriers in more concentrated health insurance markets pay lower fees to physicians.

This study is organized as follows. Section 2 describes the physician and insurance market and details how physician and insurance concentration may determine service prices. Section 3 describes the data in detail and explains the construction of service price and concentration measures. In Section 4, we use both cross-sectional and panel variation to estimate whether there is a causal relationship between physician concentration and physician service prices. In Section 5, we conclude by highlighting key limitations of our study and directions for future research to improve on our analysis.

[5] Rebitzer and Votruba (2011) report statistics from a series of physician surveys conducted by the American Medical Association (AMA)—the proportion of physicians in solo practice, groups with two to four physicians, those with five to nine, and so forth. We calculated two chain-linked series of Herfindahl-Hirschman indexes (HHIs) based on their survey information as well as the SK&A data—one based on the lower bound of the reported firm size and another based on the upper bound. The lower bound estimate implies a growth in prices of 8.15 percent, and the upper bound implies a growth in prices of 8.85 percent.

2. Physician and Health Insurance Carrier Organizations

2.1. Physician Organization

Physician consolidation has historically been a relatively uninteresting topic because of 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. According to physician surveys, the proportion of physicians in solo practices decreased from 49 percent in 1988 to 33 percent in 2001 (Rebitzer and Votruba 2011). More recently, there has been a trend of acquisition of physician practices by hospitals. The American Medical Association (2012) finds that, over the last decade, there has been a 32 percent increase in the number of physicians employed by hospitals.[6] There is concern that the passage of 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.[7] For instance, Pear (2011) reports that federal officials are seeing a wave of mergers, in part because of the incentives built into the new health care law.

As physician consolidation grew, there emerged wider variations in the types 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 (single-specialty groups), but there also exist groups with differing specialties (multispecialty groups). Physician groups can occur as part of a larger health system that contains other group practices, as well as hospitals (a physician-hospital organization). More complex forms of horizontal structures may involve group practices clustering with one another for bargaining purposes.[8]

Although there are a variety of organizational structures, this paper focuses on the horizontal aspects of 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

[6] We thank an anonymous referee for pointing this out.

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

[8] 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 compete only for capitated health maintenance organization (HMO) contracts. For noncapitated contracts, the physicians must negotiate individually unless the Federal Trade Commission rules that they are "clinically integrated" for efficiency reasons (Berenson, Ginsburg, and Kemper 2010). (Here we focus on specialists who are less often subject to capitated payments where the IPA market structure is less applicable.) In another example, two physician groups may join forces to share administrative services (for example, a group practice without walls) as well as contracting.

insurance plans.[9] The source of the bargaining power rests on the ability of a physician group to threaten to exclude itself 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 comprises a wide variety of types and sizes of firms (health insurance carriers). They can range in size from small local firms to large national firms.[10] Insurance carriers compete with one another to attract enrollees. Three important characteristics that differentiate plans in the eyes of the patient are the size of the provider network, restrictions on the patients' choices, and the overall price of the insurance contract. Generally, it is assumed that consumers prefer a large number of providers, fewer restrictions, and lower prices.

The overall size of the insurance carrier's network is determined according to the bargaining outcome with providers, which we discuss in Section 2.3. Although most commercial health insurance plans have a network of providers, these network insurance plans differ in the restrictiveness of their networks.[11] There is a spectrum of plan types ranging from the least restrictive preferred-provider organization (PPO) plans, which often contain a broad network of providers and include out-of-network coverage, to the most restrictive type of plans, health maintenance organizations (HMOs). Generally, but not always, HMOs will not cover out-of-network providers and 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 copayment.

Of course, the insurance carrier would like to increase market share, but it would also like to lower its overall costs, which include the expenditure of treating an episode of care. An insurance carrier can attempt to control expenditure for an episode of care in one of two ways. It can attempt to reduce payments (that is, fees) made to providers, or it can attempt to reduce the amount of services per episode of care (service utilization). In this study, we focus on fees that can be bargained over with providers; see Dunn and Shapiro (2012) for an analysis of service utilization.

[9] 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; Ciliberto and Dranove 2006).

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

[11] According to Kaiser's *Health Employer Benefits* (Claxton et al. 2013), fewer than 3 percent of enrollees in the United States have a conventional indemnity insurance plan.

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.[12] The relative level of concentration on each side of the bargaining table can translate into variations in service prices (physician fees). We develop an empirical framework in which the service price depends on the relative degree of bargaining power, which 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: $Z = \ln(\mathrm{HHI}^{\mathrm{Phys}}/\mathrm{HHI}^{\mathrm{Ins}})$, where $\mathrm{HHI}^{\mathrm{Phys}}$ and $\mathrm{HHI}^{\mathrm{Ins}}$ are the degrees of concentration in the physician and insurance carrier markets, respectively. These concentration ratios reflect the strength of the outside options of physicians (when considering contracts with different insurers) and insurers (when considering contracting with different physicians). To illustrate how service price may depend on *Z*, we look at two polar market structures:

$$Z_1 \approx -\infty \Rightarrow \text{Competitive Physician, Monopolistic Insurance Carrier}$$

and

$$Z_2 \approx \infty \Rightarrow \text{Monopolistic Physician, Competitive Insurance Carrier.}$$

Moving from market structure Z_1 to Z_2, we shift 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 their marginal cost of providing the service. By contrast, under market structure Z_2, the monopolistic physician can credibly threaten to exclude the insurance carrier's patients from using her services. In particular, 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.[13] Thus, any insurance carrier who wants to contract with this physician must offer the profit-maximizing service price.

It is also important to highlight that if physicians are highly mobile, then one might expect physician markets to be contestable, which leads to no relationship between concentration and price. Although this is possible, several industry features suggest that physician markets are not likely to be contestable, since there are many fixed costs and sunk information costs that prevent physicians from moving across geographic areas (for example, an established patient base

[12] Staten, Umbeck, and Dunkelberg (1987, 1988) and Sorenson (2003) show that an insurance carrier's bargaining leverage resides in its credibility of exclusion.

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

in an area, reputation in an area, cost of finding and hiring support staff, and the transaction costs of forming a group).[14]

The actual marketplace is rarely perfectly competitive or completely monopolistic. Instead, prices will be pulled toward 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, may simply recognize its relative competitive position and create a payment schedule that would entice the physician firm to participate in the plan.

3. Data

Here we give a comprehensive overview of the data sets used in this study. First, we describe the MarketScan Commercial Claims and Encounters Database, which tracks claims from all providers through a nationwide convenience sample of patients. We also provide an overview of how we calculated our physician service price measure. 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 and the Area Health Resource File data, which provide information used to make concentration measures of health insurance firms as well as demographic information.

3.1. MarketScan Data

The MarketScan Research Databases track claims from providers through a nationwide convenience sample of patients. Our collected data span 2005–8. The data include health claims from employers and insurance carriers throughout the United States; all claims have been paid and adjudicated. Geographic information is provided; however, it consists only of the patient's county of residence and physician's county of practice. We use the Commercial Claims and Encounters Database of the MarketScan Research Databases, which includes health care utilization and cost records at the encounter level. This 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 individuals covered by employer-sponsored insurance, including em-

[14] Consistent with this idea, there is relatively little movement across geographic markets in our data on physicians—only .2 percent of physicians move across state lines on an annual basis, on average.

ployees, their spouses, and dependents. Each observation in the data corresponds to a line item in an explanation-of-benefits form.

Importantly, we can differentiate between payments made to physicians from those paid to other providers (such as hospitals and pharmacies). For instance, suppose that a patient is being treated for congestive heart failure in a hospital. The claims data differentiate 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. This is the dollar amount eligible for payment after applying pricing guidelines, such as fee schedules and discounts, and before applying deductibles and copayments. MarketScan also indicates the type of plan under which the claim was made, which allows us to ignore episodes in which a capitation payment was made.[15]

3.1.1. Creating a Measure of Service Prices

Our calculation of the physician's service price is based on Dunn, Shapiro, and Liebman (2013). The service price is specific to a physician-patient-episode triple in which "episode" refers to treatment for an episode of a specific disease. Defining the observation at this level allows us to control for a host of patient- and disease-specific covariates in our estimation.

We use a three-step process in obtaining a measure of service prices. First, we obtain the expenditure by a physician for a particular episode of care. Second, we calculate the quantity of services performed by the physician during the episode of care. Finally, we calculate the service price, defined as the expenditure divided by the quantity of services.

To identify episodes of care for a specific patient with a certain disease, we apply the Medical Episode Grouper (MEG) provided by Truven Health Analytics, which assigns a procedure to an episode using information on claims and the patient's medical history. Spending is allocated to a patient between a beginning and an ending date by assigning an episode identifier (ID), n, to each claim in the data.[16] Let $\mathbf{\Gamma}_n$ 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

$$\mathrm{TE}_n = \sum_{j \in \mathbf{\Gamma}_n} p_{jn}, \tag{1}$$

where p_{jn} is the full payment (including the patient's out-of-pocket costs) to the physician for procedure j in episode n.[17] Pricing information for a specific pro-

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

[16] We isolated episodes in which the patient saw the same physician for the entire episode of care; however, results are not sensitive to this exclusion.

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

cedure is the payment attached to the specific health claim line in the MarketScan data. We identify procedure j at the most granular level possible on the basis of a specific Current Procedural Terminology code, modifier, and place of service.[18] Note that each episode uniquely identifies an individual patient k with disease d treated by physician p in county c that begins in time period t.[19] The 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 who developed the MEG software.

We calculate the quantity of services per episode of care, referred to as the service-utilization component in Dunn, Shapiro, and Liebman (2013). We measure this variable by

$$Q_n = \sum_{j \in \Gamma_n} r_j, \tag{2}$$

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 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,

$$P_n = \frac{\mathrm{TE}_n}{Q_n}, \tag{3}$$

which is the price of the episode of care in terms of its total price per service.

Table 1 shows summary statistics for the MarketScan sample.[20] Note that because of our definition of services, the mean price per service is approximately equal to 1 by construction. Prices for both samples rose only slightly over the sample period. Patient comorbidities indicate the average number of concurrent diseases identified by the MEG. The cardiology sample contains older patients and more males than the orthopedics sample. Both samples have a high proportion of PPO plans, accounting for about two-thirds of all observations.

3.2. SK&A Data

The SK&A database includes information on physician location (geocode), specialty, name, medical practice group, and health system. The database is

[18] We chose to differentiate procedures by place of service because Medicare provides higher fees for physicians who have their own office-based facilities.

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

[20] We removed outliers that we believe are attributable to clerical data input error by discarding episodes in the bottom 1st percentile and top 99th percentile based on price per service and utilization.

Table 1
MarketScan Data: Descriptive Statistics

	Cardiology			Orthopedics		
	Total Sample	2005	2008	Total Sample	2005	2008
Mean service price	.966	.947	.973	1.006	.979	1.017
	(.299)	(.307)	(.299)	(.270)	(.268)	(.277)
Patient age	51.2	51.3	51.2	40.4	40.5	40.5
	(11.1)	(11.1)	(11.1)	(17.8)	(17.8)	(17.9)
% Male	52.1	52.3	51.5	46.9	46.8	46.7
Patient comorbidities	5.9	5.9	6.0	5.6	5.6	5.7
	(3.4)	(3.4)	(3.4)	(3.2)	(3.2)	(3.2)
Employer-based plan (%)	60.7	74.2	55.7	57.7	71.3	52.0
Plan type (%):						
PPO	65.7	59.1	67.2	66.1	60.7	66.0
HMO	10.7	11.1	11.6	11.2	11.9	12.3
POS	10.6	10.8	10.4	12.1	13.4	11.4
BMCOMP	7.6	14.9	4.3	4.9	9.52	3.2
CDHP	2.0	1.7	2.2	2.4	2.0	2.7
HDHP	.2	0	.5	.2	0	.6
N	3,673,943	639,526	1,262,527	4,135,972	704,020	1,307,996

Note. Standard deviations are in parentheses. PPO = preferred-provider organization; HMO = health maintenance organization; POS = point-of-service plan; BMCOMP = basic medical and comprehensive; CDHP = consumer-driven health plan; HDHP = high-deductible health plan.

updated every 6 months, spans 2005 to 2008, and claims to include 95 percent of office-based physicians practicing in the United States.[21] An important benefit of the SK&A data relative to other data is that they provide information about physician medical practice groups (firms). Another advantage is that each physician is verified over the telephone, which increases the accuracy of the physician location and group size information.[22]

Given the different types of physician organizations, assigning each physician in the SK&A data to a specific firm is still not a straightforward task. One difficulty is how to overcome the complexity in the vertical dimension. For instance, a small portion of physicians (6 percent of physicians in the SK&A data) are listed by SK&A as being members of group medical practices as well as health systems. 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.[23] Thus, for each physician, we assign the broadest medical group or system she was assigned to in the data. If the physician is not associated with a health system, we assign her to the group medical practice with which she is listed. We summarize the number of physicians and physician firms in the SK&A data in Table 2.[24] The number of individual cardiologists and orthopedists grew over the 2005–8 sample period, as did the number of firms.

Creating a measure of physician concentration requires defining the geographic market—a challenging task that has been the subject of many antitrust cases (see Gaynor and Haas-Wilson 1999; Haas-Wilson 2003). Neither the DOJ nor the FTC has a set standard as to how to measure the size of a geographic market for medical services.[25] For this reason, in creating our measure of the geographic

[21] SK&A has a research center that verifies every field of every record in its database. The data also include the names of doctors of osteopathic medicine, nurse practitioners, physician assistants, and office managers. The SK&A data do not state whether physicians are part of a larger system that also owns hospitals or ambulatory care facilities.

[22] The 6-month frequency of the telephone survey may be important, since SK&A reports that, on average, 14.2 percent of physicians move each year. Although all the information in the survey is telephone verified, SK&A gathers information for physicians through a variety of sources. These include company and corporate directories, Web sites, state licensing information, mergers-and-acquisitions announcements, trade publications, telephone directories, professional associations, and government agencies.

[23] This is consistent with the common assumption made in the hospital literature that the hospitals bargain at the system level. SK&A does not provide information about the physician-hospital relationship, such as whether the physician is an employee of the hospital or whether the physician just has admitting privileges. As we can match SK&A data with MarketScan data only via the county (not at the provider) level, we cannot deduce the relationship through MarketScan. However, as a robustness exercise, we changed the definition of the FTHHI to include only group medical practices, and our qualitative results did not change.

[24] We compared the SK&A data set to the AMA data. The AMA data have a larger number of physicians overall. However, the counts are more similar when comparing SK&A's data to the AMA's office-based physician count.

[25] 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).

Table 2
SK&A Data: Descriptive Statistics

	Cardiology		Orthopedics	
	2005	2008	2005	2008
Physicians	17,345	18,254	17,962	18,205
Physician firms	4,085	4,660	5,999	6,220
Physicians per market:				
Median	129	129	133	134
10th percentile	11	13	15	15
90th percentile	640	654	628	673
Physician firms per market:				
Median	27	30	44	43
10th percentile	3	4	6	6
90th percentile	240	248	302	320
Physician FTHHI:				
Median	.088	.082	.061	.062
10th percentile	.011	.012	.007	.008
90th percentile	.408	.366	.301	.285
Fraction monopoly markets	.016	.016	.009	.009
Fraction duopoly markets	.025	.021	.015	.014

Note. A market is defined as the 80-minute driving time boundary surrounding the census-tract centroid. The number of physicians per market, number of physician firms per market, fraction monopoly markets, and fraction duopoly markets are population-weighted measures. FTHHI = fixed-travel-time Herfindahl-Hirschman index.

market, we test a variety of different market definitions. To do so, we use as much of the granularity of the physician location information in the SK&A data as possible. However, we are ultimately constrained by the fact that it will eventually be linked to the MarketScan data, which have geographic information only at the county level.

3.2.1. Construction of the Fixed-Travel-Time Herfindahl-Hirschman Index

We label our physician concentration measure a fixed-travel-time HHI because it is based on the assumption of a market boundary defined by a fixed driving time.[26] There is a four-step process in creating the FTHHI. First, we define a geographic market boundary. Second, we calculate the probability that a person located within the market boundary will visit a physician firm. This step is crucial, as we are calculating probabilities based solely on information about the distance between people and physicians. Third, using the probabilities of seeing each

[26] It is important to note that this is calculated in a fashion similar to the method in Kessler and McClellan (2000) in that the measures are based solely on information about the physician's group size and distance to patients. The concentration measures that we construct therefore do not include any information about the physician firms' actual shares, which may be tainted with information about the quality of the physician firm. While it would be interesting to compare our measures to an HHI based on actual market shares, we cannot construct such a measure with the MarketScan data. Although the MarketScan data do contain a provider identifier (ID), this variable is coded by the data contributors, not Truven Health Analytics. Therefore we use caution when applying the provider ID variable since distinct data contributors may assign different IDs to the same provider.

physician calculated in the second step, we calculate expected market shares. Fourth, using these expected market shares and physician group information, we construct concentration measures specific to a county and time period.

Defining the Market Boundary. We define the market boundary as a geographic distance surrounding a given patient, as would be done in a standard Hotelling problem. Since the most granular U.S. population data are at the census-tract level, we define market boundaries as fixed distances surrounding the centroid of each census tract. That is, we assume that all people reside at the census-tract centroid, and the market boundary is defined as the maximum amount of driving time $\bar{k}$ a person would be willing to travel to a physician firm.[27] In particular, for each census tract's centroid geographic location, we define a latitude and longitude location as a vector $\boldsymbol{x} = \{\text{lat}, \text{long}\}$. Using Google Maps software, we can measure a maximum radial distance surrounding the centroid based on specific length of driving time $\bar{k}$.[28] We create four FTHHI measures using $\bar{k}$ equal to 20, 40, 60, and 80 minutes.

Calculating the Probability of a Patient Visiting a Physician. To capture the idea that, all else equal, a consumer would rather receive medical care from a physician who resides closer to his or her residence, we assume that consumers earn negative utility for each extra minute of travel time to the physician. The probability of whether a patient located at census-tract centroid x_0 would be willing to travel to a physician located at x_i is based on the travel time between them. For a patient located at x_0, we define his or her driving time to a physician located at x_i as k_{xi}.[29]

We create a variable that 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_{xi} is directly proportional to travel costs. In particular, a patient 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 patient 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_{xi} minutes) with probability

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

[27] Driving times were calculated in Stata using the TRAVELTIME module developed by Adam Ozimek and Daniel Miles. This command finds the driving time between two latitude and longitude points via Google Maps.

[28] To do so, for each county c we drew a random coordinate and then calculated the average speed, Speed_c, one could travel .1 degree north, south, east, or west. This allows us to define a maximum radial distance for any latitude and longitude coordinate in county c as $\bar{k} \times \text{Speed}_c$.

[29] It follows that a patient who lives at location x_0 resides k_{xi} minutes away from the physician located at x_i.

Constructing Expected Market Shares. The probability that a patient located at centroid x_0 visits a physician located at x_i is treated as the number of patients from x_0 expected to visit a single physician located at x_i. This means that the expected market share of a single physician located at x_i for patients located at census-tract centroid 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. It follows that the expected market share at centroid x_0 for a physician group located at x_i that has N_i physicians is

$$E[S^*_{x_i}(x_0)] = \frac{N_i \Pr(\varepsilon_{i0} > k_{x_i})}{\sum_j N_j \Pr(\varepsilon_{j0} > k_{x_j})}.$$

Intuitively, one can think of the probability measure that declines with distance as assigning a lower weight to those physicians who compete from a more distant location. In other words, physicians who are more distant may be considered weaker competitors.

Constructing Concentration Measures. We first calculate an FTHHI at the census-tract level, FTHHI_{ht}, and then aggregate to construct an FTHHI at the county level, FTHHI_{ct}. For each census tract with centroid geocode x_h, we calculate a distinct $\text{FTHHI}_{ht} = \sum_i E[S^*_{x_j}(x_h)]^2$ based on the expected market shares at census-tract centroid x_h. We then create an FTHHI_{ct} as the weighted sum of the FTHHI_{ht} measures, where the weights are the proportion of the county's population from the given census tract.

3.2.2. Summary Statistics

Table 2 provides summary statistics for the SK&A data. The median number of physicians and the median number of physician firms are fairly constant over the sample period. Nevertheless, there is wide dispersion in these measures across markets. For instance, the 10th-percentile 2005 cardiology market has three physician firms, while the 90th-percentile market has 240 firms. Only 1 percent of orthopedic markets and 1.6 percent of cardiology markets are monopolies. In contrast, 95 percent of cardiology markets and 97 percent of orthopedic markets had more than two physician firms.

To limit the size of the table, we show statistics for the FTHHI where the market is an 80-minute boundary surrounding the census-tract centroid.[30] Similar to the pattern observed for the number of physician firms, the FTHHI shows limited time-series variation but wide cross-sectional variation. For instance, the median cardiology FTHHI was .088 in 2005 and .082 in 2008, but the 10th-

[30] Percentile and median measures are weighted by population. Summary statistics of the FTHHI with different market boundaries are depicted in Table 3.

Table 3
The Fixed-Travel-Time Herfindahl-Hirschman Index under Alternative Market Boundaries

	Cardiology			Orthopedics		
	Total Sample	2005	2008	Total Sample	2005	2008
20-Minute boundary	.412	.419	.403	.359	.362	.354
	(.311)	(.318)	(.308)	(.291)	(.295)	(.289)
40-Minute boundary	.269	.276	.261	.219	.220	.216
	(.276)	(.284)	(.271)	(.241)	(.243)	(.239)
60-Minute boundary	.201	.207	.194	.112	.156	.154
	(.235)	(.244)	(.231)	(.118)	(.200)	(.199)
80-Minute boundary	.161	.167	.157	.123	.122	.122
	(.206)	(.215)	(.205)	(.175)	(.176)	(.174)

Note. Values are county-population-weighted means of the concentration measures. Standard deviations are in parentheses. $N = 2{,}300$ counties.

percentile 2005 cardiology FTHHI was .011, while the 90th percentile was .408.[31] Table 3 reports county population-weighted means of the concentration measures under four distinct market boundaries. As expected, concentration declines as the market boundary lines are increased.

It is important to note that for hospitals it is possible to define the market on the basis of a demand estimate using a discrete-choice framework in which patients choose among a discrete set of hospitals (see Town and Vistnes 2001; Capps, Dranove, and Satterthwaite 2003). However, we take 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 geographic information in the MarketScan data at the zip code level (MarketScan tracks providers and patients at the county level). Second, the number of physician firms is magnitudes larger than the number of hospitals, which means that the number of possible choices of physician 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. For these reasons, this paper more closely follows papers that apply more reduced-form techniques (for example, Lynk 1995; Dranove and Ludwick 1999; Kessler and McClellan 2000; Duggan 2002; Dranove et al. 2008).

3.3. HealthLeaders-InterStudy Data

We obtain enrollment information on health insurers from the HealthLeaders-InterStudy database of insurance carriers for the years 2005–8. The enrollment data at the metropolitan statistical area (MSA) level are collected through a

[31] To compare concentration in the physician market with other industries, we calculated a metropolitan statistical area (MSA)-wide concentration index, which is around .10 for cardiologists and .06 for orthopedists for the typical individual living in an MSA. On the basis of this definition, physician markets would be considered unconcentrated by the updated merger guidelines, which consider a market with an HHI below .150 as unconcentrated.

biannual survey of health insurance carriers in which 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, point-of-service plan [POS], and HMO)[32] and whether the contract is fully insured or self-insured.[33]

Using these enrollment data, we construct an HHI concentration measure for the health insurance market. The HHI measure is constructed from the share of total enrollment for each plan. We let S_{ins} be the share of enrollment for an insurance carrier in an MSA;[34] then the concentration measure for the enrollee is

$$\text{HHI}_{\text{Ins}} = \sum_{\text{Ins} \in \text{MSA}} (S_{\text{Ins}})^2.$$

The population-weighted mean concentration over the sample period is .286.

3.4. Demographic Data: Area Health Resource File and Census Data

For additional information regarding the demographic information in a county area, we use data from the U.S. Department of Health and Human Services's Area Health Resource File, which is a database containing extensive information for U.S. counties on demographics, health facilities, health professionals, measures of resource scarcity, health status, and economic activity. The data are gathered from various sources, often on an annual basis.[35] The variables constructed from these data that are used in our analysis include median household income, education, population, population over the age of 65, and hospital facility characteristics.[36]

[32] Prior to 2004 HealthLeaders-Interstudy collected data on only HMOs, but it significantly expanded the coverage of its plan survey in 2004. Prior to 2006 it did not separately report point-of-service plans (POSs) but included this enrollment as part of the HMO category.

[33] A fully insured health insurance contract is a contract purchased from an insurer in which the insurer assumes the full risk of the individual. All other contracts are considered to be self-insured. American Medical Association (2010) contains health insurance concentration figures for MSAs across the United States from HealthLeaders-InterStudy data. In general, we follow many of the AMA guidelines for calculating concentration measures using HealthLeaders-InterStudy data. In particular, we exclude PPO rental networks (for example, Beech Street Corporation). These companies provide administrative services only and/or contract with health insurance carriers, which may result in double counting for those enrollees who are enrolled in another insurance plan that also contracts with a PPO rental network. We also exclude markets where HealthLeaders-InterStudy data do not capture a plausible fraction of the insured population. We calculate the ratio of total enrollment to the total eligible enrollment (Population − Uninsured − (Medicare + Medicaid − Dual)) estimated from the 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 include only HMO and PPO enrollment, our measures also include POS enrollment.

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

[35] Sources include the census, the American Hospital Association database, and the AMA database.

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

4. Effect of Concentration on Service Prices

4.1. Cross-Sectional Within-State Specification

The following regression quantifies the impact of the relative bargaining leverage of physicians and insurance carriers on the logarithm of service price P_{nt}:

$$\ln(P_{nt}) = \beta_1 \ln(\text{FTHHI}_{ct}) + \gamma_1 \ln(\text{HHI}^{\text{Ins}}_{mt}) + \delta' \boldsymbol{X} + \zeta_{at} + \zeta_d + \zeta_{\text{Sev}} + \varepsilon_n, \quad (4)$$

where each episode n is uniquely associated with a patient k, a disease d, severity Sev, a physician p, and an MSA m in a county c and state a. This specification essentially splits our measure of bargaining power leverage, Z, into its two components, FTHHI_{ct} and $\text{HHI}^{\text{Ins}}_{mt}$.[37]

Here we isolate variations occurring between counties within a state by including state-time fixed effects ζ_{at}. We also include disease ζ_d and stage-of-illness fixed effects ζ_{Sev}, defined by the MEG. 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.[38] To decrease computational burden, we include only the 100 most common disease groups for each specialty, which represents over 90 percent of the total sample.[39]

The vector $\boldsymbol{X}$ includes a host of covariates aimed at controlling for the physician's cost and quality, as well as the patient's demographic factors. (See Appendix A for a more comprehensive description of these variables.) It includes a third-order polynomial in the patient's age, a dummy variable indicating the patient's gender, and a polynomial in the number of comorbidities 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 or PPO), whether the patient works for a large employer,[40] the logarithm of the median income of the patient's county, and the logarithm of the fraction of college-educated individuals in the patient's county. To help control for the physician's cost, we include 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. To help control for the

[37] It would be equivalent to using Z as a covariate if we were to constrain $\beta_1 = -\gamma_1$.

[38] The Medical Episode Grouper (MEG) assigns a severity score based on the disease-staging disease progression model to each patient episode and does not depend on the utilization of care. Stage 0 represents a history or suspicion of a condition, exposure to a disease, or a well visit. Stage 1 represents a condition with no complications or a problem with minimal severity. Stage 2 represents a problem limited to a single organ or system and significantly increased risk of complication compared with stage 1. Stage 3 represents multiple site involvement, generalized systemic involvement, or poor prognosis, and stage 4 represents death.

[39] No results changed when all diseases were included in a 30 percent subsample of the data.

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

physician's quality, we include the percentage of hospitals in the physician's county that are affiliated with a university and a weighted average of the patient's county-level median income.[41] See Appendix B for specifications with additional controls that include average firm size in the county (scale effects) and the number of physicians per capita in the county (supply effects).[42]

4.1.1. Correcting for Potential Omitted-Variable Bias

The reason for including the controls described above is that they help account for the many factors used in bargaining between physicians and insurance carriers. For instance, we include cost-of-living variables because they may affect both prices and the level of concentration of physicians and insurance firms. Areas with high rents may raise prices and also dissuade physicians from locating in a given county. However, estimation bias can still arise if important variables used in bargaining are unobserved by the econometrician and affect concentration. There are many examples of omitted variables, but one that has been widely discussed in the literature is unobserved quality. Higher physician quality may result in larger negotiated fees, but it may also draw more patients to see a physician firm, thereby increasing its market share and the concentration of the market. This type of bias is particularly dangerous because it will bias the estimate on physician concentration upward, which could cause us to mistake high prices attributable to quality as being attributable to high concentration.

A major benefit of our physician concentration measures is that they are constructed with theoretically predicted market shares based on physician firm size and the distance between potential patients and physician firms. This is in contrast to constructing an HHI based on actual market shares. This approach is analogous to that taken by Kessler and McClellan (2000), who construct an HHI for hospitals that uses predicted market shares based on travel distances between patients and hospitals. Similarly, the predicted shares used in the FTHHI measure are based on the number of physicians in the firm and the patient's travel time to the firm. As mentioned previously, Kessler and McClellan argue that using predicted market shares, rather than actual shares, removes any endogeneity that may be attributable to higher quality providers attracting more patients.

Applying a predicted HHI helps address concerns about unobserved quality in the physician concentration measure. However, we have not addressed unobservable (to the econometrician) variables that affect the physician's decision to

[41] The basic idea is that the higher quality doctors may attract wealthier patients. The weighted average is the average income of patients who 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 patient income variable that enters as a demographic variable.

[42] We chose not to include these variables in our main specification because they are likely endogenous. Gaynor and Haas-Wilson (1999, p. 147) 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)."

enter a geographic market or join a group practice. We argue that this remaining bias will push the estimated coefficient on the FTHHI downward, which means that our OLS estimate should be interpreted as a lower bound of the effect of concentration on service prices. If fees are low in a particular market because of some unobserved factor, this will either entice physicians to join group practices or deter physicians from entering the geographic market. Both of these features will cause the FTHHI to be low when unobservable variables cause service prices to be high, which biases the OLS FTHHI coefficient downward.

Finally, our estimation strategy also includes an insurance market concentration measure that is based on actual, rather than predicted, market shares. This is problematic since a plan with an unobserved quality attribute or plan benefit may affect the negotiated price, but it may also increase a given insurance carrier's market share. In addition, unobservable variables that cause service prices to be high are likely to deter insurance carriers from entering the market. The latter effect will bias the insurance carrier HHI coefficient upward—higher quality plans are likely to have a higher market share, but, presumably, more market health insurers will have higher costs upon entering; hence, fewer of them will be drawn into the market.

To help mitigate this remaining omitted-variable bias, we use IVs.[43] Our instrument set is motivated by Berry and Waldfogel (2001) and Davis (2006). The key to a good IV estimation strategy is to identify competitive variation solely attributable to the long-run decisions of physicians and insurers. In particular, instruments that relate to either the fixed cost of entering the market or the market size are most appropriate, since they affect the long-run market-structure decisions of insurers and physicians but do not affect their short-run pricing decision, except through the impact on the number of rivals in the market. Berry and Waldfogel (2001) use population terms as instruments for radio broadcasting concentration, while Davis (2006) uses population counts as instruments for his market-structure variables in the movie theater industry.[44]

We also use population-based instruments and expect there to be a larger number of physician firms and insurance firms in more populated markets. However, for clean identification, the instruments must be uniquely correlated with insurance carriers' and physicians' competitive decisions. The instruments used in our study include the county population, the MSA population, the county population 65 and older, the unemployment rate, the county population ages 35–44, the county population ages 45–54, and the county population ages 55–

[43] The *p*-values of the *C*-statistic were .19 and .29 for the cardiology and orthopedics samples, respectively, which indicates that there is a fairly large probability that the concentration measures are endogenous. The *C*-statistic is based on the difference of two Sargan-Hansen statistics.

[44] Similar studies in the hospital literature have found it crucial to use instrumental variables to account for unobserved quality. As a recent example, Dranove et al. (2008) provide an instrumental variables 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) and Newhouse et al. (1982) find that physicians locate in response to effective demand.

64. Having fewer senior citizens in the population should encourage both lower levels of entry from physician firms and more physicians to form groups to attract patients. Insurance carrier firms should be less affected by this variable since these are generally 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 under the Consolidated Omnibus Budget Reconciliation Act. Unlike prior work that uses population data as instruments in a model of competition using aggregate data (for example, Davis 2006; Berry and Waldfogel 2001), here we use detailed microlevel data to control for numerous factors at the level of the patient, which reduces the possibility of endogeneity in our analysis. If, for some reason, higher quality physicians prefer to practice medicine in more populated areas, our estimates will be attenuated toward zero statistical significance. In this sense, our estimates are conservative.[45]

4.1.2. Cross-Sectional Within-State Results

Table 4 shows estimates using concentration measures under four different market boundaries: a 20-minute, 40-minute, 60-minute, and 80-minute driving time radius. Standard errors are clustered by county. This degree of clustering is meant to control for any correlation in bargaining between physicians and insurance firms within the same county.[46] There is a positive and statistically significant effect of physician concentration on service prices for all estimates. The OLS estimates indicate that a 10 percent increase in physician concentration results in an increase in fees of about .2–.3 percent; however, they also show a positive and significant relationship between insurance concentration and service prices. Using IVs on the FTHHI appears to remove some upward bias on HHI^{Ins} and some downward bias on the physician concentration measures. Estimates using IVs range from .04 to .08—approximately double the size of the OLS estimates. These results imply an economically significant effect of concentration on prices across counties. In particular, a cardiologist in the 90th-percentile market will charge 14–28 percent more than a cardiologist in the 10th-percentile market. The corresponding orthopedist will charge 15–30 percent more. Given

[45] One may be concerned that population size may be correlated with physicians per capita. However, we show in Appendix B that results do not change when we include the number of physicians per capita as a control variable.

[46] We also estimated a different specification of the episode price P_n regression in which we used procedure price p_j as the dependent variable while including procedure fixed effects. This specification will be identical to specification (4) 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 $\ln(P_n) = \ln(p_{jn}/r_j)$, which is equivalent to $\ln(\theta_n)$ as the dependent variable. No results changed using this specification, which indicates that, on average, physicians likely bargain over their entire fee schedule.

Table 4
Cross-Sectional Within-State Estimates

	Cardiology		Orthopedics	
	OLS	IV	OLS	IV
Physician FTHHI 20-minute boundary	.025**	.039*	.035**	.051**
	(.009)	(.014)	(.006)	(.020)
Insurance HHI	.029*	.083	.029**	−.023
	(.013)	(.084)	(.011)	(.099)
R^2	.117	.115	.192	.190
Physician FTHHI 40-minute boundary	.025**	.041**	.029**	.056**
	(.007)	(.011)	(.006)	(.017)
Insurance HHI	.025+	−.026	.025*	−.131
	(.013)	(.092)	(.011)	(.107)
R^2	.118	.116	.192	.177
Physician FTHHI 60-minute boundary	.028**	.052**	.026**	.065**
	(.007)	(.011)	(.006)	(.020)
Insurance HHI	.022+	−.127	.024*	−.191
	(.013)	(.107)	(.011)	(.127)
R^2	.118	.106	.192	.163
Physician FTHHI 80-minute boundary	.031**	.060**	.023**	.077**
	(.007)	(.014)	(.007)	(.026)
Insurance HHI	.019	−.182	.024*	−.234
	(.012)	(.123)	(.011)	(.149)
R^2	.119	.100	.191	.148

Note. The dependent variable is the logarithm of service price, $\ln(P_{mt})$. All regressions include the controls specified in equation (4). Standard errors clustered by county are in parentheses. OLS = ordinary least squares; IV = instrumental variables; FTHHI = fixed-travel-time Herfindahl-Hirschman index; HHI = Herfindahl-Hirschman index.

+ Significant at the 10 percent level.

* Significant at the 5 percent level.

** Significant at the 1 percent level.

that the average physician expenditure per episode of care is approximately $460,[47] a difference of $70–$138 per treatment is implied.

Estimates do vary a bit according to the market boundary. A larger physician market boundary is associated with a larger estimate of physician concentration and a larger (that is, more negative) estimate of insurance concentration. It is difficult to assess which is the correct measure of the market boundary. On the one hand, joint significance on β_1 and γ_1 tends to increase with the size of the market boundary, which may indicate that the larger boundaries provide a better match to the marketplace.[48] On the other hand, the models using smaller market boundaries produce larger R^2-values in many cases. Whichever the case, we find it striking that there remains a positive and significant effect of physician con-

[47] In the MarketScan data, the average physician expenditure per episode, defined by the MEG, is $459.90 for cardiology and $463.70 for orthopedics. This includes only the portion of expenditures in an episode paid to physician services. The distribution of expenditures per treatment is skewed. For instance, the 10th and 90th percentiles for cardiology are $24.30 and $1,298.70, respectively.

[48] The larger point estimates on the physician concentration measures with larger boundaries may also be due to the fact that the measures with larger boundaries have smaller mean concentrations.

centration on service prices even at the 20-minute travel-time boundary. This effect indicates that the physician market may be considerably smaller than a county or MSA, which is consistent with results in papers analyzing competition in hospital markets (see Capps, Dranove, and Satterthwaite 2003).

In an online appendix, we show estimates using alternative IV sets and estimates using alternative constructions of the FTHHI. As an additional robustness exercise, we include additional controls (physician firm size and physician per capita). The main results presented here do not qualitatively change under any of these different measures or IV sets.

We also conduct additional empirical analyses to investigate the strength and validity of our instruments. Looking across different instrument sets, we test the strength of the instruments by computing *F*-statistics of joint significance. We find *F*-statistics of 18–23 for the physician concentration measure and 6–8 for the insurance concentration measure. The Hansen *J*-statistic is 5.8 for cardiology and 6.6 for orthopedics, which implies *p*-values of .57 and .47, respectively. Thus, we cannot reject the null hypothesis that the instruments are uncorrelated with the error term.[49]

4.1.3. Accounting for Nonlinearity

In Section 4.1.2 we assumed that the effect of concentration on price was proportional to the concentration index. However, the effect of concentration on service prices may be nonlinear. For instance, two firms merging in a market where there are many other competitors may have no effect on prices. In contrast, two firms merging to form a monopoly may have a large effect on prices. To account for this type of nonlinearity, we include in our specification an interaction term D^l, which is a dummy variable equal to one if the FTHHI is below the *k*th-percentile FTHHI:

$$\begin{aligned}\ln(P_{nt}) = {} & \beta_1 \ln(\text{FTHHI}_{jct}) + \beta_2 D^l_{jct} \times \ln(\text{FTHHI}_{jct}) + \beta_3 D^l_{jct} \\ & + \gamma_1 \ln(\text{HHI}^{\text{Ins}}_{mt})\delta' \boldsymbol{X} + \zeta_{ct} + \zeta_d + \zeta_{\text{Sev}} + \zeta_j + \varepsilon_n,\end{aligned} \tag{5}$$

where the estimate β_1 can be interpreted as the effect of a change in log of the FTHHI, conditional on the FTHHI lying above the *l*th percentile. We run the specification seven times, for 20th, 30th, 40th, 50th, 60th, 70th, and 80th percentiles on the cardiology and orthopedics sample separately, using the FTHHI with the 80-minute travel-time boundary.[50] The instrument set is the same as

[49] As an additional validity check, we collected the second-stage residuals from equation (4) under the firm distribution instrument set and regressed these residuals on the population instrument set. If the residuals were highly correlated with the population distribution instruments, this would suggest a potential bias. The residuals are not correlated ($R^2 \approx .001$) with the population distribution instrument set. Standard errors are all large, the R^2-values of both samples are quite low, around .001, and *F*-statistics testing their joint significance are also fairly low (1.8 and 2.7 for cardiology and orthopedics, respectively).

[50] The seven cutoffs of the 20th–80th percentiles of the FTHHI for the cardiology sample are .031, .047, .062, .082, .110, .153, and .207.

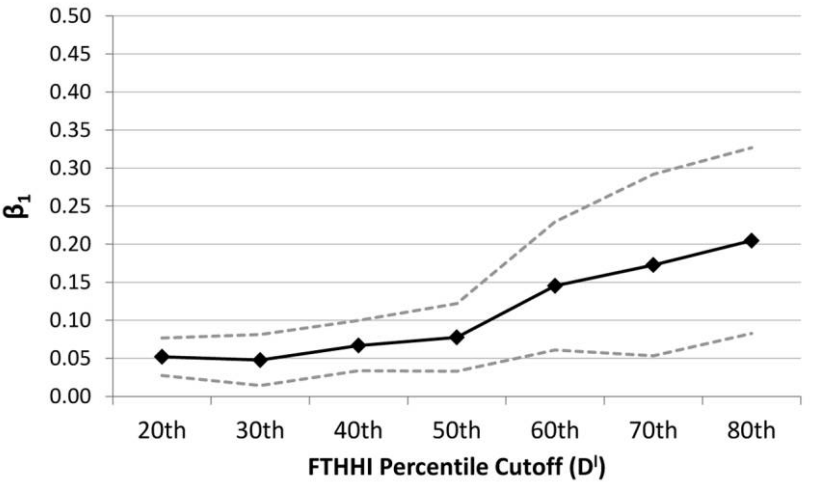

Figure 1. Cardiology sample

that used in the previous analysis but also includes the interactions of the IVs with D^l as additional instruments.

We report estimates of β_1, along with 95 percent confidence intervals, in Figures 1 and 2.[51] The figures show that the estimate of β_1 becomes larger as the percentile cutoff is increased. This indicates that the effect of a change in concentration on service prices becomes larger, the more concentrated the market.

To provide some perspective on the economic importance of these estimates, we calculate the impact of a hypothetical merger. For instance, suppose that the market is initially concentrated such that there exist three equal-sized firms (FTHHI = .33), and two of the three firms merge. The estimates imply that prices would increase 10–14 percent.[52] In a more competitive setting, the effect of a merger of two firms on prices in the market is small. For instance, the merger of two firms in a market with 30 equal-sized firms implies an increase in prices of only .1–.3 percent. Physician consolidation has a much stronger effect on prices when the market is initially more concentrated.

There is much less variation in the HHI for insurers, since we have only MSA-level data on insurance concentration. Moreover, unlike the data on physicians, the HHI is constructed with actual, rather than predicted, market shares. These two factors complicate the identification of competitive effects for the health

[51] In Figures 1 and 2, each diamond represents the estimate of β_1 from running seven separate regressions represented by equation (5). Dashed lines indicate 95-percent confidence intervals.

[52] In this case, the HHI would increase from .33 to .55. It follows that the approximate percentage change in prices is $\beta_1[\ln(.55) - \ln(.33)]$. This is equal to .102 when $\beta_1 = .2$ (cardiology estimate) and .138 when $\beta_1 = .27$ (orthopedics estimate).

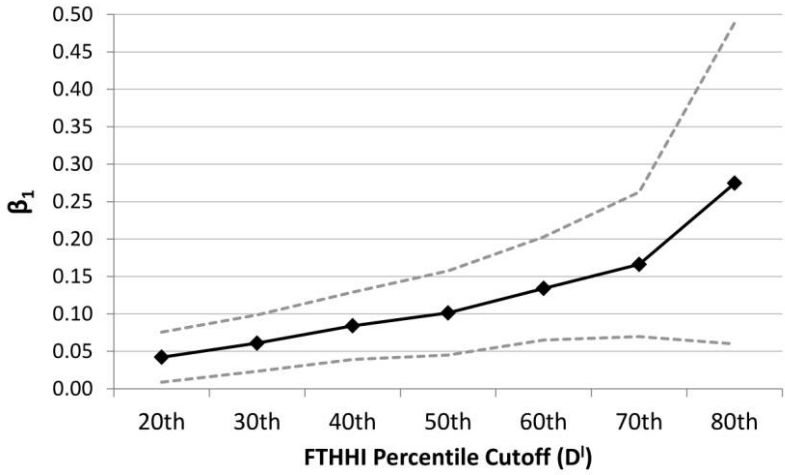

Figure 2. Orthopedics sample

insurance variable and similarly complicate looking at nonlinear effects from insurance concentration.

4.2. Cross-Sectional Within-County Specification

One potential concern from the specification in Sections 4.1.2 and 4.1.3 is that competitive effects are identified entirely from cross-regional variation. To check the robustness of this finding, we take a distinct approach to identifying competitive effects by exploiting within-county differences in concentration between cardiologists and orthopedists. For instance, certain counties may have relatively high cardiology firm concentration but low orthopedic firm concentration, and vice versa. To implement this estimation, we first combine the cardiology and orthopedics samples to create one data set. We then estimate a specification similar to equation (5); however, instead of including state-time fixed effects, we include county-time fixed effects. As our FTHHI measures are constructed at the specialty level, this specification exploits variations between different concentration levels for orthopedists' firms and cardiologists' firms that reside in the same county. In other words, this type of exercise removes the rich between-county variation from the data while hopefully also removing unobserved factors that may be correlated with physicians' competitive decisions.

As in the previous analysis, we allow for a nonlinear effect of concentration on prices by including a dummy interaction term D^l, which indicates whether the FTHHI is below the lth percentile. Our specification takes the following form:

$$\ln(P_{nt}) = \beta_1 \ln(\text{FTHHI}_{jct}) + \beta_2 D^l_{jct} \times \ln(\text{FTHHI}_{jct}) + \beta_3 D^l_{jct} + \delta' \boldsymbol{X} + \zeta_{ct} + \zeta_d + \zeta_{\text{Sev}} + \zeta_j + \varepsilon_n, \tag{6}$$

where j indexes whether the physician is a cardiologist or an orthopedist, and we exploit within-county cross-sectional variation by including county-time fixed effects ζ_{ct}. Note that in this specification, the insurance carrier concentration is not included, as it is canceled out by the county-time fixed effects.

The overall OLS estimate using the 80-minute FTHHI, for which we assume that there is no differing effect between competitive and uncompetitive markets (that is, where $D = 0$), is .015 and significant at the 5 percent level. We also construct estimates that allow for a differing effect depending on whether the market is above or below a competitive cutoff D^l. The cutoffs we choose are the 50th and 75th percentiles of the FTHHI across the entire sample. Both of these estimates imply that the relative concentration in a county determines the level of service prices. Thus, if cardiologists (orthopedists) are relatively more concentrated than orthopedists (cardiologists) in the same market, they are able to command higher prices. The effect when the FTHHI is above the median is .027 and is .045 when the FTHHI is above the 75th percentile. Both estimates are statistically significant at the 1 percent level. Similar to the estimates in Section 4.1, physician consolidation has a much stronger effect on prices when the market is more concentrated. This specification also ensures that the effects of concentration in each specialty market are distinct. Note that if we switched the cardiology FTHHI with the orthopedics FTHHI, the resulting estimate on the concentration measure would be the opposite sign, by construction.

4.3. *Panel Specification*

As a final exercise, we assess the affect of physician concentration on service prices using only time-series variation in concentration via a panel-type estimation. Instead of including state-time fixed effects ζ_{at}, as in specification (4), we include separate county, ζ_c, and time, ζ_t, fixed effects:

$$\ln(P_{nt}) = \beta_1 \ln(\text{FTHHI}_{c,t-1}) + \beta_2 \ln(\text{HHI}^{\text{Ins}}_{m,t-1}) + \delta' \boldsymbol{X} + \zeta_c + \zeta_t + \zeta_d + \zeta_{\text{Sev}} + \varepsilon_n. \tag{7}$$

Here we remove potential omitted-variable bias specific to the county; however, this comes at the expense of removing the rich cross-sectional variation in county-level concentration within a state. As in Dafny, Duggan, and Ramanarayanan (2012), we use lagged values of concentration to account for service prices that are set prospectively. We also perform our cross-sectional estimates using lagged values of concentration, but the results do not change. However, we find that using lagged values in the panel greatly affects the precision of our estimates.

Since we are using only time-series variation, we can also exploit a similar IV as that used in Dafny, Duggan, and Ramanarayanan (2012). They used the simulated change in the HHI attributable to a 1999 merger between Aetna and

Table 5
Panel Estimates

	Cardiology		Orthopedics	
	OLS	IV	OLS	IV
Lagged physician FTHHI 20-minute boundary	−.013	.308	.008	.128
	(.008)	(.247)	(.007)	(.127)
Lagged insurance HHI	.009	−.164	.003	.066
	(.006)	(.224)	(.003)	(.058)
Lagged physician FTHHI 80-minute boundary	.002	.208[+]	.011	.094
	(.009)	(.112)	(.007)	(.149)
Lagged insurance HHI	.008	−.122	.002	.092
	(.005)	(.142)	(.003)	(.067)

Note. The dependent variable is the logarithm of service price, $\ln(P_m)$. All regressions include the controls specified in equation (7). Standard errors clustered by county are in parentheses. OLS = ordinary least squares; IV = instrumental variables; FTHHI = fixed-travel-time Herfindahl-Hirschman index; HHI = Herfindahl-Hirschman index.

[+] Significant at the 10 percent level.

Prudential. As our sample covers 2005–8, we cannot use variation from this merger. Instead, we create an analogous simulated change in the HHI from a merger between United and Pacificare, which occurred in December 2005:

$$\text{Sim}\Delta\text{HHI}_m = 2 \times \text{United 2005 Share}_m \times \text{Pacificare 2005 Share}_m. \quad (8)$$

To be consistent with Dafny, Duggan, and Ramanarayanan (2012), the instrument we use is (Year $\geq$ 2007) $\times$ $\text{Sim}\Delta\text{HHI}_m$, which allows for the instrument to take effect 1 full calendar year after the merger. One drawback of our measure is that there is not as much variation in this variable as in their variable. For instance, 75 percent of counties experienced no simulated effect due to the merger. The 90th-percentile change was 8 points, and the maximum change was 697 points. We removed observations from Arizona and Colorado, where United agreed to divest. We find that removing data from these two states increases the precision of the estimates a great deal.

Since we are using simulated concentration as an instrument for the insurance concentration, we do not need all of the instruments used in the cross-sectional analysis. We use the following instruments: (Year $\geq$ 2007) $\times$ $\text{Sim}\Delta\text{HHI}_m$, county population, and county population over the age of 65, where all variables are in logs.

We report these estimates in Table 5 and the first-stage estimates in Appendix B. Again, for simplicity, we report results for the FTHHI measure constructed using a 20-minute and an 80-minute boundary with travel costs. As in the cross-sectional estimates, we cluster by county. Although coefficients on the FTHHI measure are larger than in the cross section, standard errors are much larger. There are no statistically significant estimates under the 20-minute-boundary FTHHI. For the cardiology sample with the 80-minute boundary, the estimate of the physician FTHHI is .208 and significant at the 10 percent level. For the

orthopedics sample, all estimates are of the correct sign but statistically indistinguishable from zero.

These large confidence intervals are likely due to both the small time-series horizon of our data and the small degree of time-series variation in our data as seen in Tables 1 and 2. The larger point estimates on the physician concentration measure may be attributable to a reduction in omitted-variable bias; however, the cross-sectional estimates do lie in the confidence interval of the panel estimate.

5. Conclusion

The 2011 health care reform has altered industry incentives and spurred consolidation among health care providers. While many hope that this consolidation will lead to greater coordination and efficiency, others are concerned that it will increase bargaining leverage and ultimately harm consumers. In fact, even the two primary competition authorities in the United States, the DOJ and the FTC, appear to have starkly contrasting views on the effects of the new health care law. These differing opinions should not be surprising, especially given the scant evidence regarding the effects of consolidation in physician markets. This paper attempts to provide timely empirical evidence on this topic. Combining the evidence presented here (estimates using large and small geographic markets, cross-sectional and panel regression, and IV and OLS regression), we show in this paper that physicians in concentrated markets are able to exercise market power. A physician in a market with 90th-percentile concentration will charge fees that are 14–30 percent higher than a physician in the 10th-percentile market. Linking our estimates to historical survey data discussed in Rebitzer and Votruba (2011), we find that physician consolidation has caused about an 8 percent increase in fees over the last 2 decades (1988–2008).

These findings strongly suggest that policy makers and antitrust officials should remain wary of the potential anticompetitive effects of mergers among physicians. This is especially important for mergers taking place in markets that are already concentrated. In addition, the estimates suggest that geographic markets could be as small as 20 minutes' driving time, so antitrust authorities may need to focus on very localized geographic markets when considering the effects of competition. We also provide some evidence that insurers in more concentrated markets are able to negotiate lower service prices, although these estimates tend to be imprecisely estimated and less robust.

Although we believe that our estimates provide new and important insights into the role of market power in physician markets, there are a number of limitations to our study. First, we are unable to link fees to specific contracts between insurers and physicians. This is potentially important, since it is well known that price discrimination occurs in health care markets (see Sorensen 2003). We are uncertain whether this limitation causes a bias in our estimates, but it likely reduces their precision. Second, this paper relies on reduced-form

methods for analyzing competitive effects, which makes it challenging to conduct precise counterfactual analyses. Third, most of our identification occurs in the cross section, since there is little variation in market concentration during the time period of our study. Although our panel analysis is suggestive of competitive effects, the estimates are imprecise. Finally, this study does not directly assess how quality of care affects the competitive environment. The most commonly accepted measure of quality in the health care literature is based on mortality data, which we do not observe in the MarketScan data. We hope that future research is able to address the limitations of our study.

Appendix A

Table A1
Variable Definitions

Variable	Definition
Concentration measures:	
$FTHHI_{ct}$	Fixed-travel-time Herfindahl-Hirschman index concentration measure for physicians; this measure is specific to a county and time period (half-year)
HHT^{Ins}_{mt}	Herfindahl-Hirschman concentration measure for insurance carriers; this measure is specific to each metropolitan service area and time period (half-year)
Expenditure measures:	
P_{nt}	Logarithm of price per service for episode of care n performed at time t by the physician
Q_{nt}	Logarithm of service utilization for episode of care n provided by the physician
TE_{nt}	Logarithm of total physician expenditures for episode of care n
Patient-specific controls:	
$\ln(Medinc_{Pat})$	Logarithm of the median income in the patient's county
$Educ_{Pat}$	Fraction of college-educated individuals in the patient's county
EPO	Equals one if the patient's health plan is an exclusive provider organization
HMO	Equals one if the patient's health plan is a health maintenance organization
POS	Equals one if the patient's health plan is a point-of-service plan
PPO	Equals one if the patient's health plan is a preferred-provider organization
HDHP	Equals one if the patient's health plan is a high-deductible health plan
CDHP	Equals one if the patient's health plan is a consumer-driven health plan
Employer	Equals one if the patient's health plan is employer based
Age	Patient's age
Age^2	Patient's age squared
Age^3	Patient's age cubed
Comorbid	Number of patient comorbidities (concurrent diseases)
$Comorbid^2$	Number of comorbidities squared
$Comorbid^3$	Number of comorbidities cubed
Gender	Equals one if the patient is male

Physician quality controls:	
$\ln(\text{Medinc}_{\text{Flow}})$	Logarithm of the patient-weighted median household income; $\text{Medinc}_{\text{Flow}} = \sum \omega_{cp} \text{Medinc}_c$, where Medinc_c is the median income in county c and ω_{cp} is the share of physician p's patients from county c[a]
Univ	Fraction of hospitals in the physician's county c that are affiliated with a medical university[a]
Physician cost controls:	
$\ln(\text{Rent}_{\text{Phys}})$	Logarithm of the median gross rent in the physician's county[a]
$\ln(\text{Medval}_{\text{Phys}})$	Logarithm of the median home value in the physician's county[a]
$\ln(\text{Medinc}_{\text{Phys}})$	Logarithm of the median household income in the physician's county[a]
$\ln(\text{Facwage}_{\text{Phys}})$	Logarithm of the total health care facility payrolls divided by the number of facility employees[a]
Instruments:	
ln(Pop)	Logarithm of county population[a]
ln(Pop65)	Logarithm of the county population over the age of 65[a]
ln(PopK)	Logarithm of imputed county population between ages $K - 10$ and K, where $K = 65$, 55, 45, and 35 in the Area Health Resource File; $\text{Pop}K = \text{Frac}K_c \times \text{Pop}_c$, where Frac$K$ is the fraction in the K to $K - 10$ age group for county c in the MarketScan Research Databases
$\ln(\text{Pop}_{\text{MSA}})$	Logarithm of the population of the metropolitan service area[a]
Urate	Unemployment rate in the physician's county[a]
Urate^2	Unemployment rate in the physician's county squared[a]
Urate^3	Unemployment rate in the physician's county cubed[a]

[a] From the U.S. Department of Health and Human Services, Area Health Resource File.

Appendix B

First-Stage Estimates

Table B1

First-Stage Estimates: Cross-Sectional Within-State Analysis

	Cardiology		Orthopedics	
	ln(FTHHI)	ln(HHI^{Ins})	ln(FTHHI)	ln(HHI^{Ins})
Log of county population	−.225	.532	1.545^{+}	.288
	(.796)	(.359)	(.887)	(.269)
Log of county population 65 and older	−.348	−.088	−.393^{+}	−.118^{+}
	(.293)	(.077)	(.211)	(.067)
Log of county population ages 55–64	.533^{+}	.033	−.347	.092
	(.273)	(.106)	(.284)	(.093)
Log of county population ages 45–54	−.781^{+}	−.159	.062	−.053
	(.394)	(.154)	(.384)	(.129)
Log of county population ages 35–44	.587	−.315	−.965^{+}	−.211
	(.529)	(.249)	(.569)	(.184)
Log of MSA population	−.372**	−.050**	−.348**	−.053**
	(.043)	(.012)	(.038)	(.011)
Unemployment rate	−3.452	12.33	24.99	18.18
	(29.54)	(12.10)	(37.94)	(13.87)
(Unemployment rate)^2	−553.2	−542.2^{+}	−890.7	−718.6^{+}
	(799.4)	(321.5)	(1,008.0)	(369.4)
(Unemployment rate)^3	7,598.8	4,952.0*	8,931.1	6,255.9*
	(6,096.2)	(2,451.5)	(7,312.9)	(2,784.9)
F-statistic	23.46	6.29	18.23	8.15

Note. The fixed-travel-time Herfindahl-Hirschman index is measured with an 80-minute boundary assuming travel costs. Standard errors clustered by county are in parentheses. Not shown are the estimates on the covariates of specification (4). The *F*-statistics test the null hypothesis that all instruments are jointly equal to zero. MSA = metropolitan service area.

$^{+}$ Significant at the 10 percent level.

* Significant at the 5 percent level.

** Significant at the 1 percent level.

Table B2

First-Stage Estimates: Panel Analysis

	Cardiology		Orthopedics	
	ln($FTHHI_{t-1}$)	*ln*(HHI^{Ins}_{t-1})	ln($FTHHI_{t-1}$)	*ln*(HHI^{Ins}_{t-1})
Log lagged county population	−.848*	−1.259*	−.246	−1.107*
	(.379)	(.558)	(.251)	(.475)
Log lagged county population over the age of 65	−.067	.783	.079	.705
	(.335)	(.494)	(.283)	(.456)
(Year ≥ 2007) × $\text{Sim}\Delta\text{HHI}_m$	−1.101	11.185**	.296	12.35*
	(2.270)	(4.126)	(3.48)	(5.54)
F-statistic	3.39	4.07	.470	3.29

Note. The fixed-travel-time Herfindahl-Hirschman index is measured with an 80-minute boundary assuming travel costs. Standard errors clustered by county are in parentheses. Not shown are the estimates on the covariates of specification (7). The *F*-statistics test the null hypothesis that all instruments are jointly equal to zero.

* Significant at the 5 percent level.

** Significant at the 1 percent level.

References

Aizcorbe, Ana, and Nicole Nestoriak. 2011. Changing Mix of Medical Care Services: Stylized Facts and Implications for Price Indexes. *Journal of Health Economics* 30:568–74.

American Medical Association (AMA). 2010. *Competition in Health Insurance: A Comprehensive Study of U.S. Markets.* Chicago: American Medical Association.

———. 2012. *Physician Practice Benchmark Survey.* Chicago: American Medical Association.

America's Health Insurance Plans. 2011. *2011 Health Insurance: Overview and Economic Impact in the States.* Washington, D.C.: America's Health Insurance Plans.

Berenson, Robert A., Paul B. Ginsburg, and Nicole Kemper. 2010. Unchecked Provider Clout in California Foreshadows Challenge to Health Care Reform. *Health Affairs* 29: 699–705.

Berry, Steven T., and Joel Waldfogel. 2001. Do Mergers Increase Product Variety? Evidence from Radio Broadcasting. *Quarterly Journal of Economics* 116:1009–25.

Burstein, Philip L., and Jerry Cromwell. 1985. Relative Incomes and Rates of Return for U.S. Physicians. *Journal of Health Economics* 4:63–78.

Capps, Cory, David Dranove, and Mark Satterthwaite. 2003. Competition and Market Power in Option Demand Markets. *RAND Journal of Economics* 34:737–63.

Catan, Thomas. 2011. This Takeover Battle Pits Bureaucrat vs. Bureaucrat. *Wall Street Journal*, April 12.

Chernew, Michael E., Katherine Baiker, and John Hsu. 2010. The Specter of Financial Armageddon—Health Care and Federal Debt in the United States. *New England Journal of Medicine* 362:1166–68.

Chernew, Michael, Richard Hirth, and David Cutler. 2009. Increased Spending on Health Care: Long-Term Implications for the Nation. *Health Affairs* 28:1253–55.

Ciliberto, Federico, and David Dranove. 2006. The Effect of Physician-Hospital Affiliations on Hospital Prices in California. *Journal of Health Economics* 25:29–38.

Claxton, Gary, Matthew Rae, Narmita Panchal, Anthony Damico, Nathan Bostick, Kevin Kenward, and Heidi Whitmore. 2013. *Employer Health Benefits: 2013 Annual Survey.* Menlo Park, Calif.: Henry J. Kaiser Family Foundation; Chicago: Health Research & Educational Trust.

Cuellar, Alison Evans, and Paul J. Gertler. 2006. Strategic Integration of Hospitals and Physicians. *Journal of Health Economics* 25:1–28.

Cutler, David, and Dan Ly. 2011. The (Paper)Work of Medicine: Understanding International Medical Costs. *Journal of Economic Perspectives* 25:3–25.

Dafny, Leemore, Mark Duggan, and Subramaniam Ramanarayanan. 2012. Paying a Premium on Your Premium? Consolidation in the U.S. Health Insurance Industry. *American Economic Review* 102:1161–85.

Davis, Peter. 2006. Measuring the Business Stealing, Cannibalization, and Market Expansion Effects of Entry in the U.S. Motion Picture Exhibition Market. *Journal of Industrial Economics* 54:293–321.

Dranove, David, Anne Gron, and Michael Mazzeo. 2003. Differentiation and Competition in HMO Markets. *Journal of Industrial Economics* 51:433–54.

Dranove, David, Richard Lindrooth, William White, and Jack Zwanziger. 2008. Is the Impact of Managed Care on Hospital Prices Decreasing? *Journal of Health Economics* 27:362–76.

Dranove, David, and Richard Ludwick. 1999. Competition and Pricing by Nonprofit Hospitals: A Reassessment of Lynk's Analysis. *Journal of Health Economics* 18:87–98.

Dranove, David, Mark Shanley, and William D. White. 1993. Price and Concentration in Hospital Markets: The Switch from Patient-Driven to Payer-Driven Competition. *Journal of Law and Economics* 36:179–204.

Duggan, Mark. 2002. Hospital Market Structure and the Behavior of Not-for-Profit Hospitals. *RAND Journal of Economics* 33:433–46.

Dunn, Abe, Eli Liebman, Sarah Pack, and Adam Hale Shapiro. 2013. Medical Care Price Indexes for Patients with Employer-Provided Insurance: Nationally Representative Estimates from MarketScan Data. *Health Services Research* 48:1173–90.

Dunn, Abe, and Adam Hale Shapiro. 2012. Physician Market Power and Medical-Care Expenditures. Working paper. Bureau of Economic Analysis, Washington, D.C.

Dunn, Abe, Adam Hale Shapiro, and Eli Liebman. 2013. Geographic Variation in Commercial Medical-Care Expenditures: A Framework for Decomposing Price and Utilization. *Journal of Health Economics* 32:1153–65.

FTC (Federal Trade Commision) and DOJ (Department of Justice). 2004. *Improving Health Care: A Dose of Competition.* Washington, D.C.: Federal Trade Commision and Department of Justice.

Frank, Richard G., and Judith R. Lave. 1985. The Psychiatric DRGs: Are They Different? *Medical Care* 23:1148–55.

Gaynor, Martin. 1994. Issues in the Industrial Organization of the Market for Physician Services. *Journal of Economics and Management Strategy* 3:211–55.

Gaynor, Martin, and Deborah Haas-Wilson. 1999. Change, Consolidation, and Competition in Health Care Markets. *Journal of Economic Perspectives* 13:141–64.

Gruber, Jonathan, and Michael Lettau. 2004. How Elastic Is the Firm's Demand for Health Insurance? *Journal of Public Economics* 88:1273–93.

Haas-Wilson, Deborah. 2003. *Managed Care and Monopoly Power: The Antitrust Challenge.* Cambridge, Mass.: Harvard University Press.

Keeler, Emmett B., Glenn Melnick, and Jack Zwanziger. 1999. The Changing Effects of Competition on Non-profit and For-Profit Hospital Pricing Behavior. *Journal of Health Economics* 18:69–86.

Kessler, Daniel, and Mark McClellan. 2000. Is Hospital Competition Socially Wasteful? *Quarterly Journal of Economics* 115:577–615.

Leffler, Keith B., and Cotton M. Lindsay. 1981. Markets for Medical Care and Medical Education: An Integrated Long-Run Structural Approach. *Journal of Human Resources* 16:20–40.

Liebhaber, Allison, and Joy M. Grossman. 2007. Physicians Moving to Mid-sized, Single-Specialty Practices. Health Systems Change Tracking Report No. 18. Center for Studying Health System Change, Washington, D.C. http://www.hschange.org/CONTENT/941.

Lynk, William J. 1995. Nonprofit Hospital Mergers and the Exercise of Market Power. *Journal of Law and Economics* 38:437–61.

Newhouse, Joseph P., Albert P. Williams, Bruce W. Bennett, and William B. Schwartz. 1982. Where Have All the Doctors Gone? *Journal of the American Medical Association* 247:2392–96.

Noether, Monica. 1988. Competition among Hospitals. *Journal of Health Economics* 7: 259–84.

Pear, Robert. 2011. Trade Commission Challenges a Hospital Merger. *New York Times,* August 21.

Pope, Gregory C., and Russel T. Burge. 1996. Economies of Scale in Physician Practice. *Medical Care Research and Review* 53:417–40.

Rebitzer, James, and Mark Votruba. 2011. Organizational Economics and Physician Practices. Working Paper No. 17535. National Bureau of Economic Research, Cambridge, Mass.

Schwartz, William B., Joseph P. Newhouse, Bruce W. Bennett, and Albert P. Williams. 1980. The Changing Geographic Distribution of Board-Certified Physicians. *New England Journal of Medicine* 303:1032–38.

Sirovich, Brenda, Patricia M. Gallagher, David E. Wennberg, and Elliot S. Fisher. 2008. Discretionary Decision Making by Primary Care Physicians and the Cost of U.S. Health Care. *Health Affairs* 27:813–23.

Sloan, Frank A. 1970. Lifetime Earnings and Physicians' Choice of Specialty. *Industrial and Labor Relations Review* 24:47–56.

Smart, Derek R. 2006. *Medical Group Practices in the US.* Chicago: American Medical Association.

Sorensen, Alan. 2003. Insurer-Hospital Bargaining: Negotiated Discounts in Post-deregulation Connecticut. *Journal of Industrial Economics* 51:469–90.

Staten, Michael, John Umbeck, and William Dunkelberg. 1987. Market Share and the Illusion of Power: Can Blue Cross Force Hospitals to Discount? *Journal of Health Economics* 6:43–58.

———. 1988. Market Share/Market Power Revisited: A New Test for an Old Theory. *Journal of Health Economics* 7:73–83.

Town, Robert, and Gregory Vistnes. 2001. Hospital Competition in HMO Networks. *Journal of Health Economics* 20:733–53.

U.S. Senate. 2011. Committee on Ways and Means. *Health Care Industry Consolidation: Hearing before the Subcommittee on Health of the Committee on Ways and Means.* 112th Cong., 1st Sess. September 9.

Wong, Herbert S. 1996. Market Structure and the Role of Consumer Information in the Physician Services Industry: An Empirical Test. *Journal of Health Economics* 15:139–60.