Physician Concentration and Negotiated Prices: Evidence from State Law Changes*

Naomi Hausman
Hebrew University

Kurt Lavetti
Ohio State University

Note: Preliminary and Incomplete, Please Do Not Cite

December 30, 2014

Abstract

As the sizes of physician group practices have increased over time, the once-prevailing assumption that physicians act as price-takers in negotiations with insurers has been increasingly questioned. Despite the potential consequences of this shift, relatively little is known about the relationship between the concentration of physician markets and prices negotiated with insurers. The effect of consolidation on prices is difficult to estimate because changes in physician practice sizes may have occurred in response to changes in insurance markets or demand, among other factors. Moreover, both data and computational limits have prevented researchers from adapting models of hospital-insurer bargaining to study physician markets. We use variation in state non-compete laws caused by judicial decisions as sources of plausibly exogenous shocks to the organizational incentives of physician group practices. We show that these law changes significantly affect the concentration of physician markets, and use the law changes as instruments to estimate the relationship between concentration and negotiated prices. We find that, on average, increases in the size of physician group practices have led to moderately negative price changes in localized and medically-specialized markets for physician services. The findings reduce concerns that consolidation of physician groups as Accountable Care Organizations under the Affordable Care Act may lead to price increases by reducing competition.

JEL Classifications:
Keywords:

*We are grateful to Jay Bhattacharya, Jeff Clemens, Michael Dickstein, Will Dow, Josh Gottlieb, Jesse Rothstein, and seminar participants at Berkeley, MIT, NBER, NYU, Stanford, and UGA for helpful comments, to Norman Bishara for sharing legal data, and to Eric Auerbach, Richard Braun, Akina Ikudo, and David Krosin for research assistance. This research was conducted while Lavetti was a Robert Wood Johnson Foundation Scholar in Health Policy at UC Berkeley, and their support is gratefully acknowledged. Correspondence: lavetti.1@osu.edu

1 Introduction

At 16.9% of total GDP, the share of spending that is devoted to healthcare in the US is about 82% higher than the OECD average.[1] Many studies, including Pauly (1993) and Anderson et al (2003) have shown that this difference in spending is overwhelmingly due to differences in prices, not differences in quantities. This has given rise to interest among researchers in understanding why prices are so much higher in the US. Many studies including Gowrisankaran, Nevo and Town (2014), Ho and Lee (2014) have shown that market concentration has led to significantly higher prices in hospitals, which account for about 32% of all medical spending. There is also evidence, including Dafny, Duggan, and Ramanarayanan (2012), that concentration in insurance markets leads to significantly larger prices for health insurance. These administrative costs and profits of insurance companies account for about 7% of all medical spending. By comparison, spending on physicians and other health-related professional services accounts for 27% of all healthcare spending, yet there has been far less attention devoted to understanding the extent to which levels of competition or market concentration affect prices negotiated between physicians and insurers. Hale and Shapiro (2014) is the first such comprehensive study of the correlations between market concentration and prices among physicians.

Two major challenges in making progress at understanding this relationship between physician practice sizes and prices are that longitudinal data on physician practices are exceedingly rare, and it is difficult to identify effects of physician practice sizes separately from idiosyncratic differences over time and across locations in potentially confounding unobservables like insurer bargaining power and consumer demand. To address the challenges, we construct a longitudinal dataset on the approximate universe of physician establishments in the US between 1991 and 2007 by matching physician identifiers and practice locations from Medicare Physician Identification and Eligibility Registry (MPIER). We also compare these data on the number of physicians per establishment to data from the Census Bureau's Longitudinal Business Database, which measures firm-level annual sales, payroll, and employment counts, and identifies outpatient physician offices by industry code. We then use judicial decisions that cause changes in state laws regarding the enforceability of non-compete agreements (NCAs) as instrumental variables that create shocks to the organizational incentives of physicians practices but not to insurers, to study the effects of physician firm sizes on prices negotiated with private insurance companies, using negotiated prices Medstat Marketscan data. The Medstat data include prices negotiated between physicians and a large sample of private commercial insurance companies from several hundred million medical procedures included in medical claims of the employees of a large sample of US firms between 1996-2009. The first-stage results suggest that NCA laws having both highly significant and sizable effects on the concentration of physician markets, with various specific components of the law having effects in opposing directions. We then show that these plausibly exogenous shocks to physician group practice sizes have moderately negative effects on prices negotiated between physicians and insurers, suggesting that improvements in efficiency potentially due to economies of scale appear to outweigh the effects that larger group sizes may have on physician bargaining power or on differences

[1] See OECD Health Statistics 2014

in the relative value that larger physician groups may have in insurance networks. Both the first stage results on practice sizes and the second stage results on prices are highly consistent across medical specialties and in both rural and urban markets, although estimated price decreases are larger on average in metro counties.

The paper proceeds as follows: we describe background information on non-compete agreements, the law changes that we use as instruments, and the use of NCAs in physician group practices, in Section 2. We then present a simple theoretical model of bargaining between insurers and physician groups in Section 3. The model describes why firm size may be related to market concentration, and provides a framework for interpreting our empirical estimates as combinations of specific parameters. The datasets used in the analyses are described in Section 4.1, followed by a discussion of the empirical strategy and identifying assumptions in Sections 4.2 and 4.3. The results are described in Section 5 followed by a discussion of their significance in Section 6.

2 Background

2.1 NCA Laws and Changes

The enforceability of NCAs is determined at the state level. The permissibility of NCAs dates back in English common law to at least 1621, and 39 US states still follow common law in determining the enforceability of NCAs. This means that historical precedent is the main determinant of enforceability in most US states. Across states that follow the same common law origins, current NCA laws also vary dramatically. For example, Kansas ranks second out of 51 states plus DC in NCA enforceability, while North Dakota ranks 51st, despite the fact that both states follow common law traditions that were heavily influenced by English common law.

Common law requires judges to consider three specific questions when determining the enforceability of NCAs. First, does the firm have a legitimate business interest that is capable of being protected by an NCA? Second, does the NCA cause an undue burden on the worker? And third, is the NCA contrary to the public interest? Changes in the interpretation and weighting of these questions has caused judicial decisions to frequently break from precedent, effectively changing NCA laws in the state.

For example, in Shreveport Bossier v. Bond (2001), a case in Louisiana involving a construction company attempting to enforce an NCA against a carpenter, the state Supreme Court ruled that NCAs apply only to employees that attempt to establish their own business in competition with a prior employer, but cannot prevent a worker from joining a competing firm that already existed. This sudden change allowed all workers in the state to escape the restrictions of NCAs that they had already signed and move to other firms.

We quantify NCA laws and the variation in laws over time using the methodology developed by Bishara (2012). These data are described in Section 4.1.1.

2.2 Physician Markets and the Use of NCAs

Lavetti et al (2014) document the frequent and systematic used of NCAs among physicians. About 45% of primary care physicians in group practices are bound by NCAs. In states where NCAs are easier to enforce, physician practices are much more likely to use NCAs, ranging from an average of about 30% of employed physicians in California, a low enforceability state, to 66% in Pennsylvania, based on a five-state sample. In the case of physicians, an NCA states that if a physician leaves a group practice they are generally forbidden from practicing medicine in any form in a given geographic area surrounding their former practice for a fixed period of time. Common examples are 10-15 mile radii for 1-2 years. Allowable radii depend in part on how far patients generally travel to see a doctor, which can vary by geography and physician specialty.

The evidence suggests that physician practices use NCA contracts to mitigate investment holdup problems. Holdups stem from the fact that information asymetries in high skilled services make it costly for consumers to search for physicians, which generates loyalty. The loyalty of patients is arguably the most valuable asset for many physician practices, and the patient base is generally the basis for determining a price when practices are sold. However, firms have no direct property rights or control over these valuable assets. They are threatened by the possibility that hiring a new physician to join the practice, and steering patients to the new physician, could lead to the new physician forming a relationship with the patients and then leaving the practice and taking the patients with them. NCAs can prevent this from happening, making investments in patient relationships a firm-specific form of human capital investment.

Consistent with this theory, employed physicians with NCAs have significantly higher rates of earnings growth over time. This is largely due to the fact that they treat far more patients, and the patients that they treat are more likely to be privately insured or on Medicare, and less likely to be uninsured or on Medicaid. They also have very different contract structures that tie earnings more strongly to individual revenue generated. This overcomes a dynamic bargaining power problem, which would otherwise leave workers without any leverage to negotiate earnings increases with an employer after signing an NCA. Lavetti et al (2014) also concludes that NCAs are not used primarily to reduce average hiring costs by deterring turnover.

Importantly for the analysis of practice sizes and prices, the survey data used in Lavetti et al (2014) show that there is no evidence of quality differences associated with the use of NCAs. This comes from three sources of information. First, within a given market, practices that don't use NCAs negotiate the same prices with private insurers as those that do. Although many other aspects that are believed to be associated with quality significantly affect negotiated prices, the use of NCAs does not. Second, practices that use NCAs are equally likely to hire physicians with more prior experience, which is strongly correlated with measures of patient satisfaction and perceived quality. Third, responses to vignette based questions that directly elicit clinical knowledge about best practices, diagnoses and clinical recommendations suggest that physicians with NCAs do not differ in any of these clinical skills.

These findings suggest that if laws regarding NCA enforceability affect negotiated prices these changes occur through affecting competition overall in a market, and not by affecting physician quality or through compositional changes in physician practices that are related to quality or sorting.

3 Bargaining Model

We model bargaining between physician groups and insurers following the basic setup of Ho and Lee (2014). The purpose of the model is to derive a relationship between negotiated prices and firm sizes or concentration under a set of plausible assumptions, and then use that relationship as the foundation of our empirical analysis. The market consists of a set of physician groups $\mathcal{P}$ and insurers $\mathcal{I}$. Consumers of insurance plan $i \in \mathcal{I}$ can only choose to visit a physician j that is in the network of insurer i, where the network is denoted by $\mathcal{G}_i \subseteq \{0,1\}^{|\mathcal{P}|\times|\mathcal{I}|}$. Similarly, $\mathcal{G}_j$ is the set of insurers with whom physician group j has contracted. Prices are negotiated on a capitated basis, which could be thought of as a literal description of the contract or heuristically if we consider prices to be over an ex-ante predicted bundle of services, as long as physicians' decisions about medically appropriate care do not respond to changes in negotiated prices.

In each period of the model the following events take place. First insurers and physician groups commence simultaneous bilateral bargaining over prices p_{ij}, which are private knowledge of the parties involved in the negotiation. Second, after determining prices and networks, insurers set profit-maximizing uniform premiums ϕ_i that they will charge all consumers. Third, consumers form willingnesses to pay for insurance plans based on premiums and the amount of time a one has to wait to get an appointment with a physician in network i, $w_i(\mathbf{p}, \mathcal{G})$. Fourth, consumers probabilistically get sick and then wait the required amount of time necessary to visit a physician. Physician specialties are assumed to be distinct markets, without substitutability across specialties.

There are several simplifying assumptions about consumer choices. First, consumers are assumed to be incapable of differentiating physician quality, and so they view physicians of a given specialty as homogenous and only value networks insofar as they differ in access, which can be thought of as the number of days a consumer has to wait for an appointment. Consumers are also assumed to be non-responsive to the actual prices negotiated between physicians and insurers, and only consider these negotiated prices insofar as they affect premiums. This is descriptive, for example, of the situation in which copayments are uniform for all providers in a given market, and small changes in negotiated prices do not affect copayment rates. Finally, consumers are assumed to be captive to insurers with respect to small changes in physician networks, but consumers may still change their willingness to pay for the network, which affects premiums that insurers can charge. This may be a somewhat more realistic assumption for physicians than it is for hospitals, even in the presence of competition between insurers. One reason is that insurance decisions are frequently made by individuals' employers on behalf of a large group of workers, who may all use the same hospital but many different physician groups. Even for individuals that choose their own insurers, it may be relatively easy to observe whether a network contains the highest quality hospital or the most conveniently located hospital, but hard to predict which specialist their doctor will refer them to once they need medical care. The remaining model assumptions are similar to those made in models of hospital bargaining, such as Ho and Lee (2014), Gowrisankaran, Nevo, and Town (2013), and Lewis and Pflum (2013).

The insurer and physician group problems are again similar to Ho and Lee (2014), where the profits of insurer i are:

$$\pi_{i,\mathcal{P}}(\mathbf{p},\mathcal{G}) = D_i(w_i(\mathbf{p},\mathcal{G}),\phi(\mathbf{p},\mathcal{G}))\left[\phi_j(\mathbf{p},\mathcal{G}) - \sum_{r\in\mathcal{G}_i}\sigma_{rj}(\mathcal{G})p_{rj}\right]$$

where D_i represents the number of enrollees in insurance plan i, which depends on wait times $w_i(\mathbf{p},\mathcal{G})$ in network i, and σ_{ij} is the share of insurer i's enrollees that choose physician group j. The profits of physician group j are similarly:

$$\pi_{j,\mathcal{I}}(\mathbf{p},\mathcal{G}) = \sum_{s\in\mathcal{G}_i} D_s(w_i(\mathbf{p},\mathcal{G}),\phi(\mathbf{p},\mathcal{G}))\sigma_{sj}(\mathcal{G})p_{sj}(p_{sj} - c_{sj})$$

where c_{jn} is the cost to physician group j of treating one patient covered by insurer s.

Prices are the negotiated through the result of simultaneous bilateral Nash bargains, where p_{ij} solves the problem:

$$p_{ij} = \arg\max_{p_{ij}} [\pi_{i,\mathcal{P}}(\boldsymbol{p},\mathcal{G}) - \pi_{i,\mathcal{P}}(\boldsymbol{p_{-ij}},\mathcal{G}\backslash ij)]^{\tau_i} \times [\pi_{j,\mathcal{I}}(\boldsymbol{p},\mathcal{G}) - \pi_{j,\mathcal{I}}(\boldsymbol{p_{-ij}},\mathcal{G}\backslash ij)]^{\tau_i}\,\forall ij \in G$$

where $\pi_{i,\mathcal{P}}(\boldsymbol{p_{-ij}},\mathcal{G}\backslash ij)$ represents the disagreement profits of insurer i if they fail to reach an agreement over network inclusion with physician group j, and similarly $\pi_{j,\mathcal{I}}(\boldsymbol{p_{-ij}},\mathcal{G}\backslash ij)$ are the disagreement profits of physician group j. τ_i and τ_j are the bargaining power parameters of the insurer and physician group, respectively.

Under the captive insurer assumption the first order condition of the bargaining problem between physicians and insurers simplifies to:

$$p^{\star}_{ij}\sigma_{ij}(\mathcal{G}) = \tau_j\left[\underbrace{\left(\phi_j(\mathbf{p},\mathcal{G}) - \tilde{\phi}_j(\mathbf{p},\mathcal{G})\right)}_{\Delta\text{Premiums}} - \underbrace{\left(\sum_{r\in\mathcal{G}_j\backslash ij} p^{\star}_{rj}\left(\sigma_{rj}(\mathcal{G}) - \tilde{\sigma}_{rj}(\mathcal{G})\right)\right)}_{\Delta\text{Payments to Other Physicians}}\right] + \tau_i \underbrace{\bar{c}_j\sigma_{ij}(\mathcal{G})}_{\text{Average Cost}} + \varepsilon_{ij} \qquad (1)$$

where $\phi_j(\mathbf{p},\mathcal{G}) - \tilde{\phi}_j(\mathbf{p},\mathcal{G})$ is the change in insurance premiums charged when physician group j is included in the network, which is positive. The second term equals the additional payments that the insurer will have to make to other physician groups per enrollee if group j is not included in the network, which is negative. The third term is the average cost to group j of treating an enrollee. And ε_{ij} represents *iid* cost shocks.

Conditional on getting sick, consumer k derives utility from visiting a physician j in network i, given by:

$$u_{kij} = \eta_k + \frac{1}{w_{ij}}$$

where in equilibrium wait times will be equivalent within any network, so that $w_{ij} = w_i$. The average wait time for an enrollee who gets sick in network i and visits physician j is:

$$w_j = \beta \frac{\sum_{i \in \mathcal{G}_j} \gamma N_i}{|P_j|}$$

where N_i is the number of enrollees in insurance plan i, γ is the probability of getting sick, and $|P_j|$ is the size of physician group j. The average wait time for an enrollee who gets sick in network i is:

$$w_i = \beta \frac{\sum_{r \in \mathcal{G}_{i \times j}} \gamma N_i}{\sum_{r \in \mathcal{G}_{i \times j}} |P_j|}$$

where $\mathcal{G}_{i \times j}$ denotes the connected subset of $\mathcal{G}$ that contains all insurers and physician groups that have any nodes in common with the networks $\mathcal{G}_i$ or $\mathcal{G}_j$. For an insurer i with an exclusive network of physicians that do not participate in other networks, this subset is simply $\mathcal{G}_i$.

As in Capps, Dranove, and Satterthwaite (2003) we use a measure of willingness to pay (WTP) as a proxy for the surplus that consumer k would lose if a given physician group were to leave the network of the plan in which the consumer is enrolled. That is, the change in utility that the consumer gets from physician group j exiting the network is:

$$\Delta \mathrm{WTP}_{kij} = u_{kij} \mid_{j \in \mathcal{G}_i} - u_{kij} \mid_{j \notin \mathcal{G}_i}$$

Each consumer's ex ante WTP is then $\gamma \Delta u_{kij}$. We express the WTP by the insurer for participation of group j in the network, which affects the premium charged by insurer i, as being proportional to the average consumer surplus of the consumers in the network:

$$\Delta \mathrm{WTP}_{ij} = \frac{\sum_k \Delta \mathrm{WTP}_{kij}}{N_i} \xi = \frac{|P_j|}{\beta \gamma \sum_{r \in \mathcal{G}_{i \times j}} N_i} \xi$$

As a result $\frac{\partial \mathrm{WTP}_{ij}}{\partial |P_j|} > 0$ since premiums reflect consumers' WTP. Also $\frac{\partial p^\star_{rj}(\sigma_{rj}(\mathcal{G}) - \tilde{\sigma}_{rj}(\mathcal{G}))}{\partial |P_j|} < 0$ because other firms' share sizes increase by more when a larger group exits the network. If the bargaining power parameter of physician groups is assumed to be non-decreasing in group size, then the first two terms in Equation 1 tend to cause negotiated prices to increase with group size.

However, a potentially opposing effect comes from the cost function. Without making assumptions about the cost function, it is plausible that there are economies of scale for physician groups, and that average costs are declining in group size. In this case the sign of the aggregate effect of group size on negotiated prices is ambiguous.

To generate an empirical analog of the first order condition, suppose that in disagreement the potential consumers of group j are distributed proportionally among the remaining physician groups in the network, then:

$$p^{\star}_{ij}\sigma_{ij}(\mathcal{G}) \;=\; a + |P_j| \frac{\tau_j \xi}{\beta\gamma \sum_{r\in\mathcal{G}_{i\times j}} N_i} - \frac{|P_{ij}|}{|P_j|} \sum_{r\in\mathcal{G}_j\setminus ij} \tau_j p^{\star}_{rj}\sigma_{rj}(\mathcal{G}) + \tau_i \bar{c}_j(|P_j|)\sigma_{ij}(\mathcal{G}) + \varepsilon_{ij} \quad (2)$$

$$\approx\; a + \beta_1\tau_j \times \text{Network Value}_j(|P_j|) + \beta_2\tau_i \times \text{Average Cost}_j(|P_j|) + \varepsilon_{ij} \quad (3)$$

This equation says that negotiated prices are increasing in the bargaining power of the physician group, increasing in size of the group relative to the number of consumers in the market, decreasing in the market shares of other firms relative to group j's market share, and changes depending on the slope of the cost function with respect to group size, weighted by the insurers bargaining power times group j's market share. Since the slope of the cost function with respect to group size may oppose the slopes of the first two terms, it is an empirical exercise to determine the aggregate relationship between negotiated prices and group sizes. This theoretical description of the market that leads to a relationship between firm sizes or market concentration and negotiated prices is not obvious in general, and depends strongly on the model, which we believe to be a plausible although simplified representation of the market for physician participation in insurance networks.

Since we do not observe cost functions in our data, what we can identify is the aggregate coefficient β_3 in the model:

$$\frac{\Delta p^{\star}_{ij}\sigma_{ij}(\mathcal{G})}{\Delta |P_j|} = \beta_3 \left[\tau_j \frac{\Delta \text{Network Value}_j}{\Delta |P_j|} + \tau_i \frac{\Delta \text{Average Cost}_j}{\Delta |P_j|} \right] + \varepsilon_{ij} \quad (4)$$

This allows us to test whether or not the cost efficiency effect outweighs the effect that larger groups can negotiate higher prices by increasing their value to an insurance network. In our empirical analyses we consider a variety of measures of firm size and market concentration, including HHIs and average firm sizes. Although we will only be able to identify the overall relationship between market concentration and prices, and cannot separate effects on WTP from effects on bargaining power parameters, for example, this basic model demonstrates why it may be reasonable to expect to find a relationship between negotiated prices and concentration measures in the market for physician services and motivates our empirical specifications. In future work we will also include controls for insurer market concentration, and interact insurer concentration with physician group size in order to control for potential geographic differences in the relative bargaining power of insurers, τ_i.

4 Empirical Estimation

4.1 Data

We use data from a variety of sources to construct a longitudinal database that includes physician market concentration measures, negotiated prices, and NCA laws over time. The main sample, during which all of the data components are available, covers 1996-2006.

4.1.1 NCA Law Data

To quantify the variation in NCA laws in a systematic way, we follow the measurement system developed in the legal analysis by Bishara (2011). Bishara (2011) analyzes case law in each state and scores states along 8 different dimensions, following the framework of a series of legal texts by Malsberger. Each of the dimensions was assigned a weight based on legal knowledge about their relative importance to create a weighted index score. The 8 components and scoring system is described in detail in Table 15. For example, one dimension upon which states differ is whether NCAs can be enforced when an employer decides to fire a worker. Some states allow NCAs to be enforced in this situation, while others only allow NCAs to be enforced when the worker voluntarily leaves the job.

The analysis by Bishara (2011) quantified laws in each state and each of 7 dimensions (questions Q3b and Q3c receive a combined score) in 1991 and 2009. Using these endpoints and coding methodology, we expanded upon these data by coding the timing of the time changes, creating an annually-measured longitudinal dataset that spans the period 1991-2009.[2]

In the raw data, the scores range from zero to 470, where 470 (Florida) corresponds to policies under which NCAs are easiest to enforce, and zero means that NCAs cannot be enforced in labor contracts. In our analyses we normalize the data by dividing by 470 to create a continuous measure that ranges from 0 to 1. Figure 1a shows the frequencies of these NCA index values in all state-year pairs in our sample, and the distribution of changes in index values are shown in Figure 2a. In models that use each of the components, or groups of components, each measure is normalized to range between 0 and 1, so that each variable can be interpreted as the effect of moving from the weakest to the strongest observed NCA enforceability policy.

We find that of the 7 dimensions, 4 of them tend to be positively correlated with market concentration, while 3 of them are negatively correlated. We create component groups by aggregating these two sets, and each component group is separately normalized to range between 0 and 1. Figures 1b and 1c shows the frequencies of these component group index levels, and the corresponding distributions of changes in the component index values are shown in Figures 2b and 2c. In some cases judicial decisions altered several components simultaneously, and in others a single component at a time was changed.

The components that are positively correlated with physician HHIs are questions Q1, Q2, Q3, and Q4. These questions measure whether the state has a strong statute that favors NCA enforceability, how broadly courts have defined firms' protectible interests, whether plaintiffs in litigation have a weak burden of proof, and whether courts are allowed to modify NCA contacts ex post to make them enforceable in the event that they were written too broadly. In strongly restrictive states each of these components could act as a deterrent that prevents a worker from leaving the firm, which could reasonably, all else equal, lead firms to grow larger over time. The components that are negatively correlated with market concentration are question Q3a, Q3bc, and Q8. These components measure whether the contract must be explicit about what compensation ('consideration' in legal terminology) is being made to the worker in exchange for accepting an NCA, whether being offered a job or not being

[2]We are grateful for legal expertise from Richard Braun, Esq., and for research assistance from Akina Ikudo, and David Krosin in the creation of this dataset.

fired is considered sufficient compensation, and whether an NCA can be enforced in the event that an employee is fired. Each of these components could plausibly lead to more separations between workers and firms, for example if a firm tries to impose an NCA after a job has already begun in a state where no additional compensation is required the worker may be more likely to quit, and the ability to enforce an NCA if a firm fires a worker may decrease the cost to the firm of firing the worker, making it more likely to occur.

4.1.2 MPIER Physician Panel

The Medicare Physician Identification and Eligibility Registry (MPIER) is a database collected by the Center for Medicare and Medicaid Services (CMS). The database began in 1989 when the Health Care Financing Administration assigned unique identifying numbers to all physicians associated with Medicare. Under Section 1833(q) of the Social Security Act, all physicians must have a unique identifying number to either order services on behalf of a Medicare patient, or to refer a Medicare patient to another physician for services. Since this requirement covers the nearly every physician in the US, by 1992 virtually every physician was included in the MPIER directory, and the requirement was strengthened in 1996 under HIPPA, which mandated every physician to receive an identifying number regardless of their association with Medicare. The coding system used in MPIER was in place through 2007, at which point it was replaced by a new system.

Between 1992 and 2007 the MPIER provides the street address of the practices that each physician is affiliated with. Physicians can have multiple practice affiliations at the same time, and each location was recorded in the MPIER data. The data include the physician's name, identifying number, the number of practices that the physician is associated with, the dates of any changes in practice affiliations, physician specialties, a group practice indicator, the practice billing address, and the practice's business location street address. Using the `soundex` fuzzy matching algorithm we construct a longitudinal database of the approximate universe of physician establishments by matching physicians to establishment locations, allowing the locations to have slight differences that may be due to typographical errors in street addresses, but requiring establishments to have the exact same street number and office number.

The limitation of this database is that we cannot observe connections between establishments, which could be important to the extent that multi-establishment firms negotiate as a single entity with insurers. A second limitation is that we cannot observe revenues, or allocations of time for physicians that work in multiple establishments. To calculate HHIs and other market concentration measures from these data we use the shares of the number of physicians in a given market. Each physician with multiple establishment associations is allocated in equal proportions to each of the establishments for as long as each establishment continues, so that each physician contributes exactly one to the total physician headcount at any time. However, the advantage of this dataset is that it is, to the best of our knowledge, the first constructed longitudinal database of physicians in the US that contains nearly the universe of physicians along with geographic identifiers and physician specialties.

4.1.3 Longitudinal Business Database

Several of these limitations can be overcome using data from the Census Bureau's Longitudinal Business Database (LBD), which contains plant-level data on nearly all non-farm establishments in the US, and is available from 1975 to the present. The LBD contains firm revenues, payroll, employment levels, industry codes, and establishment locations with firm linkages by IRS Employer Identification Numbers. Physician practices are identified by NAICS industry code 621111, described as 'Offices of Physicians (Except Mental Health Specialtists)' although we do not know exactly how many of the workers at the firm are physicians, and we do not observe the medical specialties of the firms. We also use the LBD to construct longitudinal measures of health insurance market concentration using data on revenue from firms in NAICS code 524114, 'Direct Health and Medical Insurance Carriers'.

4.1.4 Medstat Negotiated Prices Data

Data on prices negotiated between physicians and private commercial insurers come from the Medstat Marketscan database. The database includes the medical claims for every active employee and their dependents from a sample of large firms. We use data between 1996-2009 on average negotiated prices, counts, and variances of negotiated prices by county, by year, by physician specialty, by Current Procedural Terminology (CPT) code, by medical facility type (for example, physician office, hospital outpatient facility, hospital inpatient facility, urgent care facility, end-stage renal disease facility).

The data in our sample contain about 10 million average negotiated prices, based on prices from about 550 million procedure claims. The prices cover every state-year and nearly every county-year in the US between 1996-2009. The negotiated prices are between about 100 private insurance companies and all of the physicians that any enrollee in the sample visited. The full Medstat database includes a sample of over 138 million unique enrollees since 1995, and our data include information from all of these enrollees that visited a physician in one of the above medical facility types.

4.2 Empirical Strategy

We use two-stage least squares to estimate the effects of changes in state NCA laws on physician market concentration. Since physician practice sizes could be influenced by many factors, including insurer market concentration, consumer demand, and the dynamics of medical markets, we estimate fixed effects specifications that attempt to control for as much of this unobserved heterogeneity as possible. The first and second stages are:

$$C_{mct} = \alpha_1 + \beta_1 NCA_{ct} + \eta_m + \pi_f + \phi_t + \theta_p + \gamma_c + \nu_{dt} + \epsilon_{mct} \tag{5}$$

$$P_{mfpct} = \alpha_2 + \beta_3 \widehat{C}_{mct} + \eta_m + \pi_f + \phi_t + \theta_p + \gamma_c + \nu_{dt} + \varepsilon_{mfpct} \tag{6}$$

where m denotes medical specialty, c county, t year, f facility type, p procedure code, and d census division. NCA_{ct} is the Bishara score, which is measured at the state-level, so there is no variation across counties within a state, and C_{mct} is a measure of market concentration. In most of our analyses we use

Herfindahl indices (HHIs) as a measure of market concentration, but we also test alternative measures. The fixed effects specification controls for specialty effects, facility type effects, year effects, procedure code effects, county effects, and census-division by year effects. In all of the models presented, standard errors are clustered by state-year.

By including census-division by year effects we estimate the extent to which concentration and prices move differentially in a state that experiences a change in NCA laws relative to the other, on average, 4.56 neighboring states in the same census division, allowing census divisions to have idiosyncratic variation in both concentration and prices.

For robustness, we test similar models with different market definitions, different control groups, with time trends, with HHI measures calculated in different ways from multiple data sources, with alternative measures of market concentration and firm sizes, and controlling for insurance market HHI as well. Rather than focusing entirely on counties as market definitions, we also try using Primary Care Service Area (PCSA) definitions from the Dartmouth Atlas of Healthcare, which are calculated by analyzing patients' travel patterns to primary care providers. There are 6,542 defined PCSAs, or about 2.1 PCSAs per county on average. In specifications that use PCSAs we measure county-level average prices in the second stage, since that the finest geographic level at which our data on negotiated prices exist, but PCSA-level concentration in the first stage.

We estimate the model using HHIs based on employment counts from the MPIER, and based on sales, payroll, and employment counts from the LBD. We also compare these measures to HHIs calculated based on shares of physician revenue from a 20% sample of all Medicare claims, which we only have measures of in 2006.

4.3 IV Assumptions and Identification

The treatment that we consider is a change in law that affects the enforceability of NCAs. We rely on evidence from Lavetti et al (2014) that describes the individual-level effects of NCA enforceability on selection into contracts with NCAs and on outcomes. However, in our data we do no observe which physicians have NCAs in their contracts. As such we consider as an estimand the intention-to-treat effects of a change in NCA laws. At the physician level, a change in NCA enforceability can have two effects on outcomes. First, changing the ease with which an NCA can be enforced can alter the fraction of physicians with NCAs in their contracts, changing the probability of treatment. And second, allowing stricter NCAs to be enforced can impact the effect of treatment on the treated.

Each of these potential estimands can be useful for different purposes. To a judge who is interested in determining whether NCAs tend to cause an undue burden on workers, or whether firms have a legitimate business interest in using NCAs, observing treatment directly and estimating local average treatment effects could be the most informative way to evaluate the effects of NCAs. However, it is also of interest to know, at the state-level, how changing laws that govern NCA enforceability will affect aggregate outcomes. In evaluating these effects, the object of greater interest is the combined impact of the law change on selection into treatment and the effect of treatment on treated, which can be expressed as the intention-to-treat effect of the policy change. This is what we attempt to identify in our first-stage models.

Since we are not attempting to identify local average treatment effects, the IV assumptions required to describe the estimand as a causal estimate of the ITT are substantially weaker. Angrist et al (1996) show that causality in this case requires two assumptions. The first is the Stable Unit Treatment Value Assumption (SUTVA) of Rubin (1974), which requires, using the above notation, that:

$$\text{If } NCA_i = NCA_i', \text{ then } C_i(NCA_i) = C_i(NCA_i')$$

and

$$\text{If } NCA_i = NCA_i' \text{ and } C_i = C_i', \text{ then } P_i(NCA_i, C_i) = P_i(NCA_i', C_i')$$

This assumption says that potential prices in county i are unrelated to NCA policies in other counties, conditional on the included fixed effects. The assumption holds as long as we have properly defined geographic markets, across which agents should not constrain or impact each other. To be sure that this assumption holds, we test a variety of market definitions, including counties, PCSAs, Hospital Referral Regions, MSAs, and Hospital Service Areas, although we believe this assumption to be plausible with each of these market definitions.

The second assumption required is unconfounded assignment.

$$\Pr(NCA = r \mid X) = \Pr(NCA = r' \mid X)$$

This assumption requires that the change in NCA laws are a good as random, conditional on covariates. The assumption is satisfied as long as the judicial decisions that cause changes in NCA laws, which we use as instruments, are not correlated with physician market concentrations or on prices negotiated between physicians and insurers. We can validate that this assumption is plausible by analyzing the law changes themselves. Since judicial decisions are accompanied by opinions written by judges that describe the rationales that led them to their decisions, we can be reasonably sure whether or not a decision was made based on either physician market concentration or prices.

If both of these two assumptions hold, then β_1 is an unbiased estimator of the average intention-to-treat effect of NCA enforceability on market concentration, and β_3 is an unbiased estimator of the effect of changes in market concentration on negotiated prices.

The estimated β_3 in Equation 6 corresponds roughly to β_3 in the theoretically-motivated Equation 4, which identifies the combined effect of a measure of average firm sizes on negotiated prices. In some specifications though we use HHIs instead of average firm sizes. This combined effect is a mixture of the relative bargaining power parameters, along with the two component effects of firm size on network value and on average costs. Although we cannot identify the more fundamental parameters with available data, β_3 does provide new information about the important question: should policymakers be concerned that the growth of physician practices has caused harm to consumers by increasing prices negotiated between physicians and commercial insurers?

5 Results

5.1 Effects of NCA Laws on HHI

Figures 4, 5, 6, 7 display the average trends in physician HHIs before and after changes in NCA laws. The HHIs shown are group averages of the specialty-level HHIs, where groups are defined as primary care, surgical specialists, and non-surgical specialists. In the figures, year zero is the year during which the law change occurred. However, the change could have occurred at any point during the year, so a change in market concentration that occurs very quickly will appear as a change between year -1 and year 0. For law changes that occur late in a given calendar year, even a very quick effect could appear as an effect between year 0 and year 1. To the extent that changes may take time to occur, effects between year 1 and 2 are also reasonable. Future improvements to the database will focus on increasing the precision of the timing of law changes.

Figure 4 presents unconditional raw HHIs in an 8 year window around increases in NCA Component Group Index 1. This component group is defined by its positive correlation with HHIs, so we expect to see an upward effect on HHIs from an increase in the NCA index. The first graph in the figure shows the raw unconditional HHIs, which are declining prior to the law change, and then flatten out beginning in year zero for primary care and non-surgical specialists. The trend is less apparent for surgical specialists. However, the difficulty in interpreting these raw data is that the timing of the changes differs, and the changes occur in different states, so it is not possible to tell whether the trends are due to compositional differences in the states that experienced law changes, or causal effects of the changes. We control for these potential compositional changes one step at a time, leading up to our full regression specification. The second graph, on the top right of the Figure, shows residuals from a regression of HHIs on year effects, and the trends remain fairly similar. The third graph, on the bottom left, presents residuals from a regression of HHIs on state and year effects. The break in the downward trends at year zero become more stark when state effects are removed, although the patterns are still somewhat noisy. The fourth graph shows residuals from a regression of HHIs on state, year, and census-division by year effects, providing a relative comparison of the trends in HHIs in states that experienced law changes to the trends in neighboring states in the same census division. In this graph as well the strongest break in trends occurs among primary care and non-surgical specialists.

Figure 5 shows changes in HHIs surrounding law changes in the opposite direction–decreases in NCA Component Group Index 1. The first graph shows a similar slight downward trend in HHIs prior to law changes. In the raw data there does not appear to be a clear break from the trend among primary care physicians, but there is a sizable decrease among surgeons, and potentially a strengthening of the downward trend among non-surgical specialists. These patterns are again much clearer in the conditional HHI graphs, with non-surgical specialists experiencing an abrupt decrease in HHIs after a fairly flat trend prior to the law change.

Figure 6 graphs HHIs before and after increases in NCA Component Group Index 2. The components in this index measure the extent to which a firm can impose an NCA on a worker after a job has begun, and if so whether the firm is required to compensate the worker in exchange for restricting their job options, and whether a firm can enforce an NCA after choosing to fire a worker. Each of these components is negatively correlated with HHIs, potentially because workers who are asked to sign ex post NCAs may choose instead to leave the practice, and the ability to fire a worker and still enforce an NCA may encourage some firms to fire workers. As a result we expect to see a decrease in HHIs after the law changes, as firms either fire workers or impose NCA policies for existing workers.

The unconditional data in the first graph of Figure 6 show very distinct and large decreases in HHIs for all three groups of physicians a year after the law change. These breaks remain throughout the conditional models, and appear strongest in the fourth graph, after year, state, and census-division by year effects have been removed.

The final figure in the series, Figure 7, shows HHIs before and after decreases in NCA Component Group Index 2. Although there is a negative correlation between these NCA law components and HHIs, a decrease in these laws causes firms to be less able to fire workers, and less able to impose ex post NCAs on workers. To the extent that these laws affect HHIs, one expects these changes to occur more slowly than the other changes, perhaps changing the rate of growth of practice sizes, or subtly affecting physicians' decisions between starting new practices as opposed to joining pre-existing practices. Consistent with the rationale that these law changes are less likely to have abrupt effects, Figure 7 shows little discernible pattern in HHIs. There is potentially a break from a downward pre-trend among primary care physicians in the fourth graph, but no clear pattern among other physicians.

Estimates of Equation 5 are presented in Table 1. The first model uses the two index component groups as instruments (IV1). Controlling for county effects, year effects, census division by year effects, medical specialty effects, facility type effects, and procedure effects, we find that increasing index group 1 from 0 to 1, which corresponds to the highest observed value, increases physician HHIs on average by about 1,360 points out of 10,000, a statistically significant effect. Increasing index group 2 from 0 to 1 decreases HHIs by about 1,080 point, and is also significant at the 5% level. The F-statistic of the excluded instruments is 16.34.

The second column shows estimates from the subset of the law components that are the strongest instruments. We refer to this strategy for selecting instruments as IV2, although the components that are strongest differ across subsamples. The estimates suggest that a change from 0 to the most broadly-defined definition of protectible interest leads to a 2,240 point increase in the HHI. A comparable shift in the post-inception consideration index would be interpreted as moving from a legal regime in which post-employment NCAs cannot be imposed upon workers to one in which not being fired is sufficient compensation for forcing a worker to accept an ex post NCA. This component is statistically significant, but leads to a modest 100 point decrease in HHIs. The third component is the employer termination index, where a change from 0 to 1 corresponds to moving from a policy in which NCAs cannot be enforced upon a worker who is fired to one in which they can, and this change leads to a very large decrease in the HHI of 3,220 point on average. The F-statistic on these three components is 24.11, easily surpassing levels that would cause concern about weak instruments.

The third model uses all 7 NCA components as instruments (IV3). The coefficients on the three components included in IV2 are very similar, and two of the four additional variables are statistically significant in the first stage. A change from 0 to 1 in the ex ante consideration index leads to a 1,460 point increase in the HHI, while a comparable change in the burden of proof index leads to a 1,490 point decrease. Even including the insignificant instruments, the F-statistic of the set IV3 is still quite high, 15.21. In all three models, the fixed effects and excluded instruments explain over 75% of the variation in specialty-level HHIs.

5.2 Instrument Strength

Each of the first stage F-statistics, which range from 15.2 to 24.1, is well above common thresholds for concern about weak instruments. With one endogenous regressor and 2 to 7 instruments the Stock and Yogo critical value thresholds for 10% relative bias under 2SLS range from about 9 to 11.

Table 3 shows second-stage estimates for a variety of model specifications using IV1. The estimates using two-stage least squares, two-step feasible GMM, and limited information maximum likelihood (LIML) are very similar, ranging between -0.151 and -0.154. With weak instruments LIML is approximately unbiased, while 2SLS is biased towards OLS. The close similarity between the estimates suggests that there is not a large bias from weak instruments. Moreover, the F-statistics in the first stages using IV2 and IV3 are each more than four times larger than the critical values under LIML that imply a maximum relative bias of 10% according to simulations in Stock et al (2002). Using LIML often comes at the expense of an increase in standard errors, but the estimated standard errors are quite similar under 2SLS and LIML in these data, 0.060 compared to 0.061.

5.3 The Effect of HHI on Negotiated Prices

The second stage effects on negotiated prices are reported in Table 2. The first column shows the OLS estimate of the effect of HHI on prices, which appears to be significantly positive, although very small. This finding is similar to estimates by Dunn and Shapiro (2014) and Baker et al (2014), that use either cross-sectional or panel variation in HHIs, but do not use instruments for changes in concentration over time. The second stage estimate corresponding to IV1 suggests that a 1,000 point increase in the HHI causes a 15.2% decrease in average negotiated prices. This suggests that the effect of larger group sizes on the bargaining power of physicians, the increase in their value to insurance networks, and the effect that a larger group has on the cost of disagreement to the insurer are all outweighed by the efficiency gains of larger group practices. The second stage estimate based on IV2 is also moderately negative, implying a 6.4% decrease in prices per 1,000 point increase in HHIs, although this effect is not statistically significant at the 5% level. Still, we can rule out price increases above 0.8%, or about two months of inflation at the average inflation rate for physician services during the period, at the 5% level, from a 1,000 point increase in HHI. The third model, using IV3, yields very similar estimates, suggesting a mean decrease in prices of 5.7%, but without power to reject the null of no change in prices. In all three IV models the unexplained variation in prices is about 1% of the total sum of squares.

Tables 4 and 5 show similar estimates when the sample is broken into metro and non-metro counties, using IV1 and IV3. Both IVs are strong in each of the subsamples, with F-statistics between 12.0 and 17.3. Using IV3, five out of the seven NCA components are again statistically significant in both metro and non-metro counties. Table 5 shows that the efficiency gains that lead to lower negotiated prices are stronger in metro counties. Estimates using IV1 imply a 15.7% price reduction, and IV3 implies a 16.4% price reduction in metro counties for every 1,000 point increase in HHIs. In non-metro counties, however, IV1 implies an 11.7% reduction, while IV3 is not statistically significant and is close to zero.

Tables 6, 7, 8, 9, 10, and 11 show estimates by groups of physician specialties, overall and broken down by metro and non-metro counties. The first set includes only primary care physicians, including family practice, internal medicine, geriatrics, and pediatrics. IV2 is the strongest set of instruments, with first stage F-stats between 10 in the primary care non-metro sample, and 22 in the overall primary care sample. The second stage models have insufficient power in this subsample to infer that price changes were nonzero. Five of the six models suggest modest negative price effects on average.

Tables 8, 9 show comparable estimates for non-surgical specialist physicians, including anesthesiologists, radiologists, proctologists, urologists, dermatologists, cardiologists, neurologists, gastroenterologists, and hematologists. The first stages are again quite strong, and the only F-statistic below 10 (F=8.31) is for IV1 in metro counties. The second stage estimates using IV2 are statistically significant and meaningfully negative in every subsample. Overall, the estimates suggest that prices fall by about 13.9% when the HHI in a non-surgical specialty market increases by 1,000 points. The effect is again much larger in metro counties, about 25% compared to 4.7% in non-metro counties. Estimates using IV1 are all suggestive of price decreases as well, but lack power in the second stage.

Tables 10, and 11 show that we find no significant effects among surgical specialists. This is consistent with evidence from Lavetti (2014) that shows that hospital-based physicians, who are likely to have fewer repeated interactions with the same patient, are significantly less likely to have NCAs in their contracts, since firms are less concerned about the value of patient relationships. The specialties included in our sample are general surgery, neurological surgery, orthopaedic surgery, and thoracic surgery.

6 Discussion

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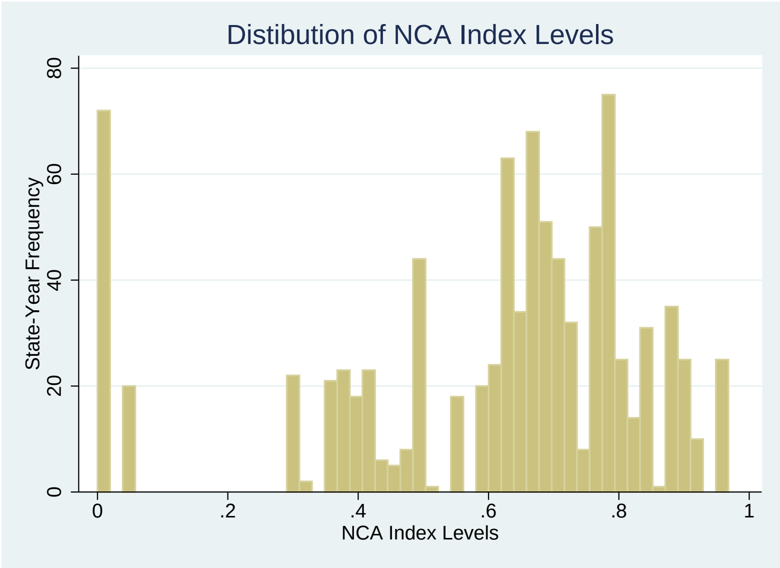
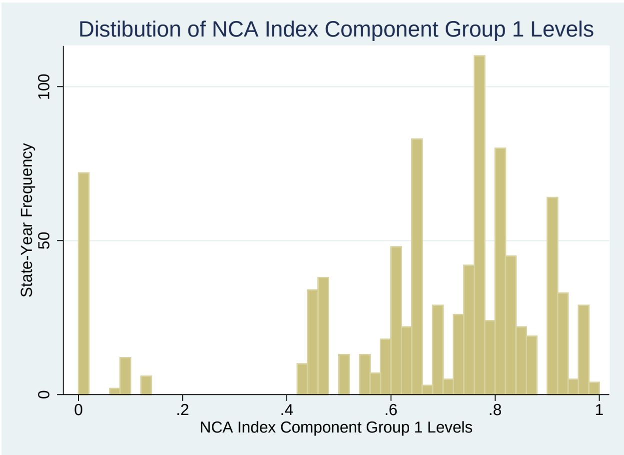
Figure 1: Distributions of NCA Index Levels

(a) Overall NCA Index Levels



(b) Component Group 1 Levels



(c) Component Group 2 Levels

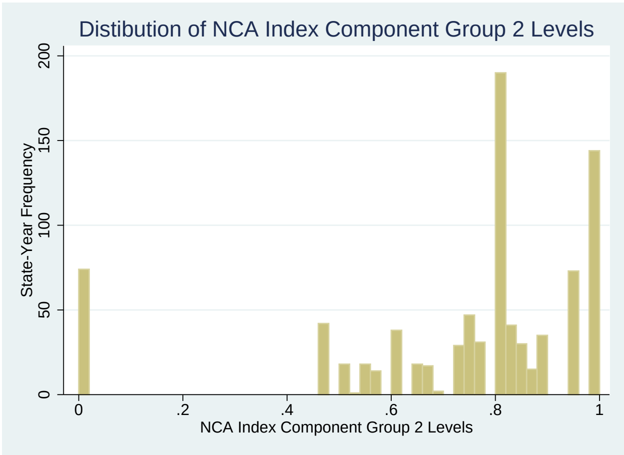
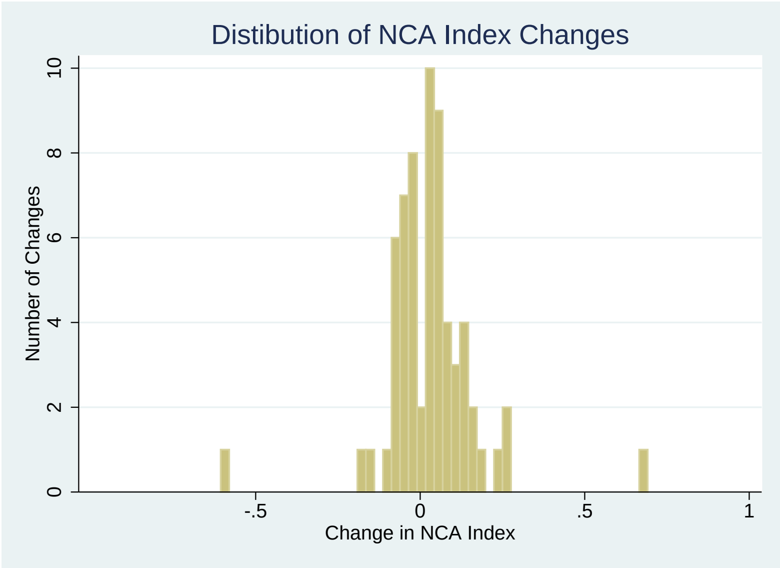
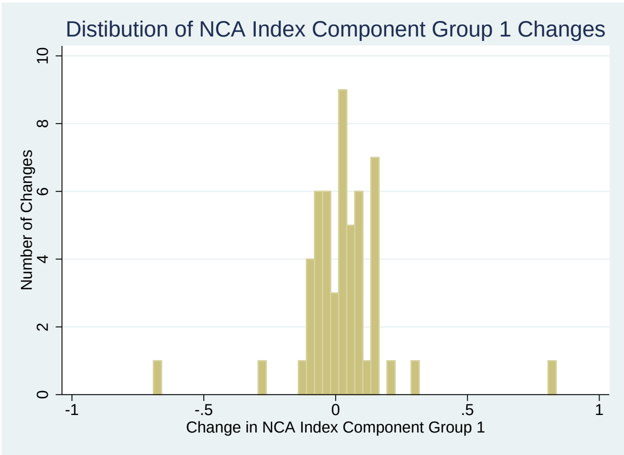


Figure 2: Distributions of NCA Index Changes

(a) Overall NCA Index Changes



(b) Component Group 1 Changes



(c) Component Group 2 Changes

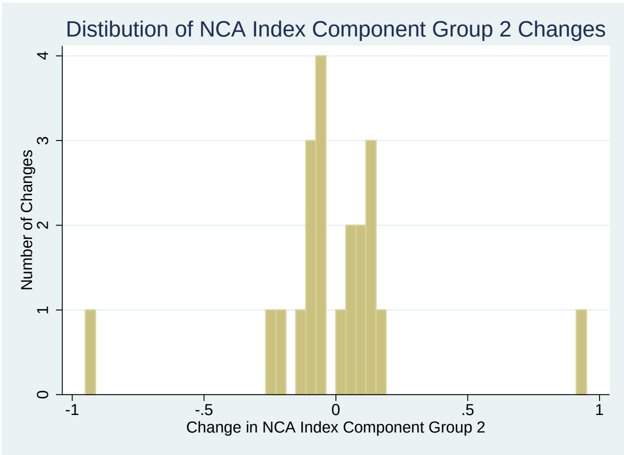
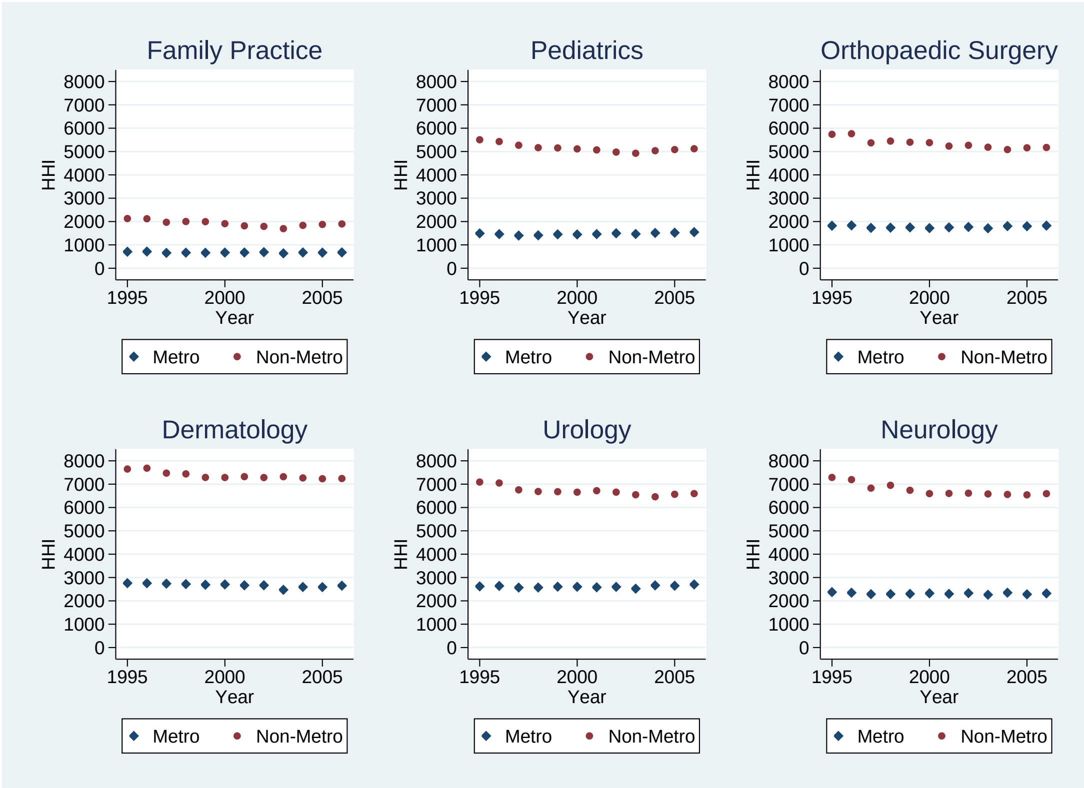


Figure 3: HHIs Trends by Specialty in Metro and Non-Metro Counties



Notes: HHIs calculated by county using establishment-level counts of physicians using MPIER data.

Figure 4: HHIs Before and After Increases in NCA Index 1

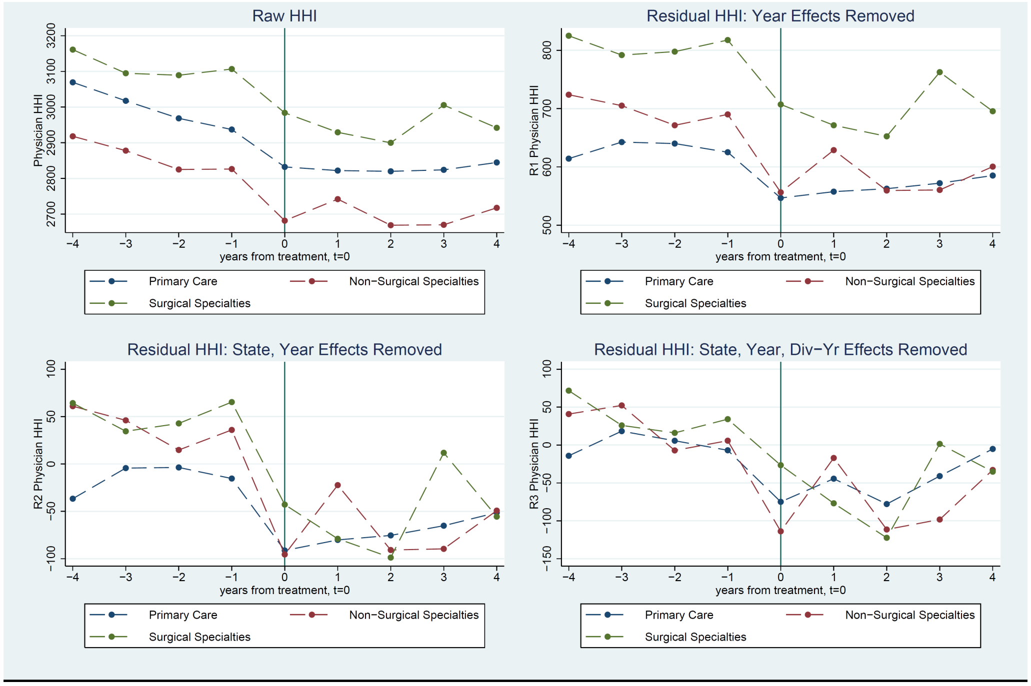


Figure 5: HHIs Before and After Decreases in NCA Index 1

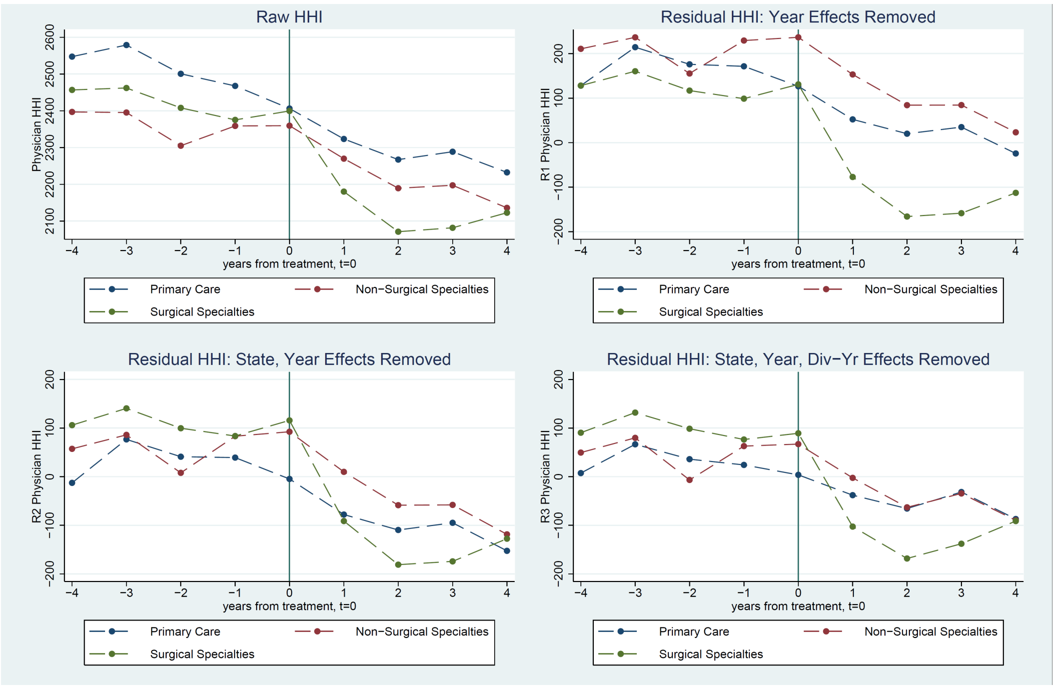


Figure 6: HHIs Before and After Increases in NCA Index 2

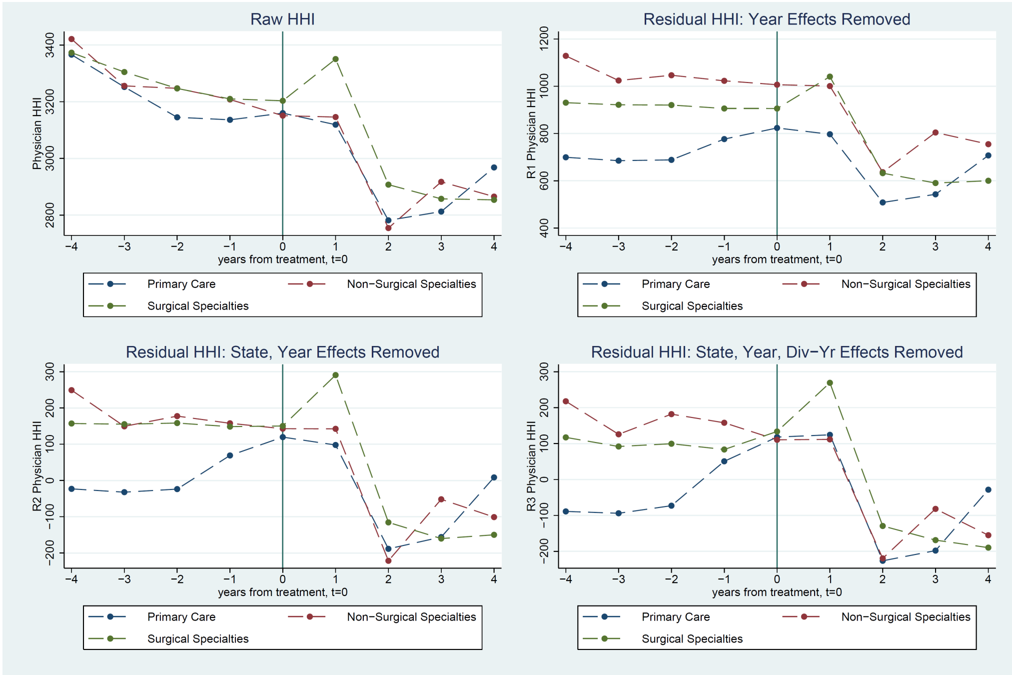


Figure 7: HHIs Before and After Decreases in NCA Index 2

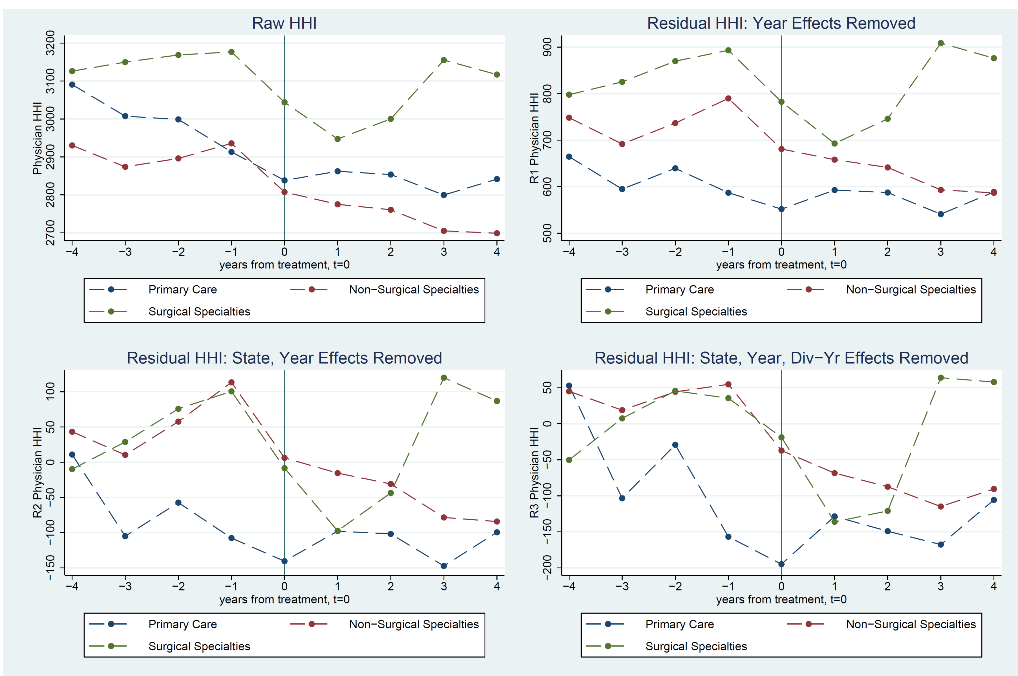


Table 1: First Stage IV Models

	Dependent Variable: HHI		
	(1)	(2)	(3)
Index Component Group 1	1.294*		
	(0.199)		
Index Component Group 2	–1.244*		
	(0.177)		
Statutory Index			–0.011
			(0.206)
Protectible Interest Index		2.240*	2.267*
		(0.472)	(0.477)
Consideration Index Inception			1.463*
			(0.443)
Consideration Index Post-Inception		–0.099*	–0.096*
		(0.030)	(0.030)
Burden of Proof Index			–1.494*
			(0.450)
Blue Pencil Index			0.134
			(0.335)
Employer Termination Index		–3.220*	–3.269*
		(0.501)	(0.516)
Constant	3.387	4.881*	4.428*
	(2.237)	(1.927)	(1.940)
N	9,815,481	7,302,217	7,058,234
N Clusters	604	389	353
R-Sq	0.756	0.757	0.758
AP F-Stat	24.71	24.11	15.21

Notes: All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) effects, physician specialty effects, and facility type effects. All independent variables are scaled to range between 0 and 1, where 1 is the strongest observed measure of the variable in any state and year in the data. HHI is scaled to range from 0 to 10, so that a 1 unit change in HHI corresponds to a 1,000 point change in the typical 10,000 point scale. The sample size drops when using IV2 and IV3 because some states have never ruled on some specific components of the NCA index. These observations are dropped in models that contain each component, but the observations are included when aggregate indices of NCA enforceability are used. All standard errors clustered by state-year. * Significant at the .05 level.

Table 2: Second Stage IV Models

	Dependent Variable: ln($Price$)			
	(1)	(2)	(3)	(4)
HHI	0.001*	–0.126*	–0.064	–0.057
	(0.000)	(0.050)	(0.036)	(0.036)
Constant	4.394*	4.744*	5.039*	5.010*
	(0.783)	(0.847)	(0.743)	(0.739)
N	9,879,974	9,815,481	7,302,217	7,058,234
N Clusters	612	604	389	353
R-Sq		0.986	0.988	0.989
1st Stage AP F-Stat		24.71	24.11	15.21

Notes: All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) effects, physician specialty effects, and facility type effects. HHI is scaled to range from 0 to 10, so that a 1 unit change in HHI corresponds to a 1,000 point change in the typical 10,000 point scale. The sample size drops when using IV2 and IV3 because some states have never ruled on some specific components of the NCA index. These observations are dropped in models that contain each component, but the observations are included when aggregate indices of NCA enforceability are used. All standard errors clustered by state-year. * Significant at the .05 level.

Table 3: Second Stage Sensitivity to Estimator

	Dependent Variable: ln($Price$)		
	2SLS	GMM	LIML
	(1)	(2)	(3)
HHI	–0.126*	–0.126*	–0.128*
	(0.050)	(0.050)	(0.050)
Constant	4.744*	4.743*	4.747*
	(0.847)	(0.847)	(0.848)
N	9,815,481	9,815,481	9,815,481
N Clusters	604	604	604
R-Sq	0.986	0.986	0.986
1st Stage AP F-Stat	24.71	24.71	24.71

Notes: All estimates are based on IV1. All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) effects, physician specialty effects, and facility type effects. HHI is scaled to range from 0 to 10, so that a 1 unit change in HHI corresponds to a 1,000 point change in the typical 10,000 point scale. All standard errors clustered by state-year. * Significant at the .05 level.

Table 4: First Stage Estimates in Metro and Non-Metro Counties

	Dependent Variable: HHI					
	Metro Counties			Non-Metro Counties		
	(1)	(2)	(3)	(4)	(5)	(6)
Index Component Group 1	1.216*			1.729*		
	(0.177)			(0.362)		
Index Component Group 2	–1.100*			–1.775*		
	(0.155)			(0.331)		
Statutory Index			0.180			–0.295
			(0.173)			(0.353)
Protectible Interest Index		1.301*	1.286*		3.972*	3.967*
		(0.367)	(0.381)		(0.586)	(0.580)
Consideration Index Inception		1.300*	1.329*		2.401*	2.494*
		(0.409)	(0.405)		(1.014)	(0.974)
Consideration Index Post-Inception		–0.106*	–0.108*		–0.111*	–0.102*
		(0.030)	(0.030)		(0.044)	(0.044)
Burden of Proof Index		–1.388*	–1.415*		–2.317*	–2.409*
		(0.414)	(0.410)		(1.025)	(0.985)
Blue Pencil Index			0.249			–0.444
			(0.308)			(0.463)
Employer Termination Index		–2.043*	–2.034*		–13.919*	–14.112*
		(0.409)	(0.421)		(6.525)	(6.394)
Constant	2.868*	2.044	2.162	7.315	16.446	14.343
	(1.370)	(1.389)	(1.424)	(7.675)	(9.176)	(8.846)
N	6,131,857	4,703,521	4,513,198	3,683,624	2,598,696	2,545,036
N Clusters	604	389	353	568	365	329
R-Sq	0.737	0.736	0.736	0.810	0.812	0.813
AP F-Stat	25.57	23.93	17.31	16.73	13.73	12.01

Notes: All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) effects, physician specialty effects, and facility type effects. HHI is scaled to range from 0 to 10, so that a 1 unit change in HHI corresponds to a 1,000 point change in the typical 10,000 point scale. The sample size drops when using IV3 because some states have never ruled on some specific components of the NCA index. These observations are dropped in models that contain each component, but the observations are included when aggregate indices of NCA enforceability are used. All standard errors clustered by state-year. * Significant at the .05 level.

Table 5: Effect of Market Concentration on Prices in Metro and Non-Metro Counties

	Dependent Variable: ln($Price$)					
	Metro Counties			Non-Metro Counties		
	(1)	(2)	(3)	(4)	(5)	(6)
HHI	–0.112*	–0.172*	–0.164*	–0.129*	0.003	0.007
	(0.054)	(0.062)	(0.061)	(0.051)	(0.021)	(0.020)
Constant	4.602*	4.702*	4.739*	5.222*	6.275*	6.169*
	(0.436)	(0.450)	(0.438)	(2.555)	(2.167)	(2.153)
N	6,131,857	4,703,521	4,513,198	3,683,624	2,598,696	2,545,036
N Clusters	604	389	353	568	365	329
R-Sq	0.987	0.984	0.985	0.985	0.989	0.989
1st Stage AP F-Stat	25.57	23.93	17.31	16.73	13.73	12.01

Notes: All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) effects, physician specialty effects, and facility type effects. All independent variables are scaled to range between 0 and 1, where 1 is the strongest observed measure of the variable in any state and year in the data. HHI is scaled to range from 0 to 10, so that a 1 unit change in HHI corresponds to a 1,000 point change in the typical 10,000 point scale. The sample size drops when using IV3 because some states have never ruled on some specific components of the NCA index. These observations are dropped in models that contain each component, but the observations are included when aggregate indices of NCA enforceability are used. All standard errors clustered by state-year. * Significant at the .05 level.

Table 6: First Stage Models for Primary Care Physicians

	Dependent Variable: HHI					
	All Counties		Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
Index Component Group 1	1.121*		0.695*		2.402*	
	(0.250)		(0.281)		(0.404)	
Index Component Group 2	–1.050*		–0.473		–2.399*	
	(0.217)		(0.248)		(0.362)	
Statutory Index				–0.667*		
				(0.267)		
Protectible Interest Index						0.763*
						(0.234)
Consideration Index Inception		1.720*				
		(0.765)				
Consideration Index Post-Inception		–0.158*				–0.315*
		(0.037)				(0.056)
Burden of Proof Index		–1.801*				
		(0.774)				
Blue Pencil Index		2.100*		1.645*		
		(0.409)		(0.388)		
Employer Termination Index		–0.897*		–0.774*		
		(0.193)		(0.157)		
Constant	–7.546	–3.449	–0.382	–0.398	10.645	5.884
	(6.121)	(6.230)	(3.128)	(3.145)	(10.391)	(10.718)
N	1,468,910	1,068,064	868,613	648,631	600,297	543,251
N Clusters	604	360	604	372	567	495
R-Sq	0.838	0.837	0.784	0.778	0.896	0.897
AP F-Stat	11.68	22.32	4.12	18.03	22.24	16.21

Notes: All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) effects, physician specialty effects, and facility type effects. Sample includes primary care MDs, Internal Medicine, Family Practice, Geriatric Medicine, and Pediatric specialists. All independent variables are scaled to range between 0 and 1, where 1 is the strongest observed measure of the variable in any state and year in the data. HHI is scaled to range from 0 to 10, so that a 1 unit change in HHI corresponds to a 1,000 point change in the typical 10,000 point scale. The sample size drops when using IV2 because some states have never ruled on some specific components of the NCA index. These observations are dropped in models that contain each component, but the observations are included when aggregate indices of NCA enforceability are used. All standard errors clustered by state-year. * Significant at the .05 level.

Table 7: Effect of Concentration on Prices for Primary Care Physicians

	Dependent Variable: ln($Price$)					
	All Counties		Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
HHI	–0.106	–0.058	–0.114	0.047	–0.064	–0.030
	(0.068)	(0.043)	(0.110)	(0.047)	(0.037)	(0.041)
Constant	3.753*	4.845*	4.588*	4.875*	4.120	5.501*
	(1.863)	(1.581)	(1.013)	(0.957)	(2.201)	(1.928)
N	1,468,910	1,068,064	868,613	648,631	600,297	543,251
N Clusters	604	360	604	372	567	495
R-Sq	0.986	0.986	0.985	0.986	0.987	0.988
1st Stage AP F-Stat	11.68	22.32	4.12	18.03	22.24	16.21

Notes: All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) effects, physician specialty effects, and facility type effects. Sample includes primary care MDs, Internal Medicine, Family Practice, Geriatric Medicine, and Pediatric specialists. HHI is scaled to range from 0 to 10, so that a 1 unit change in HHI corresponds to a 1,000 point change in the typical 10,000 point scale. The sample size drops when using IV3 because some states have never ruled on some specific components of the NCA index. These observations are dropped in models that contain each component, but the observations are included when aggregate indices of NCA enforceability are used. All standard errors clustered by state-year. * Significant at the .05 level.

Table 8: First Stage Models for Non-Surgical Specialists

	Dependent Variable: HHI					
	All Counties		Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
Index Component Group 1	2.101*		1.497*		4.860*	
	(0.346)		(0.300)		(0.784)	
Index Component Group 2	–2.175*		–1.526*		–4.843*	
	(0.315)		(0.270)		(0.721)	
Statutory Index						
Protectible Interest Index		2.657*		0.955*		2.011*
		(0.598)		(0.429)		(0.347)
Consideration Index Inception		1.596*				
		(0.624)				
Consideration Index Post-Inception		–0.249*		–0.161*		–0.797*
		(0.054)		(0.046)		(0.107)
Burden of Proof Index		–1.734*				
		(0.641)				
Blue Pencil Index				–0.738		
				(0.376)		
Employer Termination Index		–3.677*		–2.405*		
		(0.655)		(0.522)		
Constant	3.641	0.456	2.053	–0.552	–0.495	0.726
	(8.522)	(8.712)	(2.920)	(3.079)	(7.119)	(7.051)
N	973,830	736,299	687,594	511,368	286,236	263,400
N Clusters	603	388	601	352	557	486
R-Sq	0.799	0.802	0.762	0.763	0.864	0.862
AP F-Stat	29.92	18.27	17.09	10.77	26.87	30.05

Notes: All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) effects, physician specialty effects, and facility type effects. Sample includes specialists in Proctology, Urology, Dermatology, Cardiovascular Dis/Cardiology, Neurology, Gastroenterology, and Hematology. All independent variables are scaled to range between 0 and 1, where 1 is the strongest observed measure of the variable in any state and year in the data. HHI is scaled to range from 0 to 10, so that a 1 unit change in HHI corresponds to a 1,000 point change in the typical 10,000 point scale. The sample size drops when using IV2 because some states have never ruled on some specific components of the NCA index. These observations are dropped in models that contain each component, but the observations are included when aggregate indices of NCA enforceability are used. All standard errors clustered by state-year. * Significant at the .05 level.

Table 9: Effect of Concentration on Prices for Non-Surgical Specialists

	Dependent Variable: ln($Price$)					
	All Counties		Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
HHI	–0.110*	–0.169*	–0.170*	–0.249*	–0.052*	–0.032*
	(0.030)	(0.036)	(0.051)	(0.060)	(0.018)	(0.015)
Constant	3.478	4.308*	2.410*	2.242*	1.315	1.413
	(2.024)	(2.133)	(0.679)	(0.830)	(1.286)	(1.203)
N	973,830	736,299	687,594	511,368	286,236	263,400
N Clusters	603	388	601	352	557	486
R-Sq	0.990	0.987	0.987	0.981	0.993	0.994
1st Stage AP F-Stat	29.92	18.27	17.09	10.77	26.87	30.05

Notes: All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) effects, physician specialty effects, and facility type effects. Sample includes specialists in Proctology, Urology, Dermatology, Cardiovascular Dis/Cardiology, Neurology, Gastroenterology, and Hematology. HHI is scaled to range from 0 to 10, so that a 1 unit change in HHI corresponds to a 1,000 point change in the typical 10,000 point scale. The sample size drops when using IV3 because some states have never ruled on some specific components of the NCA index. These observations are dropped in models that contain each component, but the observations are included when aggregate indices of NCA enforceability are used. All standard errors clustered by state-year. * Significant at the .05 level.

Table 10: First Stage Models for Surgical Specialists

	Dependent Variable: HHI					
	All Counties		Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
Index Component Group 1	1.124*		1.482*		0.805	
	(0.280)		(0.290)		(0.476)	
Index Component Group 2	–1.087*		–1.313*		–0.889*	
	(0.248)		(0.260)		(0.429)	
Statutory Index						
Protectible Interest Index						
Consideration Index Inception						
Consideration Index Post-Inception		–0.090*		–0.263*		–0.087
		(0.036)		(0.051)		(0.047)
Burden of Proof Index						
Blue Pencil Index						
Employer Termination Index				–0.579*		
				(0.265)		
Constant	–0.753	–0.543	2.882	1.401	3.330	2.509
	(2.994)	(3.000)	(2.559)	(2.690)	(12.779)	(12.772)
N	873,539	795,216	552,751	424,379	320,788	291,682
N Clusters	604	526	604	396	568	502
R-Sq	0.774	0.774	0.733	0.732	0.841	0.842
AP F-Stat	9.65	6.38	13.23	15.97	2.61	3.49

Notes: All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) effects, physician specialty effects, and facility type effects. Sample includes specialists in General Surgery, Neurological Surgery, Orthopaedic Surgery, Thoracic Surgery, Anesthesiology, and Radiology. All independent variables are scaled to range between 0 and 1, where 1 is the strongest observed measure of the variable in any state and year in the data. HHI is scaled to range from 0 to 10, so that a 1 unit change in HHI corresponds to a 1,000 point change in the typical 10,000 point scale. The sample size drops when using IV2 because some states have never ruled on some specific components of the NCA index. These observations are dropped in models that contain each component, but the observations are included when aggregate indices of NCA enforceability are used. All standard errors clustered by state-year. * Significant at the .05 level.

Table 11: Effect of Concentration on Prices for Surgical Specialists

	Dependent Variable: ln($Price$)					
	All Counties		Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
HHI	–0.062	0.097	–0.041	0.003	–0.064	0.084
	(0.077)	(0.106)	(0.063)	(0.062)	(0.098)	(0.111)
Constant	2.302*	2.225*	2.534*	2.342*	2.019	2.119
	(0.687)	(0.723)	(0.628)	(0.608)	(2.884)	(2.601)
N	873,539	795,216	552,751	424,379	320,788	291,682
N Clusters	604	526	604	396	568	502
R-Sq	0.991	0.990	0.991	0.991	0.991	0.990
1st Stage AP F-Stat	9.65	6.38	13.23	15.97	2.61	3.49

Notes: All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) effects, physician specialty effects, and facility type effects. Sample includes specialists in General Surgery, Neurological Surgery, Orthopaedic Surgery, Thoracic Surgery, Anesthesiology, and Radiology, . HHI is scaled to range from 0 to 10, so that a 1 unit change in HHI corresponds to a 1,000 point change in the typical 10,000 point scale. The sample size drops when using IV3 because some states have never ruled on some specific components of the NCA index. These observations are dropped in models that contain each component, but the observations are included when aggregate indices of NCA enforceability are used. All standard errors clustered by state-year. * Significant at the .05 level.

Table 12: Fixed Effects Models of Establishment Sizes

Dependent Variable:	Number of FTE Physicians in Establishment		
	All Counties	Metro Counties	Non-Metro Counties
	(1)	(2)	(3)
Statutory Index	0.958*	0.952*	0.980
	(0.014)	(0.017)	(0.010)
Protectible Interest Index	0.890*	0.874*	0.967*
	(0.016)	(0.018)	(0.013)
Consideration Index Inception	1.099*	1.116*	0.997
	(0.019)	(0.022)	(0.014)
Consideration Index Post-Inception	1.010*	1.010*	1.007
	(0.004)	(0.004)	(0.004)
Burden of Proof Index	0.906*	0.899*	0.970*
	(0.016)	(0.017)	(0.015)
Blue Pencil Index	1.037	1.058	0.984*
	(0.027)	(0.036)	(0.007)
Employer Termination Index	1.134*	1.143*	1.042*
	(0.033)	(0.036)	(0.015)
Number of Physicians in County l	1.000*	1.000*	1.007*
	(0.000)	(0.000)	(0.000)
N	24,717,230	19,519,876	5,197,354

Notes: All specifications are fixed effects models and include county effects, specialty, year effects, and census division by year effects. FTE establishment sizes are estimated by assigning equal partial shares summing to one to all establishments at which a physician is active. All standard errors clustered by state-year. * Significant at the .05 level.

Table 13: Fixed Effects Poisson Models of Establishment Births and Deaths

	All Counties		Metro Counties		Non-Metro Counties	
Dependent Variable:	Births	Deaths	Births	Deaths	Births	Deaths
	(1)	(2)	(3)	(4)	(5)	(6)
Statutory Index	0.423*	0.459*	0.375*	0.333*	0.449*	0.449*
	(0.024)	(0.032)	(0.025)	(0.029)	(0.032)	(0.032)
Protectible Interest Index	0.603*	0.099*	0.611*	0.079*	0.724*	0.724*
	(0.038)	(0.009)	(0.047)	(0.009)	(0.077)	(0.077)
Consideration Index Inception	0.333*	0.950	0.263*	0.777	0.550*	0.550*
	(0.036)	(0.135)	(0.035)	(0.144)	(0.067)	(0.067)
Consideration Index Post-Inception	1.379*	2.332*	1.345*	2.328*	1.392*	1.392*
	(0.020)	(0.060)	(0.024)	(0.074)	(0.033)	(0.033)
Burden of Proof Index	2.555*	0.793	3.493*	1.071	0.804	0.804
	(0.271)	(0.113)	(0.456)	(0.200)	(0.102)	(0.102)
Blue Pencil Index	0.503*	0.553*	0.550*	0.537*	0.335*	0.335*
	(0.025)	(0.038)	(0.035)	(0.050)	(0.024)	(0.024)
Employer Termination Index	3.411*	40.486*	3.489*	52.182*	3.900*	3.900*
	(0.387)	(7.334)	(0.432)	(10.129)	(0.758)	(0.758)
Number of Physicians in County	1.000*	1.000*	1.000*	1.000*	1.047*	1.047*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)
N	742,253	725,349	356,464	348,141	385,789	385,789

Notes: All specifications are fixed effects models and include county by specialty effects, year effects, and census division by year effects. Huber-White standard errors reported in parentheses. * Significant at the .05 level.

Table 14: Fixed Effects Models of Aggregate Physician Supply

Dependent Variable:	Log Number of Physicians in County, by Specialty		
	All Counties	Metro Counties	Non-Metro Counties
	(1)	(2)	(3)
Statutory Index	–0.114	–0.194*	–0.010
	(0.061)	(0.072)	(0.067)
Protectible Interest Index	–0.318*	–0.337*	–0.280*
	(0.087)	(0.087)	(0.104)
Consideration Index Inception	0.250*	0.392*	0.143
	(0.115)	(0.136)	(0.121)
Consideration Index Post-Inception	0.115*	0.111*	0.116*
	(0.020)	(0.018)	(0.027)
Burden of Proof Index	–0.384*	–0.490*	–0.303*
	(0.111)	(0.127)	(0.116)
Blue Pencil Index	–0.046	0.046	–0.061
	(0.102)	(0.201)	(0.060)
Employer Termination Index	–0.143	–0.098	–0.282
	(0.194)	(0.173)	(0.226)
Log Population	0.470*	0.468*	0.367*
	(0.036)	(0.050)	(0.047)
Log Per Capita Income	0.137*	0.055	0.122*
	(0.033)	(0.045)	(0.039)
N	593,244	304,456	288,788

Notes: All specifications are fixed effects models and include county effects, specialty effects, year effects, and census division by year effects. All standard errors clustered by state-year. * Significant at the .05 level.

Appendices

Table 15: Bishara (2011) Rating of the Restrictiveness of Non-Compete Agreements

Question #	Question	Criteria	Question Weight
Q1	Is there a state statute that governs the enforceability of covenants not to compete?	10 = Yes, favors strong enforcement 5 = Yes or no, in either case neutral on enforcement 0 = Yes, statute that disfavors enforcement	10
Q2	What is an employer's protectable interest and how is that defined?	10 = Broadly defined protectable interest 5 = Balanced approach to protectable interest 0 = Strictly defined, limiting the protectable interest of the employer	10
Q3	What must the plaintiff be able to show to prove the existence of an enforceable covenant not to compete?	10 = Weak burden of proof on plaintiff (employer) 5 = Balanced burden of proof on plaintiff 0 = Strong burden of proof on plaintiff	5
Q3a	Does the signing of a covenant not to compete at the inception of the employment relationship provide sufficient consideration to support the covenant?	10 = Yes, start of employment always sufficient to support any CNC 5 = Sometimes sufficient to support CNC 0 = Never sufficient as consideration to support CNC	5
Q3b	Will a change in the terms and conditions of employment provide sufficient consideration to support a covenant not to compete entered into after the employment relationship has begun?	10 = Continued employment always sufficient to support any CNC 5 = Only change in terms sufficient to support CNC 0 = Neither continued employment nor change in terms sufficient to support CNC	5
Q3c	Will continued employment provide sufficient consideration to support a covenant not to compete entered into after the employment relationship has begun?	10 = Continued employment always sufficient to support any CNC 5 = Only change in terms sufficient to support CNC 0 = Neither continued employment nor change in terms sufficient to support CNC	5
Q4	If the restrictions in the covenant not to compete are unenforceable because they are overbroad, are the courts permitted to modify the covenant to make the restrictions more narrow and to make the covenant enforceable? If so, under what circumstances will the courts allow reduction and what form of reduction will the courts permit?	10 = Judicial modification allowed, broad circumstances and restrictions to maximum enforcement allowed 5 = Blue pencil allowed, balanced circumstances and restrictions to middle ground of allowed enforcement 0 = Blue pencil or modification not allowed	10
Q8	If the employer terminates the employment relationship, is the covenant enforceable?	10 = Enforceable if employer terminates 5 = Enforceable in some circumstances 0 = Not enforceable if employer terminates	10

Source: Bishara (2011).