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

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Abstract

We study the relationship between concentration in the market for physician services and prices negotiated between physician practices and private insurance companies. We develop a new instrumental variable for changes in concentration: state-level judicial decisions that change the enforceability of non-compete clauses in physician employment contracts. These law changes alter the organizational incentives of physicians, causing shocks to the concentration of physician markets without greatly affecting insurers. Using two databases on the universe of physician establishments and firms in the US between 1996 and 2007, linked to privately negotiated prices with insurance companies, we show that negotiated prices fall when physician establishments become larger due to changes in NCA laws. Our results imply that a 100 point increase in the establishment-based Herfindahl Index (HHI) causes a 1.2 to 2.6 percent decrease in negotiated prices, suggesting that insurers are able to capture efficiency gains from larger establishments. In contrast, when physically-distinct establishments negotiate jointly as a firm the opposite is true: a 100 point increase in the firm-based HHI raises negotiated prices by 1.7 percent. The price effects are largest in metropolitan markets and for non-surgical physician specialties.

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1 Introduction

Spending on physician services accounts for about 20% of all U.S. medical spending and has been rising even faster than total medical spending. [1] Meanwhile, anecdotal evidence has suggested that physician practices have consolidated during the past decade. Rising spending and concern over high service prices in the US have led numerous researchers to study the effects of market concentration on prices both in the hospital industry (Town and Vistnes (2001); Gaynor and Vogt (2003); Gowrisankaran, Nevo, and Town (2014)) and in the health insurance industry (Dafny (2010); Dafny, Duggan, and Ramanarayanan (2012); Ericson and Starc (2012)). But there is very limited evidence on the extent to which competition among physicians affects prices negotiated with insurers. Dunn and Shapiro (2014) and Baker, Bundorf, and Royalty (2014) are the first studies of the association between market concentration and negotiated physician prices.

This paper provides new comprehensive evidence on the concentration of physician markets and addresses two major challenges to understanding the causal relationship between physician concentration and negotiated prices. The first challenge is that longitudinal data on physician practice sizes and prices are extremely rare. We employ two complementary data sets on the universe of all physician practices in the US between 1996-2007 to construct measures of physician concentration in a variety of ways. The Medicare Physician Identification and Eligibility Registry (MPIER) from the Center for Medicare and Medicaid Services (CMS), which contains all practicing physicians in the US, allows us to aggregate physicians by practice location in order to calculate establishment-based and medical specialty-specific concentration measures. We also observe physicians' work spell durations and moves. In addition we use confidential Census Bureau data from the Longitudinal Business Database (LBD), Economic Censuses (EC), and Business Register (SSEL). While these data lack information on medical specialties, they allow us to observe firm-level linkages based on tax ID numbers, and to calculate concentration measures using payroll and sales data in addition to employment data. Together these data sets can provide a uniquely comprehensive picture of markets for physician services in local geographic areas nationwide from 1996-2007. We link these concentration measures to Truven Health Analytics' MarketScan data on prices negotiated between physicians and a large sample of private commercial insurance companies. The negotiated prices are based on information from roughly 550 million medical procedure claims from 138 million unique individuals through every state in the US between 1996-2009.

The second challenge is that physician market concentration may be jointly determined with insurer concentration, demand factors, and other unobserved characteristics, such as technology use. We construct a new instrumental variable to overcome this endogeneity concern. The IV uses judicial decisions that cause changes in state laws regarding the enforceability of non-compete agreements (NCAs), which restrict an employee's ability to leave a firm and compete against it. As shown by Bishara (2011), NCA laws vary along seven quantifiable dimensions across states and over time due to judicial decisions. We construct a panel of law changes using the coding methodology of Bishara (2011) on each of the seven key legal dimensions for every state between 1991-2009. Lavetti et al. (2015) provide evidence

[1] National Health Expenditure Fact Sheet 2013, CMS

from survey data that the use of NCAs in physician employment contracts is very common, with about 45% of physicians in group practices bound by NCAs. By altering the ability of workers to exit firms and compete within a local market, these law changes create shocks to the organizational incentives of physicians and have substantial effects on physician practice sizes.

We show that, even *within* a geographic market and year, NCA laws significantly affect prices of physician services. Using the natural experiment that occurs when a metro area (CBSA) spans two states, one of which experiences a change in NCA law, we show that the law changes cause significant divergences in negotiated prices across state lines within the market. Specifically, changes in certain NCA law components along the observed spectrum of state policies cause up to a 12% divergence in relative negotiated prices. We discuss the nuances of the legal components in Section 4.1.1, including why some components tend to cause price increases while others cause price decreases.

We provide a variety of evidence to suggest that the mechanism through which prices are affected occurs through changes in the sizes of physician practices. Changes in NCA laws have significant effects on the sizes of physician establishments, on the rate of births of new physician practices, on the rate of death of existing practices, and on the HHI. Evidence from survey data shows that, conditional on practice size and MSA, physicians that have NCAs in their employment contracts negotiate the same prices with insurers as those that don't (Lavetti et al. (2015)). Thus the price difference we estimate is unlikely to be due to other potential effects of NCAs, such as potential differences across firms in unobserved physician quality.

Our main results come from fixed effects instrumental variables models of the effect of concentration on negotiated prices, using judicial decisions that change NCA laws as instruments for the HHI. The detail of our data allow us to account for unobserved geographic market effects, year effects, census division-by-year effects, medical specialty effects, procedure code effects, and facility type effects. In addition to estimating average effects across all markets, we show that there is substantial heterogeneity across metro and non-metro markets and by physician specialty. Knowing that estimates can be sensitive to geographic market definitions, we test a variety of market definitions, including counties, Core Based Statistical Areas (CBSAs), Primary Care Service Areas (PCSA), and Hospital Service Areas (HSAs).

The results indicate that, though changes in concentration are slightly positively correlated with changes in prices in OLS fixed effects models, the IV estimates imply that a 100 point increase in the establishment-based HHI causes a *reduction* in negotiated prices of about 1.2% to 2.6% on average. The effect is present in both metro and non-metro counties, but is largest in urban areas and among non-surgical physician specialties. The first-stage estimates show that changes in stringency of non-compete laws strongly predict changes in physician market concentration for both primary care physicians and non-surgical specialists, but less well for surgical specialists who may be more likely to be tied to hospitals.

In contrast, IV estimates of the effect of firm-level concentration measures using tax IDs from the LBD show that larger firms tend to *increase* negotiated prices. The estimates imply that a 100 point increase in the firm-based HHI increases prices by 1.7%. Taken together, these results suggest that the effects of consolidation on prices depend on a tradeoff between the efficiency gains of larger establishments and the increased negotiating power associated with bargaining as a larger organization. Our results suggest that larger establishments allows efficiency gains via economies of scale that dominate any negotiating leverage effects. For example, larger physician practices can share nursing, laboratory, technical, and administrative resources. However, the firm-level estimates suggest that consolidation of multi-establishment firms increases the combined impact of bargaining power and the value of a larger physician practice to an insurer network by more than any efficiency gains within the practice, leading to higher negotiated prices.

Identifying the effect of physician practice concentration on prices of physician services is a fundamentally difficult task because features of the market, like patient demand, insurer concentration, and technology use, that affect prices are likely also to affect physicians' organization into practices. Previous work aiming to identify the effects of provider consolidation in medical care markets has often taken a more structural approach, modeling the bargaining game between hospitals and insurers.[2] However, these models become intractable in the context of physicians due to the large number of agents involved. With a new source of exogenous variation in physician organization from judicial decisions on NCA law, we provide an answer to this important policy question using reduced-form methods. Acknowledging the complications of the medical care market, we ground our empirical specifications in a theoretical model adapted from the Ho and Lee (2014) framework of bargaining with insurers. The main differences in our motivating theoretical model are that cost functions of firms are unobservable, since data on establishment-specific differences in physician practice input costs do not exist to our knowledge, and that physician quality is unobservable. In lieu of modeling competition over the physician component of insurance networks as a function of differences in unobserved provider quality, as is often done to model hospital networks, we model consumer willingness to pay for physician networks as being primarily affected by wait times for appointments. We show that if consumers form willingnesses to pay based on access to physicians in insurer networks this has direct implications for the relationship between practice sizes and network value in determining negotiated prices.

The effects of physician consolidation on prices are highly relevant for policy. At 16.9% of GDP, the share of income devoted to healthcare in the US is about 82% higher than the OECD average.[3] Many studies, including Pauly (1993) and Anderson et al. (2003) have shown that this difference in spending is primarily 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. Though provider consolidation is a commonly considered explanation, little systematic evidence has been put forward either on the degree to which physicians, in particular, have in fact consolidated over time or on the causal price effects of physician consolidation when it occurs. Meanwhile, national health care policy delineated in the Patient Protection and Affordable Care Act (PPACA) encourages consolidation among providers into Accountable Care Organizations. The results of this paper can shed light on the possible consequences of this policy and enrich our understanding of prices in the physician services market.

The paper is structured as follows. Section 2 provides background on non-compete laws and their

[2] See Gowrisankaran, Nevo and Town (2014) and Ho and Lee (2014)

[3] See OECD Health Statistics 2014

usage by physicians. Section 3 works through a bargaining model of physician firms negotiating service prices with insurers and motivates the estimation equations delineated in Section 4, along with the description of the multiple data sources compiled. Section 5 describes and discusses the results, and Section 6 concludes.

2 Background: Non-Compete Laws and Physicians

2.1 NCA Laws and Changes

Non-compete agreements, or NCAs, are clauses of employment contracts that prohibit an employee from leaving the firm and competing against it within a specified geographic area and period of time. Workers bound by these contracts who leave their firms may either leave the geographic area to continue in the same line of work, wait until the NCA has expired and then compete locally, or remain local and change industries so as not to compete.

But the extent to which workers are, in fact, bound by their NCAs varies geographically and over time because 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, so historical precedent is the main determinant of enforceability in most US states. But states that follow the same common law origins can still diverge dramatically in their enforcement of NCAs. For example, Kansas ranks second out of 50 states plus the District of Columbia 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), in which a Louisiana construction company attempted 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 that they cannot prevent a worker from joining a competing firm that already exists. 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.

Changes of this sort occurred in numerous states during the period we consider. To take advantage of the rich variation in the relevant legal environments, we quantify the law regarding NCAs - and its variation over time - using the methodology developed by Bishara (2012). These data are described in detail in Section 4.1.1.

2.2 Physician Markets and the Use of NCAs

In general, NCAs are useful contracting tools to mitigate investment holdup problems in firms whose critical assets can be taken with employees when they leave. This problem tends to arise in innovative firms, whose important assets are their new ideas, in firms that rely on human capital, and in service firms whose important assets are their client relationships. In these cases, owners wanting to invest in their employees' idea production, human capital development, and relationships with clients face the risk that employees will leave at any moment with the developed asset and that the investment will be lost. NCAs can thus increase the owner's incentive to invest by limiting the employee's mobility.

Physician practices in particular, because of their reliance on human capital and client relationships, can benefit from the use of NCAs. Information asymmetries between physicians and patients make search costs for physicians high and generate loyalty towards known physicians. The loyalty of patients is arguably the most valuable asset of most physician practices – the patient base is generally the basis for determining a price when practices are sold – but 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 towards them could lead to the loss of both if the physician subsequently departs to practice at another local firm and the patients follow the physician. NCAs can prevent this type of loss and thus encourage investment in physician employees and their client relationships.

The directions of the impacts of the components of NCA laws on physician HHIs are mixed. Of the seven dimensions of NCA laws, an increase in the enforceability along five dimensions tends to reduce physician HHIs, while increasing enforceability on the other two dimensions increases HHIs. For example, one dimension of the law, which we call the 'Employer Termination Index,' measures the extent to which state law allows a firm to fire a worker and still enforce the NCA. In some states this would be legal, while in other state NCAs can only be enforced if the worker quits. An increase in this component of the law causes a spike in job separations and a significant decrease in HHIs as it becomes less costly for firms to fire workers. In contrast, another component of the law, which we call the 'Blue Pencil Index,' measures variation in the extent to which contracts that are written to be overly restrictive for workers can still be enforced by allowing judges to modify contracts ex-post. Increasing this aspect of NCA law causes HHIs to increase, potentially because physicians are simply less likely to leave group practices. Each of the seven dimensions of NCA law undergoes a number of state level judicial changes during our sample period (1996-2007), and together they generate an exogenous source of variation in physician concentration measures.

An important fact to note is that physicians do, in fact, frequently and systematically use NCAs. This was documented by Lavetti et al. (2015), who show that about 45% of primary care physicians in group practices are bound by NCAs, and study the incentives behind the use of NCAs in high-skilled service firms like physician practices. They find that in states where NCAs are easier to enforce, physician practices are much more likely to use NCAs. In a five state sample, use ranges from about 30% of employed physicians in California, a low enforceability state, to 66% in Pennsylvania. In the case of physicians, an NCA usually states that if a physician leaves a group practice they are forbidden from practicing medicine in any form in a given geographic area surrounding the former practice for a fixed period of time. Common physician NCAs restrict competition within 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 NCAs to ameliorate investment holdup problems. Consistent with the theory, employed physicians with NCAs have significantly higher rates of earnings growth over time. This pattern 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 type of pay-for-performance scheme 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. (2015) 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. (2015) show that there is no evidence of quality differences associated with the use of NCAs. This conclusion 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 of practices 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 Theoretical 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.

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:

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

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:

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

As a result $\frac{\partial \text{WTP}_{ij}}{\partial |P_j|} > 0$ 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:

$$\begin{aligned} p^\star_{ij}\sigma_{ij}(\mathcal{G}) &= a + |P_j| \frac{\tau_j \xi}{\beta\gamma \sum_{r \in \mathcal{G}_{i \times j}} N_i} - \frac{|P_{ij}|}{|P_j|} \sum_{r \in \mathcal{G}_j \setminus ij} \tau_j p^\star_{rj} \sigma_{rj}(\mathcal{G}) + \tau_i \bar{c}_j(|P_j|)\sigma_{ij}(\mathcal{G}) + \varepsilon_{ij} \qquad (2) \\ &\equiv a + \beta_1 \tau_j \times \text{Network Value}_j(|P_j|) + \beta_2 \tau_i \times \text{Average Cost}_j(|P_j|) + \varepsilon_{ij} \qquad (3) \end{aligned}$$

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:

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

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. The primary purpose of this basic model is to demonstrate why it is reasonable, and under which assumptions, one would expect to find a relationship between negotiated prices and concentration measures in the market for physician services.

Although we cannot observe information about costs directly in our data, our empirical strategy allows us to estimate an establishment-based β_3 separately from a firm-based one. This turns out to be an informative distinction in our setting. For example, consider a hypothetical merger between two physician practices that remain physically distinct after the merger, but minimize costs jointly and negotiate with insurers jointly. In this model the network value of the combined firm cannot decrease, because otherwise the firm would prefer to negotiate separately by establishment, which is still within the choice set. Similarly, the average costs of the firm cannot be higher than the average of the average costs of the establishments, since minimizing costs separately by establishment is still within the choice set. If the merger were to cause a change in negotiated prices such that $\beta_3 < 0$, this would imply that declining average costs dominate the impact of any change in network value on negotiated prices. The reverse is also true.

Empirically we find that the establishment-based estimate of β_3 is negative, suggesting that insurers extract the efficiency gains from larger establishments in the form of lower prices, and that these efficiency gains outweigh any increase in network value. Moreover, the firm-based estimate suggests that the opposite is true at the firm level. Any concentration changes that occur through firms growing larger by multi-establishment consolidation yield efficiency gains that are smaller than the effects on network value, causing negotiated prices to increase.

In specifications using data from the Census LBD, we are also able to control for insurer market concentration 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 1996-2007.

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 of Bishara (2011). Bishara (2011) analyzes case law in each state and scores states along 7 different dimensions, following the framework from 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 are described in detail in Table 23.

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 the same coding methodology, we match the scores in the endpoint years code the timing of the law changes, creating an annually-measured longitudinal dataset that spans the period 1991-2009.[4]

In the raw data, the sum of scores for all seven components ranges 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, 2 of them tend to be positively correlated with market concentration and 5 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 show 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 Q2 and Q4. These questions measure how broadly courts have defined firms' protectible interests of firms and whether courts are allowed to modify NCA contracts 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. A broad definition of firms' protectible interests has important implications because it encourages firms to invest in employees' human capital and client relationships (for example, through intra-firm referrals) by removing the threat that physicians will move to a rival practice and poach clients.

The components that are negatively correlated with market concentration are questions Q1, Q3, Q3a, Q3bc, and Q8. These components measure whether the state has a strong statute that favors NCA enforceability, whether plaintiffs in litigation have a weak burden of proof, whether the contract must be explicit about what compensation ('consideration' in legal terminology) is being made to the

[4]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.

worker in exchange for accepting an NCA, whether being offered a job or not being 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 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 physicians' practice affiliations. 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.

There are two limitations with this database. First, we cannot observe connections between establishments, which could be important to the extent that multi-establishment firms negotiate as a single entity with insurers. Second, 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. Although it has limitations, this dataset is, to the best of our knowledge, the first longitudinal census of all physicians in the US that has been used to study the relationship between practice sizes and negotiated prices.

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 data on all non-farm employer establishments in the US, and is available from 1976 to the present. The LBD contains establishment employment, payroll, industry codes, and county locations with firm linkages via 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. While the LBD solves the problem of observing firm-level information, it has limitations; for physician markets, being able to calculate concentration measures by medical specialty may be quite important.

We also use the LBD to construct longitudinal measures of health insurance market concentration using data on sales from firms in NAICS code 524114, 'Direct Health and Medical Insurance Carriers'. We control for insurer HHIs along with physician HHIs in our main specifications.

4.1.4 MarketScan Negotiated Prices Data

Data on prices negotiated between physicians and private commercial insurers come from the Truven Health Analytics 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:

$$C_{mct} = \alpha_1 + NCA'_{ct}\beta_1 + \eta_m + \pi_f + \phi_t + \theta_p + \gamma_c + \nu_{dt} + \epsilon_{mct} \quad (5)$$

$$P_{mfpct} = \alpha_2 + \beta_2\widehat{C}_{mct} + \eta_m + \pi_f + \phi_t + \theta_p + \gamma_c + \nu_{dt} + \varepsilon_{mfpct} \quad (6)$$

where m denotes medical specialty, c county, t year, f facility type, p procedure code, and d census division. NCA'_{ct} is a vector of the quantified NCA law dimensions, which are measured at the state-year level. C_{mct} is a measure of market concentration. In most of our analyses we measure concentration as HHIs, 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. This allows census divisions to have unobserved idiosyncratic variation over time in both concentration and prices, which we use in lieu of making assumptions about functional forms for time trends.

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 Core Based Statistical Areas (CBSAs), Primary Care Service Areas (PCSA), and Hospital Service Areas (HSAs). PCSA and HSA definitions come from the Dartmouth Atlas of Healthcare, and are calculated by analyzing patients' travel patterns to providers. There are 6,542 defined PCSAs (or about 2.1 PCSAs per county on average) and 3,436 HSAs. 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. (2015) 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. We test a variety of market definitions to assess whether this assumption seems plausible.

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. We can also estimate the model using only states in which the judicial decisions that caused the law changes were unrelated to healthcare, so that judges decisions are less likely to have been motivated by factors that are related to physician 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 firm sizes on negotiated prices. This 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.

5 Results

5.1 Effects of NCA Laws on HHI

We present graphical analyses of HHIs around the time of changes in NCA laws, along with more formal estimates of the first stage from Equation 5. Figures 4 and 5 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, state law changes are synchronized such that year zero is the year during which the law change occurred. Because the change could have occurred at any point during the year, we expect that effects may be evident in the graphs as early as year 0 or as late as year 2. A change in market concentration that occurs very quickly will be incorporated into observed HHIs at time 0 and appear as a change between year -1 and year 0. For law changes that occur late in a given calendar year, a very quick effect would be observed at best at time 1 and appear as a change between year 0 and year 1. A slower effect for a late-in-the-year change would likely not be observed until time 2 and appear as a change between year 1 and year 2. It is quite plausible that physician practices may not adjust instantaneously to a law change, but rather may take some time to re-optimize given new circumstances.

Figure 4 shows changes in HHIs in an eight year window around a reduction in NCA Component Group Index 1. This component group is defined by its positive correlation with HHIs, so we would expect to see a reduction in HHIs with a reduction in the Index. The first graph shows unconditional raw HHIs, which appear flat until the law change and then trend slightly downward after the change. However, it is difficult to interpret the raw data because the timing of the law changes differs across states. The second graph (upper right) removes year effects and shows a stronger downward break after the decline in Index 1. This downward break remains and strengthens when state effects (lower left) and census division by year effects (lower right) are also removed. Non-surgical specialists especially experience an abrupt decline in HHIs after a fairly flat trend prior to the law change.

Figure 5 graphs HHIs before and after increases in NCA Component Group Index 2. The components in this index measure, in part, 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. In addition, the Index measures 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 5 show distinct but small declines in HHIs for all three groups of physicians a year after the law change. These breaks become substantially larger throughout the conditional models, and appear strongest in the fourth graph, after year, state, and census-division by year effects have been removed.

The figures corresponding to law changes in the opposite directions are included in the Appendix.

Figure 6 shows that following increases in NCA Component Group Index 1 a negative pre-trend in HHIs is reversed by the law change. In this graph as well the strongest breaks in trends occur among primary care physicians and non-surgical specialists. 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 and joining pre-existing practices. Consistent with the rationale that these law changes are less likely to have abrupt effects, and we find little discernible pattern in HHIs immediately following these law changes.

Estimates from the first-stage Equation 5 are presented in Tables 2 using MPIER data and 13 using LBD data. The three models presents in Table 2 shows estimates from fixed effects regression of lagged HHI on lagged NCA law components, twice lagged law components, and on both the first and second lags. Each of the models defines markets by county-specialty-years, and includes county effects, year effects, census division by year effects, medical specialty effects, facility type effects, and procedure code effects. The dependent variable is lagged HHI since prices are negotiated prospectively, and typically only every one to two years, so the second stage model regresses prices on instrumented lagged HHIs.

In model 1, six of seven law components have statistically significant effects on HHI, with an Angrist-Pischke excluded variable F-statistic of about 49. The HHI measure is scaled to range between 0 and 100, so that a 1 unit change corresponds to a 100 point change on the typical 10,000 point scale. As an example of how to interpret the coefficients, a change in the Statutory Index that moves NCA laws from the least enforceable observed policy to the most enforceable policy decreases HHIs by about 511 points. Of course, most of the variation observed in NCA laws is far less extreme. As shown in Figure 2a a fairly large law change moves the law indices by about 0.1 to 0.2 units, which would lead to an approximately 51 to 102 point decrease in the HHI. Similarly, a 0.1 unit change in the Protectible Interest Index would increase HHIs by about 130 points, according to estimates from model 1.

Two of the law components tend to increase HHIs, while the remaining four decrease HHIs. Similarly in model 2, six of the lagged NCA laws have significant effect on subsequent year HHIs, and the AP F-statistic is 105. Including all of the first and second lags in the model further improves the strength of the combined set of instruments, increasing the F-statistic to 290. In all three models, the fixed effects and excluded instruments explain about 75% of the variation in county-specialty level HHIs.

In Table 13 we present first stage estimates from the LBD data. These estimates have not yet been updated to account for lags in effects, but the results show that changes in NCA laws have significant effects on contemporaneous HHIs. In this table the components are grouped in aggregate indices, where Index Component Group 1 is defined as the set of law components that are positively conditionally correlated with HHIs, and Index Component Group 2 is the set of negatively correlated components. The first stage F-statistic is considerably smaller at 12, but not clearly too small to cause concern about weak instruments. The estimated coefficients suggest that a 0.1 unit increase in Index Component Group 1 would increase HHIs by about 55 points, while Component Group 2 is not statistically significant.

This model also controls for insurer HHI in the state. Although we have not yet had a chance to run the models including insurer HHI as a control in Table 2, alternative comparable models from the MPIER shown in the Appendix do included insurer HHI and we found that this had little effect on the second stage price effects (1.34% with, versus 1.26% without).

We also estimate heterogeneity in the 2SLS estimates according to whether the market is metropolitan or non-metro, and by different sets of physician specialty. We estimate the model for primary care physicians, which includes family practice, internal medicine, geriatric medicine, and pediatrics; for non-surgical specialists, for which we have price data from proctology, urology, dermatology, cardiology, neurology, gastroenterology, and hematology; and for surgery-related specialties including general surgery, neurological surgery, orthopaedic surgery, thoracic surgery, anesthesiology, and radiology. We construct these groupings primarily to reflect differences in the incentives to use NCA contracts, and according to the potential heterogeneity in the effects of practice sizes on negotiated prices. Surgery-related specialties are likely to behave differently for two reasons. First, surgeons are more closely tied to and reliant on hospitals and are less likely to be affected by NCAs, even if they use them. Second, as shown in Lavetti et al. (2015), physician groups use NCAs primarily to protect the value of investments in durable patient relationships, which are of lesser importance in surgical specialties, in which doctors have fewer repeat interactions with patients. As a result, there is less incentive for firms employing surgical specialists to use NCA contracts. Consistent with this idea, Lavetti et al. (2015) find that physicians employed by teaching hospitals are about 36 percentage points less likely to be bound by an NCA contract than comparable physicians in office-based practices. We find that the first stage is quite strong for primary care and non-surgical specialists, but is somewhat weaker for surgical specialists, consistent with the possibility that changes in NCA laws affect relatively fewer surgical physicians. We separate primary care from non-surgical specialists because the concentration rates among specialists is substantially higher than it is for primary care, which could lead to important heterogeneity in effects on negotiated prices.

5.2 Instrument Strength

Each of the first stage F-statistics, which range from 12.1 to 290.2, are 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 4 shows second-stage estimates for a variety of alternative IV models. The estimates using two-stage least squares, two-step feasible GMM, and limited information maximum likelihood (LIML) are very similar, ranging between -0.0126 and -0.0128. 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 Table 2 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 very similar using 2SLS and LIML in these data, both equal to 0.0050.

5.3 The Effect of HHI on Negotiated Prices

The second stage estimates of the effects on negotiated prices are reported in Table 3. Columns 1-3 in the table correspond to the same column numbers for the different sets of instruments in Table 2, and column 4 shows the OLS estimate of the conditional correlation between HHIs and negotiated prices. The OLS estimate is slightly positive and statistically significant. This finding is similar to estimates by Dunn and Shapiro (2014) and Baker et al. (2014), which use either cross-sectional or panel variation in HHIs, but do not instrument for changes in concentration over time.

The second stage IV estimate corresponding to the lagged NCA law model suggests that a 100 point increase in the HHI causes an 1.19% decrease in average negotiated prices. The sign of this estimate suggests that the efficiency gains of larger group practices outweigh any effects 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. The IV estimate using twice-lagged instruments is also negative and significant, implying a 1.66% decrease in prices per 100 point increase in HHIs. The third model using both sets of instruments suggests that a 100 point increase in HHI causes a 2.58% decrease in negotiated prices when law changes are allowed to affect HHIs in the year of the change as well as the following year. In all three IV models the unexplained variation in prices is about 2% of the total sum of squares.

Tables 5 and 6 show similar estimates when the sample is broken into metro and non-metro counties. The instruments in columns 1 and 3 are groups of lagged NCA law changes and twice lagged changes, using the same Index Component Group construction as in the graphs. The instruments in columns 2 and 4 are NCA law change components once-lagged relative to the dependent variable, which is HHI_{t-1}. The IVs are strong in each of the subsamples, with F-statistics between 13 and 87. In general, the instruments appear to be stronger for metropolitan areas. Table 6 shows the corresponding second-stage estimates, which are again negative in three of the four models, and statistically insignificant in the fourth. The estimates imply negotiated price reductions of about 1.48% to 2.38% in metro counties per 1,000 unit decrease in the HHI, with much more modest price effects in non-metro counties of about 0.66% or less.

Tables 7, 8, 9, 10, 11, and 12 show estimates by groups of physician specialties, overall and broken down by metro and non-metro counties. The first stage estimates for primary care, which includes family practice, internal medicine, geriatrics, and pediatrics, in shown in Table 7. The instruments are strongest in columns 2 and 4, using twice lagged law changes as instruments. The F-stats for the excluded instruments in these models are 63 and 35, respectively. Column 2 includes all counties in the sample, while column 4 includes only metro counties. The corresponding second stage estimates in Table 8 show that the price effects are similar for primary care physicians as the overall estimates. Column 2 implies a 1.34% overall decrease, with a slightly larger 1.75% decrease in metro counties from column 4.

Tables 9, 10 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 in the overall and metro samples, ranging between 29 and 121, but do not work as well in non-metro counties. Among all specialty groups, the second stage estimates are uniformly largest for non-surgical specialists. Overall, the estimates suggest that a 100 point increase in the HHI causes a 0.95% to 1.57% decrease in prices. The effects are even larger in metro counties, ranging from 1.58% to 2.35%.

Tables 11, and 12 show that there are some significant price effects in metro counties, ranging from about 1.39% to 1.46%, but the instruments do not work well in non-metro counties or in the overall sample. This is consistent with evidence from Lavetti (2015) 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. Consequently the ITT estimates should be lower due to the smaller probability of treatment.

6 Discussion

This paper makes two main contributions to our understanding of physician services markets in the U.S. First, we make use of two comprehensive data sets on the universe of physicians to bring new systematic evidence on the nature of physician markets. Both MPIER and the LBD data suggest that, on average, there really has not been a systematic rise in physician market concentration over the period studied, 1996-2007. Rather, some county-medical specialty markets have increased in concentration while others have declined.

However, the movements in concentration that we do see are strongly predicted by state NCA laws. This new source of plausibly exogenous variation in physician concentration is the paper's second major contribution. The rich variation along multiple dimensions of judicial law, all quantified according to an objective legal coding system, provides a solid means of identifying the effects of physician concentration on prices without estimating a structural model.

The instrumental variable results for establishment and firm level concentrations suggest an interesting story for the physician market. When establishments become larger due to non-compete law, prices negotiated between physicians and insurers drop, suggesting efficiency gains from economies of scale in a larger facility with more doctors. However, when establishments unite to generate larger multi-establishment firms negotiated prices rise, suggesting that this form of firm growth tends to increase the network value of firms by a greater amount than any cost efficiencies.

Taken together, these results suggest that consolidation of certain types may be beneficial in helping to contain health care spending. But policy makers should be aware of the differing consequences on negotiated prices from consolidation that increases the size of establishments compared to consolidation that allows practices to negotiate jointly without the physical consolidation, which appears to be the primary source of cost efficiencies.

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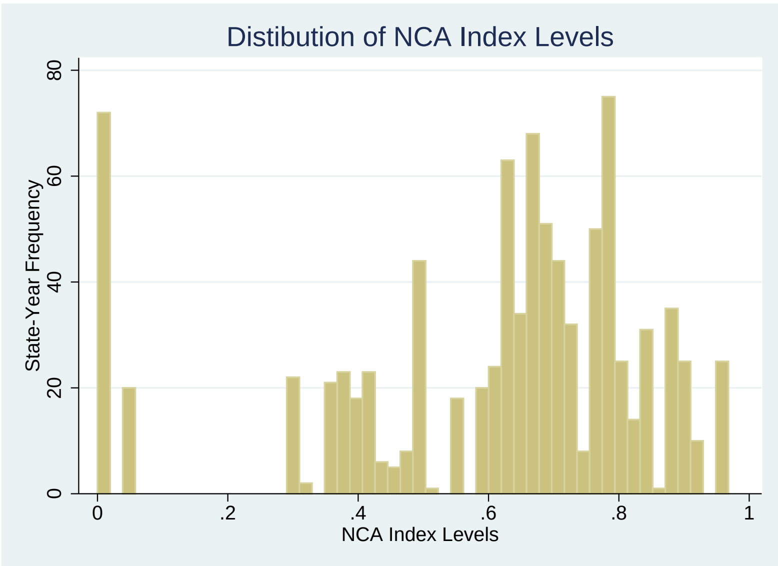
Table 1: Summary Statistics of NCA Law Components

	Mean	SD	N (State-Years)
Statutory Index	0.55	0.24	612
Protectible Interest Index	0.60	0.24	605
Consideration Index Inception	0.84	0.30	563
Consideration Index Post-Inception	0.70	0.33	526
Burden of Proof Index	0.57	0.27	602
Blue Pencil Index	0.53	0.34	538
Employer Termination Index	0.62	0.30	408

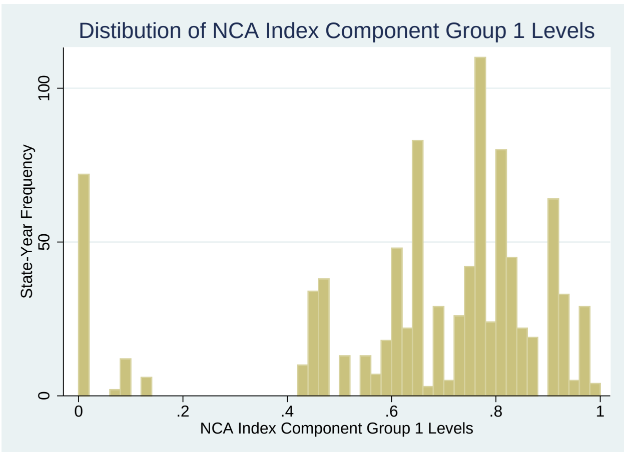
Notes: Includes data from years 1996-2007 for each component in which a legal precedent had been set in a given state. The minimum of each component is 0 and the maximum of each component is normalized to 1.

Figure 1: Distributions of NCA Index Levels

(a) Overall NCA Index Levels



(b) Component Group 1 Levels



(c) Component Group 2 Levels

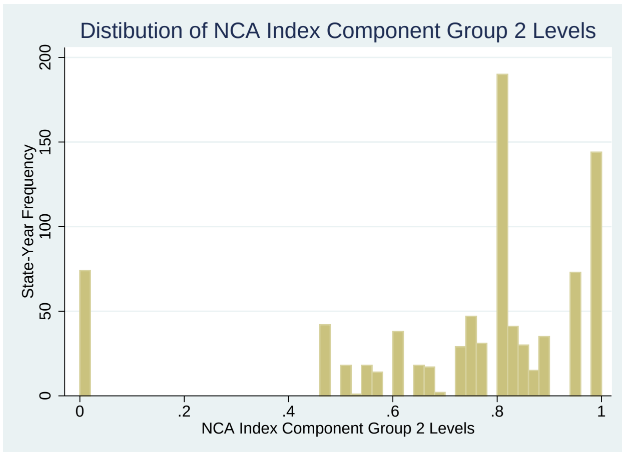
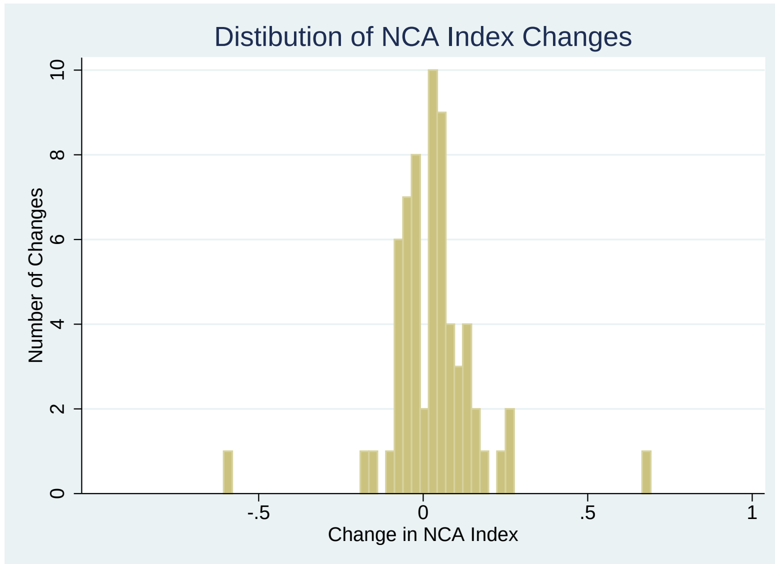
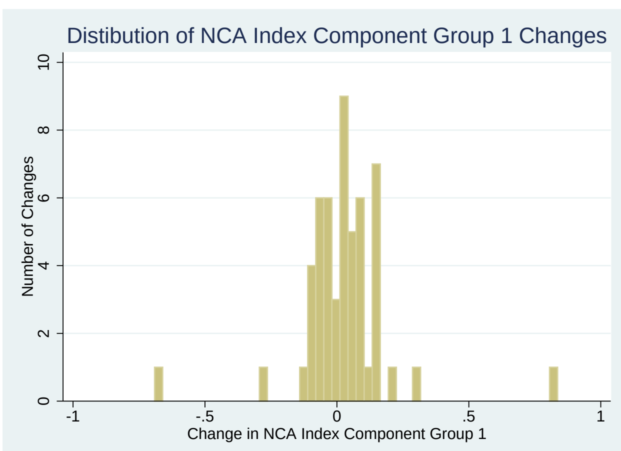


Figure 2: Distributions of NCA Index Changes

(a) Overall NCA Index Changes



(b) Component Group 1 Changes



(c) Component Group 2 Changes

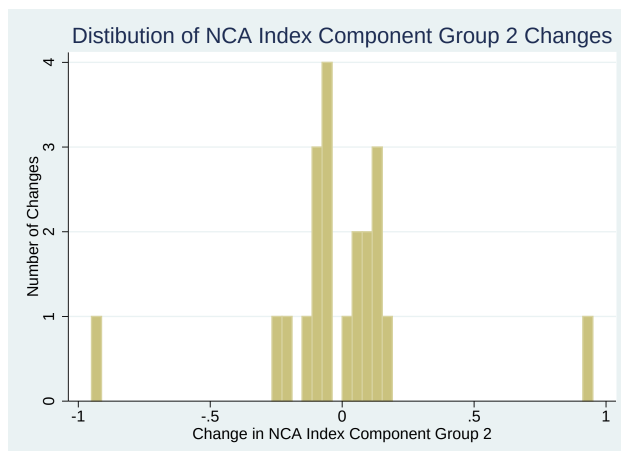
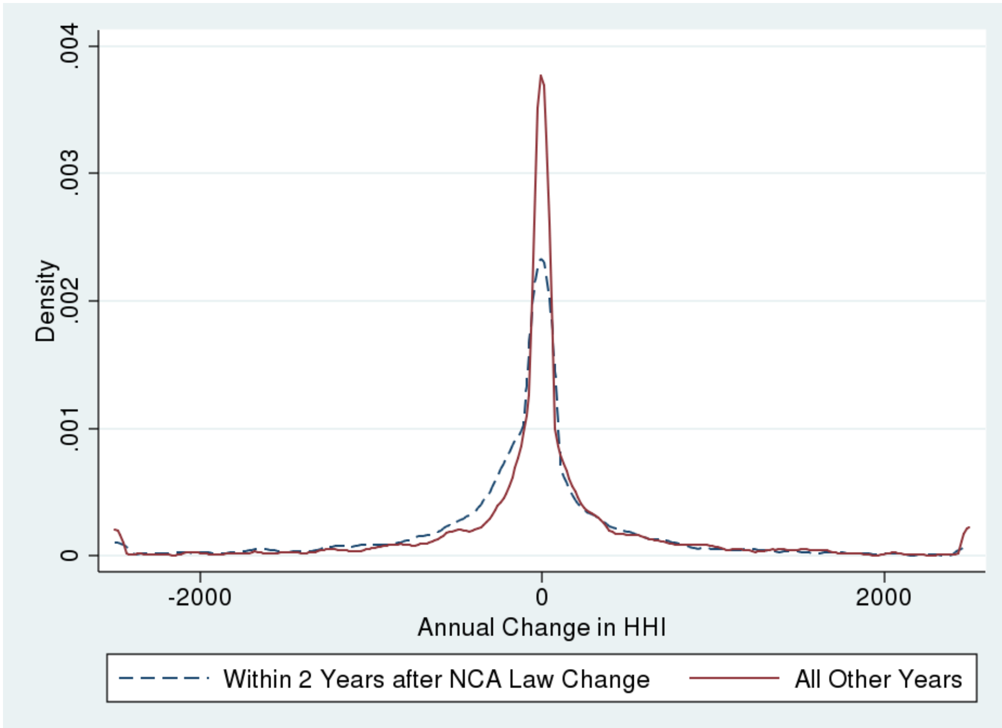
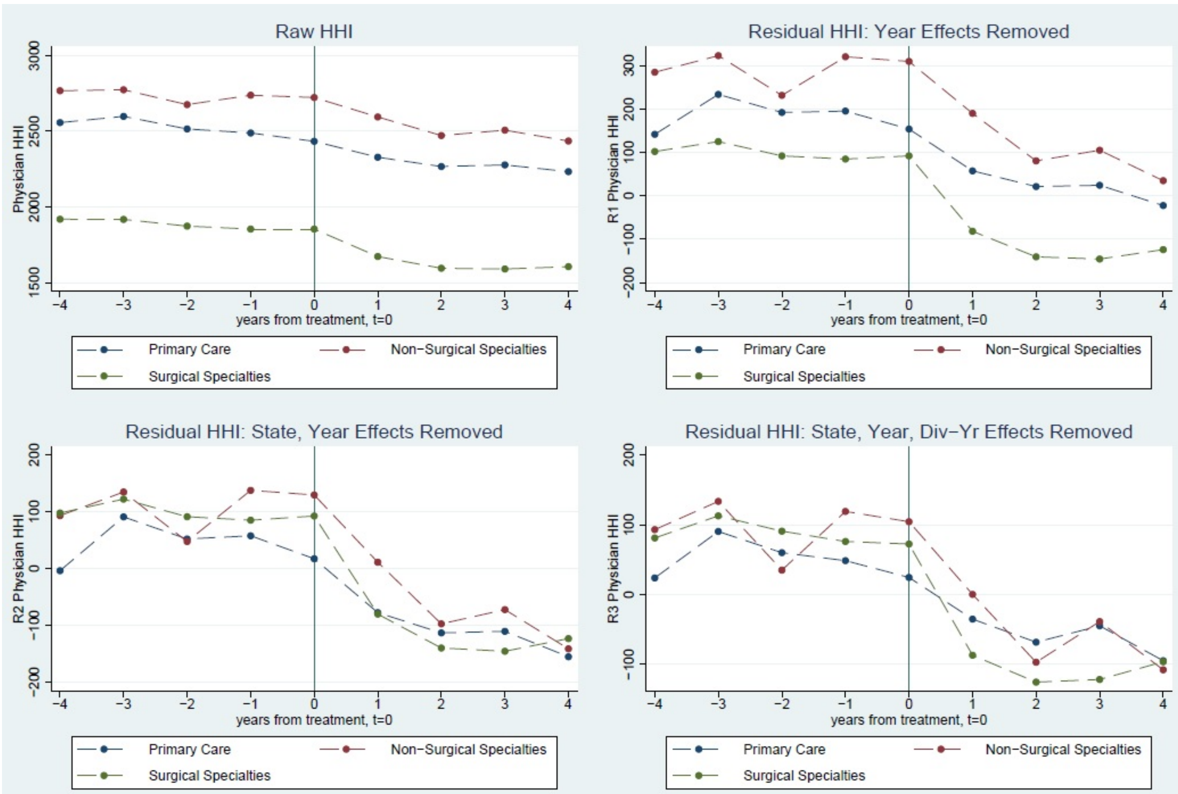


Figure 3: Distribution of HHI Changes for Specialists



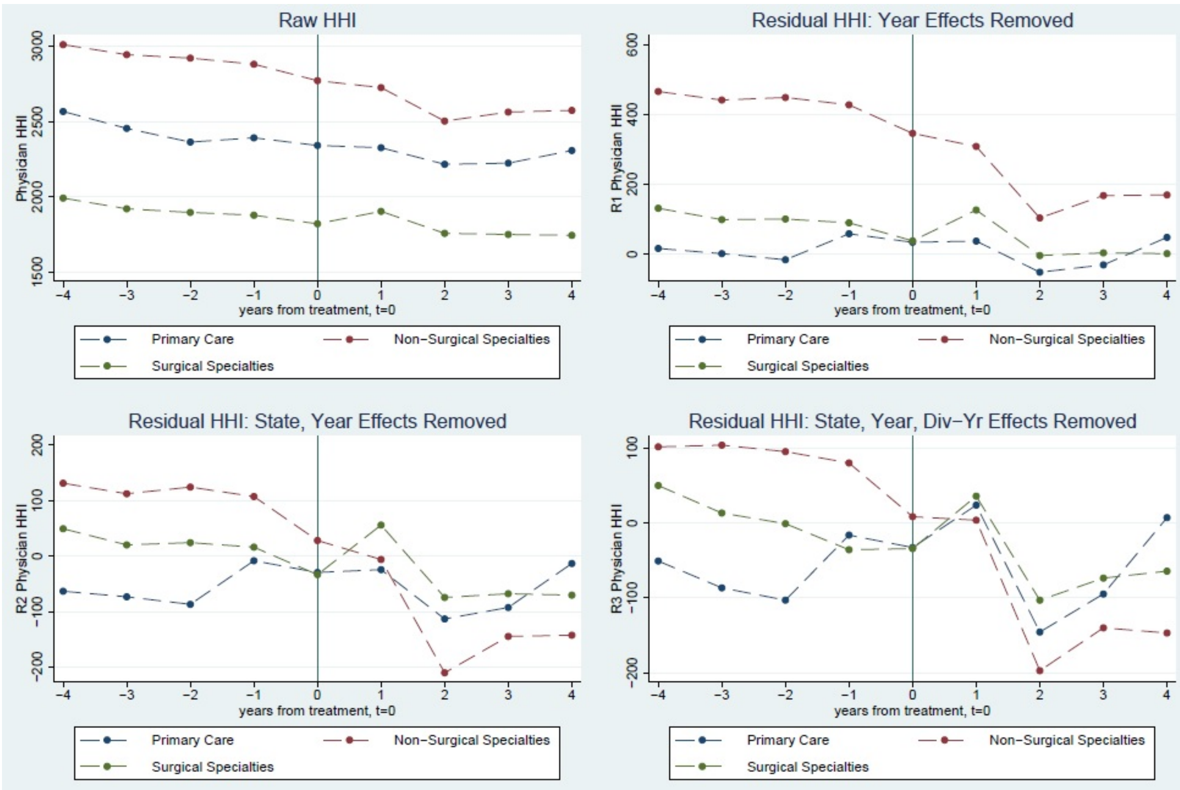
Notes: Distributions are kernel density graphs of the change in annual HHI by CBSA-specialty for non-primary care specialists only. Distributions are censored at +/− 2500 for display. p-value of Kolmogorov-Smirnov test of the equality of the uncensored distributions is <0.001.

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



Notes: This figure plots HHIs by medical specialty before and after a decline in NCA Component Index 1. Law changes in all states that experience a decline in this index are synchronized to occur at time 0. The four panels show raw HHIs and HHIs with various fixed effects removed, as noted. Physician HHIs are calculated by county and medical specialty from MPIER data on physician establishment sizes.

Figure 5: HHIs Before and After Increases in NCA Index 2



Notes: This figure plots HHIs by medical specialty before and after an increase in NCA Component Index 2. Law changes in all states that experience an increase in this index are synchronized to occur at time 0. The four panels show raw HHIs and HHIs with various fixed effects removed, as noted. Physician HHIs are calculated by county and medical specialty from MPIER data on physician establishment sizes.

Table 2: First Stage IV Models

	Dependent Variable: HHI_{t-1}		
	(1)	(2)	(3)
Statutory Index_{t-1}	–5.09*		1.61
	(1.62)		(2.02)
Protectible Interest Index_{t-1}	12.94*		7.93*
	(1.47)		(3.93)
Consideration Index Inception_{t-1}	27.61*		12.67
	(1.57)		(46.35)
Consideration Index $\text{Post-Inception}_{t-1}$	–2.48*		–1.22
	(0.32)		(0.66)
Burden of Proof Index_{t-1}	–25.38*		–11.80
	(1.31)		(37.18)
Blue Pencil Index_{t-1}	8.88*		–0.08
	(3.29)		(2.10)
Employer Termination Index_{t-1}	–19.52*		–11.02*
	(2.96)		(4.39)
Statutory Index_{t-2}		–3.50*	–1.87
		(1.22)	(1.66)
Protectible Interest Index_{t-2}		8.12*	2.59*
		(1.94)	(1.18)
Consideration Index Inception_{t-2}		–3.54*	0.63
		(1.36)	(1.14)
Consideration Index $\text{Post-Inception}_{t-2}$		–2.28*	–1.42*
		(0.35)	(0.61)
Burden of Proof Index_{t-2}		–2.39	–4.02*
		(1.30)	(0.82)
Blue Pencil Index_{t-2}		19.24*	15.58*
		(2.81)	(2.15)
Employer Termination Index_{t-2}		–8.46*	–1.28
		(2.26)	(1.31)
N	3,307,046	3,075,315	3,067,967
N Clusters	136	123	121
R-Sq	0.745	0.744	0.744
AP F-Stat	94.14	105.74	290.15

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 100, so that a 1 unit change in HHI corresponds to a 100 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 IV Models

	Dependent Variable: $\ln(Price)_t$			
	IV	IV	IV	OLS
	(1)	(2)	(3)	(4)
HHI_{t-1}	–0.0104*	–0.0166*	–0.0258*	0.0001*
	(0.0048)	(0.0043)	(0.0048)	(0.0000)
N	3,307,046	3,075,315	3,067,967	5,325,825
N Clusters	136	123	121	276
R-Sq	0.986	0.983	0.977	0.819
1st Stage AP F-Stat	94.14	105.74	290.15	

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 100, so that a 1 unit change in HHI corresponds to a 100 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 4: Second Stage Sensitivity to Estimator

	Dependent Variable: $\ln(Price)_t$		
	2SLS	GMM	LIML
	(1)	(2)	(3)
HHI_t	–0.0126*	–0.0126*	–0.0128*
	(0.0050)	(0.0050)	(0.0050)
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 100, so that a 1 unit change in HHI corresponds to a 100 point change in the typical 10,000 point scale. All standard errors clustered by state-year. * Significant at the .05 level.

Table 5: First Stage Estimates in Metro and Non-Metro Counties

	Dependent Variable: HHI_{t-1}			
	Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)
Index Component Group 1_{t-1}	3.55		6.75	
	(4.44)		(9.61)	
Index Component Group 1_{t-2}	0.19		7.30	
	(3.97)		(6.99)	
Index Component Group 2_{t-1}	–9.57*		–19.02*	
	(1.95)		(6.47)	
Index Component Group 2_{t-2}	–3.90*		–7.61	
	(1.78)		(5.73)	
Statutory Index_{t-2}		–2.09*		–5.41
		(0.81)		(2.87)
Protectible Interest Index_{t-2}		5.10*		15.39*
		(1.19)		(3.77)
Consideration Index Inception_{t-2}		–4.32*		–256.76
		(1.38)		(364.52)
Consideration Index $\text{Post-Inception}_{t-2}$		–2.22*		–2.93*
		(0.39)		(0.52)
Burden of Proof Index_{t-2}		–1.62		215.04
		(1.34)		(308.49)
Blue Pencil Index_{t-2}		18.53*		16.98*
		(2.61)		(3.77)
Employer Termination Index_{t-2}		–4.09*		
		(1.46)		
N	3,059,250	2,113,347	1,547,567	961,968
N Clusters	222	123	202	113
R-Sq	0.722	0.722	0.802	0.810
AP F-Stat	26.15	87.56	13.12	26.45

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 100, so that a 1 unit change in HHI corresponds to a 100 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: Effect of Market Concentration on Prices in Metro and Non-Metro Counties

	Dependent Variable: $\ln(Price)_t$			
	Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)
HHI_{t-1}	–0.0148*	–0.0238*	0.0006	–0.0066*
	(0.0062)	(0.0056)	(0.0035)	(0.0029)
N	3,059,250	2,113,347	1,547,567	961,968
N Clusters	222	123	202	113
R-Sq	0.985	0.980	0.989	0.988
1st Stage AP F-Stat	26.15	87.56	13.12	26.45

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 100, so that a 1 unit change in HHI corresponds to a 100 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 7: First Stage Models for Primary Care Physicians

	Dependent Variable: HHI_{t-1}					
	All Counties		Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
Index Component Group 1_{t-1}	3.47		–6.71		18.90	
	(5.73)		(6.74)		(12.77)	
Index Component Group 1_{t-2}	–7.54		–5.23		–6.75	
	(4.65)		(5.84)		(8.29)	
Index Component Group 2_{t-1}	–16.05*		–5.43*		–38.32*	
	(2.35)		(2.58)		(5.82)	
Index Component Group 2_{t-2}	1.98		–0.22		7.61	
	(2.04)		(2.49)		(4.81)	
Statutory Index_{t-2}		–4.32*		–6.53*		3.20
		(1.91)		(1.86)		(5.70)
Protectible Interest Index_{t-2}		7.70*		3.30		24.70*
		(3.54)		(2.38)		(8.17)
Consideration Index Inception_{t-2}		4.24		3.34		101.98
		(2.89)		(1.89)		(271.05)
Consideration Index $\text{Post-Inception}_{t-2}$		–1.83*		–1.36*		–2.03
		(0.67)		(0.56)		(1.36)
Burden of Proof Index_{t-2}		–9.26*		–7.93*		–88.81
		(2.35)		(1.72)		(216.97)
Blue Pencil Index_{t-2}		25.40*		21.76*		35.21*
		(2.94)		(5.57)		(11.70)
Employer Termination Index_{t-2}		–8.13*		–1.59		
		(4.02)		(2.72)		
N	709,618	473,888	441,793	307,002	267,825	166,886
N Clusters	222	123	222	123	202	113
R-Sq	0.834	0.842	0.786	0.785	0.895	0.904
AP F-Stat	19.13	63.06	9.56	34.96	13.31	4.43

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 100, so that a 1 unit change in HHI corresponds to a 100 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 8: Effect of Concentration on Prices for Primary Care Physicians

	Dependent Variable: $\ln(Price)_t$					
	All Counties		Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
HHI_{t-1}	–0.0062	–0.0134*	–0.0119	–0.0175*	0.0029	–0.0062
	(0.0051)	(0.0038)	(0.0082)	(0.0058)	(0.0032)	(0.0032)
N	709,618	473,888	441,793	307,002	267,825	166,886
N Clusters	222	123	222	123	202	113
R-Sq	0.986	0.984	0.984	0.983	0.987	0.987
1st Stage AP F-Stat	19.13	63.06	9.56	34.96	13.31	4.43

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 100, so that a 1 unit change in HHI corresponds to a 100 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 9: First Stage Models for Non-Surgical Specialists

	Dependent Variable: HHI_{t-1}					
	All Counties		Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
Index Component Group 1_{t-1}	15.61		15.29		–12.83	
	(8.00)		(8.04)		(30.52)	
Index Component Group 1_{t-2}	1.82		–7.73		21.24	
	(7.66)		(8.21)		(21.37)	
Index Component Group 2_{t-1}	–24.45*		–21.35*		–48.76*	
	(5.44)		(3.56)		(14.57)	
Index Component Group 2_{t-2}	–8.69		–4.25		–13.98	
	(5.68)		(3.32)		(15.59)	
Statutory Index_{t-2}		2.94		2.99		5.71
		(2.78)		(2.08)		(10.29)
Protectible Interest Index_{t-2}		13.76*		11.41*		17.16
		(3.24)		(2.88)		(13.85)
Consideration Index Inception_{t-2}		–9.82		–6.84		–406.90
		(11.60)		(3.74)		(1198.03)
Consideration Index $\text{Post-Inception}_{t-2}$		–7.95*		–5.22*		–11.94*
		(1.36)		(0.79)		(3.56)
Burden of Proof Index_{t-2}		1.05		–2.77		327.08
		(9.76)		(3.84)		(950.37)
Blue Pencil Index_{t-2}		–5.61		4.59		–31.03*
		(4.73)		(4.01)		(14.39)
Employer Termination Index_{t-2}		–15.38*		–11.89*		
		(3.70)		(3.31)		
N	440,364	301,199	335,471	234,562	104,893	66,637
N Clusters	222	123	222	123	194	112
R-Sq	0.795	0.802	0.759	0.764	0.870	0.876
AP F-Stat	29.32	38.44	31.56	121.72	14.61	4.27

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 100, so that a 1 unit change in HHI corresponds to a 100 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 10: Effect of Concentration on Prices for Non-Surgical Specialists

	Dependent Variable: $\ln(Price)_t$					
	All Counties		Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
HHI_{t-1}	–0.0095*	–0.0157*	–0.0158*	–0.0235*	0.0008	–0.0012
	(0.0028)	(0.0034)	(0.0034)	(0.0035)	(0.0013)	(0.0020)
N	440,364	301,199	335,471	234,562	104,893	66,637
N Clusters	222	123	222	123	194	112
R-Sq	0.991	0.988	0.988	0.984	0.994	0.994
1st Stage AP F-Stat	29.32	38.44	31.56	121.72	14.61	4.27

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 100, so that a 1 unit change in HHI corresponds to a 100 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 11: First Stage Models for Surgical Specialists

	Dependent Variable: HHI_{t-1}					
	All Counties		Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
Index Component Group 1_{t-1}	–6.99		–5.94		–6.68	
	(10.12)		(7.77)		(20.13)	
Index Component Group 1_{t-2}	1.29		–0.04		–12.03	
	(9.43)		(7.74)		(14.61)	
Index Component Group 2_{t-1}	–3.35		–10.27*		9.81	
	(5.67)		(3.62)		(14.76)	
Index Component Group 2_{t-2}	–12.55*		–4.87		–37.27*	
	(5.95)		(3.81)		(15.00)	
Statutory Index$_{t-2}$		–0.26		1.09		–3.94
		(2.40)		(1.72)		(5.65)
Protectible Interest Index$_{t-2}$		5.77		8.53*		–0.95
		(4.06)		(2.29)		(8.67)
Consideration Index Inception$_{t-2}$		2.07		1.40		–677.43
		(3.52)		(1.73)		(1104.31)
Consideration Index Post-Inception$_{t-2}$		–6.43*		–5.26*		–8.71*
		(1.81)		(1.15)		(3.80)
Burden of Proof Index$_{t-2}$		–4.67		–6.03*		553.56
		(2.84)		(1.55)		(872.84)
Blue Pencil Index$_{t-2}$		16.26*		4.19		33.11*
		(4.85)		(3.61)		(9.43)
Employer Termination Index$_{t-2}$		–4.59		–5.02		
		(4.75)		(3.01)		
N	415,006	273,326	279,942	192,022	135,064	81,304
N Clusters	222	123	222	123	202	113
R-Sq	0.769	0.775	0.739	0.737	0.839	0.847
AP F-Stat	6.23	8.52	12.11	26.07	2.98	3.98

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 100, so that a 1 unit change in HHI corresponds to a 100 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 12: Effect of Concentration on Prices for Surgical Specialists

	Dependent Variable: $\ln(Price)_t$					
	All Counties		Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
HHI_{t-1}	–0.0091	–0.0088	–0.0146*	–0.0139*	–0.0002	–0.0059
	(0.054)	(0.055)	(0.056)	(0.057)	(0.027)	(0.043)
N	415,006	273,326	279,942	192,022	135,064	81,304
N Clusters	222	123	222	123	202	113
R-Sq	0.989	0.989	0.988	0.988	0.991	0.990
1st Stage AP F-Stat	6.23	8.52	12.11	26.07	2.98	3.98

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 100, so that a 1 unit change in HHI corresponds to a 100 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 13: LBD: First Stage IV Models

Dependent Variable:	Firm-level HHI
	IV1
Index Component Group 1	5.52*
	(1.59)
Index Component Group 2	–3.07
	(1.83)
Insurer HHI	–0.003
	(0.007)
N	9,679,000
N Clusters	600
R-Sq	0.879
AP F-Stat	12.129

Notes: Physician HHIs are calculated by county and medical specialty from LBD data on physician firm sizes. Insurer HHIs are calculated by state from LBD data on insurer firm sales. All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) 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 100, so that a 1 unit change in HHI corresponds to a 100 point change in the typical 10,000 point scale. All standard errors clustered by state-year. * Significant at the .05 level.

Table 14: LBD: OLS and Second Stage IV Models

Dependent Variable:	ln($Price$)	
	OLS	IV1
	(1)	(2)
Physician Firm HHI	0.0002*	0.0167*
	(0.0000)	(0.0079)
Insurer HHI	–0.007*	–0.007*
	(0.002)	(0.002)
N	9,679,000	9,679,000
N Clusters	600	600
R-Sq		0.989
1st Stage AP F-Stat		12.129

Notes: Physician HHIs are calculated by county and medical specialty from LBD data on physician firm sizes. Insurer HHIs are calculated by state from LBD data on insurer firm sales. All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) effects, and facility type effects. HHI is scaled to range from 0 to 100, so that a 1 unit change in HHI corresponds to a 100 point change on the typical 10,000 point scale. All standard errors clustered by state-year. * Significant at the .05 level.

Table 15: LBD: First Stage Estimates in Metro and Non-Metro Counties

Dependent Variable:	Physician Firm-level HHI	
	Metro Counties	Non-Metro Counties
	(1)	(2)
Index Component Group 1	6.74*	1.15
	(1.56)	(2.87)
Index Component Group 2	–6.49*	3.69
	(1.77)	(3.19)
Insurer HHI	0.00002*	–0.00003*
	(0.00001)	(0.00001)
N	6,089,000	3,591,000
N Clusters	600	550
R-Sq	0.833	0.919
AP F-Stat	9.630	11.633

Notes: Physician HHIs are calculated by county and medical specialty from LBD data on physician firm sizes. Insurer HHIs are calculated by state from LBD data on insurer firm sales. 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 100, so that a 1 unit change in HHI corresponds to a 100 point change in the typical 10,000 point scale. All standard errors clustered by state-year. * Significant at the .05 level.

Table 16: LBD: Effect of Market Concentration on Prices in Metro and Non-Metro Counties

Dependent Variable:	$\ln(Price)$	
	Metro Counties	Non-Metro Counties
	(1)	(2)
Physician Firm HHI	0.0208*	0.0068
	(0.0093)	(0.0050)
Insurance HHI	–0.00001*	–0.000
	(0.00000)	(0.000)
N	6,089,000	3,591,000
N Clusters	600	550
R-Sq	0.988	0.989
1st Stage AP F-Stat	9.630	11.633

Notes: Physician HHIs are calculated by county and medical specialty from LBD data on physician firm sizes. Insurer HHIs are calculated by state from LBD data on insurer firm sales. 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 100, so that a 1 unit change in HHI corresponds to a 100 point change in the typical 10,000 point scale. All standard errors clustered by state-year. * Significant at the .05 level.

Table 17: Fixed Effects Estimates of NCA Laws on Prices within CBSAs Spanning State Borders

Dependent Variable:	$\ln(Price)_t$	
	(1)	(2)
Index Component Group 1_{t-1}	–0.119*	
	(0.011)	
Index Component Group 2_{t-1}	0.031*	
	(0.012)	
Statutory Index_{t-1}		–0.082*
		(0.013)
Protectible Interest Index_{t-1}		–0.017
		(0.021)
Consideration Index Inception_{t-1}		0.066*
		(0.016)
Consideration Index $\text{Post-Inception}_{t-1}$		–0.059*
		(0.012)
Burden of Proof Index_{t-1}		0.012
		(0.014)
Blue Pencil Index_{t-1}		–0.057*
		(0.008)
Employer Termination Index_{t-1}		–0.012
		(0.013)
N	3,469,202	2,670,952
N Clusters	428	290
R-Sq	0.827	0.822

Notes: All specifications are fixed effects models and include CBSA by year effects, procedure code (CPT) effects, physician specialty effects, and facility type effects. All standard errors clustered by state-year. * Significant at the .05 level.

Table 18: Fixed Effects Poisson Models of Establishment Sizes

Dependent Variable:	Number 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: Establishment sizes are calculated from MPIER data. All specifications are fixed effects models and include county effects, specialty, year effects, and census division by year effects. 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 19: Fixed Effects Models of Establishment Births and Deaths

Dependent Variable:	$Births_t$	$Deaths_t$	$Births_t$	$Deaths_t$	$Births_t$	$Deaths_t$
	All Counties		Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
Statutory Index$_{t-1}$	–0.606*	–0.730*	–0.994*	–1.415*	0.032	0.247*
	(0.092)	(0.124)	(0.172)	(0.236)	(0.033)	(0.037)
Protectible Interest Index$_{t-1}$	1.264*	1.204*	3.002*	2.477*	0.010	0.153*
	(0.159)	(0.177)	(0.323)	(0.352)	(0.050)	(0.053)
Burden of Proof Index$_{t-1}$	–3.683*	–3.658*	–4.600*	–4.319*	–1.716*	–1.854*
	(0.270)	(0.329)	(0.545)	(0.688)	(0.100)	(0.105)
Consideration Index Inception$_{t-1}$	3.391*	2.042*	4.462*	2.400*	0.497*	–0.372*
	(0.299)	(0.265)	(0.471)	(0.447)	(0.095)	(0.111)
Consideration Index Post-Inception$_{t-1}$	–0.849*	–0.460*	–1.592*	–0.960*	–0.143*	0.039
	(0.093)	(0.074)	(0.189)	(0.156)	(0.032)	(0.027)
Blue Pencil Index$_{t-1}$	0.286*	–0.308*	0.428*	–0.454*	0.282*	–0.065*
	(0.060)	(0.065)	(0.097)	(0.101)	(0.028)	(0.022)
Employer Termination Index$_{t-1}$	–4.679*	–4.539*	–4.017*	–3.694*	0.123	0.741*
	(0.630)	(0.780)	(0.878)	(1.058)	(0.140)	(0.173)
Number of Physicians in County$_t$	0.070*	0.123*	0.066*	0.124*	0.153*	0.037*
	(0.012)	(0.019)	(0.013)	(0.019)	(0.004)	(0.005)
N	599,975	599,975	284,898	284,898	315,077	315,077
R-Sq	0.435	0.340	0.449	0.353	0.320	0.099

Notes: All specifications are linear fixed effects models of the number of establishment births and deaths, 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 20: Fixed Effects Models of Aggregate Physician Supply

Dependent Variable: Log Count of Physicians in County, by Specialty			
	All Counties (1)	Metro Counties (2)	Non-Metro Counties (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: Physician counts by county are calculated from MPIER data. 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 21: First Stage IV Models

	Dependent Variable: Physician HHI		
	IV1	IV2	IV3
	(1)	(2)	(3)
Index Component Group 1	12.94*		
	(1.99)		
Index Component Group 2	–12.32*		
	(1.79)		
Statutory Index			–0.298
			(2.09)
Protectible Interest Index		22.43*	22.69*
		(4.77)	(4.80)
Consideration Index Inception			14.43*
			(4.42)
Consideration Index Post-Inception		–1.00*	–0.97*
		(0.30)	(0.30)
Burden of Proof Index			–14.74*
			(4.49)
Blue Pencil Index			1.40
			(3.41)
Employer Termination Index		–32.15*	–32.57*
		(5.02)	(5.17)
Insurer HHI	–0.009	0.002	0.004
	(0.008)	(0.008)	(0.009)
Constant	3.350	4.927*	4.501*
	(2.257)	(1.925)	(1.932)
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	23.769	24.328	15.365

Notes: Physician HHIs are calculated from MPIER data on physician establishment sizes. Insurer HHIs are calculated from LBD data and are based on sales at the firm level within a state. All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) 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 100, so that a 1 unit change in HHI corresponds to a 100 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 22: Second Stage IV Models

	Dependent Variable: ln($Price$)			
	OLS	IV1	IV2	IV3
	(1)	(2)	(3)	(4)
Physician HHI	0.0001*	–0.0134*	–0.0065	–0.0058
	(0.0000)	(0.0051)	(0.0035)	(0.0036)
Insurer HHI	–0.007*	–0.008*	–0.003	–0.002
	(0.002)	(0.003)	(0.003)	(0.003)
N	9,815,481	9,815,481	7,302,217	7,058,234
N Clusters	600	600	400	350
R-Sq		0.986	0.988	0.989
1st Stage AP F-Stat		23.769	24.328	15.365

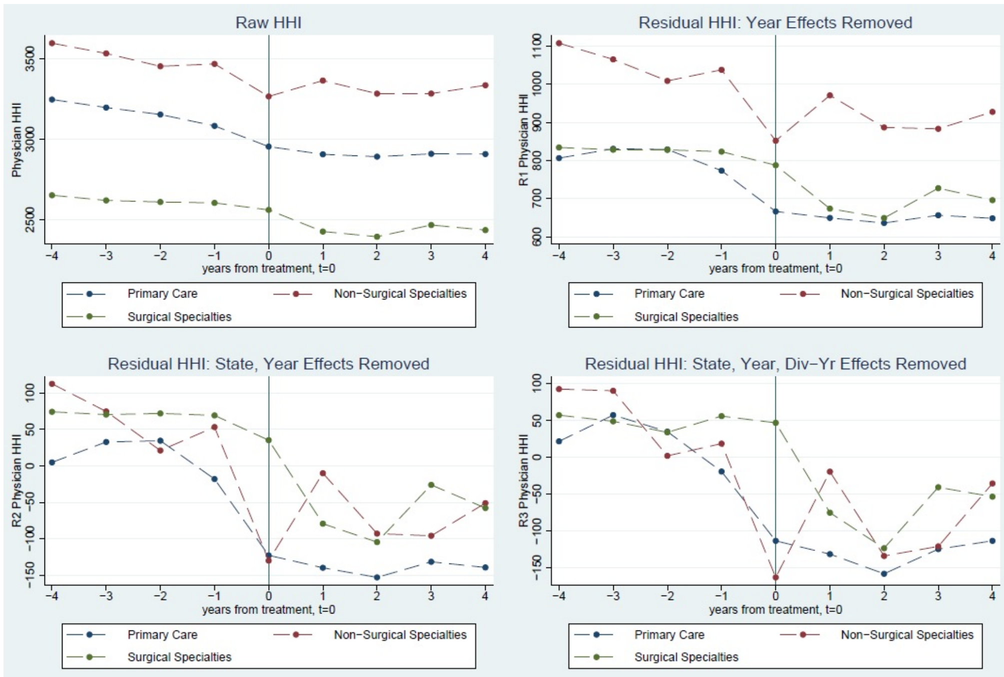
Notes: Physician HHIs are calculated from MPIER data on physician establishment sizes. Insurer HHIs are calculated from LBD data and are based on sales at the firm level within a state. All specifications are fixed effects models and include county effects, year effects, census division by year effects, procedure code (CPT) effects, and facility type effects. HHI is scaled to range from 0 to 100, so that a 1 unit change in HHI corresponds to a 100 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 23: 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

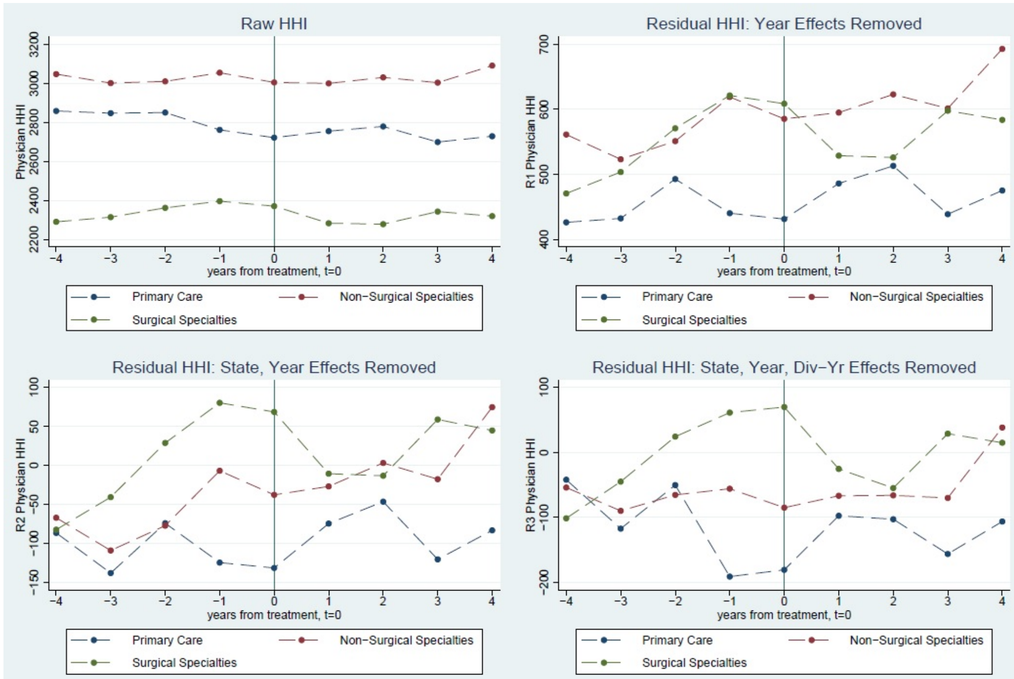
Source: Bishara (2011).

Figure 6: HHIs Before and After Increases in NCA Index 1



Notes: This figure plots HHIs by medical specialty before and after an increase in NCA Component Index 1. Law changes in all states that experience an increase in this index are synchronized to occur at time 0. The four panels show raw HHIs and HHIs with various fixed effects removed, as noted. Physician HHIs are calculated by county and medical specialty from MPIER data on physician establishment sizes.

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



Notes: This figure plots HHIs by medical specialty before and after a decline in NCA Component Index 2. Law changes in all states that experience a decline in this index are synchronized to occur at time 0. The four panels show raw HHIs and HHIs with various fixed effects removed, as noted. Physician HHIs are calculated by county and medical specialty from MPIER data on physician establishment sizes.

Table 24: First Stage IV Models

	Dependent Variable: HHI		
	(1)	(2)	(3)
Index Component Group 1	12.94*		
	(1.99)		
Index Component Group 2	–12.44*		
	(1.77)		
Statutory Index			–0.11
			(2.06)
Protectible Interest Index		22.40*	22.67*
		(4.72)	(4.77)
Consideration Index Inception			14.63*
			(4.43)
Consideration Index Post-Inception		–0.99*	–0.96*
		(0.30)	(0.30)
Burden of Proof Index			–14.94*
			(4.50)
Blue Pencil Index			1.34
			(3.35)
Employer Termination Index		–32.20*	–32.69*
		(5.01)	(5.16)
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 100, so that a 1 unit change in HHI corresponds to a 100 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 25: Second Stage IV Models

	Dependent Variable: ln($Price$)			
	(1)	(2)	(3)	(4)
HHI	0.0001*	–0.0126*	–0.0064	–0.0057
	(0.0000)	(0.0050)	(0.0036)	(0.0036)
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 100, so that a 1 unit change in HHI corresponds to a 100 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 26: Fixed Effects Poisson Models of Establishment Births and Deaths

Dependent Variable:	Births	Deaths	Births	Deaths	Births	Deaths
	All Counties		Metro Counties		Non-Metro Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
Index Component Group 1	0.996*	0.993*	0.996*	0.993*	0.996*	0.991*
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Index Component Group 2	1.006*	1.016*	1.006*	1.017*	1.007*	1.018*
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Number of Physicians in County	1.001*	1.000	1.001*	1.000*	1.049*	1.003*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)
N	1,063,152	1,031,858	488,922	476,643	574,230	555,215
R-Sq						

Notes: Estimates are incidence rate ratios from fixed effects poisson models of the number of establishment births and deaths, 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.