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ENTRY REGULATION IN HOSPITAL MARKETS: THE IMPACT OF NEED LAWS ON HOSPITAL CONCENTRATION

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Abstract:
The majority of states in the United States have Certificate of Need regulations. These regulations require state regulatory approval, before an existing provider can expand current health care services, or before new providers offer health care services. As barriers to entry, CON laws are likely to decrease the availability of healthcare providers, such as hospitals. Although previous studies suggest that CON states have fewer hospitals, the effect of CON on hospital concentration is unclear. This study examines whether hospitals in fact have a larger market share, and whether hospital services within a state with CON laws are more concentrated relative to states without Certificate of Need Laws. This study finds that CON laws are not statistically significantly correlated with an increase in HHIs.

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I. Introduction

Thirty-six states and the District of Columbia had Certificate of Need (CON) laws in 2013, with 27 of the states and the District of Columbia having CON laws covering hospitals (American Health Planning 2012). These laws prevent certain healthcare facilities from opening, expanding, or offering new services without approval of a state regulator. CON laws impose additional requirements on covered health care facilities, including hospitals, beyond the necessary state and federal safety and health certifications that are required by all states.

New York instituted the first state-level CON law in 1964. The law required the approval of a state regulator to begin construction on any new hospital or nursing home. The approval for new construction required the regulator to determine that there was a need for a new facility (National Conference of State Legislatures 2016). Within 10 years, 25 other states, including Rhode Island, Maryland, and California, adopted similar regulations requiring a determination of need by a state regulator before new facilities could open (Mitchell and Koopman 2016). In 1974, Congress passed the National Health Planning and Resources Development Act, tying federal funding to a requirement for CON laws requiring the active review of new building projects, the acquisition of major medical devices, or other large capital expenditures. By 1978, every state except Louisiana implemented a CON program (National Conference of State Legislatures 2016; Mitchell and Koopman 2016).

When the federal requirement tying funding to CON programs was repealed in 1986, several states began repealing their CON programs. By 1990, 11 states had repealed their CON programs. Wisconsin reinstated a CON program in 1993, but 3 other states (Indiana, North Dakota, and Pennsylvania) repealed their CON programs prior to 2000. In 2016, New Hampshire joined Wisconsin to become the only two states to repeal their programs after 2000, making for a total of 35 states plus DC that implement CON programs (Mitchell and Koopman 2016).

CON laws were originally adopted as cost-containment measures designed to prevent unnecessary duplication in the supply of health services. The cost containment theory is based on Roemer's law, which predicts utilization of services will increase with supply regardless of need (Weiner et al. 1998). Today, additional justifications are frequently preferred in defense of CON laws—to ensure an adequate supply of health resources, ensure rural community access to care, increase quality of care, and ensure the provision of charity care (Mitchell and Koopman 2016). CON laws require state regulatory approval, before an existing provider can expand current health care services, or before new providers offer health care services. As barriers to entry, CON laws are likely to decrease the availability of healthcare providers, such as hospitals.

CON laws presume that health policy experts can determine optimal healthcare facility placement based on need and cost factors better than hospital managers, nursing home managers, or other health care facility decision makers whose livelihoods depend on opening and maintaining care at facilities regulated by CON laws. CON laws prevent patients and families of patients from determining that a higher cost, closer care option would be a better fit for their needs. If an existing facility has an on-paper ability to care for a particular sized population, then CON programs deny an application for a new competitor, even if it would offer more up-to-date facilities or be more conveniently located for a subset of the population. The day-to-day impact of CON regulation has the potential to significantly impact the life and death of patients who may struggle to reach a hospital for cardiac care, may result in the death of infants or the separation of mothers from babies who require NICU care, and may isolate elderly patients from family by minimizing the availability of nearby nursing home care (Boehm 2017).

One way of analyzing the effect of CON laws, which I chose to examine, is how CON affects the geographic distribution of hospitals. Although previous studies suggest that CON states

have fewer hospitals, the effect of CON on hospital concentration, that is the distribution of hospitals geographically within the state, is unclear. This paper examines whether hospitals in fact have a larger market share, and whether hospital services within a state with CON laws are more concentrated relative to states without Certificate of Need Laws. This paper finds that CON laws are not statistically significantly correlated with an increase in HHIs.

II. Economic Theory and the Need for Empirical Evidence

By requiring approval to open new facilities, add equipment, and expand services, CON laws act as barriers to entry in healthcare markets. These barriers to entry are likely to favor incumbents over new entrants and may be used to stifle competition. Both U.S. antitrust agencies, the DOJ Antitrust Division (DOJ) and the Federal Trade Commission (FTC) have recognized that CON laws "create barriers to entry, and expansion, limit consumer choice, and stifle innovation" (U.S. Department of Justice 2016, 1). The Agencies have also acknowledged, "Incumbent firms seeking to thwart or delay entry or expansion by new or existing competitors may use CON laws to achieve that end" (U.S. Department of Justice 2016, 1).[1]

The absence of barriers to entry is generally regarded as a condition for perfect competition, an idealized form of competition in which numerous identical firms offering homogenous products all operate with zero economic profit. Although these conditions are rarely met in the real world, the ideal of perfect competition is often used as a ruler for determining whether markets are competitive.[2] Unsurprisingly, the economic literature on barriers to entry emerged as an

[1] See DOJ-FTC, "Joint Statement of the Federal Trade Commission and the Antitrust Division of the U.S. Department of Justice on Certificate-of-Need Laws and South Carolina House Bill 3250, January 11, 2016.
[2] The use of the Herfindahl Hirschmann Index is one such way in which firms are compared to the perfect competition ideal. A low HHI score indicates that there are numerous firms with little market power. For a critique of using the "perfect competition" model as a standard, see Friedrich A. Hayek, "The Meaning of Competition," delivered May 20, 1946, originally published in F. A. Hayek, *Individualism and Economic Order* (Chicago: University of Chicago Press, 1948), pp. 92–106, reprinted in *Econ Journal Watch* 13 no. 2 (May 2016): 359-372.

explanation of sustained profits in industries where the data did not align with the predictions of the perfect competition model (Demsetz 1987). Barriers to entry offer an explanation of why established firms can sustain higher prices—new entrants are thwarted or otherwise hampered in their ability to compete with incumbents. Where barriers to entry do not exist, i.e. where there is free entry and exit, economic theory predicts that even the threat of entry can motivate firms to price at the competitive level.[3]

An effective barrier to entry will reduce the number of actual or potential competitors. As a result, of the reduction in competition, economic theory predicts that prices will be higher in markets with barriers to entry. The question of whether CON laws serve as effective barriers to entry, that is whether CON laws effectively limit the number of new facilities and equipment as opposed to rubber-stamping new projects, is an empirical one, as are the related questions of whether CON laws reduce costs, improve quality of care, and increase the availability of charity and rural care. The variation in state implementation and repeal of CON provides a natural experiment of sorts allowing comparisons of healthcare markets in CON and non-CON states. Economists have frequently used this variation to study the impact of CON. Although some older studies examined the relationship between CON and concentration, there are few recent studies examining the effect of CON on competition, and those that exist use traditionally calculated HHIs based on patient volumes, which are likely to bias HHI measures.

As a barrier to entry, CON laws are likely to affect the number of hospitals and regulated hospital equipment and services, including beds. Studies that have examined the effect of CON on hospitals generally find that CON laws reduce the number of hospitals and or services. Santerre and Pepper (2000) found that CON laws prevent the replenishing of small hospitals. Stratmann

[3] For a summary of contestable market theory and its implications, see William Baumol, "Contestable Markets: An Uprising in the Theory of Industry Structure," *The American Economic Review* 72 no. 1 (1982):1–15.

and Koopman (2016) found that states with CON laws have fewer rural hospitals and rural ambulatory surgical centers (a hospital substitute for outpatient procedures).

Studies on CON studies frequently focus on the effect of CON on cost of services or other pricing measures. Three early studies, conducted by the FTC in the late 1980s, found that CON laws increased prices (Sherman 1988, Noether 1988, Anderson and Kass 1968). Another study in the late 1980s found that CON laws constrained hospital costs, but concentration, *ceteris paribus*, increased hospital costs (McFarland and Mayo 1989). In the late 1990s, Conover and Sloan found an association between mature CON programs and lower long-term acute care spending, but not total per capita spending (Conover and Sloan 1998). In 2000, a review of several empirical studies by Salkever (2000, 1489-90) concluded that "there is little evidence that investment controls reduced the rate of cost growth though inconsistent reports of constraining effects on numbers of beds and diffusion of some specialized services did appear." Rivers, Fottler and Younis (2007) found that CON is statistically significantly related to higher hospital costs per adjusted admission. Ho and Ku-Goto (2012) examined the effect of repealing CON on costs and reimbursements for coronary artery bypass graft (CABG) surgery and percutaneous coronary interventions. Ho and Ku-Goto found that states that dropped CON had lower costs per patient for CABG, and that average Medicare reimbursement was lower for both procedures in states dropping CON. They conclude "CON regulations for CABG may not be justified in terms of either improving quality or controlling cost growth" (Ho and Ku-Goto 2012, 185). A more recent study, Bailey (2016) found no significant difference in healthcare spending between CON and non-CON states, but his analysis suggests that CON may lead to spending increases. Another recent study by Mitchell (2016) suggests that CON does not limit healthcare price inflation, and finds little evidence to support the hypothesis that CON limits healthcare spending.

In contrast to the above findings that CON is associated with an increase in costs, studies of hospital cost-efficiencies indicate that CON laws may not be correlated with increases in cost-inefficiency measures. For instance, Rosko and Mutter (2014) found that cost-inefficiency was lower in CON states. Another similar study examined the impact of CON on technical inefficiency or X-inefficiency (using more resources than is necessary to achieve a given output) and after controlling for per capita income, hospital teaching status, and the crude mortality rate, found that CON laws are not statistically significantly correlated to an increase in X-inefficiency (Bates et al. 2006).

CON findings on price sometimes suggest that CON increases costs by decreasing competition (Rivers et al. 2007). Often studies that wish to study the impact of CON on competition use the Herfindahl Hirschman Index (HHI) to approximate concentration in the market. Although most hospital concentration studies do not directly evaluate the impact of CON laws, they often find that competition decreases costs, one of the goals of CON laws. For instance, a recent examination of healthcare costs using private insurance data estimated that "monopoly hospitals have 15.3 percent higher prices than markets with four or more hospitals" (Cooper et al. 2015, 3). Kessler and McClellan (2000) find an ambiguous effect of hospital competition in the 1980s, but find that in the 1990s, hospital competition unambiguously decreased both costs and mortality. Town and Gowrinsankaran (2003) find that increased HMO competition leads to lower hospital prices and higher hospital quality. Gaynor and Town (2011, 81) find that "most of the studies of Medicare patients show a positive impact of competition on quality."

Few studies examine the direct effect of CON on hospital concentration. One study, by Ni, Paul and Bagchi (2014), found that CON was associated with a decrease in HHI at the state

level for inpatient care. A more recent study, also by Ni, Paul, and Bagchi (2017), found a similar result for emergency services. Another notable finding in this study is that median income and population are positively correlated with competition. However, this latest study needs to be more carefully reviewed, as it states that, "CON Law could not only prevent new entrants from entering the emergency care market, but also promote competition by restricting excessive expansion" (Ni, Paul, and Bagchi 2017, 7). The restriction of new entrants and the restriction of expansion are both traditionally viewed as limiting competition.

III. An Empirical Analysis of Hospital Concentration

Because CON laws are likely to affect concentration, by lowering the number of providers, and because concentration has a direct impact on competition in healthcare markets and important effects on hospital costs, a stated goal of CON programs, understanding the direct effect of CON laws on concentration is a valuable research question that deserves further investigation.

To compare concentration in CON and non-CON states, I use a variant of a commonly used measure of market concentration—the Herfindahl-Hirschman Index (HHI). For those unfamiliar with the HHI, "the HHI is calculated by squaring the market share of each firm competing in the market and then summing the resulting numbers" (DOJ 2015). The HHI measure for a market can range anywhere from close 0 to 10,000. The higher the HHI, the more concentrated the market, i.e. there are fewer competitors with larger market shares. When 100 firms with equal market share of 1 percent occupy the market, the HHI is 100. When a monopolist controls 100 percent of the market, the HHI is 10,000.

HHIs are used in this study because calculating HHIs allows a quantitative comparison of how hospitals are distributed across different areas at a specific point in time. However, HHI

calculations have limitations and may be subject to bias. Among the many limitations of HHIs are that HHIs are highly dependent upon market definition, which may lead to biased HHIs.

For the purposes of this study, I consider implementation of the HHI a helpful, but not definitive, tool in understanding the impact of CON laws on the distribution of hospitals. HHIs only approximate the concentration of hospitals, but they do not indicate on what margins and with what methods hospitals compete. HHIs do not indicate how hospitals decide to invest in quality improvement, how they advertise to attract patients, or any other "on the merits" measure of hospital action to outdo a rival. HHIs are only a snapshot of which hospitals attracted which patients at a defined point in time. The HHI measures calculated in this study provide only a snapshot of market concentration in 2013. Although I am able to compare my measures to Kessler and McClellan (2000), my measures only capture one aspect of change over time and do not granularly examine change in response to changes in state CON administration or changes in national healthcare laws. Additionally, my HHI measures do not consider competition from hospital substitutes, such as ambulatory surgical centers.

To minimize bias in the HHI measures, I implement a methodology developed by Kessler and McClellan. I use a patient choice model to calculate the probability of a patient using any hospital within a defined geographic area[4] based on the patient's distance to the hospital in question relative to the hospital they chose (differential distance) and the teaching status of the hospital. I estimate this model separately for 12 different regions to control for likely differences in traveling preferences by geographic area. Using this model, I predict the proportion of patients from each county going to each nearby hospital. I use these predictions to create an HHI for each

[4] Any hospital within a 35 mile radius of the patient, and any teaching hospital within a 100 mile radius was included as an option for each patient. Teaching hospitals are generally regarded as higher quality and patients could be willing to travel further to receive care at these institutions.

hospital by county, then weighted the HHI based on all the counties the hospital served. For a more detailed description of my methodology, see Appendix A.

After obtaining this final HHI calculation for each county, I use regression analysis to determine whether these HHI measures are higher in CON or non-CON states using an indicator variable equal to 1 if the patient county is located in a CON state, and zero otherwise.

$$HHI_k = \alpha_0 + \beta_1 CON_k + \varepsilon_k$$

Because HHIs decrease as the number of competitors increases, and increase as inequality in size differences between competitors increase, I expect that the coefficient on CON, β_1, will be positive, indicating that a CON law is correlated with an increase in concentration.

a. Data

The patient choice model from which the HHI calculations are derived are estimated for the choice of hospital for patients diagnosed with a heart attack, medically referred to as an acute myocardial infarction (AMI). The age of these patients allows for the use of Medicare data.

Data for this analysis comes from these sources: the Medicare Limited Data Set for 2013, the December 2013 CMS Provider of Service file, the 2013 U.S. Census National Counties Gazetteer File, the CMS 2013 Crosswalk file[6], the U.S. Census Bureau's County Characteristics Resident Population Estimates,[7] the U.S. Census Bureau's Small Area Income and Poverty Estimates for 2013,[8] and the USDA's Economic Research Service Educational attainment for the U.S., States, and Counties, 1970-2015.[9] The Medicare Limited Dataset for 2013, which I used for this study, contained a 5 percent random sample of all Medicare claims for 2013. I limited the sample to include non-rural elderly Medicare beneficiaries treated for an initial primary diagnosis of AMI in 2013. A detailed discussion of exclusion criteria and limitations as a result of this criteria can be found in Appendix B.

Due to the restrictiveness of the original criteria, and as an additional measure to understand the importance and impact on certain exclusion criteria, I created an alternate Dataset B from the same base data set using relaxed criteria. Dataset B includes all Medicare beneficiaries, including non-elderly beneficiaries, treated for any incidence of AMI (initial, subsequent, and episode of care unspecified) at a non-rural, general medical hospital serving at least 3 new AMI patients. Patients with multiple admissions/entries for any AMI were dropped. This dataset also includes beneficiaries living in rural counties within a 100 mile radius of the urban facility of care to which they were admitted. Tables providing an overview of the exclusion restrictions can be found in Appendix B.

b. Understanding Potential Weaknesses in Measurement of Hospital Concentration

The primary limitation in using Medicare data on AMIs to calculate HHIs is a dependence on the assumption that private pay patients will behave in much the same way as Medicare patients. It is possible that for different patient health conditions and insurance coverage, patients may choose differently. Thus, my estimations of hospital concentration may not reflect how hospitals compete for wealthier patients treated for AMI. Additionally, preferences for non-emergency or elective procedures may be different than those for AMI treatment, and hospitals may compete in different ways for those procedures. Without access to comprehensive private payer data, it was not possible for me to address these concerns. As such, there is a need for humility in interpreting the results of this study. CON laws may have different effects on different types of hospital services that are unable to be captured by the metrics used in this study.

An additional data limitation that I faced, due to differences in data availability and access, was that while Kessler and McClellan (2000) were able to use zip code level residential data for each Medicare beneficiary, my dataset only provided county-level residential information for

beneficiaries. Unfortunately, the average size difference between county land area and zip code land area are not available. This is in part due to the fact that zip codes are based on mail routes rather than defined geographic areas (U.S Census Bureau n.d.) To understand the impact of the larger unit used in our analysis, the following section provides a hypothetical example to help the reader understand the analysis.

Figure 1 depicts a hypothetical County A with four evenly divided zip codes. Within County A there are 2 hospitals, hospitals A and B. Suppose that Hospital A is situated just west of the county center, and lies on the border between the northwest and southwest zip codes. Suppose that Hospital B is located in the southeastern most corner of the County A. In a zip code level analysis, such as in Kessler and McClellan (2000), hospital A will likely evenly draw patients from all four surrounding zip codes, while hospital B will likely only attract patients from zip codes 2 and 4 of County A. A county level analysis, however, will not be able to distinguish between patients in zip code 1 from 4, and will therefore treat hospital B as equally close to all patients within County A, despite the fact that hospital B is not situated in the center of the county. As a result, the HHI estimation for Hospital A will be lower in a county level analysis compared to the zip code level of analysis. Depending on the prevalence of similar situations throughout the US, our analysis at the zip code level may underestimate the market share for some hospitals (those like A), but overestimate shares for hospitals like B.

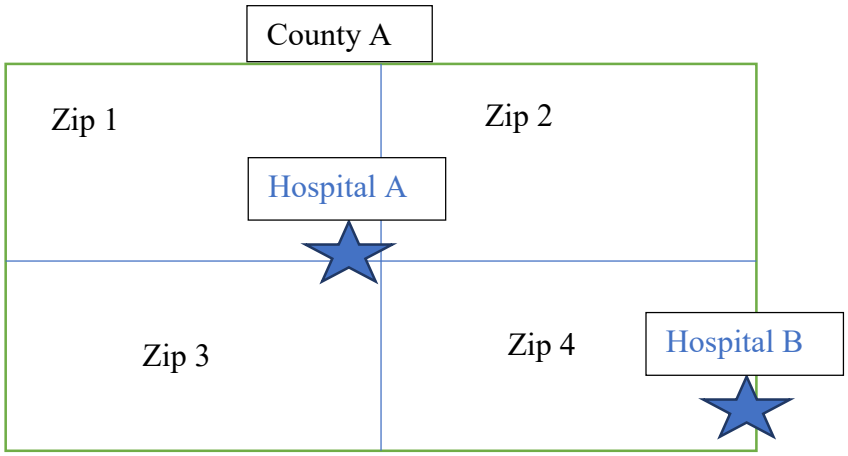

Figure 1.

IV. Results

Table 4 (see Appendix B) shows the summary statistics for the hospital markets. There are a total of 607 county-level HHIs in our final dataset A and 1,389 county-level HHIs in Dataset B. In both datasets, beneficiaries were, on average, admitted to hospitals that were further away than their nearest hospital, indicating that distance is not the sole criteria for choosing a hospital. Patients chose hospitals that were not the closest to their residences.

Beneficiaries in Dataset A were, on average, located closer to hospitals and were admitted to hospitals that were closer to their county of residence than beneficiaries in Dataset B. This result is unsurprising, as Dataset B includes beneficiaries from rural counties that were within a 50 mile radius of the non-teaching hospital to which they were admitted or within 100 miles of the teaching hospital to which they were admitted. The increase in county observations for Dataset B therefore comes from the rural counties on the fringe of urban areas.

Compared to the zip-code level HHIs of Kessler and McClellan (2000), these county level HHIs are much higher, 0.593 compared to 0.369 for 1994. These county-level HHIs should underestimate concentration compared to Kessler and McClellan for hospitals similar to hospital A, but overestimate HHI for hospitals similar to hospital B, so this difference is not sufficiently

explained by the difference in methodology, since the errors should average out. The significantly higher HHI I find can be explained by 2 trends documented by Cutler and Morton (2013): a declining use of hospitals and a significant trend towards hospital consolidation. Cutler and Morton (2013, 1965) find that between 1981 and 2011, "hospital days declined by 33 percent despite a growing and aging population. Coincident with the decline in use, more than 15 percent of hospitals closed." Although this timeframe includes the time periods covered by Kessler and McClellan (2000), it extends past over a decade and a half beyond Kessler and McClellan (2000)'s last HHI calculations. Hospital closures can account for the increase in the HHIs as calculated in this model. In addition to hospital closures, hospital mergers have increased consolidation in the industry. "From 2007 to 2012, 432 hospital merger and acquisition deals were announced, involving 835 hospitals" (Cutler and Morton 2013, 1965). Analyzing hospital market HHIs by hospital referral region (HRR), they find that "hospital HHI has increased by 40 percent since the mid-1980's, changing from a market with on average 5 independent firms (there were greater than 5 independent hospitals, but approximately 5 major ones) to a market with approximately 3 independent firms" (Cutler and Morton 2013, 1966). These hospital mergers, all of which happen long after Kessler and McClellan's data are likely to explain the bulk of the HHI increases from their calculations to the one in this paper. The drive towards consolidation, with fewer independent firms, is consistent with the finding of a significantly higher HHI than those from Kessler and McClellan.

Table 5 (see Appendix B) shows the regression results obtained from the analysis. I find that in 2013, CON laws are not statistically significantly associated with hospital concentration. I observe that the coefficient on CON is positive in Dataset A, but is negative in Dataset B. In none

of the regressions is CON statistically significant. This result suggests that, contrary to my prediction, CON is not a determining factor in hospital concentration in 2013.

The regression results suggest a plausible reason for this finding. In the regressions, median income, total population, and educational markers are statistically significant. This finding suggests that hospital markets are more likely to be determined by market indicators that signal to hospitals that an area is likely to offer an attractive business opportunity for hospitals. Insofar as this result holds, CON programs are duplicating a market mechanism for determining hospital distribution across counties. If CON programs were in fact affecting the distribution of markets, then CON would have a statistically significant impact on hospital concentration. The lack of effect from CON indicates that CON is not particularly influential in affecting hospital distribution.

If CON is not affecting distribution, then CON programs for hospitals are needlessly wasting state resources reviewing hospital proposals for entry and expansion. Since CON programs are not observably decreasing the concentration of hospitals in the urban areas analyzed in this study, CON programs are presumably rubber-stamping projects for which there is actual market need. If the key determinants of hospital concentration are population, income, and education measures, and hospital markets are not markedly different in non-CON states, then CON laws are not limiting hospital location choices, market determinants are. Contrary to original arguments that hospitals and other medical institutions would engage in a medical arms race that would result in the needless duplication of medical resources, these results suggest that hospitals respond to market incentives and are more likely to proliferate in areas where there is a larger patient pool, and those patients are likely to be able to pay, as measured by county median income.

One additional reason that CON laws may not significantly be affecting concentration is that the trend towards hospital consolidation may be driven in part by changes to national

healthcare law that equally affect all states, namely the 2010 Patient Protection and Affordable Care Act (ACA). Two features of the ACA encourage hospital consolidation—the promotion of Accountable Care Organizations and the bundling of payments (Gaynor and Town 2012). If the ACA is driving the consolidation and high HHIs seen in my data, it is unsurprising that I do not see a difference in consolidation between CON and non-CON states.

Ni, Paul, and Bagchi's (2014) finding that CON decreases concentration for inpatient care is intriguing, but unsubstantiated by my own calculations, since I find no statistically significant difference between concentration in CON and non-CON states. The difference in our findings is likely due to the differences in calculating HHI measures. Where HHI measures are calculated based on inpatient volume data, the data Ni, Paul, and Bagchi use, HHI measures are likely to incorporate outcomes of the competitive process into the HHI calculation (see Appendix A for futher discussion).

It is important to recognize the limitations of my findings. First, my data only evaluates Medicare patients, whom hospitals may be less eager to compete for than private patients. Because heart attack patients are likely to be elderly patients covered by Medicare, hospitals may invest less in equipment and experience that would make them more likely to attract this set of patients. In a recent study, Paul, Quosigk, and MacDonald (2017) found that in not-for-profit hospitals, a higher percentage of Medicare patients was negatively correlated with competitiveness (Medicare patients were associated with a higher HHI). Since I do not have data on the share of Medicare patients at each hospital, I am unable to control for this factor in my analysis. If it is the case that hospitals differentiate investment by payors, and invest less in treatment that is likely to be covered by Medicare, such as AMI treatment, then my HHI measures likely overestimate concentration in hospital markets. My measures may not accurately reflect hospital competition for more elective

services or treatments likely to be covered by private health insurers. Future work which estimates HHIs based on more elective treatments, or based on a representative basket of hospital services, using private and public insurer data would offer increased insight into whether CON affects different services differently.

Second, my analysis is limited to understanding the effect of CON on the concentration of urban hospital providers. My analysis does not simultaneously address cost nor does my analysis does consider the impact of CON laws on rural health care provision.

Third, my findings are limited by my inability to compare HHIs in multiple years. If I were to compare HHIs in multiple years, I might be able to find a trend in the data over time, potentially analyzing years just prior to the adoption of the ACA, or observe the results of state repeal of CON. This analysis can be extended to multiple years to determine whether there are differences between HHI trends in CON and non-CON states. Another opportunity for further work is to follow Kessler and McClellan (2000) in analyzing the impact of concentration in the following year's hospital spending.

V. Conclusion

Based on these findings, I cannot conclude that CON laws are significantly affecting hospital concentration. In my analysis the control measures of median income, total population, and education are better predictors of hospital competition than a CON law. One likely reason for this is that income, population, and education are reliable indicators for a patient pool that has the ability to pay for hospital services. If CON laws are not significantly affecting concentration, then they may be requiring states to needlessly spend money on administering a program that is not providing any public benefit. Without a demonstrable benefit from CON laws, states should

reconsider expending state resources on agencies or programs such as this one that duplicate market mechanisms, and divert valuable funds from potentially more productive uses.

States have a responsibility to incorporate humility in the development and administration of their laws. After programs have been introduced and implemented, states should assess the opportunity cost of continuing to continue to allocate resources to these programs. States should consider humbly admitting that CON laws are not meaningfully affecting concentration, and consider eliminating their CON programs where clear benefits are not produced, to allow either tax payers to keep more of their money or to fund other, more effective programs.

As frustrating as a statistically insignificant result is after the hard work of data analysis, the lack of significance of these findings reinforces the need for humility in healthcare policy making. When only studies with statistically significant results are published, methods which identify these results but are otherwise biased (such as those using simpler HHI measures, see appendix A) will bias the overall findings on the effects of healthcare policies such as CON laws, suggesting via flawed methodology that CON laws are unequivocally helpful or harmful. By contrast, my findings indicate that CON laws may be duplicating a market mechanism limiting the growth of hospitals. Alternatively, some other law or market condition, such as the implementation of the ACA, may be acting as the effective limit on hospital concentration. Eliminating CON laws as the determinant of hospital concentration and potentially competition is an important step in identifying the healthcare policies that hamper innovation and improvement of hospitals.

While these further research areas can more fully develop an understanding of CON laws, there will always be limitations on quantifying the effects of CON policy, or indeed any similar policy. Rivalrous competition is not fully quantifiable. However, the infeasibility of a full measure should not paralyze policy makers from making the best determination possible with available

information and knowledge. While the seen effects of CON laws may be duplicative services, the unseen effects of CON laws may be more costly. It is impossible to know how CON might limit innovation in service provision or care.

Ending CON programs would reintroduce a needed dose of humility in healthcare policy. Contrary to the belief that ending CON programs would result in an unsustainable expansion of healthcare facilities and services, I found that the distribution of hospitals is similar in both CON and non-CON states. This indicates that the centralized decision-making process of CON is not necessarily revealing important new information that requires limiting the provision of certain healthcare facilities and services. Rather, the decentralized decision-making of individuals whose livelihoods depend on these decisions results in similar service and facility numbers without the cost of administering a state review program.

Appendix A: Methodology

This study uses Kessler and McClellan (2000)'s methodology to calculate an HHI measure for each urban county. Although other studies, most recently Ni, Paul, and Bagchi (2014) have analyzed the relationship between CON and hospital concentration based on normalized HHIs using inpatient volume data by state, these HHI measures are likely to be biased, as explained below.

Calculating the HHI requires clearly defining a market and allotting shares proportionally between all firms deemed to compete within the market. For hospital markets, traditional HHI measures are typically based on patient volume or bed count data within defined geographic areas. Because many of these measures incorporate endogenously determined variations in data, researchers using traditional HHI measures may incorporate bias into their HHI calculations. Although it is impossible to eliminate all sources of bias, this study relies on Kessler and McClellan's method to reduce the bias incorporated into HHI measures:

> Kessler and McClellan identify four sources of bias in conventional share measures. First, the specification of geographic market size as a function of actual patient choices leads to market sizes and measures of competitiveness that are increasing in unobservable (to the researcher) hospital quality, if patients are willing to travel farther for higher-quality care (e.g., Luft et al. [1990]). In this case, estimates of the effect of market competitiveness on costs or outcomes are a combination of the true effect and of the effects of unobservable hospital quality (e.g., Werden [1989]). Second, the discrete nature of market boundaries assume that hospitals are either completely in or completely out of any relevant geographic market. This leads to measurement error in geographic markets, which in turn biases the estimated effect of competition toward zero. Third, the measures of output conventionally used to construct indices of competitiveness like the HHI-such as hospital bed capacities and actual patient flows-may themselves be outcomes of the competitive process. Fourth, assigning hospital market competitiveness to patients based on which hospital they actually attended-rather than their area of residence-can induce a correlation between competitiveness and unobservable determinants of patients' costs and outcomes, because patients' hospital of admission may depend on unobserved determinants of their health status. (Kessler and Mclellan 2000, 582–83)

While Kessler and McClellan (2000)'s third critique is most applicable to Ni, Paul, and Bagchi (2014)'s research, all of the sources of bias which they identify are likely to affect the accuracy of their HHI measures. In an effort to avoid these sources of bias, Kessler and McClellan developed their own HHI measures based on predicted, rather than actual patient flows. This study follows their method, described below, for calculating HHI using Medicare data on elderly patient admissions for an initial episode of AMI.

First, I estimate a patient level choice model based on exogenous (to patients) determinants for all hospitals. I allow a patient to choose from any non-teaching hospital within a 35 mile radius of the patient's county and any teaching hospital within a 100 mile radius if the hospital admitted at least 5 initial AMI cases for elderly patients within 2013. Using Stata's xtlogit command, I predict patient choice based on the differential distance between the potential hospital provider and the patient's chosen provider and the hospital's teaching status (*T*). I follow Kessler and McClellan (2000) in incorporating differential distance (*DD*)[5] in the model based on McClellan's intuitive 1994 finding that the distance between a patient's residence and different types of hospitals are a strong predictor of hospital admission. However, in incorporating differential distance into the model, I differ from Kessler and McClellan (2000) by using the precise differential distance, rather than a quartile indicator. The increased variation from using precise differential distance increased the accuracy of the choice model, making precise specification preferable. I also deviate from Kessler and McClellan (2000) in using a simplified choice model that does not include the hospital's ownership status or the bed count. I also only estimate patient

[5] As differential distance increases, patients should be less likely to choose the potential provider. For example, if the potential provider is 30 miles from the patient, but the patient's chosen provider is 5 miles away, the differential distance would be 25. However, if the patient's chosen provider is also 30 miles away, the patient should value the two hospitals more similarly.

choice for patients who have multiple providers within the defined radius. As such, a patient *i*'s indirect utility function from choosing hospital *j* is:

$$Y_{ij}=(DD_{ij}, T_j) + \epsilon_{ij}$$

It may be the case that patients in Montana are likely willing to travel further than patients in Connecticut. To account for likely differences between regions, I estimated this model separately for twelve different regions. Each region includes only CON or non-CON states.[6]

Next, I use the predicted probabilities of admission to calculate the likelihood for each patient to go to every hospital within the 35/100 mile radius. For every county of patient residence k = 1, …, K, the predicted probabilities are translated into a predicted share $\hat{\alpha}_{jk}$ of patients from each county k going to hospital j:

$$\hat{\alpha}_{jk} = \frac{\Sigma_i \; living \; in \; k \; \hat{\pi}_{ij}}{\Sigma_{j=1}^{J} \Sigma_i \; living \; in \; k \; \hat{\pi}_{ij}}$$

If hospitals face separate demand functions based on a patient's county of residence, then the predicted HHI for patients in county k is:

$$HHI_k^{pat} = \sum_{j=1}^{J} \hat{\alpha}_{jk}^2$$

As Kessler and McClellan (2000) explain, this measure improves upon traditional HHI calculations for hospital markets in the following ways:

[6] The regions are: 1) Alaska, Hawaii, Washington, Arizona, and Nevada (CON); 2) California and Oregon (non-CON); 3) Colorado, Idaho, Kansas, Minnesota, Montana, Nebraska, North Dakota, South Dakota, Utah, Wisconsin, Wyoming (non-CON); 4) Illinois, Iowa, Michigan, and Missouri (CON); 5) Arkansas, Louisiana, New Mexico, Oklahoma, Texas (non-CON); 6) Alabama, Florida, Georgia, Mississippi, South Carolina (CON); 7) Delaware, DC, Kentucky, Maryland, North Carolina, Tennessee, Virginia, West Virginia (CON); 8) Indiana, Ohio, and Pennsylvania (non-CON); 9) Massachusetts (non-CON); 10) Maine, New Hampshire and Vermont (CON); 11) Connecticut, New Jersey, New York, and Rhode Island except CBSA 35644 (NY-White Plains-Wayne CBSA NY-NJ) (CON); 12) NY White Plains-Wayne CBSA 35644 (CON).

> First, it uses expected patient shares based on exogenous determinants of patient flows, rather than potentially endogenous measures such as bed capacity or actual patient flows. Second, it assigns patients to hospital markets based on an exogenous variable (zip code of residence), rather than an endogenous one (actual hospital of admission). Third, it defines geographic markets to include all potentially competitive hospitals, but only to the extent that they would be expected to serve a geographic area, rather than defining geographic markets to include arbitrarily all hospitals located within a fixed distance or within the minimum distance necessary to account for a fixed share of admissions (Kessler and McClellan 2000).

Although this measure improves upon traditional HHI calculations, it estimates demand for each separate county. More realistically, hospitals would estimate total demand for all counties served. As such, the HHI for hospital *j* is more accurately the weighted average of the HHIs for all patient counties, *k*, whom it serves. Where β_{kj} represents the share of a hospital's predicted demand coming from county *k*, then the hospital's HHI is:

$$HHI_j^{hosp} = \sum_{k=1}^{K} \hat{\beta}_{kj} \cdot (\sum_{j=1}^{J} \hat{\alpha}_{jk}^2) = \sum_{k=1}^{K} \hat{\beta}_{kj} \cdot HHI_k^{pat}$$

Where:

$$\hat{\beta}_{kj} = \frac{\Sigma_i \; living \; in \; k \; \hat{\pi}_{ij}}{\sum_{i=1}^{N} \hat{\pi}_{ij}}$$

To incorporate this more accurate measure of hospital HHI into a patient county level HHI, the hospital's HHI measure is weighted according to the hospital's expected share of patients for that county.

$$HHI_k^{pat*} = \sum_{j=1}^{J} \hat{\alpha}_{jk} \cdot \left[\sum_{k=1}^{K} \hat{\beta}_{kj} \cdot \left(\sum_{j=1}^{J} \hat{\alpha}_{jk}^2 \right) \right] = \sum_{j=1}^{J} \hat{\alpha}_{jk} \cdot HHI_j^{hosp}$$

Although I use Kessler and McClellan's methodology to minimize bias in the HHI calculations, it is possible that the HHI measures used here are still biased. My measures are based only on concentration in treatment for initial AMI. HHI calculations based on concentration measures for different hospital procedures or a mixed basket of procedures could yield different

results and could potentially better represent the market served by a hospital. Also, the dataset used in this study comes from Medicare patients. If hospitals compete for Medicare patients differently than for privately insured patients, then the dataset could bias the HHI calculations.

Appendix B

Data for this analysis comes from these sources: the Medicare Limited Data Set for 2013, the December 2013 CMS Provider of Service file, the 2013 U.S. Census National Counties Gazetteer File, the CMS 2013 Crosswalk file[7], the U.S. Census Bureau's County Characteristics Resident Population Estimates,[8] the U.S. Census Bureau's Small Area Income and Poverty Estimates for 2013,[9] and the USDA's Economic Research Service Educational attainment for the U.S., States, and Counties, 1970-2015.[10]

The Medicare Limited Dataset for 2013, which I used for this study, contained a 5 percent random sample of all Medicare claims for 2013. I limited the sample to include non-rural elderly Medicare beneficiaries treated for an initial primary diagnosis of AMI in 2013. My sample is intended to be comparable to that of Kessler and McClellan (2000), but differs in a few significant ways due to data limitations. First, my data is a 5 percent random sample of beneficiaries rather than a comprehensive, longitudinal dataset (Kessler and McClellan 2000). Although the random sample should accurately reflect the larger population, without comprehensive data and access to a longitudinal dataset, I was unable to eliminate beneficiaries treated in the prior year for an AMI. Second, beneficiary location information in Kessler and McClellan (2000) is available at the zip code level, but in my sample, the data only provides the beneficiaries' county of residence. Third,

[7] See "CMS' SSA to FIPS State and County Crosswalk," 2013, NBER, http://www.nber.org/data/ssa-fips-state-county-crosswalk.html.
[8] See United States Census Bureau, "County Population by Characteristics Datasets: 2010-2015," County Characteristics Datasets: Annual County Resident Population Estimates by Age, Sex, Race, and Hispanic Origin: April 1, 2010 to July 1, (estimates for 2013 coded as year 6), released June 2016, at https://www.census.gov/data/datasets/2015/demo/popest/counties-detail.html.
[9] See U.S. Census Bureau, Small Area Income and Poverty Estimates, State and County Estimates for 2013, https://www.census.gov/did/www/saipe/data/statecounty/data/2013.html.
[10] See United States Department of Agriculture, Economic Research Service, "County-level Data Sets," Education, https://www.ers.usda.gov/data-products/county-level-data-sets/.

I do not extend the analysis to Medicare spending for years following AMI hospitalizations, also due to lack of data.[11]

Additionally, although I do not believe that the following differences are the driving source of the differential findings, my data sources differ from those used by Kessler and McClellan (2000) based on differences in data availability. Whereas Kessler and McClellan (2000) use hospital characteristic information from the American Hospital Association, I use the Provider of Service data collected directly by the CMS.

Information on hospital teaching status, state and county location information (SSA codes), and provider urban indicators comes from the CMS Provider of Service File for December 2013. Consistent with Kessler and McClellan (2000), I classify hospitals as teaching hospitals if they report at least 20 full-time residents. A location identifier for each hospital was generated by fully concatenating the 2-digit SSA state code and 3-digit SSA county code. The Provider of Service file includes an urban-rural indicator for each provider. All rural providers were dropped from this study. Medicare-approved hospital providers have a unique 6-digit identification number. Providers with an E or F instead of a number as the last character are non-participating hospitals that have been designated as emergency providers.[12] These hospitals were not included in the study as eligible providers.

The CMS Crosswalk File for 2013 provided urban-rural classification information for beneficiaries. The crosswalk file identifies the CBSA (core based statistical area) for each matched SSA and FIPS fully concatenated state-county code. Rural counties have no CBSA listed. Any beneficiary with a location identifier lacking a CBSA identification was considered rural and

[11] For a description of Kessler and McClellan's data sources and methodology, see Kessler and McClellan, 584-600.
[12] See http://www.nber.org/data/provider-of-services.html, accessed Jan. 6, 2017; see also CMS Manual System, Pub 100-07 State Operations Provider Certification (Oct. 12, 2007), Transmittal 29, at https://www.cms.gov/Regulations-and-Guidance/Guidance/Transmittals/downloads/R29SOMA.pdf

dropped from this study for the main dataset. In the alternate dataset, rural beneficiaries who were admitted to an urban hospital within a 100 mile radius were included.

Coordinates for the center of each county come from the U.S. Census National Counties Gazetteer File (2013). Because the coordinates are given for each FIPS county but CMS information on provider and beneficiary location uses SSA state and county codes, I used the CMS's 2013 crosswalk file to link the FIPS coordinates to the unique five-digit SSA state-county identifiers.

Travel distances for each beneficiary to nearby hospitals was calculated from the center of each beneficiary's county to the center of the county where the provider was located. This method is comparable to the method used by Kessler and McClellan (2000), which used the center of the beneficiary's zip-code to the center of the provider's zip-code.[13] However, it should be noted that my method is less precise due to the increase in average size of the area identifiers. Distances in this study were calculated using the geodist and geonear Stata applications developed by Robert Picard. By default, the geodist application uses the Vincenty (1975) formula for calculating distance.[14] Ellipsoidal distances were specified in the geonear application to ensure the calculation of comparable distances.[15]

For control variables in the final regression, I use population and income estimates from the U.S. Census Bureau's County Characteristics Resident Population Estimates (Vintage 2015)[16]

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[13] Based on Kessler and McClellan's description p. 586 n 3, the methodology in this chapter replicates theirs. However, Kessler and McClellan do not specify the program or methodology used to calculate the distance from zip code to zip code center, nor do they specify how the zip code centers were selected, since zip codes do not define geographic areas.

[14] Robert Picard, GEODIST: Stata module to compute geodetic distances, https://ideas.repec.org/c/boc/bocode/s457147.html.

[15] The geonear application uses spherical distances by default to improve run-time. Robert Picard, GEONEAR: Stata module to find nearest neighbors using geodetic distances, https://ideas.repec.org/c/boc/bocode/s457146.html.

[16] U.S. Census Bureau, County Characteristics Datasets:2010-2015, available at https://www.census.gov/data/datasets/2015/demo/popest/counties-detail.html. As of March 31, 2017, Vintage 2016 racial demographics were not available.

and Small Area Income and Poverty Estimates, respectively.[17] Education estimates for 2013 by county came from the USDA's Economic Research Service Educational attainment for the U.S., States, and Counties, 1970-2015.[18]

Exclusion Criteria

Claims for non-elderly beneficiaries were excluded first, followed by claims with any beneficiaries or providers with addresses outside the 50 states and the District of Columbia. Following these exclusions, beneficiaries and providers without complete CMS and location information were excluded. Next, claims for beneficiaries treated by providers treating fewer than 5 initial AMI cases were eliminated. Lastly, claims for beneficiaries living outside a 35 mile radius of a non-teaching hospital and 100 miles of a teaching hospital were excluded.

Due to the restrictiveness of the original criteria, and as an additional measure to understand the importance and impact on certain exclusion criteria, I created an alternate Dataset B from the same base data set using relaxed criteria. Dataset B includes all Medicare beneficiaries, including non-elderly beneficiaries, treated for any incidence of AMI (initial, subsequent, and episode of care unspecified) at a non-rural, general medical hospital serving at least 3 new AMI patients. Patients with multiple admissions/entries for any AMI were dropped. This dataset also includes beneficiaries living in rural counties within a 100 mile radius of the urban facility of care to which they were admitted.

[17] U.S. Census Bureau, Population Division, File 7/1/2015, County Population Estimates, released March 2016 and https://www.census.gov/did/www/saipe/data/statecounty/data/2013.html.
[18] United States Department of Agriculture, Economic Research Service, "County-level Data Sets," Education, https://www.ers.usda.gov/data-products/county-level-data-sets/.

Table 1 provides an overview of the exclusion restrictions imposed by the data requirements for each dataset. Tables 2 and 3 describe beneficiaries and hospital providers who meet the exclusion criteria.

Table 1. Data Restrictions and Number of Observations Meeting Selection Conditions

	Observations	
	Dataset A	**Dataset B**
Provider and beneficiary address in the US	580,112	580,112
Elderly	449,658	--
Beneficiary address is urban	347,258	--
With a single, primary diagnosis code of AMI, initial episode of care[19]	6,747	10,654 (includes unspecified episodes of care)
Treated at a non-rural, non-federal, ever general medical hospital	6,613	9,323
With valid CMS Provider of Service and CMS Crosswalk 2013 information	6,611	9,320
Treatment provided by a hospital provider serving at least 5 new AMI patients	4,321	8,516 (at least 3 AMI)
The beneficiary lived within the 35/100 mile radius of the hospital	3,936	7,426 (within 50/100 radius)
Number of providers	543	1,115

[19] Beneficiaries with ICD-9 codes for subsequent or unidentified episodes of care were excluded. ICD-9 codes included are: 41011, 41021, 41031, 41041, 41051, 41061. 41071, 41081, 41091. For a complete list of ICD-9 codes for AMI for 2013, see http://www.icd9data.com/2013/Volume1/390-459/410-414/410/default.htm.

Table 2. Descriptive Statistics for Beneficiaries

	Dataset A			Dataset B		
	All	**CON States**	**Non-CON States**	**All**	**CON States**	**Non-CON States**
Below 65	--	--	--	13.6%	13.3%	14.0%
Age 65-69	20.6%	19.9%	21.7%	18.8%	18.5%	19.1%
Age 70-75	19.1%	19.1%	19.2%	16.6%	16.6%	16.7%
Age 75-79	17.8%	17.2%	18.6%	15.4%	14.9%	16.0%
Age 80-84	17.7%	17.9%	17.5%	14.8%	15.1%	14.3%
Age 84 and above	24.7%	25.9%	23.0%	20.9%	21.6%	19.9%
Black	8.7%	11.1%	5.0%	10.6%	13.0%	7.5%
Female	45.9%	47.4%	43.6%	44.2%	44.7%	43.5%

Table 3. Descriptive Statistics for Hospitals/Providers Matching Selection Criteria

	Dataset A			Dataset B		
	All	**CON States**	**Non-CON states**	**All**	**CON states**	**Non-CON states**
Certified Bed Count	467.88	487.76	439.99	410.13	422.411	369.75
Teaching	32.2%	34.4%	29.2%	26.5%	28.9%	23.8%

Table 4. Descriptive Statistics for Hospital Markets

	Dataset A (original)			Dataset B (less restrictive)		
	All Observations	CON states	Non-CON States	All Observations	CON states	Non-CON States
Mean Distance to Nearest Hospital (miles)	3.48	3.24	3.86	6.98	7.27	6.58
Median Distance to Nearest Hospital (miles)	0	0	0	0	0	0
Mean Distance to Hospital of Admission (miles)	6.55	6.49	6.631	11.20	11.70	10.52
Median Distance to Hospital of Admission (miles)	0	0	0	0	0	0
County-level HHI	.593	.597	.588	.423	.427	.417
Number of Counties	607	361	246	1,389	811	578
County Median Income	54,616.76	54,956.27	54,118.53	49,065.75	48,246.9	50,214.68
County Total Population	380,722	313357.7	479,577.7	205,911	172,746.1	252,445.4
County Black Population	11.7%	14.9%	7.0%	11.5%	14.7%	7.0%
County Hispanic Population	10.9%	8.1%	14.9%	8.8%	6.3%	12.3%
County Population with High School Diploma only (2015)	30.0%	29.8%	30.1%	33.3%	33.2%	33.4%
County Population with a Bachelor's Degree or above (2015)	27.7%	28.2%	27.1%	22.9%	22.9%	23.0%

Table 5. Regression Results-Effects of CON laws on Hospital Market Concentration

	Dataset A			Dataset B		
	1	2	3	4	5	6
CON on Hospitals	0.009	0.006	0.018	0.009	-0.011	-0.000
	(0.04)	(0.05)	(0.05)	(0.03)	(0.02)	(0.03)
Median Income (logged)		-0.555***	-0.526***		-0.286***	-0.303***
		(0.09)	(0.10)		(0.04)	(0.06)
Total Population (logged)		-0.057	-0.047**		-0.046***	-0.043***
		(0.02)	(0.02)		(0.01)	(0.01)
Percent of County Population that is Black		-0.004*	-0.003		-0.002	-0.001
		(0.00)	(0.00)		(0.00)	(0.00)
Percent of County Population that is Hispanic		-0.002	0.000		-0.001	0.001
		(0.00)	(0.00)		(0.00)	(0.00)
Percent of County Population with only a High School Diploma		-0.013***			-0.009***	
		(0.00)			(0.00)	
Percent of County with a Bachelor's Degree or Above			0.005**			0.005**
			(0.00)			(0.00)
Constant	0.588***	7.776***	6.753***	0.417***	4.366***	4.056***
	(0.03)	(1.04)	(1.10)	(0.02)	(0.55)	(0.64)

* p<0.05, **p<0.01, ***p<0.001 (All regressions use robust standard errors clustered by state)

References

American Health Planning Association. 2012. "State CON Websites." National Directory.

Anderson, Keith B. & David I. Kass, 1986. "Certificate of Need, Regulation of Entry into Home Health Care: A Multiproduct Cost Function Analysis," Staff Report to the Bureau of Economics, *Federal Trade Commission*. https://www.ftc.gov/sites/default/files/documents/reports/certificate-need- regulation-entry-home-health-care/231954.pdf.

Bailey, James. 2016. "The Effect of Certificate of Need Laws on All-Cause Mortality." *Health Services Research*/ doi:10.1111/1475-6773.12619.

Bates, LJ, K. Mukherjee and RE Santerre. 2006. "Market Structure and Technical Efficiency in the Hospital Services Industry: A DEA Approach." *Medical Care Research and Review* 63 (4): 499–524.

Boehm, Eric. 2017. "How Virginia's Hospital Licensing Laws Led to an Infant's Death." *Reason.* https://reason.com/archives/2017/01/25/virginia-certificate-of-need-hospital.

Center for Medicare & Medicaid Services, 2013 POS File, December 2013, https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Provider-of-Services/POS2013.html.

Center for Medicare & Medicaid Services. 2013. 2013 POS File, https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Provider-of-Services/POS2013.html.

"CMS' SSA to FIPS State and County Crosswalk," 2013, *NBER*. http://www.nber.org/data/ssa-fips-state-county-crosswalk.html.

Conover, CJ, and FA Sloan. 1998. "Does Removing Certificate-of-Need Regulations Lead to a Surge in Health Care Spending?" *Journal of Health Politics, Policy and Law* 23 (3): 455–81, https://www.ncbi.nlm.nih.gov/pubmed/9626641.

Cooper, Zack, Stuart V. Craig, Martin Gaynor, and John Van Reenen. 2015. "The Price Ain't Right? Hospital Prices and Health Spending on the Privately Insured," *(No. w21815. National Bureau of Economic Research, 2015).* http://www.healthcarepricingproject.org/sites/default/files/pricing_variation_manuscript_0.pdf.

Cutler, David M., and Fiona Scott Morton. 1964-1970. "Hospitals, Market Share, and Consolidation," *JAMA* 310 (18).

Demsetz, Harold. 1982. "Barriers to Entry," *The American Economic Review* 72, no. 1: 47–57.

DOJ-FTC. 2016. "Joint Statement of the Federal Trade Commission and the Antitrust Division of the U.S. Department of Justice on Certificate-of-Need Laws and South Carolina House Bill 3250.

DOJ. 2015. "Herfindahl-Hirschman Index," available at https://www.justice.gov/atr/herfindahl-hirschman-index

Gaynor, Martin, and Robert Town. 2012. "The Impact of Hospital Consolidation- Update," *The Synthesis Project*, available at http://archwayhealth.com/wpcontent/uploads/2016/10/Gaynor_Town_rwjf_update.pdf.

Ho, Vivian, and Meei-Hsiang Ku-Goto. 2012. "State Deregulation and Medicare Costs for Acute Cardiac Care," *Medical Care Research and Review* 70 no. 2:185– 205, DOI: 10.1177/1077558712459681.

Kessler, Daniel P., and Mark B. McClellan. 2000. "Is Hospital Competition Socially Wasteful?" *The Quarterly Journal of Economics* 115, no. 2: 577–615.

Koopman, Christoper, and Matthew D. Mitchell 2016. "40 Years of Certificate-of-Need Laws Across America," (*Mercatus Research, Mercatus Center at George Mason University, Arlington, VA, September 2016).* https://www.mercatus.org/publication/40-years-certificate-need-laws-across-america.

Koopmen, Christopher, and Thomas Stratmann. 2016. "Entry Regulation and Rural Health Care: Certificate-of-Need Laws, Ambulatory Surgical Centers, and Community Hospitals," (*Mercatus Working Paper, Mercatus Center at George Mason University, February 2016)*. https://www.mercatus.org/publication/entry-regulation-rural-health-care-certificate-of-need-laws-ambulatory-surgical-centers.

Martin, Gaynor and Robert J. Town. 2011. "Competition in Health Care Markets." *NBER Working Paper* No. 17208.

McFarland, Deborah A, and John W Mayo. 1989. "Regulation, Market Structure, and Hospital Costs", *Southern Economic Journal* 55, no. 3: 559-569. https://www.jstor.org/stable/1059572?seq=1#page_scan_tab_contents.

Mitchell, Matthew. 2016. "Do Certificate-of-Need Laws Limit Spending?" (Mercatus Working Paper, *Mercatus Center at George Mason University,* Arlington, VA: September 2016).

National Conference of State Legislatures. 2016. "CON-Certificate Of Need State Laws," last updated 8/25/2016, http://www.ncsl.org/research/health/con-certificate-of-need-state-laws.asp

National Health Planning and Resources Development Act of 1974. 1975. Pub. L. No. 93–641.

Ni, Huan, Jomon Aliyas Paul, and Aniruddha Bagchi. 2017. "Effect of Certificate of Need Law on the Intensity of Competition: The Market for Emergency Care," *Socio-Economic Planning Sciences*, doi:10.1016/j.seps.2017.02.002.

Noether, Monica 1988. "Competition among Hospitals," Journal of Health Economics 7 (3).

Paul, J., B. Quosigk, and L. MacDonald. 2017. "Factors Impacting Market Concentration of Not-for-Profit Hospitals," *Journal of Business Ethics*.

Paul, Jomon Aliyas, Huan Ni, and Aniruddha Bagchi. 2014. "An Empirical Analysis of the Impact of Certificate of Need Law on Competition in Inpatient Care Market," http://coles.kennesaw.edu/coles-overview/faculty-and-research/working-paper-series/documents/FALL14-03.pdf.

Picard, Robert. GEODIST: Stata module to compute geodetic distances, https://ideas.repec.org/c/boc/bocode/s457147.html.

Rivers, P., M. Fottler, and M. Younis. 2007. "Does Certificate of Need Really Contain Hospital Costs in the United States?" *Health Education Journal*, 66 no. 3:229–244.

Roemer, Milton. 1961. *Bed Supply and Hospital Utilization: A Natural Experiment*, quoted in Joshua M. Weiner, David G. Stevenson and Susan M. Goldenson, "Controlling the Supply of Long-Term Care Providers at the State Level," Occasional Paper Number 22, The Urban Institue, Dec. 1998, citing M. Roemer. 1961. "Bed Supply and Hospital Utilization: A Natural Experiment." Hospitals, *The Journal of the American Hospital Association* 35: 36–42.

Rosko, M., and R. Mutter. 2014. "The Association of Hospital Cost-Inefficiency with Certificate-of-Need Regulation," *Medical Care Research and Review* 71 no. 3: 280–298.

Salkever, David S. 2000. "Regulation of Prices and Investment in Hospital in the United States," in *1B Handbook of Health Economics*, 1489-90 (A.J. Culyer & J.P. Newhouse eds.).

Santerre, Rexford E., and Debra Pepper. 2000. "Survivorship in the US hospital services industry," *Managerial and Decision Economics* 21, no. 5: 181–189.

Sherman, Daniel. 1988. "The Effect of State Certificate-of-Need Laws on Hospital Costs: An Economic Policy Analysis," Staff Report of the Bureau of Economics, *Federal Trade Commission*, Washington, DC, January 1988, https://www.ftc.gov/sites/default/files/documents/reports/effect-state-certificate-need-laws-hospital-costs-economic-policy-analysis/232120.pdf.

Town, Robert, and G. Gowrisankaran. 2003. "Competition, Payers, and Hospital Quality," *Health Services Research* 38: 1403–1422.