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Abstract

Increasing healthcare costs and the deterioration of healthcare quality have always been major concerns to policy makers in the United States, and Certificate of Need (CON) Law has been implemented as one way to curb wasteful healthcare resource use. Theoretically, CON can lead to a reduction in the number of beds as well as in the number of inpatient days (possibly by shortening the length of patient stay). However, these two effects impact inpatient occupancy rate in opposite directions. We test empirically to find out which of these two effects dominate. In this study, we investigate the impact of CON and its stringency (which is different across states with CON Laws) on inpatient occupancy rate using panel data, and find that on average CON legislation reduces occupancy rate in inpatient units. Our tests evaluating CON and its features for endogeneity fail to obtain statistical support.

Keywords: CON Law; Health Policy; Occupancy Rate; Inpatient Care

I. Introduction

The U.S. per capita healthcare expenditure is one of the highest in the world. According to a study by the Centers for Disease Control and Prevention, it accounted for 17.9% of Gross Domestic Product (GDP) in 2010 (NCHS, 2012). Nearly one-third of this expenditure is attributed to inpatient hospital services and related utilization. Specifically, between 1997 and 2011, aggregate inflation-adjusted hospital costs grew by 3.6 percent annually (Weis, Barrett and Steiner, 2014). Equally unfortunate is that the quality of healthcare outcomes has not improved at par with the utilization rates, and the United States lags behind all other industrialized nations in this regard (OECD, 2009).

A number of laws have been implemented over the years to make sure the utilization of healthcare resources and related costs do not get out of hand. The 1946 federal Hill-Burton program was aimed at funding new hospital construction in areas that most needed it. However, a state would only receive these funds if it adopted a plan to evaluate the proposed projects (Lave and Lave, 1974). Another significant milestone in this regard was the Certificate of Need (CON) Law. The National Health Planning and Resource Development Act (NHPA) passed this law in 1974 to curtail unnecessary spending. Healthcare service availability, superior care quality and enhanced competition without it leading to excess capacity or costly service redundancy were the law's intended goals (Conover and Sloan, 1998). [1] Thirty-six states still pursue it in various forms and the law continues to have an impact on the healthcare industry within those states. Previous literature has provided mixed findings on the effects of CON Law on entry to market, competition, cost, and quality of care. A report from the Department of Justice and Federal Trade Commission in 2004 and another from Zeta in 2008 both point out that CON Law leads to higher prices as it protects incumbents by acting as an entry barrier. Adding support to this argument, Greenberg (1998) argues that CON Law causes difficulties both for hospitals trying to enter the healthcare market and for existing hospitals trying to justify expenditures on a medical procedure already available in other hospitals. Vaughan-Sarrazin et al. (2002) find that the law negatively impacts health outcomes. In their study featuring coronary artery bypass graft surgery (CABG) patients, they find mortality rates of CABG patients to be 22% higher in states with CON Law relative to states without the law. Grabowski et al. (2003), in their study on Medicaid nursing home and long-

[1] An overview of the CON Law in each state can be found in Hellinger (2009).

term care find that repeal of CON Law led to a statistically insignificant increase in related expenditures in these states.

The proponents of the law argue that the law deters excessive investments in expensive technologies. They contend that hospitals given their ability to compete on the basis of non-price attributes can very easily pass on the investment costs to the consumers (or the insurers). Ferrier et al. (2010) similarly find CON Law to have a positive impact on healthcare costs. Specifically, they demonstrate that CON Law states are able to deliver higher efficiency with regard to resource allocation and outputs. Moreover, they find that longer the law has been in effect greater the positive impact. Paul et al. (2014) find that CON Law statistically significantly reduces the average Length of Stay (LOS) in the Emergency Department (ED) and therefore positively impacts health care quality in the ED.

The primary goal of this study is to analyze empirically the impact of CON Law on inpatient occupancy rate. Our measure of inpatient occupancy rate for each hospital is constructed using total number of inpatient days (this is basically the sum of all patients days in a given year) divided by total bed-days (365 times number of beds available). Our main contribution is that we are one of the few studies that empirically investigate the theoretically unclear effects of CON Law on inpatient occupancy rate, which is important for the improved understanding of the efficiency of utilizing hospital facility. Theoretically, CON Law could affect both the numerator (inpatient days) and denominator (number of beds) of the inpatient occupancy rate. On the one hand, CON could reduce (or limit) the number of beds available as the law is designed to prevent the waste of healthcare resources, which could result in a higher occupancy rate (through a decrease in the denominator of the occupancy rate). This could lead to a decrease in healthcare costs because of fewer beds (Gaynor and Anderson 1995, Keeler and Ying 1996, and Grabowski et al. 2003). On the other hand, CON may reduce inpatient days (or replace inpatient with outpatient care) since hospitals in states with CON have an incentive to demonstrate better use of their facility.[2] Hence, this could decrease the inpatient occupancy rate (by reducing the numerator). It is, however, not clear which of the effects will dominate. Therefore, it is worth exploring this question empirically.

We also contribute to the literature by controlling not only whether a state has CON Law or not (represented by CON indicator variable in this study), but also the thresholds on expenditures beyond which hospitals in a state with CON Law would have to put their expenditure request through a formal review. Beyond such thresholds, a hospital or healthcare provider would have to obtain approvals from the government if they were considering significant additions to their capacity or entering a new service market. Generally, a higher threshold represents the less stringent law, as in such a scenario only a handful of projects would have to go through a formal review. In this study, we devote our attention to stringency as it applies to thresholds on service expenditures.[3]

In line with the extant literature, both the supply and demand sides of the inpatient market are also considered in our study. Examples include measures on health care supply, demographics, socio-economic features, population health status and health insurance coverage, and state political indicators. Finally, we also investigate potential endogeneity concerns associated with CON indicator and its stringency.

Our paper has the following outline. We first discuss data and related summary statistics. This is followed by a discussion of the empirical specification(s) we employ in section 3. Next, we

[2] Prior literature such as Thomas et al. (1997), Kossovsky et al. (2002), Thi et al. (2004), Coffman and Rundall (2005), White and Glazier (2011) to name a few show that shorter LOS is associated with improved patient care quality and satisfaction.

[3] In line with concerns raised about CON thresholds in prior literature such as Paul et al. (2014), we only consider the threshold associated with service related expenditures.

discuss results from our cross-sectional and panel models and related implications. We conclude in the final section 5 with a discussion about potential avenues for future research.

II. Data and Summary Statistics

The goal of this research endeavor is to analyze the effect of CON Law on inpatient occupancy rate in the United States. We accomplish this using hospital-level data from American Hospital Association (AHA). We measure occupancy rate as follows for each hospital: ($Occupancy\ Rate = \left[\frac{\text{Annual Inpatient Days}}{\text{Number of Beds}*365}\right]$) following extant literature (such as Sampson et al., 2006; Connecticut Department of Public Health, 2013 among others). Inpatient Days data from AHA from the years 2000, 2002, 2004, 2006 and 2009 is used to build our dependent variable[4]. Before we elaborate on other variables employed in our modeling specifications, we would like to demonstrate the directional nature of this variable. Possibly, one might be inclined to interpret higher values of occupancy rate to represent an efficient utilization of resources. However, higher occupancy rate could be result of either more inpatient days or of the reduced number of beds. If it is the former, then higher occupancy rate is not necessarily a positive outcome especially if it entails a patient staying in a bed much longer than necessary. This instead would mean the care delivery processes are actually inefficient. This notion finds some support in the extant literature. For example, Scholle et al. (2005) highlight a negative correlation between quality of inpatient care and inpatient days. Similarly, Madsen et al. (2014) find that high bed occupancy rates were associated with a significant 9 percent increase in rates of in-hospital mortality and thirty-day mortality, compared to low bed occupancy rates. The other side of this story is that lower

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[4] To mitigate any concerns that our data is not randomly selected due to longer gap between year 2006 and 2009, we tested the robustness of our results by excluding 2009 from our sample. Our main results still hold.

occupancy rate could be due to reduced inpatient days or an increase in number of beds. If it is the former, then it is a positive outcome (Thomas et al., 1997; Kossovsky et al., 2002; Thi et al., 2004; Coffman and Rundall, 2005; White and Glazier, 2011). Nonetheless, if it is the latter, then it could also imply there are too many empty beds, which is a waste of resources and increases health care costs (Gaynor and Anderson 1995, Keeler and Ying 1996, and Grabowski et al. 2003). In order to bring some clarity to the picture, we estimate the relationship between CON Law and hospital occupancy rate in inpatient care. Following are the variables featured in our modeling specifications.

Our primary focus is on CON Law and a key feature - its stringency. The binary variable helps us capture which states have CON Law. The stringency helps us differentiate between these states as well as capture differences between those that have the Law and those that don't. As noted earlier, we capture stringency through an index that is modeled around the Law's threshold for service expenditures. Specifically, any service that involves expenditures beyond this threshold would have to be approved by the state government. Further, low values of the threshold imply a stringent CON Law whereas higher values represent a laxed law and therefore would be equivalent in principle to those states without the law We define the index as as follows.

$$\left(Stringency\ Index_{State_i} = \left[\frac{\max_{j \in I} CON\ Threshold_{State_j} - CON\ Threshold_{State_i}}{\max_{j \in I} CON\ Threshold_{State_j}} \right] \right),$$

where $state_i$ is the state whose stringency index is calculated, and $state_j$ is any one of the states that have reported some threshold in its CON law.

Notice that the index takes a value of 0 if the law is lenient (this is a case where the state threshold equals to the maximum threshold of all states with CON Law) and it takes a value 1 if the law is stringent (this is a case where the state requires all applications go through a review, meaning the threshold is zero)[5]. Also, the continuous nature of the index helps us capture the variability noted among states in stringency within and over the years. Intuitively, inpatient occupancy rate could be affected not only by inpatient care demand but also the market supply. Additionally, it is plausible that the political and economic environment of a state could affect the inpatient care market; hence, we include relevant measures in our modeling specifications.

To be more specific, on the supply side, we take into account important hospital characteristics, such as: whether a hospital has at least 100 beds[6], number of full-time physicians; number of full-time nurses; whether the hospital is a member of Council of Teaching Hospitals and Health Systems (COTH); whether the hospital has residency training approval by Accreditation Council for Graduate Medical Education (ACGME); whether the hospital has accreditation by Joint Commission on Accreditation of Health Care Organizations (JCAHO). Furthermore, type of hospital could influence the type of patients accepted as well as their use of inpatient services (length of stay, for instance), whether the hospital is in a rural or urban location. Therefore, we also construct a measure of hospital type to differentiate long-term care hospitals from the rest. We also consider type of ownership (not for profit, for profit, government-owned) as a control in our models as these hospitals operate under different legal rules (tax exemptions, non-distribution constraint, etc.) and therefore, face different constraints in terms of productivity, and respond to profitability differently when making supply decisions (for example, government hospitals are most likely to supply the unprofitable services that are disproportionately needed by

[5] The value of the CON stringency is set to zero for states without CON Law, which implies no applications or reviews are needed in such states.

[6] We prefer to use the indicator of whether a hospital has at least 100 beds instead of the number of beds since the latter is also used as part of the denominator of our dependent variable. This is a standard proxy of hospital size. For instance, Disproportionate Share Hospital (DSH) uses statutory formulas to determine payments made to hospitals. The formulas used for urban hospitals with 100 or more beds are more liberal than those applied to urban hospitals with fewer than 100 beds. This suggests there is an incentive for hospitals to meet or exceed the 100- bed threshold, pitting DSH payment formulas against CON Laws.

poor and underinsured patients, etc.). All of these aspects associated with ownership type could, in turn, impact inpatient occupancy rate.

On the healthcare demand side, we include demographic measures. Specifically, we include variables that capture the age, gender and racial characteristics of the state population Their inclusion finds support in the literature. For example, it is well known that health care needs of the female population are more pronounced than the males and this can potentially affect the inpatient care demand and related occupancy rate (NCHS, 2012). Similar reasoning motivates inclusion of different age groups, in particular, the elderly who have increased health care needs compared to the younger age groups. There is significant racial variability when it comes to health care outcomes and socio-economics and this can potentially have an impact on inpatient care demand and related occupancy rate motivating its inclusion (Census Bureau, 2013; NCHS, 2012).

As a second measure, we include the health insurance coverage of a state's population. We contend that population with employer-provided insurance have a better access to health care, are more health conscious and generally younger. Such a population would be associated with reduced inpatient care demand. Those on Medicare and Medicaid are expected to have an opposite reality hold true.

As a third measure, we include the prevalence of obesity, extent of population that smoke daily, drink heavily and the infant mortality rate in a state (CDC, 2014a; CDC, 2014b; CDC, 2014c; CDC, 2014d). This we believe effectively captures the health status of the population. For example, life style and behavioral choices made by expecting women are found to be associated with infant mortality (CDC, 2014d). Further, a positive association between behavioral choices such as smoking, drinking and obesity and healthcare costs is well documented (NCHS, 2012).

As a fourth measure, we include median household income to capture the economic environment in a state.[7] The reason is that in economically well-off state, there might be a strong incentive for the inpatient care providers to increase occupancy rate of inpatient services even if there is no real demand to justify it as such patients have a greater ability to pay for these services and hospitals might also not be faced with payment constraints that might be imposed by Medicare and Medicaid. Similar motivation guides inclusion of variables that capture the state's political environment. These include the governor and senators' political affiliation, the voting record of these senators, affirmative votes cost, and deviation in their voting records. Their inclusion is now well supported in the extant literature (Paul et al., 2014, 2017). For example, the voting record of senators well captures the state's political climate as rational senators are less likely to vote such that it affects their future electoral opportunities.

Our research indicates that there exists no database that singularly contains all the data we need and so we created a database for our needs borrowing from several sources (Appendix Table A.1). Our final sample contains 20,277 observations at the hospital level with data pooled from 2000, 2002, 2004, 2006, and 2009 years. This data set is at the national level which covers almost all states. We lost 10,206 observations (30,483-20,277) due to missing information on variables included in our study: whether the hospital is a member of COTH, JCAHO (loss of 98), thresholds of CON Law (loss of 1,369), indicator for urban (328), senators opinions on proposals (loss of 826), proportion that drink heavily (loss of 4,930), infant mortality rate (loss of 250), hospital type – acute long term care (loss of 1,415), median income and unemployment rate (loss of 85

[7] We have accounted for the effect of inflation on our monetary variables in our empirical analyses. For consistency, we did so in 1998 dollars.

observations). We do not notice any pattern of missing information that raises concerns about sample selection.

Note that variables such as population demographics, and those capturing political environment, economic environment, population health status variables, population insurance coverage, Gini index and index of science and technology are collected at the state level as several of them (health status, political variables, and health insurance coverage for instance) are not available at the community level (such as health service area). Besides, compared to emergency care, the concept of "service area" could be less influential to inpatient care since unlike urgent care, patients have more flexibility when they choose the place where they receive inpatient care due to the less urgent nature of inpatient care in many cases. In order to maintain the consistency of the measures we employ, we measure them all at the state level. However, we incorporate an indicator of rural (urban) area of the hospital location hoping to capture the major differences across various health service areas within a given state. Table 1 provides the summary statistics of our sample with a comparison between hospitals in states with and without CON Law. The variables are described in more detail in Appendix Table A.2.

----------------------Table 1 about here-----------------------------

It follows from Table 1 that CON states on average have smaller populations, larger proportion of blacks and a lower proportion of people covered by privately purchased health insurance compared to non-CON states. A higher proportion of hospitals in states with CON are members of COTH, have approval for residency training, have JCAHO Accreditation, and are not for profit. Similarly, they have an increased number of full-time physicians and nurses. CON states are more likely to have Democrat governors and their senators are more cooperative as well.[8] The CON States are

[8] These differences have been tested to be statistically significant at the 5% level.

also associated with: 1) higher Gini indices, which indicates more income inequality; and 2) lower tech index, which indicates a slower rate of innovation adoption.

III. Econometric Specifications

In this empirical study, we would like to explore the relationship between CON Law and hospital inpatient occupancy rate. While the effect of CON Law on healthcare costs has been extensively investigated, to the best of our knowledge, there is no prior literature that studies the effects of CON Law on inpatient occupancy rate. Our analysis starts with a binary control of CON Law as mostly used in previous studies, then we extend it with measures on the stringency of the law, and finally, test the endogeneity of CON Law measure(s). In all our models, we also control for other previously described important variables that capture the characteristics of the inpatient care market, as well as the economic and political environment of a state.

We first estimate a pooled cross-sectional regression model as follows:

$$HospOcc_{it} = \alpha_0 + \alpha_1 CON_{it} + \alpha_2 X_{it} + \varepsilon_{it} \text{ ,} \tag{1}$$

where $HospOcc_{it}$ measures the inpatient occupancy rate in a given hospital *i* in time period *t*, CON is a dummy variable that captures whether a state has CON Law or not, X includes all the other covariates (such as hospital resources and characteristics, population characteristics in the state where the hospital is located, and macro political and economic environment of the state), and ε represents the error term.[9] We have also treated hospitals in the same state as a cluster to adjust for the standard error.

In order to tackle the existence of unobserved hospital heterogeneity, such as hospital expectation regarding its own market power, or its plan for any changes to the size, we seize on

[9] Given concerns about the existence of autocorrelation in the error term, we test for it. We do not find sufficient statistical evidence to support the existence of autocorrelation with a p-value of 0.0939.

advantages afforded to us by the panel setting of our data and focus on the following modeling extension.

$$HospOcc_{it} = \alpha_0 + \alpha_1 CON_{it} + \alpha_2 X_{it} + \tau_i + \varepsilon_{it}\,, \qquad (2)$$

where τ_i represents time invariant unobserved hospital heterogeneity. If we assume there is no correlation between τ_i and the observables, we can use the Random Effect (RE) model to estimate the CON Law effects. Since we cannot rule out the possibility that the unobserved heterogeneity could be correlated with some observables, the type of the hospital for, example, we further relax the assumption by allowing for the existence of an arbitrary relationship between τ_i and the observables, where we use the Fixed Effect (FE) model to uncover the story. We use a Breusch-Pagan Test to check the existence of this unobserved heterogeneity of hospital by comparing the RE model with the pooled cross sectional one, and then use a Hausman type of test to compare the estimation results from our RE and FE models[10].

Worth noticing is that CON Indicator, our key variable of interest, is time-invariant in the periods considered in this study.[11] Therefore, theoretically, we are not able to estimate the effect of CON in the FE model. In order to obtain some estimates of this key variable of interest that is

[10] The reason we extend RE model to FE model is because we cannot rule out the possibility that the strong assumption made in an RE model and that of no correlation between the observed and unobserved heterogeneity may not hold. Therefore, we need to run an FE model and use Hausman test to investigate such a potential correlation. To be more specific, the Hausman test sets its null hypothesis as "there is no correlation between the unobserved and observables (RE is the preferred model)", see chapter 9 in Greene (2008). The results of Hausman test reject the null hypothesis and shows evidence of the existence of correlation between observed and unobserved heterogeneity. This means RE model does not provide unbiased estimates. However, we are aware of the fact that we cannot estimate the effects of time invariant variable (in our case, the indicator of CON Law is time invariant) in a FE model. This motivated selection of Hausman Taylor approach for our research purposes. This specification not only allows us to estimate the effect of CON indicator but also allows for the existence of correlation between observed and unobserved heterogeneity.

[11] During the period of study, the set of states with the CON Law has stayed the same, although variation in some rules has taken place.

time-invariant and at the same time allowing for some relationship between the observed and the unobserved heterogeneity, we apply a Hausman Taylor (HT) type of model to obtain Generalized IV (GIV) estimates. In this model, we allow correlation to exist between time-varying observables and unobserved heterogeneity, with an assumption that CON (indicator) is exogenous (uncorrelated with the unobserved heterogeneity) first.[12] We then use a Hausman type of test to compare the result of the HT model with that of the FE model.

Notice that the decision to persist with the law in a state depends on state-specific characteristics, all of which are not observed (for example, a state's attitude towards the rate of inpatient occupancy rate). Hence, we need to test and find out if the CON Indicator is correlated with the error term in equation (1) and (2). If the CON Indicator is indeed endogenous, then we may end up with biased estimates of CON Law effects. Therefore, we first use a two-stage least squares (2SLS) model[13] to estimate the effects of the CON Law treating CON Law indicator as endogenous. We follow this up with Durbin-Wu test to check whether empirical evidence supports endogeneity associated with CON Indicator i.e. if it merits treatment as an endogenous variable. We conduct the 2SLS estimation using the following specifications:

Stage one: $CON_{it} = \theta_0 + \theta_1 X_{it} + \theta_2 IV_{it} + \vartheta_{it}$ (3)

Stage two: $HospOcc_{it} = \gamma_0 + \gamma_1 \widehat{CON}_{it} + \gamma_2 X_{it} + \mu_{it}$ (4)

The likelihood of a state having CON Law as a function of Instrumental Variables (IVs) and other covariates is estimated in the first stage. In the second stage, the inpatient occupancy rate

[12] We treat CON Indicator as an endogenous variable next and test for this endogeneity.

[13] We performed a robustness check with the help of a discrete model in the first step. We then used the predicted probability of having CON from this stage as the IV in a 2SLS. Results of our main equation were found to be consistent with the 2SLS specification. Only the results of 2SLS are reported as it makes for an easy comparison to the results of models wherein CON Law indicator and the stringency of the law are both controlled.

is estimated as a function of the predicted likelihood of having CON Law obtained from the first stage and other covariates. Theoretically, at least one IV is to be included for each endogenous variable for identification purposes. We use the index of science and technology[14] and the Gini in a state as our IVs.

The following explains our motivation behind choice of these IVs, i.e., we posit that they are likely to influence whether a state has CON Law but not likely to influence the inpatient occupancy rate because:

1) The index of science and technology in a state is likely to be associated with the speed of technology adoption in a state. A technologically advanced state will usually have a large technology sector. Such a state is therefore less probable to have the law due to the hurt it can inflict on business interests within the state. On the other hand, states that worry that the costs of such investments are less than the benefits are more likely to have the law. These concerns that the effort to innovate often overtakes the effort to economize find adequate support in extant literature (Bodenheimer, 2005). This might also lead to a scenario wherein such states are technologically less innovative than those without CON Law. This measure is based on how new technology is implemented in all industries including but not limited to healthcare market. Hence, this measure is unlikely to be determined only by the environment of healthcare market.

[14] As per the Milken Institute (http://statetechandscience.org/statetech.taf?page=outline), "The State Technology and Science Index provides a benchmark for states to assess their science and technology capabilities as well as the broader ecosystem that contributes to job and wealth creation. The index computes and measures 79 individual indicators relative to population, gross state product (GSP), number of establishments, number of businesses, and other factors. Data sources include government agencies, foundations, and private sources. The states are ranked in descending order with the top state being assigned a score of 100, the runner-up a score of 98, and the 50th state a score of 2.". Detailed discussion of the methodology used to compute the index can be found at http://statetechandscience.org/statetech.taf?page=outline.

2) The Gini index is a measure of distribution of income. An increase in this index indicates an increase in income inequality in a state (World Bank, 2013). Hospitals in states with more poor patients receive subsidies because poor people are unlikely to have the ability to pay for inpatient services. In particular, under the Inpatient Prospective Payment System (IPPS), the base payment rate (based on the patient diagnosis-related group (DRG)) to hospitals is adjusted to include an add-on payment - the Disproportionate Share Hospital (DSH) adjustment (CMS, 2014). DSH permits a percentage increase in Medicare payment to those hospitals serving large proportion of indigent patients. Additionally, it includes a provision to increase this IPPS payment for expensive patient cases. Therefore, governments of states with more poor people would have valid concerns that hospitals could easily pass on the cost of unnecessary treatment to them and use the additional payments to expand capacity. In such cases, the corresponding state has a strong incentive to retain the law in an effort to hinder capacity expansion by hospitals. This indicates that Gini index is less likely to influence inpatient occupancy rate, which is usually determined by patients' health need once hospital capacity is fixed, but rather, is more likely to impact whether a state has CON Law or not.

The validity of these two IVs is ascertained via statistical tests. Finally, we perform Durbin-Wu (Hausman type) test to check whether empirical evidence supports endogeneity associated with CON Indicator i.e. if it merits treatment as an endogenous variable.

We also test on the endogeneity of CON Indicator in the panel setting first in an RE specification, and then in an HT Type of model (since our key variable is time-invariant).

Stage one: $CON_{it} = \theta_0 + \theta_1 X_{it} + \theta_2 IV_{it} + \phi_i + \vartheta_{it}$ (5)

Stage two: $HospOcc_{it} = \gamma_0 + \gamma_1 \widehat{CON}_{it} + \gamma_2 X_{it} + \omega_i + \mu_{it}$ (6)

In the RE model where we treat the CON Indicator as the only endogenous variable, we actually estimate a Generalized 2SLS (G2SLS) model: first, we regress the CON Indicator on exogenous variables X_{it} and IVs; second, we regress HospOcc on the estimated CON Indicator from stage1 and X_{it} assuming no relation between all the covariates and the unobserved heterogeneity in an RE specification. Then we relax this assumption by allowing relationships between the covariates (we assume CON Indicator to be endogenous in this specification) and the unobserved heterogeneity in an HT Type model. We use a Hausman type of test to assess the endogeneity of CON Indicator in both RE (by comparing it to the RE with CON Indicator as exogenous) and Hausman Taylor specifications (by comparing it to an HT model where the CON Indicator is treated as exogenous).

Next, we extend our analysis by controlling for the stringency of the CON Law on service spending using a similar configuration. Theoretically, it is vital to take this measure of the stringency of CON Law into account[15] to understand the relationship between CON Law and inpatient occupancy rate as discussed in a previous section. Similar to the previous section, we start our analysis by treating the stringency of CON Law as exogenous in a pooled OLS specification as follows:

$$HospOcc_{it} = \alpha_0 + \alpha_1 CON_{it} + \alpha_2 CON\ strigency_{it} + \alpha_3 X_{it} + \varepsilon_{it} \qquad (7)$$

We then extend our study to control for the existence of unobserved hospital heterogeneity by taking advantage the panel setting of our data. Our model of interest is presented below:

$$HospOcc_{it} = \alpha_0 + \alpha_1 CON_{it} + \alpha_2 CON\ strigency_{it} + \alpha_3 X_{it} + \tau_i + \varepsilon_{it}\ , \qquad (8)$$

where τ_i represents time invariant unobserved hospital heterogeneity. There are two types of specifications possible known as fixed effects and random effects. The fixed effects model allows

[15] To assuage any concerns about the possible existence of multicollinearity between CON indicator and this measure on its stringency, we computed the variance inflation factor (VIF=7.69) and tolerance (0.130). Our findings ease such concerns about our study models and related results..

τ_i to be correlated with the observed explanatory variables. In contrast, the random effects model assumes that these are not correlated. Using a Hausman test, we can test which of these specifications is valid. We can also test between a random effects model and pooled OLS regression using a Breusch-Pagan test. For the reason provided earlier in this section, we use an HT model to identify the effects of the time invariant CON Indicator while allowing the existence of relationship between the observed factors and the unobserved heterogeneity. We then use a Hausman type of test to compare our results of the FE and HT model.

As noted earlier in this section, it is worth testing whether the CON Stringency should be treated as an endogenous variable. We tackle this empirical issue using a 2SLS Model as follows[16]:

Stage one: $CON\ Stringency_{it} = \theta_0 + \theta_1 CON_{it} + \theta_2 IV_{it} + \theta_3 X_{it} + \vartheta_{it}$ (9)

Stage two: $HospOcc_{it} = \gamma_0 + \gamma_1 CON\ \widehat{Stingency}_{it} + \gamma_2 CON_{it} + \gamma_3 X_{it} + \mu_{it}$ (10)

In this specification, we use the following IVs for stringency: tech index, and GINI index. The relationship between tech index and service stringency could go either way. This is because a technologically advanced state with CON Law could be strict in approving hospital capacity expansions. This, in turn, would help improve the technological innovativeness standing of the state. One can find analogies to this effect in student selection procedure employed by Ivy League schools. The rigor employed helps them select the best students which in turn contributes to sustenance and improvement of the school's notable standing in the field. In sum, a positive relationship between tech index and service stringency finds support.

On the other hand, there could also be technologically advanced states with a large technology sector that provides both jobs and taxes. Such states will not be in favor of a strict CON Law if they believe it could hurt business interests in the state. A low stringency index (equal to

[16] Based on insights from the Hausman test regarding the endogeneity of CON Law in equation (3) and (4), CON Law indicator is treated as exogenous in this model.

zero) would also capture those states that do not have CON Law for similar reasons. This would support a negative relationship between tech index and service stringency.

As indicated earlier, hospitals in states that have higher low-income patient base proportion get subsidies towards the cost of care and provisions to increase such payments for expensive patient cases. Therefore, the governments of such states would have valid concerns that hospitals could easily pass on the cost of unnecessary treatment to them and use resulting revenues for capacity expansion purposes. This would, in turn, provide the state an incentive to curb the excessive expansion of hospitals by lowering the threshold or by increasing the stringency of the Law. This indicates that GINI index is less likely to influence inpatient occupancy rate but is more likely to impact the CON Law stringency. Furthermore, we test the endogeneity of CON Stringency in the panel setting first in an RE/FE specification (as below), and then in an HT Type of model (since our other key variable-CON Indicator is time-invariant).

Stage one: $CON\ Stringency_{it} = \theta_0 + +\theta_1 CON_{it} + \theta_1 IV_{it} + \theta_3 X_{it} + \phi_i + \vartheta_{it}$ (11)

Stage two: $HospOcc_{it} = \gamma_0 + \gamma_1 CON\ \widehat{Stringency}_{it} + \gamma_2 CON_{it} + \gamma_3 X_{it} + \omega_i + \mu_{it}$ (12)

In the RE model, we treat the CON Stringency as the endogenous variable. We then relax this assumption by allowing relationships between the covariates (we assume CON Stringency as endogenous and CON Indicator to be exogenous in this specification) and the unobserved heterogeneity in an HT Type model. We use a Hausman type of test to assess the endogeneity of CON stringency in both RE (by comparing it to the RE model where both CON Stringency and CON Indicator are treated as exogenous) and Hausman Taylor specifications (by comparing it to a HT model where both CON Stringency and CON Indicator are treated as exogenous).

IV. Results

Tables 2-5 below showcase our main empirical results. Table 4 includes our preferred specification. Our key results are as follows.

1) CON Law (represented by the variable CON Indicator) helps reduce inpatient occupancy rate by 46% (0.268/0.577)[17] on average.[18,19]
2) The stringency of the law measured by service expenditure thresholds employed by states with CON Law does not have a statistically significant impact on occupancy rate once we control the CON Law indicator.
3) Hausman type of test indicates the existence of unobserved heterogeneity. And Durbin-Wu test results indicate that the hypothesis that CON Law and its stringency could be treated as exogenous in estimation cannot be rejected. This means that CON law and its stringency are uncorrelated with the existing unobserved heterogeneity.

Table 2 below presents the results of estimation of inpatient occupancy rate only controlling

[17] 0.268 is the regression coefficient of CON Indicator (Table 4, Hausman Taylor - Preferred Specification) and 0.577 is the average inpatient occupancy in states without CON Law (Table 1).

[18] We also use quantile regression to investigate whether the effects of CON Law differ in different states with various occupancy rates. The results show the magnitude of CON indicator decreases by 10% with increases in occupancy (from 1st to the 3rd quartile), while the magnitude of the stringency of CON increases by 90%. Further, given concerns that occupancy could also decrease if states with CON Law had an increase in bed supply over the years that are focus of this study, we performed some additional analysis. We compared the trend in changes in number of beds over time for hospitals in states with and without CON Law. Our results show that, on average, hospitals in states with CON Law were downsizing over the time period we study, while those in states without CON Law expanded their bed supply slightly even though they already have lower bed occupancy compared to states with CON Law. This may indicate some unnecessary expansion in states without CON Law. Further, difference in changes of number of beds between hospitals in states with (without) CON Law is statistically significant. This downsizing trend is in line with the increased utilization concerns that exists with regard to inpatient care in the United States and also implies that CON Law does have effects on curbing unnecessary hospital expansion.

[19] To assuage any concerns that reduction effects re driven by time effects, we include dummy variables for years. Our results do not exhibit any noticeable patterns. Further, using a treatment effect model, we find that if all states in U.S. had CON Law, the national average occupancy rate in our sample will be 58.29%, and if all states in US had no CON Law, the average is 69.28%, which leads to a difference of 10.99% in occupancy rate of Inpatient care.

for a binary indicator of whether a state has CON Law or not.[20] We have included results from OLS and HT specifications, where CON Indicator is treated as exogenous[21]. Our main result is that CON Law is negatively associated with the inpatient occupancy rate. This effect becomes more statistically significant once we take into account the unobserved heterogeneity. This possibly indicates that the effect of CON Law on reducing the length of stay dominates the effect on reducing the number of beds in a given healthcare market.

Other findings include the following:

1). Many hospital characteristics are significantly associated with inpatient occupancy rate. For example, hospitals who have more full-time nurses, or have at least 100 beds, or are located in urban areas, or are a member of the council of teaching, or are approved for resident training are likely to have higher occupancy rate. Hospitals owned by government compared to for-profit hospitals have lower occupancy rate.

2). Inpatient occupancy rate reduces with an increase in the size of the population in a state. Intuitively, this could mean given constraints on inpatient care resources, these states tend to use available capacity more judiciously so the population that requires inpatient care can still receive it.

[20] We also check the robustness of our results by including a group of dummies for each state to take care of the state fixed effect beyond the economic and political measures already in control. Our results do not change in any significant way, and these state dummies are not jointly significant, which might indicate our other measures of state environment are able to capture the state effects reasonably well.

[21] We only report these two specifications based on the results of relevant statistical tests: 1) Breush Pagan test comparing RE and OLS models provides some evidence of the existence of unobserved heterogeneity of hospital (p-value<0.01); 2) A Hausman type of test comparing RE versus FE models indicates that RE is inconsistent or misspecified (p-value <0.01), hence an FE model is more appropriate; 3) A Hausman type of test comparing FE with HT model results indicates that HT estimates are adequate (p-value>0.1). We do not notice any significant change in magnitudes and directional nature of coefficients associated with variables that have a statistically significant impact on inpatient occupancy in both these models. As mentioned above, the motivation for developing an HT type of model is the inability of FE to estimate coefficients of time invariant variables, in this case a key variable considered in our study. In short, we prefer the Hausman Taylor specification in Table 2 based on the test results mentioned above.

3) States with a larger proportion of population younger than 18 years old are associated with lower occupancy rate, which might be a result of lower health (inpatient care) demand.

4) States with more Democratic senators have lower inpatient occupancy rate.

5) States with higher unemployment rate are associated with lower occupancy rate. This possibly implies that when residents of a state cannot afford healthcare, they either reduce or delay their health care consumption (inpatient care) that is not urgently needed.

----------------------Table 2 about here-----------------------------

As a next step, we investigate whether CON Indicator should be treated endogenously. These results are presented in Table 3 (the first stage of the estimation are presented in Table A.3). In the endogenous OLS model, the Durbin-Wu test (with a p-value of 0.7326) shows that we cannot reject the hypothesis that CON Indicator could be treated as exogenous.[22] We also perform an endogeneity test for our RE and HT specifications. A Hausman type test for both specifications (RE – p-value>0.1 and HT – p-value>0.1) indicates that we are not able to reject the hypothesis that CON Indicator could be treated as exogenous.

----------------------Table 3 about here-----------------------------

We next take into account a characteristic of the CON Law known as stringency index of service (discussed above). In Table 4, we present our estimates of CON Law effects with the stringency of the law.

----------------------Table 4 about here-----------------------------

[22] The first stage F-test yielded a p-value<0.0001. The over-identification test indicated a p-value= 0.6097. In the Stock-Yogo test, Cragg-Donald Wald F statistic is 232.00. These indicate we have strong and valid IVs.

As in the case of exogenous models (Table 2), we have included results from pooled (OLS) and HT Type model given the inability of FE to estimate coefficients of time-invariant variables. Compared to Table 2, after we take into account the stringency of CON law, our estimation results present a similar story which is that CON law reduces the inpatient occupancy rate. Other findings that we described earlier in this section remain the same, such as the effects of population size, the proportion of female, patients covered by Medicare, and so on and so forth.[23]

As a next step, we investigate the potential issue of endogeneity for CON Stringency. The results of the first stage estimation are reported in Table A.4. As we have explained in the data section, the tech index and Gini index could be related to the likelihood whether a state keeps CON Law. As can be noted from Table A.4, the estimates of these two variables turn out to be positive and statistically significant, which supports our earlier argument. The estimates of the main stage are presented in Table 5. In the endogenous OLS model, the Durbin-Wu test (with a p-value of 0.6748) shows that we cannot reject the hypothesis that CON Stringency could be treated as exogenous.[24] We also perform an endogeneity test for our RE and HT specifications. A Hausman test for both specifications (RE – p-value>0.1 and HT – p-value>0.1) indicates that we are not able to reject the hypothesis that CON Stringency could be treated as exogenous. In the endogenous FE model, the Durbin-Wu test (with a p-value of 0.7666) shows that we cannot reject the hypothesis that CON stringency could be treated as exogenous.[25]

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[23] A few important items to note: 1) Breush Pagan test comparing RE and OLS models indicates existence of unobserved heterogeneity of hospital (p-value<0.001); 2) A Hausman type of test comparing RE versus FE models indicates that RE is inconsistent or misspecified (p-value <0.001) hence a FE model is appropriate; 3) A Hausman type of test comparing FE with HT model results indicates that HT estimates are adequate (p-value>0.1).

[24] The first stage F-test yielded a p-value<0.0001. The over-identification test indicated a p-value= 0.6510. In the Stock-Yogo test, Cragg-Donald Wald F statistic is 1741.81. These indicate we have strong and valid IVs.

[25] The first stage F-test yielded a p-value<0.0001). The over-identification test indicated a p-value= 0.8752. In the Stock-Yogo test, Cragg-Donald Wald F statistic is 871.026. These indicate we have strong and valid IVs.

-----------------------Table 5 about here------------------------------

In light of our findings that both CON Law and its stringency could be treated as exogenous, we next elaborate on results from exogenous specifications included in Table 4, our preferred models. All of our findings noted earlier in Table 2 hold. The main result is that CON Law has a statistically significant negative impact on inpatient occupancy rate.

To summarize, in all specifications presented in Tables 2 through 5, we report the results of four different models. i) Control for CON Law indicator and treat it as exogenous (Table 2). ii) Control for CON Law indicator and treat it as endogenous (Table 3). iii) Control for CON Law indicator and its stringency and treat both as exogenous (Table 4). iv) Control for CON Law indicator and its stringency and treat CON Law stringency as endogenous (Table 5). Based on a variety of appropriate statistical tests, such as the Durbin-Wu test, and Hausman type of test, we reach the general conclusion that the Hausman Taylor specifications in Tables 2 and 4 are our preferred specification. This is because of several reasons viz. the existence of observed heterogeneity, no change in CON Law existence for each state over time in the period of our study, and the exogeneity found in CON Law. In both preferred specifications, we see the estimates of the CON Law effects on occupancy rate in inpatient care are negative and statistically significant.

V. Conclusions

As discussed in the first section of the paper, CON Law was designed to reduce healthcare costs. Given that increased inpatient care utilization and related costs have been continuously highlighted as a serious concern in the United States, to study whether or not the law is accomplishing its original intention is worthwhile. As we discussed in the introduction, whether CON Law has a positive or negative relation on inpatient occupancy rate remains an open question. This is mainly because CON Law could be associated with a higher occupancy rate by reducing number of empty beds, or it could be associated with a lower occupancy by helping shorten the average length of stay.

We use a panel data set of hospitals in our empirical study. Our results indicate that CON Law on average has a negative impact on the rate of occupancy. This could imply the effects of CON on reducing LOS dominate its effects on reducing number of beds available. Moreover, we do not find sufficient statistical evidence to reject the assumption that CON and its features are exogenous.

Other key results are as follows.

1) Inpatient occupancy rate reduces with increase in the size of the population in a state.

2) Inpatient occupancy rate is positively related to the proportion of females in the state.

3) A statistically significant negative relationship is noted between occupancy rate and proportion of the population on Medicare.

4) Some key features of hospital, such as hospital size (number of beds, full-time nurses), ownership type, membership of council of teaching, approval of residency training, and hospital urban (versus rural) location, all have a significant impact on inpatient occupancy rate.

In summary, our results indicate that CON Law can help mitigate the increased inpatient care utilization issues. Our findings have significant policy implications with regard to CON Law's impact on healthcare. This paper considers the effect of the CON Law on one particular measure of quality. It will be interesting to check if the results are robust to other measures of quality.

It is worth noticing that we do not analyze in detail how CON law reduces occupancy rate of inpatient care. Namely, we do not investigate whether CON law directly reduces the average length of stay or it encourages hospitals to replace inpatient care with another type of care (outpatient care for instance). This topic in itself is very interesting and we plan to pursue it in future.

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Table 1: Summary Statistics for Variables (Hospital-Years Level)

	Sample (n=20277)		**Hospitals in states without CON** (n=7516)		**Hospitals in states with CON** (n= 12761)	
	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation
Inpatient Occupancy	0.595	(0.252)	0.577	(0.312)	0.606	(0.207)
CON Law						
CON Indicator	0.629	(0.483)	0.000	(0.000)	1.000	(0.000)
Stringency Index – Service	0.401	(0.477)	0.000	(0.000)	0.638	(0.459)
Stringency Threshold – Service (Billions of Dollars)	0.147	0.319	0.000	(0.000)	0.234	0.376
Hospital Characteristics						
Full Time Physicians and Dentists	16.120	(65.359)	12.339	(54.253)	18.347	(71.001)
Full Time Nurses	167.788	(264.758)	152.740	(247.132)	176.652	(274.234)
Member of Council of Teaching	0.065	(0.246)	0.046	(0.209)	0.076	(0.265)
Resident Training Approval	0.183	(0.387)	0.146	(0.353)	0.205	(0.404)
JCAHO Accreditation	0.733	(0.442)	0.679	(0.467)	0.764	(0.424)
Not For Profit	0.542	(0.498)	0.486	(0.500)	0.574	(0.494)
Government Ownership	0.032	(0.177)	0.031	(0.173)	0.033	(0.179)
Acute Long Term Care Hospital	0.071	(0.257)	0.076	(0.265)	0.068	(0.252)
Urban	0.788	(0.409)	0.789	(0.408)	0.788	(0.409)
Number of Beds	162.737	(181.644)	146.045	(170.256)	172.569	(187.340)
Hospital Size	0.491	(0.500)	0.438	(0.496)	0.522	(0.500)
Demographics						
Population Size (in millions)	10.913	(9.800)	16.573	(12.775)	7.579	(5.149)
Proportion - Female	0.493	(0.006)	0.497	(0.005)	0.490	(0.005)
Proportion - Male	0.507	(0.006)	0.503	(0.005)	0.510	(0.005)
Proportion (age 0-17)	0.250	(0.017)	0.261	(0.018)	0.244	(0.012)
Proportion (18-44)	0.380	(0.016)	0.386	(0.017)	0.376	(0.014)
Proportion (45-64)	0.245	(0.017)	0.236	(0.018)	0.251	(0.014)
Proportion (65 and older)	0.125	(0.018)	0.117	(0.018)	0.129	(0.015)
Proportion - White	0.813	(0.092)	0.846	(0.050)	0.793	(0.104)
Proportion - Black	0.125	(0.090)	0.075	(0.036)	0.153	(0.098)
Proportion - Asian	0.035	(0.039)	0.045	(0.041)	0.030	(0.037)
Proportion - Amer Indian	0.011	(0.018)	0.016	(0.021)	0.008	(0.015)
Proportion - Pacific	0.002	(0.006)	0.002	(0.002)	0.002	(0.008)
Proportion - Oth Race	0.015	(0.013)	0.016	(0.005)	0.014	(0.015)
Health Status						
Obesity	24.851	(3.554)	24.294	(3.581)	25.178	(3.496)

Proportion - Smoke Daily	15.389	(3.483)	13.642	(3.290)	16.418	(3.169)
Proportion - Drink Heavily	5.170	(1.071)	5.227	(0.969)	5.136	(1.125)
Infant Mortality Rate	2.067	(0.492)	1.993	(0.370)	2.111	(0.546)
Health Care Access and Supply						
Proportion - Emp Ins	0.535	(0.053)	0.521	(0.051)	0.544	(0.053)
Proportion - Priv Ins	0.091	(0.023)	0.096	(0.026)	0.088	(0.021)
Proportion - Medicaid	0.117	(0.030)	0.116	(0.030)	0.117	(0.030)
Proportion - Medicare	0.123	(0.018)	0.114	(0.016)	0.128	(0.016)
Proportion - Uninsured	0.134	(0.043)	0.154	(0.053)	0.123	(0.030)
Political and economic environment						
Senator Mean	0.514	(0.361)	0.427	(0.372)	0.565	(0.344)
Senator Deviation	0.226	(0.275)	0.192	(0.231)	0.245	(0.296)
Number of Democratic Senators	1.017	(0.870)	0.772	(0.896)	1.161	(0.822)
Democrat Governor	0.427	(0.495)	0.284	(0.451)	0.510	(0.500)
Republican Governor	0.565	(0.496)	0.698	(0.459)	0.486	(0.500)
Independent Governor	0.009	(0.092)	0.018	(0.131)	0.003	(0.057)
Proportion - Inpatient Days - Medicare	0.452	(0.238)	0.453	(0.248)	0.452	(0.233)
Proportion - Inpatient Days - Medicaid	0.184	(0.183)	0.176	(0.178)	0.188	(0.185)
Unemployment Rate	0.061	(0.020)	0.061	(0.018)	0.061	(0.021)
Median Income	41.676	(6.463)	42.553	(5.676)	41.159	(6.832)
Instrumental Variables						
Gini	0.452	(0.020)	0.451	(0.019)	0.452	(0.020)
Tech Index	55.144	(13.567)	61.603	(11.244)	51.340	(13.378)

Table 2: Effect of CON Indicator on Inpatient Occupancy

	CON Indicator as Exogenous			
	Cross Sectional		Hausman Taylor	
Variables	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
CON Indicator	-0.112	(0.080)	-0.266**	(0.126)
Full Time Physicians and Dentists	0.00001	(0.00003)	-0.0001	(0.00004)
Full Time Nurses	0.0001***	(0.00001)	0.0001***	(0.00002)
Member of Council of Teaching	0.009	(0.008)	0.055***	(0.021)
Resident Training Approval	0.002	(0.005)	0.026***	(0.010)
JCAHO Accreditation	0.048***	(0.004)	0.004	(0.007)
Not For Profit	-0.003	(0.003)	0.032***	(0.011)
Government Ownership	-0.164***	(0.010)	-0.160**	(0.071)
Acute Long Term Care Hospital	0.113***	(0.006)	-0.010	(0.008)
Urban	0.070***	(0.004)	0.095***	(0.008)
Hospital Size	0.062***	(0.004)	0.024***	(0.006)
Population Size	-0.013***	(0.004)	-0.010**	(0.004)
Proportion - Female	7.052	(4.368)	7.227*	(3.967)
Proportion (age 0-17)	-3.123**	(1.421)	-2.483**	(1.215)
Proportion (18-44)	-1.187	(1.373)	-0.501	(1.263)
Proportion (45-64)	-1.491	(1.630)	-0.803	(1.340)
Proportion - Black	0.432	(0.388)	0.967	(0.720)
Proportion - Asian	4.530***	(1.613)	4.067***	(1.407)
Proportion - Amer Indian	2.616**	(1.274)	-2.308	(4.250)
Proportion - Pacific	-4.971	(8.543)	7.440	(27.976)
Proportion - Oth Race	-6.327	(4.928)	-5.787	(5.234)
Proportion - Emp Ins	-0.292	(0.202)	-0.307*	(0.158)
Proportion - Priv Ins	-0.004	(0.254)	-0.091	(0.204)
Proportion - Medicaid	-0.0353	(0.229)	-0.041	(0.180)
Proportion - Medicare	-0.390	(0.315)	-0.247	(0.244)
Obesity	0.000	(0.001)	0.0004	(0.001)
Proportion - Smoke Daily	-0.001	(0.002)	-0.001	(0.002)
Proportion - Drink Heavily	0.002	(0.003)	(0.002	(0.002)
Infant Mortality Rate	0.001	(0.006)	0.002	(0.005)
Senator Mean	0.029	(0.024)	0.029	(0.019)
Senator Deviation	0.002	(0.009)	0.004	(0.007)
Number of Democratic Senators	-0.014	(0.009)	-0.014**	(0.007)
Gov_demo	-0.007	(0.005)	-0.005	(0.004)
Gov_ind	0.015	(0.021)	0.021	(0.016)
Proportion - Inpatient Days - Medicare	-0.292***	(0.008)	-0.193***	(0.014)

Proportion - Inpatient Days - Medicaid	0.054***	(0.010)	-0.002	(0.014)
Unemployment Rate	-0.592***	(0.171)	-0.613***	(0.138)
Median Income	0.002	(0.001)	0.002*	(0.001)
Constant	-1.182	(2.809)	-1.694	(2.571)
N	21396			21396

* indicates statistical significance at the 10% level
** indicates statistical significance at the 5% level
*** indicates statistical significance at the 1% level

Table 3: Effect of CON Indicator on Inpatient Occupancy

	CON Indicator as Endogenous			
	Cross Sectional		Hausman Taylor	
Variables	Coef.	Std. Error	Coef.	Std. Error
CON Indicator	-0.296	(0.546)	-0.182	(0.120)
Full Time Physicians and Dentists	0.00001	(0.00003)	0.000001	(0.00003)
Full Time Nurses	0.0001***	(0.00001)	0.0001***	(0.00001)
Member of Council of Teaching	0.009	(0.008)	0.021*	(0.011)
Resident Training Approval	0.002	(0.005)	0.014**	(0.007)
JCAHO Accreditation	0.048***	(0.004)	0.026***	(0.005)
Not For Profit	-0.003	(0.003)	-0.005	(0.005)
Government Ownership	-0.164***	(0.010)	-0.121***	(0.016)
Acute Long Term Care Hospital	-0.013	(0.004)	0.049***	(0.007)
Urban	0.113***	(0.006)	0.090***	(0.007)
Hospital Size	0.070***	(0.004)	0.037***	(0.005)
Population Size	0.062***	(0.004)	-0.010**	(0.004)
Proportion - Female	12.978	(17.886)	7.782**	(3.941)
Proportion (age 0-17)	-4.595	(4.536)	-2.336*	(1.206)
Proportion (18-44)	-2.368	(3.719)	-0.409	(1.254)
Proportion (45-64)	-2.601	(3.634)	-0.595	(1.331)
Proportion - Black	0.782	(1.096)	1.115	(0.713)
Proportion - Asian	4.803***	(1.799)	4.352***	(1.392)
Proportion - Amer Indian	5.175	(7.598)	-2.419	(4.220)
Proportion - Pacific	-0.880	(14.701)	4.890	(27.758)
Proportion - Oth Race	-8.100	(7.150)	-5.801	(5.199)
Proportion - Emp Ins	-0.322	(0.219)	-0.296*	(0.157)
Proportion - Priv Ins	-0.011	(0.255)	-0.053	(0.203)
Proportion - Medicaid	0.064	(0.371)	-0.032	(0.179)
Proportion - Medicare	-0.485	(0.421)	-0.223	(0.243)
Obesity	0.000	(0.001)	0.000	(0.001)
Proportion - Smoke Daily	-0.001	(0.003)	-0.001	(0.002)
Proportion - Drink Heavily	0.002	(0.003)	0.002	(0.002)
Infant Mortality Rate	0.001	(0.006)	0.0022	(0.005)
Senator Mean	0.021	(0.032)	0.028	(0.019)
Senator Deviation	0.004	(0.011)	0.003	(0.007)
Number of Democratic Senators	-0.012	(0.012)	-0.014*	(0.007)
Gov_demo	-0.006	(0.007)	-0.005	(0.004)
Gov_ind	0.020	(0.026)	0.020	(0.016)
Proportion - Inpatient Days - Medicare	-0.292***	(0.008)	-0.178***	(0.013)

Proportion - Inpatient Days - Medicaid	0.054***	(0.010)	-0.001	(0.014)
Unemployment Rate	-0.736	(0.455)	-0.590***	(0.137)
Median Income	0.002	(0.001)	0.002*	(0.001)
Constant	-3.028	(6.090)	-2.192	(2.555)
N	21396			21396

* indicates statistical significance at the 10% level
** indicates statistical significance at the 5% level
*** indicates statistical significance at the 1% level

Table 4: Effects of CON Indicator and its Stringency on Inpatient Occupancy

	CON Threshold as Exogenous			
	Cross Sectional		Hausman Taylor	
Variables	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
CON Indicator	-0.100	(0.082)	-0.268**	(0.130)
CON Stringency - Service	-0.004	(0.014)	-0.002	(0.008)
Full Time Physicians and Dentists	0.00001	(0.00003)	-0.0001*	(0.00005)
Full Time Nurses	0.0001***	(0.00001)	0.0001***	(0.00002)
Member of Council of Teaching	0.010	(0.008)	0.058***	(0.022)
Resident Training Approval	-0.002	(0.005)	0.027***	(0.010)
JCAHO Accreditation	0.047***	(0.004)	0.006	(0.007)
Not For Profit	-0.003	(0.004)	0.036***	(0.012)
Government Ownership	-0.163***	(0.010)	-0.179**	(0.086)
Acute Long Term Care Hospital	0.110***	(0.006)	-0.009	(0.009)
Urban	0.068***	(0.005)	0.093***	(0.008)
Hospital Size	0.062***	(0.004)	0.022***	(0.006)
Population Size	-0.013***	(0.004)	-0.010**	(0.005)
Proportion - Female	6.643	(4.480)	6.731	(4.164)
Proportion (age 0-17)	-3.290**	(1.464)	-2.533**	(1.247)
Proportion (18-44)	-1.179	(1.420)	-0.548	(1.366)
Proportion (45-64)	-1.589	(1.670)	-0.840	(1.378)
Proportion - Black	0.419	(0.396)	0.977	(0.737)
Proportion - Asian	4.499***	(1.685)	3.987***	(1.430)
Proportion - Amer Indian	2.445*	(1.335)	-2.685	(4.365)
Proportion - Pacific	-6.196	(8.844)	7.668	(31.290)
Proportion - Oth Race	-5.670	(5.210)	-5.598	(5.976)
Proportion - Emp Ins	-0.238	(0.217)	-0.268	(0.172)
Proportion - Priv Ins	0.081	(0.270)	-0.040	(0.217)
Proportion - Medicaid	0.066	(0.252)	0.035	(0.202)
Proportion - Medicare	-0.393	(0.328)	-0.234	(0.258)
Obesity	0.000	(0.001)	0.000	(0.001)
Proportion - Smoke Daily	-0.001	(0.002)	-0.0006	(0.002)
Proportion - Drink Heavily	0.001	(0.003)	0.002	(0.002)
Infant Mortality Rate	0.000	(0.006)	0.002	(0.005)
Senator Mean	0.030	(0.025)	0.029	(0.020)
Senator Deviation	0.002	(0.009)	0.003	(0.007)
Number of Democratic Senators	-0.015	(0.010)	-0.015*	(0.008)
Gov_demo	-0.008	(0.005)	-0.006	(0.004)
Gov_ind	0.015	(0.022)	0.021	(0.017)

Proportion - Inpatient Days - Medicare	-0.290***	(0.008)	-0.200***	(0.014)
Proportion - Inpatient Days - Medicaid	0.056***	(0.010)	-0.001	(0.015)
Unemployment Rate	-0.596***	(0.175)	-0.612***	(0.141)
Median Income	0.002	(0.001)	0.002*	(0.001)
Constant	-1.849	(2.900)	-1.444	(2.692)
N	20277			20277

* indicates statistical significance at the 10% level
** indicates statistical significance at the 5% level
*** indicates statistical significance at the 1% level

Table 5: Effects of CON Indicator and its Stringency on Inpatient Occupancy

	CON Threshold as Endogenous			
	Cross Sectional		Hausman Taylor	
Variables	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
CON Indicator	-0.098	(0.082)	-1.031***	(0.220)
CON Stringency - Service	-0.015	(0.027)	0.006	(0.009)
Full Time Physicians and Dentists	0.00001	(0.00003)	-0.0001	(0.0001)
Full Time Nurses	0.0001***	(0.00001)	0.0001***	(0.00002)
Member of Council of Teaching	0.010	(0.008)	0.055**	(0.024)
Resident Training Approval	-0.002	(0.005)	0.023**	(0.011)
JCAHO Accreditation	0.047***	(0.004)	0.004	(0.008)
Not For Profit	-0.003	(0.004)	0.033**	(0.013)
Government Ownership	-0.163***	(0.010)	-0.108	(0.099)
Acute Long Term Care Hospital	0.110***	(0.006)	-0.007	(0.010)
Urban	0.068***	(0.005)	0.086***	(0.010)
Hospital Size	0.062***	(0.004)	0.007	(0.008)
Population Size	-0.013***	(0.004)	-0.001	(0.005)
Proportion - Female	6.852	(4.491)	11.190**	(4.683)
Proportion (age 0-17)	-3.392**	(1.474)	-3.274**	(1.409)
Proportion (18-44)	-1.415	(1.497)	1.089	(1.535)
Proportion (45-64)	-1.770	(1.705)	0.170	(1.554)
Proportion - Black	0.349	(0.420)	3.180***	(0.808)
Proportion - Asian	4.750***	(1.757)	3.852**	(1.616)
Proportion - Amer Indian	2.600*	(1.367)	-15.444***	(4.806)
Proportion - Pacific	-6.093	(8.791)	-31.280	(35.155)
Proportion - Oth Race	-6.266	(5.330)	-0.388	(6.733)
Proportion - Emp Ins	-0.178	(0.248)	-0.351*	(0.194)

Proportion - Priv Ins	0.067	(0.271)	-0.075	(0.245)
Proportion - Medicaid	0.111	(0.268)	-0.122	(0.228)
Proportion - Medicare	-0.350	(0.339)	-0.295	(0.292)
Obesity	0.0004	(0.001)	0.000	(0.001)
Proportion - Smoke Daily	-0.001	(0.002)	-0.001	(0.002)
Proportion - Drink Heavily	0.001	(0.003)	0.003	(0.003)
Infant Mortality Rate	-0.0003	(0.006)	0.000	(0.006)
Senator Mean	0.025	(0.027)	0.024	(0.022)
Senator Deviation	0.001	(0.009)	0.002	(0.008)
Number of Democratic Senators	-0.013	(0.011)	-0.015*	(0.009)
Gov_demo	-0.008	(0.005)	-0.003	(0.004)
Gov_ind	0.015	(0.022)	0.027	(0.019)
Proportion - Inpatient Days - Medicare	-0.290***	(0.008)	-0.200***	(0.016)
Proportion - Inpatient Days - Medicaid	0.056***	(0.010)	-0.001	(0.017)
Unemployment Rate	-0.605***	(0.175)	-0.584***	(0.160)
Median Income	0.002	(0.002)	0.003*	(0.001)
Constant	-0.872	(2.853)	-3.664	(3.059)
N	20277		20277	

* indicates statistical significance at the 10% level
** indicates statistical significance at the 5% level
*** indicates statistical significance at the 1% level

APPENDIX

Table A.1: Variable Description and Data Source

No	Variables	Detail Level	Type	Data source
1	Inpatient Days	Hospital	Dependent	www.aha.org
2	Hospital variables such as type of hospital (not for profit, government ownership, etc.), number of full time physicians and nurses, etc.	Hospital	Independent	www.aha.org[1]
3	Extent of Con - stringency, None etc.	State	Independent	Hellinger (2009) see reference section for more details
4	CON Law characteristics such as service threshold	State	Independent	http://www.ahpanet.org/websites_copn.html
5	Age distribution	State	Independent	http://www.census.gov/popest/estbygeo.html
6	Race Distribution	State	Independent	http://factfinder.census.gov/servlet/DatasetMainPageServlet?_program=PEP
7	Population	County	Independent	http://www.census.gov/popest/data/
9	% of uninsured, Medicaid, Medicare patients in state	State	Independent	http://www.statehealthfacts.org/profileind.jsp?cmprgn=1&cat=3&rgn=12&ind=125&sub=39
10	Percentage of obese population	State	Independent	www.cdc.gov
11	Percentage of population that smoke daily	State	Independent	www.cdc.gov

[1] All the American Hospital Association (AHA) data we use for this study comes from the Annual Survey Database.

12	Percentage of population that drink heavily	State	Independent	www.cdc.gov
13	Infant Mortality Rate	State	Independent	www.cdc.gov
15	Inpatient days covered by Medicare and Medicaid	State	Independent	www.aha.org
16	Median Income	State	Independent	http://www.bea.gov/regional/gsp/
18	Senators State Voting Record	State	Independent	http://www.adaaction.org/
19	Party in Power	State	Independent	http://www.nga.org/cms/home/governors/past-governors-bios.html;jsessionid=567B4C3B27E3CF6210B93BC608D3FED5
20	Gini coefficient	State	Instrumental	www.census.gov
21	Index of Science & Technology	State	Instrumental	http://www.milkeninstitute.org/tech/tech2010.taf?sub=tswf

Table A.2: Variable Categorization and Description

Variable name	Variable Description
Outcome Variable	
Inpatient Occupancy	Measure built using Inpatient days and beds in a hospital
Inpatient LOS	Measure built using Inpatient days and Inpatient discharges from a hospital
Independent Variables	
CON Law	
CON Indicator	Dummy variable for con law coverage
Stringency Index - Service	Index of strictness of con threshold on service, can take values between 0 and 1
Hospital Characteristics	
Full Time Physicians and Dentists	Number of full time physicians and dentists in a hospital
Full Time Nurses	Number of full time nurses in a hospital

Member of Council of Teaching	Dummy variable – whether hospital is a member of council of teaching
Resident Training Approval	Dummy variable – whether hospital has approval for resident training
JCAHO Accreditation	Dummy variable – whether hospital has Joint Commission of Healthcare Organizations Accreditation (JCAHO)
Not For Profit	Dummy variable – whether hospital is not for profit
Government Ownership	Dummy variable – whether hospital has government ownership
Urban	Dummy variable – whether hospital is in a urban (1) location or rural (0)
Acute Long Term Care Hospital	Dummy variable – whether hospital is an acute long term care facility or not
Hospital Size	Dummy variable – whether hospital has at least 100 beds
Demographics	
Population Size	Population size (millions)
Proportion - Female	Proportion of female
Proportion (age 0-17)	Proportion of people aged 17 or under
Proportion (18-44)	Proportion of people aged between 18 and 44
Proportion (45-64)	Proportion of people aged between 45 and 64
Proportion - Black	Proportion of population that is Black
Proportion - Asian	Proportion of population that is Asian

Proportion - Amer Indian	Proportion of population that is American Indian
Proportion - Pacific	Proportion of population that is Pacific Islander
Proportion - Oth Race	Proportion of population that belongs to two or more races

Health Status

Obesity	Proportion of population that is obese
Proportion - Smoke Daily	Proportion of population that smoke daily
Proportion - Drink Heavily	Proportion of population that drink heavily
Infant Mortality Rate	Death rate of children 5 and under

Health Care Access and Supply

Proportion - Emp Ins	Proportion of individuals with employer provided insurance
Proportion - Priv Ins	Proportion of individuals with privately purchased insurance
Proportion - Medicaid	Proportion of individuals with Medicaid
Proportion - Medicare	Proportion of individuals with Medicare

Economic and Political Environment

Median Income	Median Income
Unemployment Rate	Self-explanatory
Proportion - Inpatient Days - Medicare	Proportion of Inpatient days covered by Medicare
Proportion - Inpatient Days - Medicaid	Proportion of Inpatient days covered by Medicaid
Democrat Governor	Dummy variable of Democratic party governor
Independent Governor	Dummy variable of governor who is an Independent

Instrumental Variables	
Gini	Gini Index (measure of Inequality)
Tech Index	Index of Science & Technology

Table A.3: First Stage Regression of CON Indicator on Exogenous Variables

	CON Indicator as Endogenous	
	Cross Sectional	
Variables	**Coef.**	**Std. Error**
Full Time Physicians and Dentists	-0.000003	(0.000002)
Full Time Nurses	0.0000005	(0.000001)
Member of Council of Teaching	0.0003	(0.001)
Resident Training Approval	0.00008	(0.0004)
JCAHO Accreditation	-0.001***	(0.0004)
Not For Profit	0.001***	(0.0003)
Government Ownership	0.0003	(0.001)
Acute Long Term Care Hospital	-0.001***	(0.0003)
Urban	0.001**	(0.001)
Hospital Size	-0.001	(0.0004)
Population Size	0.0002	(0.0003)
Proportion - Female	32.588***	(0.322)
Proportion (age 0-17)	-7.438***	(0.117)
Proportion (18-44)	-6.514***	(0.114)
Proportion (45-64)	-5.488***	(0.147)
Proportion - Black	1.715***	(0.032)
Proportion - Asian	2.620***	(0.147)
Proportion - Amer Indian	14.053***	(0.054)
Proportion - Pacific	20.954***	(0.722)
Proportion - Oth Race	-11.390***	(0.423)
Proportion - Emp Ins	-0.109***	(0.017)
Proportion - Priv Ins	-0.032	(0.022)
Proportion - Medicaid	0.568***	(0.019)
Proportion - Medicare	-0.382***	(0.027)
Obesity	-0.0001	(0.0001)
Proportion - Smoke Daily	0.002***	(0.0002)

Proportion - Drink Heavily	0.001***	(0.0002)
Infant Mortality Rate	-0.001	(0.001)
Senator Mean	-0.041***	(0.002)
Senator Deviation	0.013***	(0.001)
Number of Democratic Senators	0.015	(0.001)
Gov_demo	0.008***	(0.0004)
Gov_ind	0.026***	(0.002)
Proportion - Inpatient Days - Medicare	-0.002**	(0.001)
Proportion - Inpatient Days - Medicaid	0.000	(0.001)
Unemployment Rate	-0.748***	(0.014)
Median Income	-0.001***	(0.0001)
Tech Index	0.001***	(0.0001)
Gini	-0.518***	(0.038)
Constant	-10.3192***	(0.242)
N	21396	

[*] indicates statistical significance at the 10% level
[**] indicates statistical significance at the 5% level
[***] indicates statistical significance at the 1% level

Table A.4: First Stage Regression of CON Stringency on Exogenous Variables

	CON Stringency as Endogenous	
	Cross Sectional	
Variables	Coef.	Std. Error
CON Indicator	0.253***	(0.052)
Full Time Physicians and Dentists	0.000009	(0.000017)
Full Time Nurses	-0.000004	(0.000006)
Member of Council of Teaching	0.0018	(0.005)
Resident Training Approval	-0.001	(0.003)
JCAHO Accreditation	-0.002	(0.0027)
Not For Profit	-0.002	(0.0022)
Government Ownership	-0.0002	(0.007)
Acute Long Term Care Hospital	-0.002	(0.004)
Urban	0.002	(0.003)
Hospital Size	0.002	(0.003)
Population Size	-0.041***	(0.002)
Proportion - Female	-35.345***	(2.992)
Proportion (age 0-17)	-27.116***	(0.973)
Proportion (18-44)	-36.624***	(0.933)
Proportion (45-64)	-44.464***	(1.147)
Proportion - Black	-4.490***	(0.255)
Proportion - Asian	26.791***	(1.136)
Proportion - Amer Indian	15.257***	(0.848)
Proportion - Pacific	-45.374***	(5.652)
Proportion - Oth Race	-35.963***	(3.369)
Proportion - Emp Ins	4.173***	(0.135)
Proportion - Priv Ins	-0.868***	(0.172)
Proportion - Medicaid	3.213***	(0.158)
Proportion - Medicare	2.394***	(0.214)
Obesity	0.0063***	(0.0007)
Proportion - Smoke Daily	0.033***	(0.0014)
Proportion - Drink Heavily	-0.001	(0.0019)
Infant Mortality Rate	-0.010**	(0.004)
Senator Mean	-0.178***	(0.016)

Senator Deviation	-0.107***	(0.006)
Number of Democratic Senators	0.076***	(0.006)
Gov_demo	0.001	(0.0031)
Gov_ind	-0.024*	(0.014)
Proportion - Inpatient Days - Medicare	0.000	(0.005)
Proportion - Inpatient Days - Medicaid	0.005	(0.007)
Unemployment Rate	-1.591***	(0.111)
Median Income	-0.015***	(0.0009)
Tech Index	0.012***	(0.0005)
Gini	14.773***	(0.297)
Constant	39.985	(1.918)
N	21396	

[*] indicates statistical significance at the 10% level
[**] indicates statistical significance at the 5% level
[***] indicates statistical significance at the 1% level