The Impact of State Regulations on Hospital Capacity Adjustment

Decisions

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Abstract

In many states, hospitals must apply to a state health board before making large investments to demonstrate that there is need for the proposed expenditure. Capacity increases are among these regulated investments and I use a dynamic model to estimate if the presence of the regulations impacts hospital capacity decisions. My results indicate that, controlling for demand and competitive conditions, hospitals are more likely to increase capacity when no regulations are in place. I run simulations that estimate the long term effect of implementing the regulations in states where they do not exist, and discontinuing the regulations where they are currently in place. The simulations estimate that the regulations’ decrease long term total hospital capacity and most significantly impact smaller and for-profit hospitals. In addition, hospitals are more likely to turn patients away due to overcrowding when the regulations are present. I also estimate patient utility parameters in my empirical model which allows me to predict the total patient demand for each facility. Applying the hospital capacity parameters to the simulations for each regulatory environment and using the patient demand parameters to estimate utility indicates that the regulations decrease total patient welfare. To make patients indifferent between the two policies, the distance traveled when regulations are present would have to decrease by 5.1 percent. I also investigate whether hospitals turn patients away randomly by investigating whether their patient composition changes as they become more crowded. My results indicate that as a hospital turns away more patients, the fraction of mental health patients and minority patients decreases. This result suggests that there may also be distributional concerns to the regulations because they increase hospital turnaway probabilities.
1 Introduction

For decades, policy makers have debated how to best control the increasing costs of health care while maintaining high quality service for patients. During this period, numerous proposals have been discussed and enacted that attempted to keep health spending from growing too rapidly. One key policy aimed at decreasing spending is Certificate of Need (CON), a state level regulation that was first introduced in the 1960s. CON requires hospitals to apply to a state health board before making costly investments and is intended to limit hospital investment to instances where there is a demonstrated need from consumers that is not served by the hospital’s local competitors. Its advocates argue that it limits wasteful and unnecessary spending by hospitals and these savings are passed along to consumers (New York Department of Health, 2012). Adversaries claim that it decreases competition without lowering costs thus hurting patients through higher prices and lower quality (Department of Justice and Federal Trade Commission, 2004).

This paper studies how one type of investment covered under CON, hospital bed increases, impacts hospital capacity decisions. A hospital’s ability to adjust capacity is important for two reasons. First, if a hospital is constantly full, it may wish to add beds to better meet patient demand. Second, demand may be endogenous to capacity decisions if patients prefer hospitals that have more beds.

There is considerable debate about CON’s effectiveness in limiting spending, as well as its impact on the quality of care patients receive. This is best demonstrated by the fact that approximately half of all states currently have CON laws governing hospital investment. Additionally, health organizations such as the American Hospital Association (AHA) and American Health Planning Association (AHPA) endorse CON whereas the Department of Justice and Federal Trade Commission argue that it hurts consumers by limiting competition and should be uniformly repealed. In the continuing debate over CON’s effectiveness as a policy, my analysis helps to illustrate how one key dimension of the regulation impacts patient welfare thus contributing to the debate over whether CON’s total net impact is positive or negative.

More generally, this study addresses two classic questions in economics – when do markets perform suboptimally, and how can regulations improve welfare in such instances? As discussed in Mankiw and Whinston (1986), firms may invest more than the socially optimal level when unregulated because they do not consider that investing to increase demand steals business from competitors. This phenomenon may be more pronounced with hospitals than in other industries because the health care market is unique in several ways. First, the set of patients is relatively inelastic meaning that if a hospital receives an additional patient, it is likely stealing him from another hospital as opposed to increasing total market demand. Second, hospital prices do not fall when the hospital has excess capacity. Finally, researchers have argued that hospital utility
increases in the number of patients served which suggests that hospitals are not simple profit maximizers and may supply more quality than is socially optimal.

My analysis considers whether state regulations effectively curb investment spending by decreasing capacity without negatively impacting consumer welfare. The utility implications of this question in the health care market are greater than in many other industries studied because health spending comprised 17.9 percent of the United States’ GDP in 2010 (World Health Organization). This indicates that health care represents a large portion of consumer spending and if hospital capacity is suboptimal, consumer welfare could be negatively affected in a significant way.

To address these questions empirically, I use a dynamic model of firm behavior that follows from the methodology outlined in Ericson and Pakes (1995). The model has two types of agents - patients and firms, and uses an infinite horizon with discrete time. Patients choose the hospital that provides the highest utility based on observable firm characteristics, though they may be turned away if the hospital is full. I use a nested logit framework to estimate patient preferences for hospital characteristics as is done in Gowrisankaran et al. (2010). The parameters for patient utility include measures of distance and hospital capacity and the nesting parameter is hospital ownership type. They can be used to predict how demand for a facility would change based on its capacity decisions as well as those of its competitors.

Hospitals use Markov strategies to determine whether to keep capacity unchanged, or adjust it up or down in the following period. If they decide to change capacity, they must determine the size of this adjustment. These decisions depend on the hospital’s current state, where the state space includes all variables that impact a hospital’s returns from investment. Hospitals choose the capacity action in each period that maximizes their expected lifetime utility. Demand is estimated using the parameters generated by the nested logit model where I allow for patients to be turned away from their first choice hospital. I follow Benkard, Bodoh-Creed, and Lazarev (2010) to perform counterfactuals without estimating all of the underlying model parameters. This requires estimating the probability that a hospital increases or decreases its capacity conditional on the observed state. For hospitals that adjust capacity, I also estimate the magnitude of this change based on the hospital’s state.

I use a simple queuing model for hospital admissions discussed in Joskow (1980) to estimate the probability that a patient is turned away based on the hospital’s average daily census and total number of beds. Including this measure allows for a hospital’s “crowdedness” to negatively affect patient welfare as some patients will be turned away from their first choice facility and instead will be admitted to their second choice where they receive less utility.
The estimated patient utility parameters indicate that patients prefer hospitals that are closer to their home which suggests that travel is costly. Additionally, patients receive more utility when facilities are larger meaning that hospital size affects patient welfare. The hospital capacity decision parameters estimate that the presence of CON decreases the probability that a hospital adds beds by 8 percentage points. This finding indicates that CON either leads to proposed capacity increases being rejected by the state health board, or deters hospitals from applying to add beds.

I use the parameters for patient utility and hospital capacity decisions to simulate how the hospital industry would evolve differently over time if CON was implemented in states where it does not exist, or was discontinued where it is currently in place. The simulations assume that each hospital starts with its observed capacity in the first year of data. After the first year, I predict how hospital capacity would adjust in the following year conditional on the state variable in the current year under two scenarios. The first assumes that CON regulations are present and the second assumes they are not. The simulations’ estimates illustrate how hospital capacity would evolve under each regulatory policy over a long time horizon.

The simulations indicate that total hospital capacity is smaller when CON regulations are present over a 25 year period. Their impact varies depending on hospital characteristics, however, they predict that smaller and for-profit hospitals are more likely to see their capacity decreased under CON. This finding is consistent with qualitative evidence which suggests that these hospital types are disproportionately affected by the regulations (Yee et al, 2011). While CON’s effect on total capacity is modest, its impact on turnaway probabilities is more significant. The model predicts that turnaway probabilities increase on average from 1.5 percent to 2.2 percent when CON is present indicating that the regulations lead to fewer patients being admitted to their preferred hospital.

The simulations allow for the comparison of distances traveled and total patient utility across the regulatory policies over time. The presence of CON decreases total patient utility by 1.2 percent over the simulation period with the difference increasing over time. To make patient welfare equal in each of the two regulatory environments, patient distance traveled would have to decrease by 5.1 percent when CON regulations are present. These results suggest that CON regulations have a real impact on hospital capacity decision which ultimately hurts patient welfare.

These findings contribute to the debate about the merits of CON and whether it should be implemented or discontinued at the national level. While only analyzing a part of CON’s overall impact on welfare, my findings indicate that the regulations decrease patient welfare. These results will be informative to state and federal policy makers trying to better understand how regulations in the hospital industry affect both
patients and hospital decisions and ultimately their impact on total welfare.

My analysis also addresses the possibility that not all patient types are equally affected by CON regulations. Specifically, I consider whether hospitals turn individuals away randomly, or if they are more likely to pass over specific types of patients by looking how the patient composition changes as hospitals becomes busier. My results suggest that mental health patients and minorities are less likely to be admitted as a hospital’s estimated turnaway probability increases suggesting that if CON increases overall turnaways as my estimates predict, these patient groups may be disproportionately affected by the regulations.

The rest of the paper is organized as follows. Section 2 provides background information on CON. Section 3 discusses the data. Section 4 outlines the empirical model used to estimate patient utility and hospital capacity decisions. Section 5 estimates the results from the empirical model. Section 6 uses simulations to analyze the impact of CON over a longer time horizon. Section 7 discusses how turnaways impact specific patient groups. Section 8 concludes.

2 Background on CON

2.1 History of CON

Real per-capita health spending in the United States increased by 44 percent between 1950 and 1960, and by 76 percent from 1960 to 1970 (Newhouse, 1995). As a result of this growth, policy makers sought to slow health spending. The first related policy related to CON was enacted in Rochester, New York in 1964 and required evaluation of community need prior to the approval of large expenditures. In 1966, New York passed the first state CON law requiring hospitals to receive state approval before making large capital investments. Several states followed New York’s lead and passed similar CON laws. The Federal government believed CON was limiting hospital expenditures and required every state to adopt CON by 1980 to be eligible for full Federal Medicaid reimbursements (Sagness, 2007). All 50 states eventually adopted the regulation.

CON supporters argued for the regulation for two reasons. First, hospitals were fully compensated for costs by insurers through the fee for service (FFS) payment system, giving hospitals little incentive to control costs (Conover and Sloan, 1998). Second, as most patients had health insurance, they were responsible for a small fraction of their total costs. As a result, patients made decisions regarding hospital choice based on quality of service rather than cost (Sagness, 2007).

In the mid-1980s, the Federal government stopped requiring states to have CON to receive Federal reimbursements. Early research on the regulation suggested that its impact on total health expenditures was
minimal. Health spending was still growing rapidly and two studies by Salkever and Bice (1976, 1979) found CON had little to no impact on overall health spending. Sloan and Steinwald (1980) concluded that under CON regulations hospitals shifted spending from capital investments to labor, which was not regulated by CON policies.

The hospital reimbursement structure changed in the mid-1980s and this also may have impacted the government’s decision to stop requiring that states have CON. Hospitals no longer received reimbursements for services provided based on costs and instead received a fixed payment based on the patient’s diagnosis related group (DRG). This reduced incentives for hospitals to perform expensive procedures if they had little benefit to patients, as the hospital would not be fully reimbursed for the costs of these procedures. This gave hospitals a powerful incentive to provide more efficient care (Sagness, 2007).

Although the Federal government discontinued the CON policy requirements, a majority of states kept these regulations in place. Several states also chose to end their CON programs in the 1990s. At present, 36 states have CON regulations in place, although in some cases their regulations no longer govern hospitals and instead focus primarily on nursing homes.\(^1\)

### 2.2 CON Justification and Procedures

The New York policy states, “The objectives of the CON process are to promote delivery of high quality health care and ensure that services are aligned with community need. CON provides the Department of Health oversight in limiting investment in duplicate beds and medical equipment which, in turn, limits associated health care costs.” (New York Department of Health). This is similar to the language used to justify CON regulation in many states. CON programs are designed to limit investment to proposals that improve the quality of care in a community. In theory, an application from hospital A for an expensive piece of equipment (e.g. catheterization lab) should be rejected if hospital B in the same market already has the equipment and there is not sufficient demand in the market for two sets of the equipment.

CON regulation applies to a wide range of hospital expenditures, with the specific policies varying by state. CON regulated hospital expenditures typically include expensive technologies that may not be necessary to have at each hospital in a market, such as a catheterization laboratory. Additionally, there is a total spending limit above which CON approval is required even if the investment is for a technology not specifically regulated under CON. This threshold varies by state but is typically in the hundreds of thousands or millions. For example, the threshold value requiring CON application in Washington is $2.4

\(^1\)For more information on which states have CON programs and what is covered under each, see National Conference of State Legislatures.
If a hospital wants to increase its capacity by adding beds to its facility, CON approval is required. CON supporters worry that if hospital investment is unregulated, hospitals may expand capacity beyond the socially optimal level. Excess capacity is costly, and these expenses may be passed along to consumers through higher prices. While the rules and enforcement surrounding CON regulation of capacity increases vary by state, a common target used is 80 percent at either the hospital or market level.²

The CON application process varies by state, but is typically similar to the procedure outlined in Figure 1. When a hospital decides to make an investment regulated by CON, it must file an application with the state governing board. The application process requires the hospital to demonstrate a community or market need for the service provided by the investment. The need criteria vary by state and may not be transparent to hospitals (Yee et al, 2011).

For a set period after an application is filed, competitors may contest the application by showing the investment duplicates services already available to patients in the community. Public hearings are also held where local citizens can voice their support or concerns with the proposed expenditure. If approved,

²This value was recommended by the National Guidelines for Health Planning (Finch and Christianson, 1981).
competitors have a second change to appeal; if rejected, the applying hospital can appeal the decision or reapply after modifying its application. According to qualitative research in Yee et al. (2011) there may be politics involved in the approval process with wealthier and larger hospitals more likely to receive approval.

The presence of CON regulations is likely to impact the probability that a hospital changes its capacity in several ways. Most importantly, there is the possibility a hospital’s application will be rejected, thus preventing the facility from adjusting capacity, even if it wishes to. Rejections are not common, but a recent study of six states shows that between 6 and 12 percent of applications were rejected in 2009 (Yee et al. 2011). These percentages may not represent the full impact of CON, however, as a hospital that would have invested if no regulations were in place may choose not to apply if it believes there is a high chance of its application being rejected.

There are also significant time and financial costs associated with CON. For example, the regulation imposes a time cost on applicants as they must wait to receive approval before making proposed changes. Even without the potentially length appeals process, the application process lasts several months. The CON process typically allows two rounds of appeals from competitors. Yee et al. (2011) find it is common for rivals to appeal an application that is likely to be approved to delay its implementation, in some cases by several years.

A hospital must pay an application fee to submit an application. This fee varies by state and may also depend on the cost of the proposed expenditure. For example, hospitals pay a fixed fee of $40,470 in Washington whereas in New York, they pay a fixed cost of $2,000 and then 0.3 percent of estimated the costs of the investment. These application fees increase the costs of adjusting capacity to a hospital. Larger hospitals may have a team of experts responsible for CON regulatory issues as substantial financial and legal resources are necessary to file a CON application and monitor the appeals process. Many smaller hospitals are unable to afford such a team as it is costly to maintain (Yee et al, 2011). The financial costs associated with CON regulation may disproportionately affect smaller and for-profit hospitals that are less likely to have the resources necessary to file and navigate the application process.

2.3 Debate Over CON’s Impact

Due to certain characteristics of the health industry, government regulation may be useful. In particular, consumers do not have full price information when making consumption decisions. This is due to the fact that patients may not receive information on hospital prices or charges until well after the episode of care. The services incurred, particularly in an inpatient setting, may not be known in advance meaning the patient
will not know the cost of service even if he is aware of hospital prices. Additionally, consumers may not be very price sensitive due to health insurance coverage which covers a large fraction of their expenses.

If the health industry operated as a more traditional market where consumers paid for services received in full, with complete information about prices and qualities, government regulation of the health industry could be harmful; regulation might prevent hospitals from setting prices or qualities optimally. If hospitals compete primarily on quality, the level provided may be above the socially optimal quality because patients do not face the full cost and therefore prefer a higher quality level than if they paid the full cost for the services provided.

CON’s effectiveness can be measured on two primary dimensions: health care costs and quality of care. The original intent of policy makers in enacting CON was to lower costs without sacrificing quality, but early research indicated that it was ineffective in this capacity. A number of more recent studies have examined the effects of CON on health spending CON has little to no impact on overall health spending (Conover and Sloan, 1998; Rivers et al, 2010). In fact, one study found CON increased total hospital spending (Lanning et al, 1991).

An additional body of literature focuses on how CON regulation impacts quality of care. Burda (1991) finds CON decreases competition between hospitals and has negative effects on quality. This is consistent with the Department of Justice and Federal Trade Commission (2004) who conclude that CON enacts barriers to competition that may increase prices for consumers. Kessler and McClellan (2000) find greater hospital competition in the 1990s led to better patient outcomes; this suggests that if CON restricts competition, quality is likely to suffer.

There is limited research studying CON’s effects on hospital occupancy and capacity decisions. Joskow (1980) focuses on the impact of CON on hospital quality using a measure of the hospitals turnaway probability. The study considers this measure a proxy for quality of care, with higher quality corresponding to a lower turnaway probability.\(^3\) Joskow uses hospital data from 1976 to analyze the impact of CON on turnaway probability and finds CON positively influences this value, thus decreasing his measure of hospital quality.

While limiting competition and capacity may decrease quality, some studies find that CON increases quality for specific procedures. CON has been shown to improve outcomes for two heart procedures requiring

\(^3\)While turnaways are rarely observed in hospital data, they do occur. This is evidenced by ambulance diversions where a hospital alerts local ambulances that their emergency department is overcrowded and patients should be transported elsewhere. This phenomenon is consistent with findings in Bagust et al. (1999) which uses simulations and finds that hospitals with an average occupancy of 85 percent being to have problems with overcrowding, as as the average occupancy climbs to 90 percent, this issue becomes significantly worse.
specialized equipment regulated by CON (Vaughan-Sazzarin et al. (2002) and Ross et al. (2007)). This finding may be explained by the volume-quality relationship found in many procedures (Peterson et al, 2004). As fewer hospitals conduct these procedures in states without CON, the hospitals with the necessary equipment perform the procedure more frequently. If the quality of the procedures improves with volume, this may lead to better outcomes in states where CON is present. Additionally, states may grant approval for the investments required to perform these procedures to hospitals considered capable of performing them with the highest quality. While these studies suggest that outcomes for selected interventions are better in states with CON, they are less informative in evaluating the effects of CON regulation on patient access.

Despite suggestions in the academic literature that CON’s effect on spending is minimal, with mixed implications for quality, the regulation is still present in a majority of states. Organizations representing hospital interests, including the American Hospital Association (AHA) and American Health Planning Association (AHPA), support CON regulation. My analysis will therefore be useful in helping to estimate CON’s impact on hospital capacity decisions and patient welfare. These results will be informative to policy makers considering whether to implement or discontinue the regulations.

3 Data

I use two datasets for my analysis that provide information at the patient and hospital levels. Patient data are from State Inpatient Databases (SID) from selected states. The American Hospital Association (AHA) annual survey provides data on hospital characteristics. I discuss important characteristics of each dataset and the construction of the final dataset below.

3.1 State Inpatient Data

I use SIDs from Arizona, New Jersey, New York, and Washington for the period of 1995 to 2009. For the duration of my data, Arizona does not have CON regulations in place. The other three states have CON regulations governing major investment decisions, which include hospital capacity. The data are distributed by the Healthcare Cost and Utilization Project (HCUP). I use this subset of states and years because they include detailed information on the patient residence.

The data include observations for each inpatient visit to a hospital in the state excluding those that are

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4The two procedures, percutaneous coronary intervention (PCI) and coronary artery bypass graft (CABG) both use a catheterization lab. These labs costs several million dollars to construct and require CON approval in many states.

5The data for New Jersey starts in 1997 and for Washington, it begins in 1999.
Federally owned.\(^6\) The SID data contain the full universe of hospitals and patients within these hospitals, thus allowing me to fully characterize hospital and patient behavior in each state. I use inpatient visits for all diagnoses and admissions sources in my analysis.

The SIDs include detailed information about the patient admission including the length of stay, whether the visit was elective or an emergency, the hospital where the patient was admitted, patient ZIP code, payment method, and diagnosis and procedure codes. The data do not include outpatient visits to hospitals or other clinics, or emergency department visits not resulting in admission to the hospital.

The price paid by the patient is not available in the data. While it includes hospital charges, these values are not an accurate reflection of the price facing the patient. Insurance companies negotiate the fraction of charges to be paid with the hospital, and this value varies across insurance providers, hospitals, and procedures. Charges are often reduced substantially for patients without insurance; these patients may qualify for charity care or arrange payment plans for a negotiated percentage of the final bill. I discuss my strategy related to the lack of availability of price data in more detail in the Section 5.\(^7\)

### 3.2 Hospital Data

The AHA survey data uses the hospital-year as the unit of observation and includes detailed information about each hospital including information on its location (ZIP code), ownership type, and number of beds.\(^8\) A hospital identifier allows for tracking individual hospitals over time and for linkages to the SIDs.

### 3.3 Combined Dataset

I merge the two datasets using a hospital identifier variable included in each dataset. I then use geographic information systems (GIS) software to estimate the distance from the centroid of each patient’s ZIP code to the centroid of the hospital’s ZIP code. This provides a measure of the distance each patient traveled to receive care.

I reshape the data so that the unit of observation becomes the patient ZIP-hospital-year combination as is done in Berry (1994). I calculate the share of patients from each ZIP code, admitted to each hospital. For my analysis, I consider any hospital that is further than 100 kilometers away, or receiving less than 5 percent of all patients from a ZIP code to be part of the outside option.\(^9\)

\(^6\)Federally owned hospitals are often run by the military or Department of Veteran Affairs and serve specific population subgroups. These hospitals are a small proportion of the total patient population for acute care hospitals.

\(^7\)For more information on hospital charges and how they relate to prices, see Lane et al. (2001) and Dobson et al. (2005).

\(^8\)The beds variable corresponds to the number of beds in the facility. During periods of low demand, some of these beds may not be staffed but I do not observe this in the data.

\(^9\)Gowrisankaran et al. (2010) also use a distance measure to determine the outside option in their hospital patient utility.
Summary statistics are provided in Table 1. The distance traveled is similar across states, with patients in New Jersey traveling a shorter distance. New Jersey is more densely populated than the other states in the sample, making this an expected finding. The observed share is the fraction of patients from the ZIP code who select that hospital. Average observed shares are similar across the four states with their values being slightly higher on average in Washington. Hospitals in New Jersey and New York have higher average capacity than those in Arizona and Washington.

<table>
<thead>
<tr>
<th></th>
<th>All States</th>
<th>AZ</th>
<th>NJ</th>
<th>NY</th>
<th>WA</th>
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<tbody>
<tr>
<td>Distance (km)</td>
<td>23.5</td>
<td>25.5</td>
<td>14.9</td>
<td>24.2</td>
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<td></td>
<td>(21.6)</td>
<td>(25.3)</td>
<td>(12.8)</td>
<td>(21.3)</td>
<td>(24.3)</td>
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<tr>
<td>Observed Share</td>
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<td>0.224</td>
<td>0.237</td>
<td>0.229</td>
<td>0.273</td>
</tr>
<tr>
<td></td>
<td>(0.199)</td>
<td>(0.202)</td>
<td>(0.237)</td>
<td>(0.191)</td>
<td>(0.220)</td>
</tr>
<tr>
<td>Total Beds</td>
<td>272.1</td>
<td>190.7</td>
<td>312.6</td>
<td>325.9</td>
<td>131.0</td>
</tr>
<tr>
<td></td>
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<td>(154.2)</td>
<td>(207.3)</td>
<td>(292.9)</td>
<td>(129.9)</td>
</tr>
<tr>
<td>Unique Hospitals</td>
<td>478</td>
<td>75</td>
<td>86</td>
<td>226</td>
<td>91</td>
</tr>
<tr>
<td>Unique Patient ZIP Codes</td>
<td>3,875</td>
<td>523</td>
<td>661</td>
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<td>696</td>
</tr>
<tr>
<td>N</td>
<td>145,876</td>
<td>20,683</td>
<td>21,653</td>
<td>84,863</td>
<td>18,677</td>
</tr>
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</table>

Each observation in N represents a unique ZIP-hospital-year combination. Values in parentheses represent standard deviations. Total beds is calculated at the hospital-year level.

Table 1: Summary Statistics

### 3.4 Is State Level Data Representative?

I analyze AHA data on capacity changes to determine whether trends observed in the four states in the combined patient-hospital dataset are consistent with hospitals nationally. I estimate two probit regressions with the dependent variable equaling an indicator for whether the hospital adjusts capacity up (specifications (1) and (2)) or down (specifications (3) and (4)). I control for hospital and market characteristics available in the AHA data. Additionally, I include a dummy variable for whether the hospital is located in a state with CON regulations. I include two sets of regressions - the first use all hospitals and the second are restricted to the sample of states used in my primary analysis. If the coefficients for the CON variable are similar between all hospitals nationally and the sample, this result will suggest that the regulations’ impact on hospital capacity can be generalized from my sample to all states.

As demonstrated in Table 2, the impact of CON regulation on the probability that a hospital increases capacity nationally is similar in magnitude and direction to the effect in my sample. CON has a slightly larger impact on bed decreases in my sample, but neither estimate is significantly different from zero. As framework. I check the sensitivity of this assumption to different distance and percentage cutoffs for the outside option and find similar results.
<table>
<thead>
<tr>
<th></th>
<th>Bed Increase</th>
<th></th>
<th>Bed Decrease</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>National</td>
<td>Sample</td>
<td>National</td>
<td>Sample</td>
</tr>
<tr>
<td>CON</td>
<td>-0.013</td>
<td>-0.014</td>
<td>-0.002</td>
<td>0.027</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.025)</td>
<td>(0.004)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>N</td>
<td>45,421</td>
<td>4,533</td>
<td>45,421</td>
<td>4,533</td>
</tr>
</tbody>
</table>

The unit of observation is the hospital-year. Coefficients are marginal effects. Standard errors are in parentheses. Controls are included for changes in patient days at the state level, hospital occupancy level, hospital ownership type, and year.

Table 2: National versus Sample Regressions

CON’s impact on capacity decisions is similar in my sample to national estimates, my results likely generalize to all 50 states.

4 Empirical Model

My empirical model features a set of hospitals competing over an infinite horizon in discrete time and follows from the framework outlined in Ericson and Pakes (1995). In each period \( t \), hospitals make capacity decisions for \( t + 1 \). If a hospital elects to increase or decrease capacity, it must also determine the magnitude of this change. I introduce a state space that includes any variable which affects a hospital’s returns from investment. Hospitals make capacity decisions that maximize their expected lifetime utility.

In each period, an exogenous set of patients select the hospital that provides the highest utility. The patient’s static hospital decision is based only on hospital characteristics and an unobserved error term. In some instances, the patient’s first choice hospital may be full in which case he attends the hospital that provides the second highest utility.

In the remainder of this section, I first outline the estimation of a hospital’s turnaway probability that determines whether the patient is admitted to his first choice hospital. I then discuss a model of patient utility and how its parameters are estimated after allowing for patients to be turned away from their first choice hospital. Finally, I discuss the dynamic model that characterizes the hospital capacity decision and how I solve for the parameters that impact hospital decisions.
4.1 Turnaway Probability

Joskow (1980) estimates turnaway probability using a simple queuing model introduced in Shonick (1970) and used by state planning agencies studying hospital capacity (Joskow, 1980). To estimate the turnaway probability, he assumes that patients arrive with a Poisson distribution of $\lambda$ and patient length of stay has a negative exponential distribution with a mean of $1/\mu$. If a hospital has $b$ beds, then the probability that $j$ of them are full at a specific time is given in equation (1).

$$P_j = \frac{(\lambda/\mu)^j/j!}{\sum_{h=0}^{b}(\lambda/\mu)^h/h!}$$

(1)

The distribution of $P_j$ is not Poisson due to the truncation at $b$. However, as $b$ becomes large relative to the mean number of patients, Poisson becomes a good approximation. In this distribution, the mean and variance are equal and when they become large, the Poisson can be well approximated by a normal distribution. Using these assumptions, the probability that a hospital is full can be rewritten in the following form where $\Phi$ represents a normal cumulative density function. The hospital’s average daily census, ADC, is calculated using the average length of stay and patient arrival rate.

$$P_f = 1 - \Phi\left(\frac{b - \text{ADC}}{\sqrt{\text{ADC}}}\right)$$

(2)

While Joskow estimates the turnaway probability as a proxy for hospital quality, I use this variable for what it measures - the probability that a patient is turned away from a hospital. In the literature, patient utility parameters are typically estimated based on the hospital to which the patient is admitted. Incorporating an estimate of the turnaway probability allows these parameters to account for the possibility that some patients may not end up at their first choice hospital.$^{10}$

4.2 Patient Utility

Patient utility follows the nested multinomial logit form discussed in Berry (1994). This functional form uses patients’ hospital choices to estimate patient utility parameters and the nest is the hospital ownership type. This is the same functional form to measure patient utility parameters as in Gorrisankaran et al. (2010).$^{11}$

$^{10}$ I estimate that a small number of hospitals have large turnaway probabilities. Throughout my analysis, I cap the estimated turnaway probability at 25 percent so that no hospital turns away more than a quarter of its patients. When I used other turnaway caps, the results do not significantly change.

$^{11}$ In Gorrisankaran et al. (2010), the authors include an unobserved time-varying hospital quality term, $\xi_{jt}$. But they assume that hospital shares are observed without measurement error which allows them to treat $\xi_{jt}$ as the error term. This simplifies estimation by reducing the equation to a nested multinomial logit model. I make the same assumption in my estimation.
is used to model patients choosing between hospitals in Gowrisankaran et al. (2010) to estimate patient utility where the nest is the hospital ownership type. Patient $i$ receives the following utility from visiting hospital $j$ in period $t$.

\[ u_{ijt} = \alpha_1 X_{ijt} + \alpha_2 Y_{jt} + \kappa_j + \epsilon_{ijt} \tag{3} \]

$X_{ijt}$ is a vector of variables that are specific to the patient and hospital such as the distance between $i$’s home ZIP code and hospital $j$. $Y_{jt}$ includes variables that impact the hospital’s quality and vary over time such as the hospital’s total capacity. $\kappa_j$ is a time-invariant hospital fixed effect which captures the baseline quality of hospital $j$. Finally, $\epsilon_{ijt}$ is an error term containing two components.

\[ \epsilon_{ijt} = (1 - \sigma)\epsilon_{1ijt} + \epsilon_{2igt} \tag{4} \]

$\epsilon_{1ijt}$ is distributed extreme value and is i.i.d. $\epsilon_{2igt}$ is drawn from the distributional form that allows $\epsilon_{ijt}$ to be generated from an extreme value distribution. While patient $i$ gets a separate draw of $\epsilon_{1ijt}$ for each hospital $j$, he only receives a draw $\epsilon_{2igt}$ for each hospital ownership type. This allows patients to have their unobserved preferences for hospitals be correlated by hospital ownership type. $\sigma$ is assumed to be between zero and one and represents this correlation. A higher value of $\sigma$ indicates that preferences between hospital ownership types plays a larger role in determining patient utility. When $\sigma$ is equal to 0, equation (3) reduces to a standard multinomial logit as the nest-specific error term drops out of the equation. When $\sigma$ is 1, the only error term for each patient occurs at the nest level.

Each patient chooses the hospital that provides the highest utility. If no hospital provides positive utility, the patient chooses the outside option and receives zero utility. The outside option still requires that each patient attends a hospital meaning I assume no patients skip or postpone medical treatment due to unsatisfactory hospital choices. Berry (1994) shows that the nested logit equation can be transformed into the following form.

\[ \log(s_{zjt}) - \log(s_{z0t}) = \alpha_1 X_{ijt} + \alpha_2 Y_{jt} + \alpha_j D_j + \sigma \ln(\bar{s}_{j/g}) + \xi_{zjt} \tag{5} \]

This transformation converts the unit of observation from the patient to the ZIP-hospital-year level. $s_{zjt}$

---

12In Gowrisankaran et al. (2010), the authors assume that there is an unobserved time-varying hospital quality term, $\xi_{jt}$. But they also assume that hospital shares are observed without measurement error which allows them to treat $\xi_{jt}$ as the error term. This simplifies estimation by reducing the equation to a nested multinomial logit model. I make the same assumption in my estimation.

13For more information on this distribution, see Cardell (1997).
represents the fraction of patients in ZIP code $z$ at period $t$ that choose hospital $j$ and $s_{z,0}$ is equal to the fraction that choose the outside option. $\bar{s}_{j/g}$ is the share of patients from ZIP code $z$ in period $t$ that choose $j$, conditional on selecting a hospital with the same ownership type as $j$. $\bar{s}_{j/g}$ will likely be endogenous and I instrument using the distance to the closest hospital of $j$’s ownership type that is not $j$.

I calculate the patient shares which make up the dependent variable in equation (5) in two ways. The first method assumes that patients are never turned away and attend the hospital that provides the highest utility. To estimate the parameters under this assumption, I use the fraction of patients from ZIP code $z$ who choose hospital $j$ in period $t$.

The assumption that all patients attend their first choice hospital is problematic if hospitals turn away patients when they are full. If turnaways occur, the share of patients visiting each hospital does not represent patient preferences. If the data included information on patients’ first choice hospitals (in addition to the hospital attended), the estimation would again follow equation (5) using the first choice hospital as the dependent variable.

First choice hospitals and turnaways are not observed in the data. I therefore use the following identity to calculate the share of patients who consider a hospital their first choice, $s_f$.\footnote{My notation drops hospital and time subscripts for simplicity.} $s_0$ represents the observed share that visit the hospital in the data, $s_t$ is the share that want to visit the hospital but are turned away, and $s_s$ is the share that are admitted to the hospital after being turned away from their first choice hospital.

$$ s_f = s_o + s_t - s_s $$

First choice shares are equivalent to the sum of the observed share in the data and the share who would have chosen the hospital had they not been turned away, less the share of patients who chose the hospital because they were turned away from their first choice. The only variable in identification (6) that is observed in the data is $s_o$ meaning both $s_t$ and $s_s$ must be estimated to predict $s_f$.

To estimate the number of patients who are turned away from the hospital, $s_t$, I use equation (2) which generates a measure of the turnaway probability. The share of patients who choose a hospital because their first choice was full also depends on these turnaway probabilities. To predict $s_s$, I estimate substitution patterns between hospitals. More detail on how these values are calculated is provided in Appendix 1.

Accurately predicting each hospital’s turnaway probability and substitution patterns requires that the coefficients estimated from equation (5) are correct. However, to accurately estimate these coefficients I need unbiased estimates of the turnaway probability and substitution patterns. To get unbiased estimates of both
of these sets of parameters, and therefore of first choice shares, I use the iterative process outlined below. I begin by setting $s_f$ equal to $s_o$.

(1) Given the current estimates of $s_f$, I calculate the values of $\log(s_{zjt})$, $\log(s_{z0t})$, and $\log(\bar{s}_{j/g})$, and use these values to estimate the coefficients in equation (5) via instrumental variables regression.

(2) Conditional on the parameters estimated in (1), I estimate the turnaway probabilities and substitution patterns for each hospital. Appendix 1 provides more detail on these calculations.

(3) Using the turnaway probabilities and substitution patterns estimated in (2), I calculate new values of $s_t$ and $s_s$ and use these values and $s_o$ to generate an updated estimate of $s_f$.

(4) I return to (1) until $s_f$ converges.

4.3 Hospital Capacity Decisions

I use an infinite horizon discrete time model where hospitals make capacity decisions in each period to maximize their expected lifetime utility. The model follows from the framework outlined in Ericson and Pakes (1995) and assumes that all hospitals simultaneously decide in period $t$ whether to adjust capacity for $t + 1$. Hospital $h$’s decision in $t$ affects its expected lifetime utility in two ways. First, this decision directly impacts utility in $t + 1$ as it determines $h$’s capacity and any associated adjustment costs in this period. Second, hospital $h$’s action in $t$ affects the competitive environment from which it makes its capacity decision in $t + 1$, which may impact its capacity decision in $t + 1$ and affect its expected lifetime utility.

I characterize this competitive environment using a state vector, $\omega_{ht}$, which includes hospital and market variables that influence the hospital’s returns from capacity. This vector includes key hospital variables such as capacity in period $t$, ownership type, and turnaway probability. Additionally, it features market level variables such as the metropolitan statistical area (MSA) size and the number of hospitals in the health service area (HSA).\(^{15}\)

The model assumes that hospital $h$ receives a shock vector, $\gamma_{ht}$, in each period that is generated from a function $F(.)$ and is not observed by its competitors or the econometrician. The vector represents unobserved factors that may impact the hospital capacity decision such as shocks to hospital adjustment costs.\(^{16}\) In each period, the hospital will choose a capacity action, $a_{ht}$, which characterizes whether the hospital increases or decreases its capacity, and the magnitude of any change.

\(^{15}\) HSAs were developed by the National Center for Health Statistics to estimate geographic markets for hospital care (National Cancer Center).

\(^{16}\) Shock values are assumed to be distributed iid over time and across hospitals.
To estimate hospital utility parameters, I would specify a functional form. However, my estimation focuses on estimating the hospital capacity actions, which are observed in the data. As a result, I do not need to specify a functional form for hospital utility and can keep the equation general. Hospital h’s utility in period t is assumed to be a function of its action in this period, the current state, and its shock vector.

$$U_{ht} = U(a_{ht}, \omega_{ht}, \gamma_{ht})$$

I define a Markov strategy for hospital h as a function, \(\sigma_h\), that maps each potential state and unobserved shock into an action. I can therefore replace the firm’s action, \(a_{ht}\), with its strategy function, \(\sigma(\omega_{ht}, \gamma_{ht})\), in equation (7) to describe utility as a function of a hospital’s strategy, state, and shock vector. A key feature of a Markov strategy is that conditional on the state and shock vector, h will choose the same action regardless of the period, thus allowing me to drop the time subscript.

I construct a value function for hospital h using equation (7) which gives h’s expected lifetime utility conditional on its current state and Markov strategy. The value function assumes that all hospitals have a common discount factor \(\beta\), and conditional on the current state and hospital h’s action in t, the state variable in t + 1 is generated from a probabilistic function \(P\). These assumptions are necessary to ensure the hospital capacity action and transition between states depend only on the current state variable and are not influenced by hospital actions or states in previous periods.

$$V(\omega_h, \sigma_h, \gamma_h) = U(\sigma_h(\omega_h, \gamma_h), \omega_h, \gamma_h) + \beta \int \int V(\omega'_h, \sigma_h, \gamma'_h) dP(s'|\sigma_h(\omega_h, \gamma_h), \omega_h) dF$$

The value function consists of two parts. The first is equal to the utility that the hospital receives in the current period based on its strategy function, the state vector, and the shock vector. This is simply the per-period hospital utility function defined in equation (7). The second part of the equation represents the expected lifetime utility that h receives beginning in the following period, conditional on using its strategy function, \(\sigma_h\), in the current period. Because the state and shock vectors in the following period are unknown, I integrate over each of their distributions to generate an expected value of the value function beginning in the following period.

Let \(\sigma\) be a set of Markov strategies for all hospitals, \(\sigma = (\sigma_1, \sigma_2, \ldots, \sigma_H)\). \(\sigma\) represents a Markov Perfect Equilibrium (MPE) if no hospital h has an incentive to deviate from its strategy function, \(\sigma_h\), assuming all other hospitals play their equilibrium strategies. A set of strategies, \(\sigma\), is therefore an MPE if for all states,
\( \omega \), and all hospitals, \( h \in [1, \ldots, H] \), the following condition holds.

\[
E(V(\omega_h, \sigma_h)) \geq E(V(\omega_h, \sigma'_h)) \quad \forall h \in [1, \ldots, H]
\]  

Following the methodology in Benkard, Bodoh-Creed, and Lazarev (2010), I make three assumptions about the MPEs for hospitals in my model that are necessary to solve the model and estimate its parameters. First, I assume that at least one pure strategy MPE exists. Second, all hospitals play the same MPE, even if it is not unique. Finally, we can think of this game as being played in two regulatory environments. Third, we can think of firms as making decisions under two regulatory environments - one where CON regulations are present and another where they are not. I assume that the state vector captures how returns to capacity vary in each environment and hospitals play the same Markov strategy in each case. This assumption is consistent with Benkard, Bodoh-Creed, and Lazarev (2010) which assumes that airline merger strategies are not impacted when other mergers are approved or rejected.

Using the value function in equation (8), I can solve for the strategy function, \( \sigma \), which maps states and \( \gamma \)'s into hospital actions. This estimation is difficult for several reasons. First, one must specify a functional form for hospital utility. If the form of this equation is misspecified, the estimates will be incorrect. Secondly, such estimation requires distributional assumptions about the unobserved vector, \( \gamma \). Finally, estimating these parameters requires multidimensional integration, which is computationally very challenging for my analysis.

Instead, I follow the estimation strategy outlined in Benkard, Bodoh-Creed, and Lazarev (2010) which estimates the probability of each hospital capacity action directly from the data, conditional on the current state. The primary advantage of this approach is that it does not require any functional form assumptions about hospital utility or capacity adjustment costs. Additionally, this method is less computationally demanding because probabilities can be estimated without integration. The primary drawback to this methodology is that it does not generate estimates of additional parameters in the empirical model, such as those hospital utility. These parameters are not needed to predict hospital capacity decisions or patient utility, however, and are therefore not necessary for my analysis.

I estimate the hospital choice probabilities using a simple two-step model. The first step uses a probit model where the dependent variable is an indicator for whether the hospital increased capacity between \( t \) and \( t + 1 \) and the independent variables are the set included in the state vector at time \( t \), \( \omega_{ht} \). These estimates generate predicted probabilities that the hospital increases capacity conditional on the state. Second, I estimate the amount by which the hospital changes capacity conditional on adding beds. In this OLS regression, I restrict the sample to hospitals that add capacity between \( t \) and \( t + 1 \) and use the same set
of independent variables; the dependent variable is the magnitude of the capacity change. For both the probit and OLS regressions, I include a dummy variable for whether CON is present among the independent variables to control for the regulatory environment. After estimating these parameters for capacity increases, I repeat this process with hospital capacity decreases.

5 Results

Based on my empirical model, I present two sets of results: parameters associated with patient utility and those corresponding to hospital capacity adjustments.

5.1 Patient Utility

Table 3 uses equation (5) to estimate the patient utility that using two specifications. The first specification, labeled “No Turnaways” assumes that each patient is admitted to his first choice hospital. The second specification labeled “Turnaways” allows for a patient to be turned away from his first choice hospital if it is full. When this occurs, he chooses his second choice hospital. The calculation of these turnaway probabilities and substitution patterns is outlined in more detail in Section 4.2. The primary difference between these regressions is that I now use estimated first choice shares rather than observed first choice shares. Both regressions include hospital fixed effects to control for unobserved time-invariant hospital quality as well as other hospital level variables such as ownership type.

<table>
<thead>
<tr>
<th></th>
<th>No Turnaways</th>
<th>Turnaways</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance (km.)</td>
<td>-0.025</td>
<td>-0.023</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Distance²</td>
<td>0.0002</td>
<td>0.0001</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.00004)</td>
</tr>
<tr>
<td>Distance³</td>
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<td>1.31e-07</td>
</tr>
<tr>
<td></td>
<td>(6.03e-07)</td>
<td>(2.96e-07)</td>
</tr>
<tr>
<td>Closest Hospital</td>
<td>0.242</td>
<td>0.307</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Distance*Gov’t</td>
<td>-0.003</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Distance*Nonprofit</td>
<td>-0.005</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Log(Beds)</td>
<td>-0.047</td>
<td>-0.054</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Log(Beds)*Gov’t</td>
<td>0.064</td>
<td>0.063</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.010)</td>
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<tr>
<td>Log(Beds)*Nonprofit</td>
<td>0.138</td>
<td>0.125</td>
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<tr>
<td></td>
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<td>(0.011)</td>
</tr>
<tr>
<td>σ</td>
<td>0.515</td>
<td>0.446</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>N</td>
<td>145,876</td>
<td>145,876</td>
</tr>
</tbody>
</table>

Standard errors are clustered by hospital and in parentheses. Regressions include hospital and year fixed effects. N corresponds to ZIP-hospital-year combinations. σ is the correlation of the nesting parameter.

Table 3: Patient Utility Regressions

The results in the two specifications are similar suggesting that patient turnaways do not substantially
impact the patient utility parameters. This is not surprising given that I estimate that the mean hospital turnaway probability in the data is 1.2 percent suggesting that a large majority of patients are accepted at their first choice hospital. While the distance coefficients are difficult to interpret directly due to the squared and cubic terms, they indicate patients prefer hospitals closer to their homes. For example, an increase in the distance traveled to a nonprofit hospital from 10 to 15 kilometers corresponds to utility decrease equaling 24 percent of the total value associated with travel distances. The dummy variable for being admitted to the closest hospital is also positive and significant indicating that patient utility increases when the patient is admitted to the closest hospital to his home.

While the coefficient on the log of beds is negative, when it is interacted with a dummy variable for being a nonprofit hospital, the overall effect is significant and positive. This suggests that for nonprofit hospitals, patient demand is endogenous to capacity and a nonprofit facility will get more patients if it adds beds.

The correlation for the nesting parameter is significantly different than zero indicating that some patients do have a preference for certain hospital ownership types. These estimates are comparable to the correlation coefficient found in Gowrisankaran et al. (2010) which estimates patient preferences among rural hospitals.

As mentioned earlier, I do not include a measure of hospital prices. By including a hospital fixed effect, I capture the relative time-invariant prices of hospitals. Additionally, patients rarely know the price of a procedure or visit when choosing a hospital, and in many cases, only pay a small fraction of the total price with insurance covering the rest.\textsuperscript{18} For these reasons, I am confident that omitting prices does not substantially impact my estimates.

In these regressions, I have treated all patients as having homogenous preferences for hospital characteristics (e.g. distance, ownership type, capacity). However, in practice, patients who are hospitalized for an emergent health problem may have different preferences for distance traveled than those admitted for an elective procedure. Likewise, my analysis is restricted to general hospitals, whereas some patients may have a preference for certain hospitals based on the type of procedure performed (e.g., heart surgery). While my nesting parameter may capture a portion of this effect if hospital ownership types are correlated with the characteristics desired by patients, future research will address this in more detail.

\textsuperscript{18}I ran similar regressions to those in Table 3 where I limited the regressions to Medicare patients and found similar results. As all Medicare patients have substantial coverage of the hospital costs, they may have lower sensitivity to prices than other patient subgroups.
5.2 Hospital Capacity Decisions

Using probit regressions, I estimate hospital choice probabilities analyzing the effect of variables in the state vector impact on the likelihood the hospital increases capacity in the following year. Separately, I estimate these probabilities for contractions in capacity. Additionally, conditional on making an adjustment, I estimate the magnitudes of the capacity adjustment in separate OLS regressions.

One of the key variables of interest is an indicator variable for the presence of CON in the state where the hospital is located, which does not change over the time period of interest. I therefore cannot include hospital fixed effects in these regressions as they would eliminate the coefficient estimates on CON. I therefore include numerous variables to control for hospital characteristics and the competitive environment.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<td></td>
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<td>Up</td>
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<tr>
<td>Log(Beds)</td>
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<td>-0.203</td>
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<td></td>
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<td>(0.008)</td>
<td>(0.016)</td>
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<td>(0.012)</td>
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<tr>
<td></td>
<td>(0.022)</td>
<td>(0.019)</td>
<td>(0.024)</td>
<td>(0.101)</td>
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<td>(0.037)</td>
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<td>Turnaway Prob.</td>
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<td>0.132</td>
<td>-0.059</td>
<td>-0.560</td>
<td>0.149</td>
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<tr>
<td></td>
<td>(0.106)</td>
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<td>(0.094)</td>
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<td>(0.150)</td>
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<tr>
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<td>(0.00001)</td>
<td>(7.19e-06)</td>
<td>(0.00002)</td>
<td>(9.19e-06)</td>
<td>(0.0002)</td>
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<td>7.16e-06</td>
<td>-0.005</td>
<td>-0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.0006)</td>
<td>(0.0003)</td>
<td>(0.004)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Market Hosps</td>
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<td>-0.0006</td>
<td>-0.048</td>
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<tr>
<td></td>
<td>(0.018)</td>
<td>(0.018)</td>
<td>(0.003)</td>
<td>(0.039)</td>
<td>(0.004)</td>
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<td>Market Beds</td>
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<td></td>
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<td>(0.018)</td>
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<td>(0.023)</td>
<td>(0.004)</td>
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<tr>
<td>( \hat{p} )</td>
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<table>
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<td>0.047</td>
<td>0.211</td>
<td>0.216</td>
<td>0.097</td>
<td>0.111</td>
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<td>1,113</td>
<td>1,113</td>
<td>1,114</td>
<td>1,114</td>
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</tbody>
</table>

"Adjust" regressions give probit marginal effect coefficients whereas the "How Much" regressions provide OLS coefficients. Robust standard errors are in parentheses. All regressions include time fixed effects. \( \hat{p} \) refers to the estimated probability from specification (1) or (2) that the hospital adjusts capacity. N corresponds to hospital-years. \( R^2 \) refers to the pseudo-R2 value for the probit regressions.

Table 4: Hospital Capacity Adjustment Regressions

Both the probit and OLS results are presented in Table 4. The specifications in the first two columns are probit regressions where the dependent variable is a dummy for whether the hospital increased or decreased its capacity in the following year.\(^{19}\) The third through sixth specifications use OLS where the dependent

\(^{19}\) I also combine these first two probit regressions using an ordered probit specification equaling 0 if the hospital decreases
variables is the difference between the log of the new capacity total and the log of the old capacity total. For the capacity increase specification, the dependent variable will always be positive, and for the capacity decrease specification, it will be negative.

The coefficients in the first column indicate a hospital is more likely to add capacity if it has a larger number of beds. Additionally, the presence of CON in the state where the hospital is located decreases the probability that a hospital adds beds. This result indicates that regulations affect hospital capacity decisions and hospitals in states with CON are less likely to add beds.

The probit regression on capacity increases also indicates that a hospital with a higher turnaway probability is more likely to increase capacity. The elasticity measure, which indicates how many additional patients a hospital is expected to receive if it increases capacity by one bed, is positive; this suggests hospitals that are better suited for business stealing are more likely to add capacity. The coefficients on the market’s total number of hospitals and total beds suggest a hospital is more likely to increase capacity when there are more local competitors, but as these competitors get larger, this likelihood decreases.

The coefficients for the model estimating the probability a hospital adjusts capacity downwards are less definitive as the only statistically significant coefficient is the logged number of beds. As with capacity increases, a hospital is more likely to decrease its capacity when has a larger number of beds. The presence of CON in the hospital’s state does not significantly affect the probability that a hospital adjusts capacity downwards.

While the pseudo-$R^2$ values for my probit regressions are small, they are comparable to the values found using this sort of dynamic model of firm behavior such as Ryan (2011).\textsuperscript{20} For the simulations, I use similar regressions, but include additional variables and interactions to more fully characterize what impacts the probability that a hospital adjusts its capacity. In these probits, the pseudo-$R^2$’s increase to 0.067 and 0.056 respectively.

While the results become more difficult to interpret with the additional variables, the estimated impact of CON regulations on a hospital with mean characteristics is similar to those values estimated in Table 4. For example, the total marginal effect of CON on the probability that a hospital increases capacity is -0.059, whereas the value in Table 4 is -0.082. Because I allow the impact of CON to vary based on hospital characteristics, some hospitals will be more affected by the presence of regulations than others. For example, capacity, 1 if it makes no change, and 2 if it increases capacity. The coefficient estimates were similar, but did not fit as well for some variables. For example, larger hospitals are more likely to both increase and decrease capacity and this is difficult to capture in an ordered probit model.

\textsuperscript{20}When looking at the probability of entry, Ryan reports likelihood ratio test values under 0.03 when excluding region fixed effects.
if a hospital decreases from having the median capacity (214 beds) to the 25th percentile (110), but keeps all other characteristics constant, CON’s decreases the probability that it adds capacity by an additional 0.6 percent.

I include four regressions estimating the amount by which a hospital adjusts its capacity conditional on having changed capacity between \( t \) and \( t + 1 \). Specifications (3) and (4) estimate the effect of variables on the amount by which a hospital increases capacity, conditional on adjusting upwards. Specifications (5) and (6) focus on cases where the hospital decreases capacity.

\( \hat{p} \) is a variable equal to the estimated probability that the hospital increases or decreases its capacity using the coefficients estimated in the probit regressions. For example, in specification (4), \( \hat{p} \) is equal to the probability that the hospital increased its capacity as estimated using the probit regression in specification (1). I include this variable to allow this probability to impact the amount by which hospitals change capacity. The inclusion of \( \hat{p} \) makes the remaining coefficients more difficult to interpret so I also include specifications that exclude this variable. Specifications (3) and (4) indicate that as a hospital becomes larger, the log of its capacity change decreases. This result is explained by the definition of the dependent variable in the OLS regressions. The change in capacity is equal to the difference in log capacity values. As a result, an increase of 5 beds will yield a larger dependent variable when the original capacity is small than when it is great.\(^{21}\) Similarly, the results suggest that the measure of capacity decreases by a larger amount when they the hospital’s original capacity is smaller. In specifications (4) and (6), the coefficients on \( \hat{p} \) indicate that as a hospital becomes more likely to adjust capacity, the expected magnitude of the change is greater, even after controlling for hospital observables.

6 Simulations

6.1 Methodology

I use simulations to predict how the U.S. hospital market would evolve over an extended period of time both with and without CON regulations. They are informative in two ways. The first benefit of these simulation model is that instead of estimating how CON regulations impact the likelihood of a capacity change between periods \( t \) and \( t + 1 \), simulations allow for hospitals to adjust to the regulatory policy over several periods. This is important for assessing the impact of the policy over a longer time horizon.

The second benefit of the simulations is that I am able to estimate how patient welfare changes from

\(^{21}\)For example, \( \log(25) - \log(20) > \log(100) - \log(95) \).
the hospital capacity decisions associated with each regulatory policy. This is done by simulating patient hospital choices conditional the the hospital capacity decisions in the simulations. Estimating CON’s impact on patient decisions is critical because I am ultimately interested in assessing the regulation’s effect on patient welfare; this framework will allow for the estimation of total patient distance traveled and total patient utility.

I assume that in the first year of the simulations, hospitals have the capacity observed in the data. Beginning in the next period, however, I consider two worlds: one in which the hospital is subject to CON regulations, and a second where it is not. Conditional on having an estimate of the hospital’s capacity in \( t \), the simulation model estimates capacity in \( t + 1 \).

Conditional on capacity in \( t \), I estimate values for each variable necessary to predict the probability of adjusting capacity up or down for \( t + 1 \). These include variables from the empirical model such as turnaway probability and elasticity. Once I have estimated all of the variables that affect a hospital’s probability of adjusting capacity, I use these values and their corresponding coefficients to estimate the probability that a hospital adjusts its capacity up or down.\(^{22}\) For each hospital, I draw a random number from a uniform distribution and use this value and the estimated probability to determine whether the hospital increases or decreases capacity in this instance.\(^{23}\) If I predict that the hospital adjusts capacity, I estimate the magnitude of this change using the estimated variables and coefficients from the OLS regressions. Having simulated hospital capacities in \( t + 1 \), I repeat this process to estimate capacities in \( t + 2 \).

I estimate capacity for each period observed in the data, which ends in 2009. I continue simulating hospital decisions for an additional 10 years to get a longer time horizon in which to evaluate the CON regulation’s impact. This requires assumptions about how the number of patients in each ZIP will change over the final 10 years. I assume that for each ZIP code, the annual patient growth rate is equal to rate over the past three years observed in the data. Additionally, I assume that during this time period, there is no hospital entry or exit.\(^{24}\)

I differentiate between the two regulatory policies using the dummy and interaction variables associated with whether the hospital is in a state with CON. In the first simulation, I set the CON dummy variable equal to one and turn on all of the interaction variables that include CON status. In the second, the CON dummy and interaction variables are set to zero. This will lead to different probabilities that the hospital increases or decreases capacity, even if all of the other hospital variables are equal.

\(^{22}\)In a very small number of cases, the sum of these two probabilities exceeds one. In these cases, I deflate the probabilities so that their ratio is unchanged, but they sum to one.

\(^{23}\)All of the simulated values reported in this section take the mean value from across 50 simulations.

\(^{24}\)This assumption is reasonable given the low levels of entry and exit observed in the data.
After running the simulations, I compare how hospital capacity decisions vary based on whether CON regulations are in place to determine the impact of CON regulations on hospital capacity. Additionally, I estimate the share of patients from every ZIP code who choose each hospital under both policy scenarios using the patient utility parameters and estimates of each hospital’s turnaway probability. These predicted shares are used to estimate total patient utility.

6.2 Fit of Simulations

As discussed in the results section, the pseudo-$R^2$ values for the probit regressions are comparable to other papers using dynamic models of firm behavior. However, I study the fit of the simulations using two additional methods.

In the first, I compare the mean value of hospital capacity and turnaway probability for hospitals in the observed data with that in the simulation that uses the regulatory policy that is in place. If the simulations accurately reflect how hospitals make capacity decisions, these mean values should be similar to those observed in the data. The mean values are presented in Table 5.

<table>
<thead>
<tr>
<th></th>
<th>CON Data</th>
<th>Model</th>
<th>No CON Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Beds)</td>
<td>5.27</td>
<td>5.27</td>
<td>4.88</td>
<td>4.87</td>
</tr>
<tr>
<td>Turnaway Probability</td>
<td>1.2%</td>
<td>1.4%</td>
<td>0.9%</td>
<td>1.2%</td>
</tr>
</tbody>
</table>

Observations are at the hospital-year level. All values are means. This table compares the mean values observed in the data with those predicted in my model and separately consider hospitals subject to CON and those without regulations.

Table 5: Mean Values in Data Versus Simulations

Overall the means for both the estimates of capacity and turnaway probability are similar for the observed data and the model predictions in both regulatory environments. While the mean values from the simulations show that the models appear to fit the data well, this does not necessarily indicate that the hospitals that are observed to adjust capacity in the data are the same who are predicted to adjust capacity in the simulation models. To address this, I sum the total number of times a hospital is observed to increase capacity in the data, as well as in the number of times it increases capacity in the simulations using the observed regulatory environment. I run regressions where the unit of observation is the hospital, the dependent variable is the number of times that a hospital increases or decreases capacity in the simulations, and the only independent

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25 For example, when looking at hospitals in New York, I compare the observed data to values from my simulations that assume CON is present because New York has CON regulations.
variable is the number of capacity increases or decreases observed in the data.

<table>
<thead>
<tr>
<th>Observed Data Changes</th>
<th>Increase</th>
<th>Decrease</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model Total Changes</td>
<td>0.382</td>
<td>0.143</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.051)</td>
</tr>
</tbody>
</table>

The observations occur at the hospital level. In the first specification, the dependent variable is the number of times in the model that the hospital increases capacity. The independent variable is the number of times this hospital increases capacity in the data. Robust standard errors are given in parentheses.

Table 6: Regressions Analyzing Fit of Simulations

The coefficients suggest that while the simulations do not perfectly predict hospital capacity behavior, there is a strong positive correlation between the number of capacity increases observed in the data and the simulations. Based on the coefficient sizes, the model appears to better fit capacity increases than decreases. These results hold when I run separate regressions for hospitals in states with CON, and without it.

6.3 Estimates

Table 7 only uses simulated data and compares the mean estimated capacities and turnaway probabilities under each regulatory policy. I look at the entire sample as well as breaking the analysis into years observed in the data and those that are simulated.

<table>
<thead>
<tr>
<th>Observed Years</th>
<th>2010-2019</th>
<th>Combined</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CON</td>
<td>No CON</td>
</tr>
<tr>
<td>Log(Beds)</td>
<td>5.19</td>
<td>5.19</td>
</tr>
<tr>
<td>Turnaway Probability</td>
<td>1.5%</td>
<td>1.4%</td>
</tr>
<tr>
<td>N</td>
<td>5,578</td>
<td>5,578</td>
</tr>
</tbody>
</table>

All values are means. The unit of observation is the hospital-year. “Observed Years” refers to estimates from 1995 through 2009.

Table 7: Comparison of Mean Values For CON Regulations and No CON

In the observed years, the both regulatory policies have similar values for overall capacity and the turnaway probability indicating that if a state added or dropped regulations, the impact on these variables would be minimal. When looking at the projected impact from 2010 to 2019, however, hospitals have more capacity when they are not subject to CON regulations. While this difference in capacity is relatively small, the subsequent change in average turnaway probabilities is larger with CON regulated hospitals turning
away an estimated 82 percent more patients.\textsuperscript{26}

While the regulation’s overall impact on hospital capacity is small, it is possible that CON’s impact differs across hospitals based on their characteristics. Table 8 considers this possibility and looks at the mean predicted capacity and turnaway probability values based on the hospital’s size, ownership type, and whether it is in a large metropolitan area.

<table>
<thead>
<tr>
<th></th>
<th>Log Beds</th>
<th>Turnaway Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CON</td>
<td>No CON</td>
</tr>
<tr>
<td>Log(Beds) &gt; 5.5</td>
<td>5.91</td>
<td>2.5%</td>
</tr>
<tr>
<td></td>
<td>5.86</td>
<td>2.1%</td>
</tr>
<tr>
<td>Log(Beds) &lt; 5.5</td>
<td>4.55</td>
<td>2.0%</td>
</tr>
<tr>
<td></td>
<td>4.61</td>
<td>1.1%</td>
</tr>
<tr>
<td>Local Gov’t Owned</td>
<td>4.64</td>
<td>1.1%</td>
</tr>
<tr>
<td>Nonprofit</td>
<td>5.27</td>
<td>2.4%</td>
</tr>
<tr>
<td>For-Profit</td>
<td>4.53</td>
<td>3.4%</td>
</tr>
<tr>
<td>Small MSA</td>
<td>4.65</td>
<td>2.1%</td>
</tr>
<tr>
<td>Large MSA</td>
<td>5.56</td>
<td>2.1%</td>
</tr>
</tbody>
</table>

All values are means. The unit of observation is the hospital-year. The categorization by log beds uses the number of beds observed in the data. For observations after 2009, I use the observed bed value from 2009. Using this criteria, any hospital with 245 or more beds is categorized as large. A hospital is categorized as being in a small MSA if it is not in an MSA, or if it is in an MSA with a population less than 1,000,000. It is categorized as being in a large MSA if it is an MSA with a population greater than 1,000,000.

Table 8: Comparison of Simulation Means by Hospital Characteristics

The results suggest that CON regulation affects the average capacity of both large and small hospitals, but in opposite directions. Large hospitals actually have slightly higher capacity when CON is in place whereas small hospitals have lower capacity under CON regulation. Turnaway probabilities are lower without CON for both large and small hospitals, though the disparity is greater for smaller hospitals. When looking at hospitals by ownership type, the difference in capacity with and without CON regulation is minimal for local government and nonprofit hospitals. For-profit hospitals are most affected and have a higher capacity when no CON regulations are in place. The turnaway probabilities are again larger for all ownership types when CON regulations are in place. These findings are consistent with the qualitative research from Yee et al. (2010) suggesting that smaller hospitals are disproportionately affected by CON.

CON also impacts patient welfare through its effect on hospital capacity decisions. I therefore estimate

\textsuperscript{26}The divergence in turnaway probabilities later in the sample occurs most noticeably in Arizona. During this time period, the number of patients in Arizona is estimated to grow rapidly and my simulations predict that under these conditions, CON regulations prevent the hospitals from increasing capacity sufficiently to meet the growing demand. While the patient growth rate in Arizona may be larger than nationally, this finding indicates that CON regulations may be problematic nationally if the population continues to age and demand more hospital services going forward.
this impact and present the results in Table 9. I measure utility in several ways. I first look at the difference in the distance traveled under the two regulatory policies. The percentage difference between the policies is small with patients traveling 0.3 percent further over the full simulation period when CON regulations are present. I then consider how total patient utility changes based on the regulatory environment. Calculating total utility using the patient utility parameters, I estimate that utility is 1.2 percent higher when there are no CON regulations in place. The majority of this difference occurs in the last ten years of the simulation period. This percentage is not informative by itself, however, as utility is not expressed in a meaningful unit measure. I therefore estimate the necessary change in distance traveled for all patients when CON regulations are in place to get the same total utility as when no regulations are present. This value is estimated to be -5.1 percent indicating that if all patients decreased their distance traveled by 5.1 percent under CON their total utility would be equal to the case where no regulations are present.

<table>
<thead>
<tr>
<th></th>
<th>1995-2009</th>
<th>2010-2019</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel Change (%)</td>
<td>0.2</td>
<td>-1.0</td>
<td>-0.3</td>
</tr>
<tr>
<td>Utility Change (%)</td>
<td>0.1</td>
<td>2.4</td>
<td>1.2</td>
</tr>
<tr>
<td>Compensating Distance Change (%)</td>
<td>-0.7</td>
<td>-10.2</td>
<td>-5.1</td>
</tr>
</tbody>
</table>

All values are percent changes. In the first two rows, the percent difference represents the change when going from having CON regulations to no regulations. The third row represents the change in distance traveled for patients when CON is present so that total patient utility is equal to that when there are no regulations.

Table 9: Utility Comparison Based on CON Status

7 Impact of Higher Turnaway Probability

Throughout my empirical analysis, I have assumed that the set of patients who are turned away from a given hospital is random and not correlated with observed or unobserved patient characteristics. If this assumption does not hold, there may be additional distributional effects to consider when assessing the impact of CON.

To test the validity of this assumption, I use a simple regression framework and look specifically at two types of hospital admissions. I first focus on the fraction of hospital admissions where the patient was admitted for a mental health related diagnosis related group (DRG). As discussed in many sources including Horwitz (2005), patients with severe mental illness are typically among the least profitable for a hospital. As a result, if the assumption that a hospital was turning patients away randomly was violated by selecting patients to turn away based on their diagnosis, hospitals may turn away a greater fraction of patients diagnosed with mental illness.
In addition to looking at the DRG, I also consider whether the patient belongs to a racial/ethnic minority group. Hsia et al. (2011) find hospitals that are more likely to divert ambulances (thus turning patients away) tend to serve a larger fraction of minority patients. This result suggests that minority populations are disproportionately affected by hospital crowding. My analysis addresses a different but related question—how does a hospital’s racial composition change as it becomes more crowded?

To estimate the effect of turnaway probability on mental health and minority patients, I use a simple regression framework. I first estimate the turnaway probability for each hospital and month using equation (2). The regressions take the following form.

\[ s_{ht} = \alpha_1 P_{ht} + \alpha_h + \alpha_t + \epsilon_{ht} \]  

\( s_{ht} \) is the fraction of patients who are admitted to hospital \( h \) in month \( t \) who have a mental health diagnosis (column 1), or are characterized as a member of a racial/ethnic minority group (column 2). \( \alpha_1 \) is the parameter of interest. It is the coefficient on the turnaway probability estimated at hospital \( h \) in month \( t \), \( P_{ht} \). The regressions also include hospital and admission month and year fixed effects. The coefficient \( \alpha_1 \) captures the impact of a change in turnaway probability for a given hospital on its share of patients who have a mental health diagnosis or are characterized as a member of a racial/ethnic minority group. Because of the fixed effects, this coefficient analyzes how a change in turnaway probability at hospital \( h \) impacts the share of mental health or minority patients at this hospital.

The results are presented in Table 10 and suggest that the composition of hospital admissions are affected by turnaway probability. The coefficient on the turnaway probability in the first model is negative and statistically significant. This indicates that as a hospital becomes more crowded, the fraction of mental health patients admitted decreases. This is consistent with the notion that as hospitals become full, they are more likely to turn away mental health patients than other types of patients. Similarly, the fraction of minority patients decreases as a hospital becomes closer to full capacity.

While these results do not necessarily indicate that hospitals discriminate against certain types of patients, they do show that the composition of patients varies based on turnaway probability. This finding suggests that there may be distributional concerns associated with the presence of CON are not considered in my model. I intend to explore these questions of turnaway probability and how it relates to patient access.

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27 I define a minority as anyone in the data identified as “Black,” “Hispanic,” “Asian or Pacific Islander,” “Native American,” or “Other.”

28 It does not estimate the impact of turnaway probability on patient composition between hospitals. There are many potential reasons why turnaway probability may affect patient composition across hospitals.
In the first specification, the dependent variable is the fraction of patients at the hospital in that month who have a mental health diagnosis. In the second specification, I use the fraction of minority patients. The coefficients represent the turnaway probability’s effect on the fraction of hospital patients who have a mental health diagnosis or are minorities. I include hospital, year, and month fixed effects. Standard errors are clustered at the hospital level and included in parentheses. The regression using minority share as the dependent variable has fewer observations because race is not available in the Washington data.

Table 10: Impact of Turnaway Probability on Patient Composition

<table>
<thead>
<tr>
<th>Turnaway Probability</th>
<th>Mental Health</th>
<th>Minority</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.0063</td>
<td>-0.0202</td>
</tr>
<tr>
<td></td>
<td>(0.0030)</td>
<td>(0.0035)</td>
</tr>
<tr>
<td>N</td>
<td>73,960</td>
<td>61,843</td>
</tr>
</tbody>
</table>

particularly for vulnerable subpopulations, in more detail in future work.29

8 Conclusion

I use patient and hospital data to build an empirical model that estimates the probability that hospitals adjust capacity. The model analyzes the impact of CON regulations on hospital capacity decisions and find that the presence of CON decreases the probability that a hospital adds capacity. Additionally, I estimate patient demand by using a nested logit model to estimate how parameters such as distance traveled and hospital size affect patient hospital preferences.

Using the parameters for hospital capacity decisions and patient utility estimated in the model, I run simulations that predict how hospital capacity would evolve under CON regulations and an unregulated environment. The simulation results suggest that CON has a limited effect on mean hospital capacity and turnaway probabilities in the short term, but over time hospitals have more capacity and turn away fewer patients when there are no regulations in place. Additionally, the simulation results indicate that the differences in capacity are greater for smaller and for-profit hospitals. The simulations allow for the estimation of patient welfare using the patient utility parameters estimated in the empirical model. They find that the presence of CON regulations decreases patient welfare considerably and to make patients as

29As I noted in the literature review, one major gap in the CON literature relates whether CON leads to some patients never making it to a hospital. While this analysis does not answer that question, it relates to the issue of access and may serve as a starting point for such an analysis.
well off under CON as when no regulations in place, each patient would have to decrease his distance traveled by 5.1 percent.

I also study how different patient types are affected by hospital turnaways. My results indicate that as a hospital becomes more crowded and turns away a larger fraction of patients, its total patient composition changes such that it has fewer mental health patients and minorities admitted. As my primary results indicate that turnaways increase when CON regulations are in place, these findings suggest that there may be distributional effects to the regulation. I plan to study this question in more detail in future research.

This analysis is informative in detailing how CON regulations’ impact hospital capacity, and ultimately how this affects patient welfare. My findings suggest that patients are made worse off by CON regulations. In future research, I will develop a model that also estimates the impact of CON on hospital investment costs which will allow for a more complete welfare comparison between the regulatory policies. As debate over CON’s impact on total welfare continues, this research will help to inform policy makers about a major component of CON regulations and how it impacts both patients and hospitals, as well as total welfare.
9 Works Cited


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Appendix 1: Estimation of Hospital Turnaway Probabilities and Substitution Patterns

This section outlines how I calculate the substitution patterns between hospitals, and the two other variables used in the estimation of first choice shares, $s_t$ and $s_s$. $s_t$ represents the share of patients who wanted to attend the hospital, but do not because they were turned away. $s_s$ is equal to the share of patients who are admitted to the hospital after being turned away from their first choice hospital. My methodology follows from the nested logit equations outlined in Berry (1994). The values for $s_t$ and $s_s$ are calculated assuming that I have already estimated the regression coefficients in equation (5) and that these coefficients represent the true patient parameters. Using these coefficients, I calculate the predicted share of patients for each hospital from each ZIP code, $\bar{s}_j$.

Equation (11) estimates the within-nest share which is equal to the fraction of patients in ZIP code $z$ who choose hospital $j$, conditional on choosing a hospital of $j$’s ownership type, $g$. This is equivalent to a standard multinomial logit equation for all patients and hospitals with ownership type $g$. Equation (12) predicts the nest shares which are equal to the fraction of patients in $z$ who choose a hospital of ownership type $g$. In both of these equations, $\delta_j$ is the predicted utility for hospital $j$ and $\sigma$ is the nesting parameter’s correlation as calculated from the parameter estimates generated in equation (5). The share is equal to the hospital’s within-nest share multiplied by the nest’s share as given in equation 13.

\[
\bar{s}_{j/g}(\delta_j, \sigma) = \frac{e^{\delta_j/(1-\sigma)}}{\sum_{j \in G} e^{\delta_j/(1-\sigma)}}
\]

\[
\bar{s}_g(\delta_j, \sigma) = \frac{\left[\sum_{j \in G} e^{\delta_j/(1-\sigma)}\right]^{1-\sigma}}{\sum_{G} \left[\sum_{j \in G} e^{\delta_j/(1-\sigma)}\right]^{1-\sigma}}
\]

\[
\bar{s}_j = \bar{s}_{j/g} \bar{s}_g
\]

To estimate the substitution patterns for hospital $j$, I decrease the utility associated with $j$, $\delta_j$, by a small amount, $\epsilon$ while holding the utility for all other hospitals constant. I compare how the predicted share of patients changes based on this decrease in $\delta_j$ and determine how the fraction of patients who no longer select $j$ reallocate among the remaining hospitals by reestimating equations (11) and (12). I repeat this calculation for each hospital to get a complete set of substitution patterns.

I estimate the share of patients turned away from each hospital using the formula for turnaway probability
given in equation (2). Multiplying the turnaway probability by the total number of patients whose first choice is \( j \) gives an estimate for the number of turned away patients, \( s_t \). I reallocate these patients to other hospitals using the substitution patterns for hospital \( j \).\(^{30}\) After reallocating all turned away patients, I sum the total number of additional patients each hospital receives because they were turned away from their first choice hospital to generate \( s_s \). Having solved for these two variables, I now estimate the first choice shares, \( s_f \).

\(^{30}\)For example, if the substitution patterns estimate that one quarter of patients who leave hospital \( h_1 \) now select hospital \( h_2 \), then one quarter of the patients turned away from \( h_1 \) will be admitted to \( h_2 \).