Government policy and the dynamics of market structure: Evidence from Critical Access Hospitals

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Abstract

This paper seeks to understand the impact of the Medicare Rural Hospital Flexibility Program. The overarching goal of this legislation is to maintain access to quality hospital care for rural residents. To achieve this objective, the program created a new class of hospital, the Critical Access Hospital (CAH), to which rural hospitals can convert. Like many other government policies, the CAH program targets the underlying supply infrastructure, in this case by providing generous cost-plus reimbursement to converting hospitals in exchange for capacity and service limitations. We specify a dynamic oligopoly model of the rural hospital industry with hospital investment in capacity, exit and conversion to CAH status. We develop new methods that allow us to estimate the structural parameters efficiently and compute counterfactual equilibria. We use the methods to estimate the impact of eliminating and modifying the CAH program on access to hospitals and patient welfare. Our methods may be more broadly useful in estimating and computing other dynamic oligopoly games with investment in capacity.

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1 Introduction

As part of the Budget Balance Act of 1997, the Congress passed and the President signed the Medicare Rural Hospital Flexibility Program. The overarching goal of this legislation is to maintain access to quality hospital care for rural residents. To achieve this objective, the program created a new class of hospital, the Critical Access Hospital (CAH), to which rural hospitals can convert. This paper seeks to understand the impact of this program on the rural hospital infrastructure by estimating a dynamic oligopoly model of the rural hospital industry. The paper has two interrelated objectives. First, we aim to quantify the impact of this important policy which coincided with and likely caused large effects on the supply infrastructure of rural healthcare delivery. Second, we develop methods to compute dynamic oligopoly models of capacity games that may be useful for other industrial organization questions and that allow us to compare the efficiency of recently developed methods for estimating dynamic oligopoly models.

The policy strategy embodied in the CAH program is not unique to this specific intervention as many other government policies seek to achieve their goals by targeting the underlying supply infrastructure. Examples abound and span countries and industries. Agricultural price supports impact the number and size distributions of farms. Education vouchers and the Charter school option affect the number and size distribution of private schools. Given the magnitude of these supports the welfare consequences of these programs are likely large. As these programs affect the returns to market participation, their impact is an indirect consequence of their effect on entry, exit and investment decisions by a potentially large number of market participants. The decisions by market participants in turn are typically generated by the equilibrium of a dynamic game whose payoffs vary with policy changes. For this reason, assessing the impact of these programs on welfare and other outcomes is often a difficult task, requiring solving and estimating dynamic oligopoly models.

In this paper we seek to understand the impact of the CAH program on the U.S. rural hospital infrastructure and societal welfare.[1] The overarching purpose of this program is

[1]For expositional ease we refer to the Medicare Rural Hospital Flexibility Program as the CAH program.

to improve the access to care of the rural population by keeping open hospitals that would otherwise close and to provide additional resources to hospitals to improve the quality of care. The CAH initiative is a voluntary program in which participating hospitals comply with a number of restrictions, principally, limits on their capacity to 25 beds or less and limits on services and length-of-stay to proscribed levels. In return for participating, hospitals opt out of the standard Prospective Payment System (PPS) and receive cost-based reimbursements from the Medicare program. These payments are generally significantly more generous than what the hospital would earn under PPS. Since the implementation of the program, over 1,200 rural hospitals (roughly 25% of all US hospitals) have converted to CAH status. CAH status also coincided with a dramatic reduction in the capacity of rural hospitals: in 1997, 15% of rural hospitals had 25 beds or less, while that figure rose to 45% by 2004. In 2006, government estimates find that CAH hospitals received $5 billion in cost-based reimbursements, $1.3 billion more than what they would have received under PPS (MedPAC 2005).

The large scale of the CAH program, its costliness and the subsequent change in hospital market structure all suggest that an evaluation of the consequences of the CAH program is important. Specifically, an evaluation can inform us about the impact of the CAH program on rural hospital infrastructure and alternate counterfactual policy programs on welfare and industry structure.

To evaluate the impact of the CAH program, we specify a dynamic model of rural hospital exit, investment and CAH status.[2] Each period, hospitals endogenously select their investment or disinvestment in beds, decide whether to exit and post-1997 select whether or not to invest in converting to a CAH. Prior to making its investment decision, each firm obtains a private information shock to its capacity investment cost. We allow for non-linear adjustment costs in beds and a stochastic outcome to the CAH investment decision. The private information shock and stochastic CAH outcome generate randomness in the outcomes of the model, necessary both for the existence of pure strategy equilibria and a well-defined likelihood function. Following the hospital decisions, in each period, with some probability, individuals fall ill and decide at which hospital to seek treatment. Hospitals earn revenue and

[2]Entry is rare in rural hospital markets and therefore our analysis does not consider it.

incur costs from treating patients that are admitted to their facility.[3] They seek to maximize an objective function that includes profits, volume and the provision of service, in the case of not-for-profit (NFP) and government hospitals. The decisions are made in a Markov Perfect equilibrium, where hospitals take account of the effect of their investment and conversion decisions on other hospitals in their market. Our model is a function of unknown parameters that pertain to the objective functions for NFP and government hospitals, the cost function for investing or disinvesting in capacity and exit, the costs of obtaining CAH status and the size of the random cost shock.

One could estimate the policy impact of the CAH program by evaluating the role that exposure to the CAH program had in affecting changes in industry structure using reduced-form regressions of hospital exit and investment on exposure to the CAH program. This potential approach has two important limitations. First, as is well-known, such a reduced-form estimation can at most be used to derive the impact of the CAH program on hospital exit or capacity and cannot be used to understand the welfare implications of this policy or the impact of counterfactual CAH policies. Second, and perhaps less appreciated, the structural estimation has much more transparent and less demanding identification. This is because the structure imposed by our model allows us to identify only structural parameters rather than more complicated equilibrium policy responses. Specifically, the reduced-form regressions above would have to include regressors to capture current and future information about the hospital and all its competitors, and interactions of these variables with the CAH legislation. In contrast, our structural approach has relatively few structural parameters to identify but then it aggregates them into industry and welfare impacts using a dynamic oligopoly structure. Moreover, it is straightforward to understand how these structural parameters are identified. For instance, the cost of investment in beds or CAH status are identified by the extent to which gross profits change following the change in state variables relative to the likelihood of choosing that policy. Thus, if CAH status increases profits for certain hospitals significantly but those hospitals rarely convert our model infers that conversion is very costly.

[3]A companion paper (in process), analyzes the static patient choice model for rural hospital patients and the determinants of static profits for hospitals.

Thus, we proceed by estimating the parameters of the dynamic oligopoly model. A number of recent papers have developed methods to estimate the parameters of such models. The idea behind these methods was first developed by Hotz and Miller (1993) in the context of dynamic single-agent models with discrete choices. Hotz and Miller (1993)'s insight is that future observed strategies can be used in place of optimizing behavior, thereby averting the computational burden of solving for the dynamic decision problem when estimating the structural parameters of the model. This insight was extended to dynamic oligopoly models with many or continuous choices by Bajari et al. (2007) (henceforth BBL).[4] BBL extend the original Hotz and Miller (1993) idea to compare the observed choices against a menu of counterfactual policies and the transition matrix implied by the data. This effectively eliminates both the need to compute dynamic oligopoly behavior and even to solve for optimal policies given other firms' actions and thereby reduces computation time.

There are two issues with using the BBL method in our context. First, they do not provide a method for computing the equilibrium of the model and this computation is necessary to compute the impact of counterfactual policies. Second, while BBL reduces computation time, it does so at the cost of a higher requirement on the data and a potentially large loss in efficiency. Specifically, with BBL, the data must be sufficiently rich to estimate accurately the dynamic transition matrix and the set of alternative policies must be sufficiently broad to identify the structural parameters.

These concerns suggest that it is necessary to compute the dynamic oligopoly directly. Dynamic oligopoly models that are most frequently computed are based on the Pakes and McGuire (1994) model and specify quality ladder games with a stochastic and discrete, typically binary, investment realization. These models are not designed for capacity accumulation games such as ours.[5]

We develop new methods to compute dynamic oligopoly models for capacity games where firms have private information and choose their new level of capacity given their information.

[4]Pakes et al. (2007), Aguirregabiria and Mira (2007) and Pesendorfer and Schmidt-Dengler (2007) have also suggested approaches to estimate parameters of dynamic games.

[5]These models also do not have any private information and hence do not generate a well-defined likelihood.

A standard approach to computing a monopoly capacity model is to choose a finite number of grid points and solve the optimal policy for these grid points. This approach runs into difficulties when analyzing multiple firms as the finite approximation model may not have a pure strategy equilibrium even when the limiting game has such an equilibrium. This is because the reaction functions are no longer continuous. Our approach differs by deriveing the exact cutoff points between different values of investment. Specifically, using the supermodularity of our investment decision, we show that the capacity decisions that will be chosen with positive probability are those which lie on a discrete analog of a convex hull of the choice-specific value function, defined as the value function conditional on any capacity decision. We use this result to derive an algorithm that iteratively discards investment levels that are not in the discrete convex hull and then solves for the exact cutoff values of the private information shocks that result in indifference between any two remaining investment levels. By calculating the exact probability of each investment decision, pure-strategy equilibrium for our model exists and is relatively easily computable.

We use our equilibrium computation method in three ways. First, we estimate the parameters of the model using maximum likelihood. This estimation is limited to markets with one or two firms as markets with more than two firms is too computationally intensive. Second, we modify the BBL method: while BBL compare the observed policy to a selected set of alternative policies, we solve for the optimal policy given any vector of structural parameters and then use this to derive the quasi-likelihood of the observed policy and estimate the parameters using likelihood methods. We expect that this modification will vastly increase the efficiency of the method. Finally, we use it to derive the equilibria corresponding to counterfactual policies. Our counterfactual policies include having no CAH program, having different hospital size thresholds and changing the CAH policy to a lump-sum transfer.

The remainder of this paper is divided as follows. Section 2 provides the institutional background of the CAH program. Section 3 describes our data. Our model is presented in section 4, and section 4.1 describes our estimation method. The results and policy experiments are presented in sections 5 and 6 respectively, and section 7 concludes.

2 The Critical Access Hospital Program

2.1 Background

The CAH program was enacted in the Balanced Budget Act (BBA) of 1997.[6] Designated CAHs receive cost-based Medicare reimbursements for inpatient, outpatient post-acute (swing bed) and laboratory services. To qualify for the program, hospitals must be 35 miles from a primary road and 15 miles by a secondary road to the nearest hospital. However, this distance requirement can be waived if the hospital is declared a "necessary provider" by the state, and, until 2006, the distance requirement does not appear to be binding. Most CAHs are less than 25 miles from a neighboring hospital. The BBA legislation stated that CAHs can only treat 15 acute inpatients and 25 total patients including patients in swing beds. A swing bed is one which can be used to provide either acute or skilled nursing facility care. The 1997 legislation set the maximum hospital size to 15 beds and the length of stay for any patient was limited to 4 days.

CAH hospitals are required to provide inpatient, laboratory, emergency care and radiology services. A CAH must also develop agreements with an acute care hospital related to patient referral and transfer, communication, emergency and non-emergency patient transportation. The CAH may also have an agreement with their referral hospital for quality improvement or choose to have that agreement with another organization. Lastly, the CAH legislation provides resources for hospitals to hire consultants to project revenues and costs under the CAH program and determine which strategy is best for the hospital given their objectives.

The program's rules have been modified several times since its inception. Table 1 summarizes the important legislative and regulatory changes in the program. The most important of these changes likely are: 1) The Balanced Budget Reconciliation Act (BBRA) of 1999 changed the length of stay requirement and allowed states to designate hospitals in Metropolitan Statistical Areas 'rural' for CAH classification; 2) The Medicare Prescription Drug, Improvement and Modernization Act (MMA) of 2003 increased the acute inpatient

[6] Much of the information in the section is culled from MedPAC (2005), which contains much more background that we provide.

limit from 15 to 25 acute patients and increased the payments from 100 to 101 percent of costs. Thus, there is variation in payoffs to becoming a CAH across both time and hospitals.

Figure 2 shows the rate of CAH conversion among all general acute care hospitals in the U.S. Conversion rates were very low until 1999. Starting in 1999, there is roughly a 4% conversion rate per year until the end of our sample period. The delay between the enactment of BBA in 1997 and the timing of conversion is likely due to the application process, which requires large amount of paperwork, the timing of inspections necessary for Centers for Medicare and Medicaid Services (CMS) approval and some uncertainty regarding the administration of the program.For example, in the state of Wisconsin, the application process is an 18-step process, detailed at http://www.worh.org/pdf_etc/AppFlowChart.pdf By 2005, 25% of candidate hospitals have adopted CAH. After 2006, when the minimum distance requirement was enforced, the number of CAH conversions declined precipitously (MedPAC 2005).

The spatial distribution of CAHs is shown in Figure 1. CAHs are present in most states, except New Jersey, Delaware, Rhode Island, Connecticut, and Massachusetts, which do not participate in the program. CAHs concentrate in the Midwest, and are mostly outside of MSAs.

The CAH program affects the incentives of hospitals and patients along a number of dimensions. These different incentives may have opposing impacts on welfare and thus the aggregate welfare effects of the program are not obvious. The program affects the size of rural hospitals as well potentially impacting exit probabilities, keeping open hospitals that would otherwise close. Residents of rural areas may benefit from from the reduction in exit because they would have to travel longer distances to receive medical care had the closest hospital exited the market. This is indeed one of the purposes of the program. However, insofar has hospital size is valued because of its direct and indirect relationship to the the scope and quality of services provided by the hospital, the CAH program may reduce patient welfare. In addition, impact of the CAH program on hospital prices for private pay patients is unclear and the program is estimated to have increased Medicare expenditures. Finally, the program lowers the incentives of hospitals to minimize costs and may interfere with the evolutionary improvement of the industry trapping capital and utilizing resources that would generate higher value elsewhere Jovanovic (1982).

2.2 Previous Research on Dynamics of Hospitals

A number of studies examine the exit behavior of hospital in a reduced form framework and thus relate to the CAH program. For example, Lillie-Blanton et al. (1992) and Ciliberto and Lindrooth (2007), find that smaller hospitals are more likely to close. Wedig et al. (1989) finds that for-profit hospitals are more likely to exit due to competing uses of capital. Similar conclusions are reached by Ciliberto and Lindrooth (2007) and Succi et al. (1997). Hansmann et al. (2002) consider four types of ownership and they also find that for-profit hospitals were the most responsive to reductions in demand by exiting the market, followed by public nonprofits, religiously affiliated nonprofits, and secular nonprofits responded the least. These papers have studied what determines exits, without taking into account strategic interactions, as our work does.

With respect to the effect of closures on surviving hospitals, Lindrooth et al. (2003) focused on urban hospitals and found that the costs per adjusted admission declined by 2-4% for all patients and by 6-8% for patients who would have been treated at the closed hospital. They abstract from the issues of access to care that closures generate due to their focus on urban hospitals within 5 miles from the closing one. In contrast, McNamara (1999), studies the impact of rural hospitals closures on consumers' surplus using a discrete choice travel-cost demand model. He finds that the average compensating variation for the closure of the nearest rural hospital that makes the average shortest distance increase from 9 miles to 25 miles is about $19,500 dollars of 1988 per sample hospitalization. These papers all consider the period before 1998, before hospitals were effectively converting into CAH.

Several more recent studies examine aspects of the CAH program. Stensland et al. (2003) studies the financial effects of CAH conversion. Comparing hospitals that converted in 1999 to other small rural hospitals, they find a significant association of CAH conversion with increases in Medicare revenue, increases in hospital profit margins from -4.1% to 1.0%, and increases in costs per discharge of 17%. They state that local patients and CAH employees benefit from the improved financial conditions, but do not calculate whether the benefits are worth their cost. Stensland et al. (2004) redo their analysis for hospitals converting in 1999 and 2000, reaching similar conclusions. Casey and Moscovice (2004) studies the quality improvement initiatives of two CAHs after conversion, and conclude that the cost-based payments help the hospitals to fund activities that would improve quality of care such as additional staff, staff training and new medical equipment.

Although this literature has enhanced our understanding of hospital exits and the CAH program, it does not explicitly examine the welfare impact of the CAH program. Furthermore, this literature does not take into account the strategic interactions between hospitals. Thus, it cannot be used to analyze the impact of CAH and of counterfactual policies for rural hospitals.

A previous paper, **?** developed an empirical framework to estimate structural parameters from dynamic oligopoly model of the hospital industry. That paper focused on the impact of the prospective payment system (among other policy counterfactuals) on hospital market structure and welfare. In comparison to the previous paper, our current work incorporates a much richer model of the hospital sector that allows for variation in geography, size and hospital characteristics. Also, the current model is also more cleanly identified as we have assembled a richer panel data set.

3 Data

We construct our dataset by by pooling and merging information from various sources. Primarily, we use the publicly available Hospitals Cost Reports Information System (HCRIS) panel data set from CMS for the years 1994-2005. Hospitals are required to file a cost report at the end of each fiscal year, where they report detailed financial and operational information needed to determine Medicare reimbursements, and this dataset contains the resulting information. For our purposes, these data report the number of beds, inpatient discharges, inpatient and outpatient revenues, salaries, and accounting information such as inpatient and outpatient costs, depreciation, asset values and profits, as well as a unique provider number assigned by CMS.[7] Our HCRIS sample is the set of non-federal general acute care hospitals.

The information from the HCRIS was complemented with data on the timing of conversion to CAH from the Flex Monitoring Team (Flex).[8] When hospitals convert to CAH, a new provider number is issued by CMS, even if ownership does not change, thus tracking hospitals has they convert is a data challenge. By using the Flex data, we were able to link the new and old provider numbers, which is necessary to understand the dynamics of the industry. Using the merged data, we find that only 14 hospitals entered a particular market as a new facility, and therefore, we do not model entry. In addition, the Flex data contains accurate information on the number of beds for the hospitals that converted, which was used to verify the HCRIS information.

We link these two datasets with the American Hospital Association Annual Survey (AHA), using the CMS provider number to perform the linkage. Our primary use of the AHA data is to determine hospital latitude and longitude which we use to compute distances between patients and hospitals and to identify a hospital's competitors.

We complete our hospital data with information from the Department of Health and Human Services' Office of Inspector General's (OIG) reports on hospital closures, years 1994-2000. These reports contain a list of the hospitals that exited the market during the year. Because the year of exit in the OIG reports differs to the last report filed for about a third of the exitors, we use the OIG information to identify exitors and we assume the hospital exits at the end of the year of their last report. After 2000 we proceed in the same fashion, but our source of data to identify closures are the Registered Deletions section from the AHA Survey, years 2001 to 2005.

[7]The reporting periods for hospitals differs in length, and beginning and end dates. We created a panel with one observation per calendar year, by disaggregating the data to the quarter level and then aggregated it back to the calendar year level.

[8]The Flex Monitoring Team is a collaborative effort of the Rural Health Centers at the Universities of Minnesota, North Carolina and Southern Maine, under contract with the Office of Rural Health Policy. The Flex Monitoring Team monitors the performance of the Medicare Rural Hospital Flexibility Program (Flex Program), with one of its objectives being the improvement of the financial performance of CAH.

We rely on two data sources in order to construct measures of hospital inpatient flows by payer class. From the CMS, we use the Health Services Area File which contains Medicare hospital level discharge information by Medicare beneficiary ZIP code and year. We also use data from the 2000 U.S. census under 65 year old population. This data is used to roughly capture the geographic distribution of the non-Medicare population. We restrict our attention to the population that is above the poverty line as the margins for treating those patients with low income is low (if they are on Medicaid) or negative (if they are uninsured). For our purposes, these data provide information on the number of people by age in each census ZIP code.

Using the hospital data, we designate a set of hospitals that we determine are candidates for CAH conversion. Because the policy's stated objective is to maintain access to emergency and inpatient care for rural residents we let rurality be a necessary condition for conversion. We characterize rurality using the Rural-Urban Commuting Area Codes (RUCA), version 2.0.[9] This measure is based on the size of cities and towns and their functional relationships as identified by work commuting flows, and have been used by CMS to target other rural policies, such as the ambulance payments. CMS considers a census tract to be rural if and only if it has a RUCA greater or equal than 4, and we adopt the same criterion in this paper.[10] The definitions of the RUCAs are shown in Table 2. Since only small hospitals ever convert to CAH status, we also allow only hospitals with 225 beds or less to be candidates for CAH conversion. These two criteria determine our sample for 'at-risk' hospitals.

We then use the location data to determine geographic markets. We first define a 150 km circle about the hospital. All hospitals in this circle, including those that are not candidates for CAH conversion, are included in the market. Hospitals that are further away have a lesser strategic impact than nearby hospitals.

[9]These measures are developed collaboratively by the Health Resources and Service Administration, the Office of Rural Health Policy, the Department of Agriculture's Economic Research Service, and the WWAMI Rural Health Research Center.

[10]Department of Health and Human Services, Medicare Program, Revisions to Payment Policies, etc.; Final Rule. Dec 2006.

4 Model, computation and estimation

4.1 Model

We specify a dynamic oligopoly model where the strategic players are all hospitals with 225 beds or less in 1997 located in a zip code with a RUCA of four or higher.[11] A market in our model corresponds to a mutually exclusive geographic area where all players are within 50 KM of other players in the market but not within 50 KM of any player outside the market.

Denote the players in a market $1, \ldots, J$. Players are differentiated by their location, CAH status, capacity (measured by beds), ownership type own_j and productivity. Time is discrete with a period corresponding to a year and hospitals discount the future with the same discount factor β.

Each period, we model a game with three stages. First, nature moves and provides each hospital with a period-specific investment cost shock. Second, knowing the value of their individual shocks – but not of other hospitals' shocks – players in the market simultaneously choose investment strategies for capacity, exit and CAH status. Finally, a static production game occurs where each patient makes a discrete choice among available hospitals. While we allow a hospital to change its capacity and CAH status, we assume that its other characteristics are fixed. Denote the industry characteristics that are fixed within a market $\overline{\Omega}$ and denote the capacity and CAH status of each hospital in the market Ω. Since $\overline{\Omega}$ is invariant, we suppress it below to economize on notation. The environment for hospital j can thus be written as (Ω, j).

Hospitals choose actions in order to maximize the expected discounted values of their net future returns where returns depend on own_j. We model three ownership types: for-profit (FP), not-for-profit (NFP) and government (Gov). For a FP hospital, returns in any period are synonymous with profits, while for NFP and government hospitals, returns are a weighted

[11]We choose this limit for the set of strategic players because large or urban hospitals would be unlikely to qualify for CAH status and likely do not make their decisions in response to small rural hospitals located in an area around them.

sum of profits, patient volume and the provision of service.[12] For NFP hospitals, we let the weights on volume and the provision of service be denoted α_v^{NFP} and α_p^{NFP} respectively; for government hospitals we use α_v^{Gov} and α_p^{Gov}, where the α values are parameters to estimate. We normalize the weights on expected net profits to 1 as such coefficients would not be identified.

We now detail the exit and capacity investment process. In the hospital industry – and in most industries – firms do not alter their capacity levels in most years, suggesting that the marginal costs of positive investment may be very different than the marginal costs of negative investment. We model an investment process with quadratic adjustment costs, a fixed cost of non-zero investment and different costs of positive and negative investment, which allows for both asset specificity and fixed costs to explain this phenomenon. A hospital can exit the industry by disinvesting in beds until it has none left. In addition to the cost of disinvestment, the exiting hospital obtains a scrap value from selling its physical property. Exits are permanent: hospitals with 0 beds cannot build beds or otherwise earn profits.

Let $B(\Omega, j)$ denote the capacity, in terms of beds, for hospital j at some time t. At time t, hospitals choose their $t+1$ capacity, which we denote x_j. The choice set depends on the current CAH status of the hospital as CAH hospitals are restricted to 25 beds or less. We denote the conditional choice sets X^{CAH}. Both these sets have a finite number of elements: firms cannot own fractional beds and the maximum number of beds is restricted to 225. We

[12] There is a long tradition in the health economics literature in which the objective function of not-for-profit hospitals includes arguments other than net profits. Newhouse (1970) first proposed that NFP hospitals maximize a combination of quality and quantity subject to a profit constraint. In order to explain hospital cost-shifting behavior, Dranove (1988) and Gaynor (????) both construct models in which imperfectly competitive hospitals maximize a combination of profits and output. Gowrisankaran and Town (1997) estimate parameters from a dynamic model of entry and exit in which not-for-profit hospitals a linear combination of profits and quality. Lakadawalla and Philipson (1998) analyze a dynamic model of hospital entry and exit in which not-for-profit organizations maximize a linear combination of profits and quality.

let the mean cost of capacity investment (not accounting for the cost shock) be

$$\begin{aligned} MeanInvCost(B,x) = & -1\{x=0 \text{ and } B>0\}\phi \\ & + 1\{x>B\}\left(\delta_1+\delta_2(x-B)+\delta_3(x-B)^2\right) \\ & + 1\{x<B\}\left(\delta_4+\delta_5(x-B)+\delta_6(x-B)^2\right), \end{aligned} \tag{1}$$

with ϕ, the scrap value, and $\delta_1,\ldots,\delta_6$ being parameters to estimate. The total investment cost adds the cost shock:

$$\begin{aligned} InvCost(B,x,\varepsilon) = & \; MeanInvCost(B,x) \\ & + \left(1\{x>B\}\sigma_1 + 1\{x<B\}\sigma_2\right)(x-B)\varepsilon. \end{aligned} \tag{2}$$

We let ε_{jt} be distributed $N(0,1)$ and restrict $\sigma_1,\sigma_2>0$. The terms σ_1 and σ_2 are parameters to estimate, which we allow to differ for flexibility. To ease notation, let

$$\sigma^{x,B} = \begin{cases} \sigma_1 & \text{if } x \geq B \\ \sigma_2 & \text{if } x < B. \end{cases}$$

Thus, we can write $InvCost(B,x,\varepsilon) = MeanInvCost(B,x) + \sigma^{x,B}(x-B)\varepsilon$.

$MeanInvCost$ is similar to the investment cost specified in Ryan (2007) and a long literature that he cites but is different from earlier quality-ladder dynamic oligopoly models[13] in that we assume that firms deterministically choose the level of future capacity and can change capacity quickly, albeit at a potentially high cost.The form of the uncertainty in (2) is, to our knowledge, new, but we believe that it is intuitive given $MeanInvCost$.

Concurrently with the investment decision, each eligible non-CAH hospital simultaneously decides whether it wants to convert to CAH status. Given the length and uncertainty of the CAH approval process, we model the process as stochastic, with the outcome occurring at the start of the next period. The hospital pays a cost $c \geq 0$ in order to attempt to convert to CAH status in the following period. Higher costs imply a higher probability of successful CAH conversion, specifically,

$$Pr(\text{CAH approval}|c) = \gamma c/(1+\gamma c), \tag{3}$$

[13]See Ericson and Pakes (1995), Pakes and McGuire (1994) and **?**.

where γ is a parameter to estimate. The specification implies that a zero investment expenditure results in a zero conversion probability. Consistent with government limitations, we define eligibility for conversion at time t as having beds after investment $x_{jt} \leq 25$. CAH hospitals are not allowed to revert to non-CAH status in our model and spend $c = 0$. We make this assumption because our data contain only 2 instances of hospitals that abandoned CAH status.

We do not model entry since entry is very rare in the rural areas that are in our data. In particular, among hospitals in our sample, 97 percent existed at the first period of our estimation, in 1998. Given this limited amount of entry, it would be hard to credibly identify the parameters on the entry distribution. In the long run, we would expect entry in the industry due to random firm-specific shocks and thus our model will not accurately capture the steady state of the industry. However, for the 20 year time period that we examine for our counterfactual policy analysis, we believe our omission of an entry process is reasonable.

We now briefly sketch the static decisions with details in the companion paper (add cite). Each period, there is an identical set of consumers $1, \ldots, I$, who seek treatment for their illness. Consumers are differentiated by their location and all live within 50 KM of some strategic player hospital in the market. Even though non-rural hospitals and hospitals with over 225 beds are not strategic players, we allow these hospitals to be in the patient choice set – as non-strategic players whose characteristics are fixed – if they are within 50 KM of a strategic player in the market. This captures the fact that patients in a rural county may travel to a big-city hospital located relatively nearby and is also consistent with the referral regulations.

Each patient makes a discrete choice of one of the hospitals in the choice set or the outside alternative, which corresponds to treatment outside the local market. An important determinant of hospital choice is distance. Other important determinants include hospital characteristics, notably the CAH status and size as well as a hospital fixed effect. The inclusion of a hospital fixed-effect allows for a "difference-in-difference" type identification. We use a multinomial logit utility model and estimate the utility coefficients following the approach in Berry (1994). For this paper, we are ultimately interested in the volume of patients for a given hospital and any industry configuration, which we denote $Vol(\Omega, j)$.

Expected gross profits for a hospital are a function of its patient demand, level of competition, area characteristics, bed size and CAH status. Importantly, CAH hospitals may obtain profits from inpatient services as well as outpatient services and from providing services to non-Medicare patients. Since we directly observe profits but the production and demand functions of hospitals are multi-faceted and not all observable, we directly model profits as a function of these characteristics.[14] We model profits with a linear regression where the demand fixed effect is allowed to enter hospital profits in a flexible form to capture hospital productivity differences. We also experiment with other specifications where we use the fixed effect from a pre-CAH regression in a flexible form. This is consistent with a model where there are differences in fixed costs related to productivity in the pre-CAH period that then affect the relative profits of a CAH hospital in a flexible way. We denote gross profits for any industry configuration $\Pi(\Omega, j)$.

4.2 Markov Perfect Equilibrium

A Markov Perfect Equilibrium (MPE) is a subgame perfect equilibrium of the game where the strategies are restricted to be functions of payoff-relevant state variables (see Maskin and Tirole (1988)). For firm j, the payoff-relevant state variable is $(\Omega, j, \varepsilon_j)$.

In order to define the MPE, we start by expositing the dynamic optimization problem for the individual firm. This requires several definitions. Denote the expected static gross returns (gross of investment) for firm j as:

$$\begin{aligned} EGR(\Omega, j) = E\,[\Pi(\Omega, j) \\ + 1\{own(j) = NFP\}\left(\alpha_v^{NFP} Vol(\Omega, j) + \alpha_p^{NFP} \cdot 1\{B(\Omega, j) > 0\}\right) \\ + 1\{own(j) = Gov\}\left(\alpha_v^{Gov} Vol(\Omega, j) + \alpha_p^{Gov} \cdot 1\{B(\Omega, j) > 0\}\right)\big], \end{aligned} \tag{4}$$

where we are explicitly denoting B and own to be a function of the state. Denote the value function for any state as $V(\Omega, j, \varepsilon_j)$ and denote the expected value of firm j before its

[14] This contrasts with a traditional approach of estimating demand and costs and then using this information to derive profits.

realization of ε_j as $EV(\Omega, j)$. Let x_{-j} denote an action x for all firms other than firm j; let $p(x_{-j}, c_{-j}|\Omega)$ denote the density of hospital j's beliefs regarding its rivals' strategies at Ω; and let $g(\Omega'|x_j, c_j, x_-j, c_{-j}, \Omega)$ be the probability of future beds and capacity levels Ω' given current values Ω and actions x_j, c_j, x_{-j} and c_{-j}. Given beliefs about rivals' actions, we can write the Bellman equation for a hospital with $B > 0$ as:

$$
\begin{aligned}
V(\Omega, j, \varepsilon_j) = \max_{x_j, c_j} \{ & EGR(\Omega, j) - InvCost(B(\Omega, j), x_j, \varepsilon_j) - c_j + \beta \\
& 1\{x_j > 0\} \int \sum_{\Omega'} EV(\Omega', j) g(\Omega'|x_j, c_j, x_-j, c_{-j}, \Omega) dp(x_{-j}, c_{-j}|\Omega) \Bigg\}.
\end{aligned} \tag{5}
$$

We now further exposit the optimal choices of investment necessary to compute and estimate the model. Recall that firm j chooses c_j and x_j concurrently. Let us now consider the optimal c_j conditioning on a given choice of x_j. Many terms in (5) do not have c_j in them and can be dropped – in particular, all the terms with ε. For $x_j \in \{1, \dots, 25\}$, the optimal choice, which we denote $\hat{c}(\Omega, j|x_j)$, satisfies

$$
\begin{aligned}
\hat{c}(\Omega, j|x_j) = & \operatorname*{argmax}_{c_j} \\
& \left\{ -c_j + \beta \int \sum_{\Omega'} EV(\Omega', j) g(\Omega'|x_j, c_j, x_-j, c_{-j}, \Omega) dp(x_{-j}, c_{-j}|\Omega) \right\};
\end{aligned} \tag{6}
$$

for other values of x_j, $\hat{c} = 0$. The CAH investment technology is the same as the investment technology in Pakes and McGuire (1994). Pakes et al. (1992) derive the unique optimal level for investment for the Pakes and McGuire (1994) model ensuring that the maximum in (6) is well-defined. We can use (6) to define the optimal choice of x_j. We start by defining the "choice-specific value function" $\overline{V}(\Omega, j, x_j)$ to be the value for a given choice of capacity x_j gross of the ε term. Specifically,

$$
\begin{aligned}
\overline{V}(\Omega, j, x_j) = & -MeanInvCost(B(\Omega, j), x_j) - \hat{c}(\Omega, j|x_j) + \beta 1\{x_j > 0\} \\
& \int \sum_{\Omega'} EV(\Omega', j) g(\Omega'|x_j, \hat{c}(\Omega, j|x_j), x_-j, c_{-j}, \Omega) dp(x_{-j}, c_{-j}|\Omega).
\end{aligned} \tag{7}
$$

Finally, we define the optimal level of investment as

$$
\hat{x}_j(\Omega, j, \varepsilon_j) = argmax_{x_j} \left\{ \overline{V}(\Omega, j, x_j) - \sigma^{x_j, B(\Omega, j)}(x_j - B(\Omega, j))\varepsilon_j \right\} \tag{8}
$$

We can now define a MPE and prove existence. The MPE is a set of investment strategies for every state, $\hat{x}(\Omega, j, \varepsilon)$ and $\hat{c}(\Omega, j, \hat{x}(\Omega, j, \varepsilon))$, for which the following holds: for each state $(\Omega, j, \varepsilon_j)$, $\hat{x}(\Omega, j, \varepsilon)$ and $\hat{c}(\Omega, j, \hat{x}(\Omega, j, \varepsilon))$ satisfy the Bellman equation (5) using the equilibrium strategies $p(\hat{x}_{-j}, \hat{c}_{-j}|\Omega)$ for rivals. This ensures that no unilateral deviation is profitable at any state, which is the definition of a MPE. We now show existence of pure strategy equilibrium, which relies on the presence of the unobservable cost shock ε:

Proposition 4.1. *For a given vector of parameters (α, δ, σ) and given fixed characteristics of a market, a pure strategy MPE exists for our model.*

Proof The method of proof follows Ericson and Pakes (1995) and Gowrisankaran (1995).[15] Let $o(x)$ denote the dimensionality of x and let Δ^N denote the N-dimensional simplex. We define a function $f : (\Re \times \Delta^{o(X)-1} \times \Re^{o(X)})^{o(\Omega)\times J} \longrightarrow (\Re \times \Delta^{o(X)-1} \times \Re^{o(X)})^{o(\Omega)\times J}$ and will show that a fixed point to f exists and constitutes a MPE. The domain of f is as follows: for each firm (of which there are J) and each Ω, the first element provides the expected value function; the second element provides the probability of each given capacity investment decision (and hence lies in the simplex); and the third element provides a CAH investment cost for each capacity choice.

The function f is the convolution of two functions. The first function specifies the expectation of the Bellman equation (5) using the expected value function and perceptions as specified in the domain of f. The second function applies (6) and (8), specifying the probabilities and actions that are consistent with the new value function. By construction, a fixed point of this mapping constitutes a MPE.

We now show that f is defined on a compact, convex interval of $\Re^N$ (for some N) and that it is continuous. We start with the compact, convex part. Even though ε has unbounded support, note from (2) that the expected value of the gain or loss from ε is bounded above by some multiple of $E|max_{x \in X} x\varepsilon|$. Combined with the facts that profits are bounded, implying that gross returns are also bounded, and that the gain from mean investment is bounded, the

[15] Doraszelski and Satterthwaite (2007) provide general proofs of existence for Pakes and McGuire (1994) type models, although their assumptions are not applicable to our model.

expected value function can be uniformly bounded above. Given the fixed scrap value of exit ϕ, the expected value function is bounded below and thus lies in some compact, convex subset of $\Re^{o(\Omega)}$ for each firm. For each firm, the probabilities lie in the $o(X)-1$ dimensional simplex which is a compact, convex interval of $\Re^{o(X)}$. The CAH investment cost is bounded below by 0 and can be bounded above using the bounds in the value function (see the discussion of the bounds on investment in Gowrisankaran (1995)) since the marginal cost of increasing the probability of CAH acceptance approaches infinity. Thus, f lies in a compact, convex interval of $\Re^N$.

Now we discuss continuity. As is commonly true, the expectation of the Bellman equation is continuous in the probabilities of other firms and in the value function. Showing the continuity of actions is more subtle. We derive a closed form for the probability of each capacity investment x below and those probabilities are continuous in the expectation of the value functions, in other firms' probability of capacity levels, and in the CAH probabilities for other firms at each capacity level. The CAH investment probability is continuous for the same reasons given for investment in Gowrisankaran (1995). Compactness, convexity and continuity imply there exists a fixed point by Brouwer's theorem. $\blacksquare$

4.3 Efficient Computation of Equilibrium

In order to compute the dynamic equilibrium of the model, we use a variant of the method of successive approximations, adapted from Pakes and McGuire (1994) and other papers. The idea is essentially to repeatedly compute f until a fixed point. Specifically, we start with a value function and a law of motion for each firm. For each firm j and each vector of shocks ε, we then solve for its optimal policies $\hat{c}^{CAH}(\Omega, j, \varepsilon_j)$ and $\hat{x}(\hat{c}(\Omega, j, \varepsilon_j), \Omega, j)$. By integrating over ε, this then implies a new industry law of motion and a new expected value.

The central difficulty with this approach is in calculating the optimal strategies for each state. In particular, a standard approach, which would be to take a finite number of simulation draws for ε and simulate over these draws, would not work because this approximate model will generally not have a pure strategy equilibrium even though the limiting model does have one. To understand the lack existence, consider our proof of existence of equilibrium. The proof relies on the continuity of f. Yet, for the approximate model, the second part of the second mapping of f – the probability of being at any capacity – will be discontinuous in valuations because it is the sum of a finite number of draws each of which has one associated optimal policy.

Thus, we develop an algorithm that allows us to identify the exact cutoffs in ε_j between different levels of capacity. It is easy to verify that the investment cost function is supermodular in x and ε_j. Hence, the optimal investment x is monotone in ε_j. Our algorithm relies heavily on this monotonicity property. We first show that it is simple to solve in closed form for the ε_j that makes the firm indifferent between two choices of beds x_1 and x_2. We then show how to find the subset of X^{CAH} whose elements will be chosen with positive probability, and to assign a probability to each of these elements. The subset will consist of those choices of $x \in X^{CAH}$, that make $\overline{V}(\cdot)$ be the discrete equivalent of a concave function. Since our algorithm concerns only one firm j at one state for which $B(\Omega_j)$ does not vary, in what follows we drop all but the last argument from $\overline{V}$, denote beds just by B and refer to X instead of X^{CAH}.

We start with some definitions. First, we denote the real valued function $\overline{V}(x)$ where $x \in X$ to be d-concave with respect to $\sigma^{x,B}$ at x if and only if for every $x_1 < x < x_2 \in X$, $\lambda\overline{V}(x_1) + (1-\lambda)\overline{V}(x_2) \leq \overline{V}(x)$ for $\lambda = \frac{\sigma^{x_2,B}(x_2-B)-\sigma^{x,B}(x-B)}{\sigma^{x_2,B}(x_2-B)-\sigma^{x_1,B}(x_1-B)}$. Note that for the special case of $\sigma_1 = \sigma_2$, this simplifies to $\lambda = \frac{x_2-x}{x_2-x_1}$ and hence the familiar $x = \lambda x_1 + (1-\lambda)x_2$. Second, define the *concave envelope* of X, $CE(X)$, to be the set of $x \in X$ for which $\overline{V}$ is d-concave. Last, for $x_1 < x_2 \in X$ define $\overline{\varepsilon}_{x_1,x_2}$ to be the ε_j that will make firm j indifferent between x_1 and x_2.

Note that $\overline{\varepsilon}_{x_1,x_2}$ must satisfy

$$\begin{aligned} \overline{V}(x_1) - \sigma^{x_1,B}(x_1-B)\overline{\varepsilon}_{x_1,x_2} &= \overline{V}(x_2) - \sigma^{x_2,B}(x_2-B)\overline{\varepsilon}_{x_1,x_2} \\ \Rightarrow \qquad \overline{\varepsilon}_{x_1,x_2} &= \frac{\overline{V}(x_2)-\overline{V}(x_1)}{\sigma^{x_2,B}(x_2-B)-\sigma^{x_1,B}(x_1-B)}. \end{aligned} \tag{9}$$

We now show the relation between these concepts:

Lemma 4.2. *(a) For $x_1 < x_2$ and $\varepsilon \in \Re$, firm j will strictly prefer x_1 to x_2 $\iff$ $\varepsilon > \overline{\varepsilon}_{x_1,x_2}$*

(b) Using the above definition of λ, for $x_1 < x < x_2$, $\overline{\varepsilon}_{x_1,x} > \overline{\varepsilon}_{x,x_2} \iff \lambda\overline{V}(x_1) + (1 - \lambda)\overline{V}(x_2) \leq \overline{V}(x)$.

Proof (a)

$$\begin{aligned}
&\overline{V}(x_2) - \sigma^{x_2,B}(x_2 - B)\overline{\varepsilon}_{x_1,x_2} = \overline{V}(x_1) - \sigma^{x_1,B}(x_1 - B)\overline{\varepsilon}_{x_1,x_2} \\
&\Rightarrow \overline{V}(x_2) - \overline{V}(x_1) = \overline{\varepsilon}_{x_1,x_2}\left(\sigma^{x_2,B}(x_2 - B) + \sigma^{x_1,B}(B - x_1)\right) \\
&\Rightarrow \overline{V}(x_2) - \overline{V}(x_1) > \varepsilon\left(\sigma^{x_2,B}(x_2 - B_j) + \sigma^{x_1,B}(B - x_1)\right) \iff \varepsilon < \overline{\varepsilon}_{x_1,x_2} \\
&\Rightarrow \overline{V}(x_1) - \sigma^{x_1,B}(x_1 - B)\varepsilon > \overline{V}(x_2) - \sigma^{x_2,B}(x_2 - B)\varepsilon \iff \varepsilon < \overline{\varepsilon}_{x_1,x_2}.
\end{aligned} \tag{10}$$

The key step is the transition from the second to third line, which relies on the fact that the right hand side is positive. For the cases where $x_1, x_2 \geq B$ or $x_1, x_2 < B$, $\sigma^{x_2,B} = \sigma^{x_1,B}$ is positive since $x_2 > x_1$ and the two terms involving B cancel. If $x_1 < B \leq x_2$, then both terms in the sum are positive also implying that the sum is positive.

(b)

$$\begin{aligned}
&\overline{\varepsilon}_{x_1,x} > \overline{\varepsilon}_{x,x_2} \\
&\iff \frac{\overline{V}(x) - \overline{V}(x_1)}{\sigma^{x,B}(x - B) + \sigma^{x_1,B}(B - x_1)} > \frac{\overline{V}(x_2) - \overline{V}(x)}{\sigma^{x_2,B}(x_2 - B) + \sigma^{x,B}(B - x)}.
\end{aligned} \tag{11}$$

Multiplying (11) by both denominators and dividing by $\sigma^{x_2,B}(x_2 - B) - \sigma^{x_1,B}(x_1 - B)$ yields the desired result. Note that both multiplicands and the divisor are positive using the same logic as in the proof of part (a). ∎

By Lemma 4.2 part (a), x will be preferred against both x_1 and x_2 exactly when $\varepsilon \in [\overline{\varepsilon}_{x,x_2}, \overline{\varepsilon}_{x_1,x}]$. By part (b), this set will be a positive interval exactly when x is not excluded from the discrete convex envelope due to x_1 and x_2. Thus, x must be in the discrete convex envelope to be chosen with positive probability. It is also easy to show conversely that any x that is in the concave envelope $CE(X)$ will be chosen with positive probability. To see this, first let $\underline{\underline{\varepsilon}}(x) = \{max_{x_2>x}\overline{\varepsilon}_{x,x_2}\}$ if $max_{x_2>x}$ is nonempty and $-\infty$ otherwise. Similarly, let $\overline{\overline{\varepsilon}}(x) = min_{x_1<x}\overline{\varepsilon}_{x_1,x}$ if $min_{x_1<x}$ is nonempty and ∞ otherwise. Then, by Lemma 4.2 part (a), x will be chosen exactly in the interval $\varepsilon \in [\underline{\underline{\varepsilon}}(x), \overline{\overline{\varepsilon}}(x)]$. By Lemma 4.2 part (b),

$[\underline{\underline{\varepsilon}}(x), \overline{\overline{\varepsilon}}(x)]$ must be a positive interval for $x \in CE(X)$, as otherwise the convex combination of the highest element in $\underline{\underline{\varepsilon}}(x)$ and the lowest element in $\overline{\overline{\varepsilon}}(x)$ would dominate x. Thus, we have shown:

Proposition 4.3. *(a) A firm facing action set X will choose $x \in X \iff \varepsilon \in \left[\underline{\underline{\varepsilon}}(x), \overline{\overline{\varepsilon}}(x)\right]$ (b) $\varepsilon \in \left[\underline{\underline{\varepsilon}}(x), \overline{\overline{\varepsilon}}(x)\right]$ will be a positive interval $\iff x \in CE(X)$.*

Denote the set of $x \in CE(X)$ as $x_1^{CE}, \ldots, x_J^{CE}$. Then, our above results allow us to further characterize the optimal solution. The following Corollary states that the cutoffs between neighboring $x \in CE(X)$ are monotonic:

Corollary 4.4. *$\overline{\varepsilon}_{x_{j-1}^{CE}, x_j^{CE}} < \overline{\varepsilon}_{x_{j-2}^{CE}, x_{j-1}^{CE}}$ for all $j = 3, .., J$.*

Proof This follows from Lemma 4.2 together with the fact that each of the elements in $CE(X)$ is chosen with positive probability.

Thus, x_J^{CE} is chosen in the range $(-\infty, \overline{\varepsilon}_{x_{J-1}^{CE}, x_J^{CE}}]$, x_{J-1}^{CE} is chosen in the range $[\overline{\varepsilon}_{x_{J-1}^{CE}, x_J^{CE}}, \overline{\varepsilon}_{x_{J-2}^{CE}, x_{J-1}^{CE}})$, all the way to x_1^{CE}, which is chosen in the range $[\overline{\varepsilon}_{x_1^{CE}, x_2^{CE}}, \infty)$.[16]

Note also that Proposition 4.3 provides an algorithmic method for solving for the elements of $CE(X)$ and associated cutoffs $\underline{\underline{\varepsilon}}(x)$ and $\overline{\overline{\varepsilon}}(x)$: for each x, compute $\underline{\underline{\varepsilon}}(x)$ and $\overline{\overline{\varepsilon}}(x)$ and keep x if $\underline{\underline{\varepsilon}}(x) < \overline{\overline{\varepsilon}}(x)$. Since the algorithm involves the calculation of cutoffs for each element against each other, it involves $o(X)(o(X)-1)$ computations of $\overline{\varepsilon}$ values. Our actual algorithm optimizes the number of computations by using the fact that the binding cutoff is always against the neighboring element in $CE(X)$. Thus, we start by assuming that all $x \in CE(X)$ and assigning tentative values of $\overline{\overline{\varepsilon}}$ and $\underline{\underline{\varepsilon}}$ starting with the highest element of x. We check each value against its neighboring element in the presumed $CE(X)$ set, in turn. If we find an element to not be in $CE(X)$, then we discard this element from further consideration and go back and revise our cutoffs as necessary based on the new presumed neighbors. We then proceed forward again. The end result is an algorithm that makes $o(X) - 1$ computations of $\overline{\varepsilon}$ values if every element $x \in CE(X)$ to $2o(X) - 3$ computations when $CE(X)$ contains only two values – always much less than the brute force algorithm above. The reduction

[16]Note that the firm is indifferent at the end points, which we assign, arbitrarily to the higher x.

in computation time is important since this step is repeated many times in the dynamic oligopoly computation. sectionInference

4.4 Overview of method

The structural parameters of our model are the α objective function parameters, the δ investment cost parameters, the discount factor β, the CAH conversion cost parameter γ, the static marginal cost and fixed cost parameters, and the τ consumer utility parameters. We deal with these parameters with a variety of methods. We estimate the consumer utility parameters τ using a standard multinomial logit maximum likelihood model, as the consumer does not face a dynamic problem. We observe profits in the data and hence do not need to estimate the cost function parameters. It is difficult to identify the discount factor and hence we set it to $\beta = .95$.

The remaining parameters, α_p^{NFP}, α_v^{NFP}, α_p^{Gov}, α_v^{Gov}, γ, $\delta_1, \ldots \delta_7$ and σ are not directly observable in the data but can, in principle, be identified by firm behavior. Since firm behavior is a function of the dynamic oligopoly model evaluated at the Markov Perfect equilibrium, identification of these parameters generally requires imposing the structural model.

A method for estimating the structural parameters of dynamic models was developed by Rust (1987) and applied to the dynamic oligopoly setting by **?**. The idea of these methods is to perform a non-linear search for the structural parameters that best fit the data. For any vector of structural parameters, one solves for the Markov Perfect equilibrium of the industry and then evaluates "fit" as the closeness of the actions predicted by the equilibrium of the model to those reported in the data. The problem with these methods is that they are extremely computationally intensive as they require solving the Markov Perfect equilibrium repeatedly, which is very time-consuming.

More recent methods to estimate dynamic models are based on the idea that one can use the data themselves to predict the future actions of the firm and its competitors, rather than solving for the Markov Perfect equilibrium for each parameter vector, since the data reflect Markov Perfect equilibrium play. To implement these methods, one generally predicts future decisions with a non-structural first stage. The second stage then involves a non-linear search over structural parameters where the econometrician has only to solve for the optimal current decision of the agent taking the future actions as given.

We base our estimation algorithm for these remaining parameters on one variant of these methods, that developed by Bajari et al. (2007). The BBL method has two useful features for our purposes. First, rather than solving for the overall optimal decisions (as above) they show that one can estimate the structural parameters by finding the policies that are optimal within a finite set of alternate policies. This is particularly useful for models with continuous action spaces as otherwise, solving for optimal decisions is computationally difficult. Second, they show that the second stage can be evaluated with a very quick computational process, which is similar to non-linear least squares, provided that one can express the expectation of the total return for any state, action and unobservable, $TR((x,c),(\Omega_t,j),\varepsilon)$ as a linear combination of the structural parameters and functions of the data, which we can.

Following BBL, we develop the linear representation for our model, by writing

$$E\left[TR((x,c),(\Omega_t,j),\varepsilon)\right] = \Psi((x,c),(\Omega_t,j),\varepsilon)\cdot\theta, \tag{12}$$

where Ψ is a vector-valued function of the data, θ are the structural parameters, and the (linear) dot product of these two terms generates expected total returns. We use (12) to exposit the value function similarly as:

$$V(\Omega_t,j) = E_t\left[\sum_{\tau=t}^{\infty}\beta^{\tau-t}\Psi((\hat{x}(\Omega_t,j,\varepsilon),\hat{c}(\Omega_t,j,\varepsilon)),(\Omega_t,j),\varepsilon)\right]\cdot\theta, \tag{13}$$

where the expectation is over current and future unobservables and future states given unobservables and equilibrium actions. Define $W(\Omega_t,j)$ to be the expectation term in (13).

Using these definitions, which are analogous to BBL, we adapt the BBL methods to our model and data with the following algorithm. First, we approximate the law of motion for the industry as a function of states and actions, and static gross profits and actions as a function of states. Second, we forward simulate the industry given equilibrium actions to approximate $W(\Omega_t,j)$ for every state observed in the data. Third, we choose a set of counterfactual investment policies. Let there be P such policies in the set. By the Markov

Perfect equilibrium assumption, each such policy must yield a weakly lower expected value when chosen by a firm faced by firms playing the Markov Perfect equilibrium strategies. Thus, for each counterfactual policy, we forward simulate to evaluate an analog to $W(\Omega_t, j)$ where the state transitions are determined by the counterfactual policy. Let $\hat{W}^p(\Omega_t, j)$ denote one such vector. Fourth, using (13), the calculated $W(\Omega_t, j)$ and the set of $\hat{W}^p(\Omega_t, j)$, we estimate the vector of structural parameters as the values for which the true policies are most closely optimal.

Recall that in our model, the unobservable investment shock ε will affect the choice of investment at any state. The models given in Bajari et al. (2007) and Ryan (2006) do not allow for private information shocks to investment or other choice variables that affect the state. In estimating (12), one must take into account the correlation between the investment level and ε in order to accurately recover the cost of investment. To see this, note that in our model, the investment policy $\hat{x}(\Omega_t, j, \varepsilon)$ is weakly declining in ε for any given state, or alternately put, firms with a low cost of investment invest more at any state. If one instead assumed that the distributions of investment and cost shocks were uncorrelated, one would overstate the costs of investment. The difficulty is that we do not directly observe the cost shock for any investment level, and hence cannot directly compute $\Psi((x, c), (\Omega_t, j), \varepsilon)$.

We develop a method that allows us to account for this endogeneity of investment in a way that preserves the linearity of the estimation specification in (12). Our method rests on a simple consequence of the monotonicity of investment: a firm that invests in the xth percentile of the investment distribution must have obtained a draw of ε that is in the $1-x$th percentile of the ε distribution. Let $F_{\Omega_t,j}(x)$ denote the c.d.f. for investment at state (Ω_t, j). Then, for any observed investment level x, in equilibrium,

$$\varepsilon_{j,t} = \sigma\Phi^{-1}(1 - F_{\Omega_t,j}(x)), \tag{14}$$

where Φ^{-1} is the inverse of the standard normal c.d.f. Since the only component of (14) that is unobservable is σ and σ enters linearly in (14), we can construct terms in Ψ that account for this correlation, as we do below.

A potential problem to this approach is the fact that investment is only weakly monotonic in ε: because of the fixed costs of investment, there wil be a discrete mass of ε for which investment is 0. However, the lack of strict monotonicity is not problematic, since the only mass point is at investment of 0, and the value of ε does not affect costs when investment is 0.

Another issue is how to estimate the costs of CAH conversion. Note that the CAH conversion strategy is a function, effectively of state variables and investment. Let $P^{CAH}(\Omega_t, j, x)$ denote the probability of CAH conversion for any state and investment level. Then, from (3),

$$\gamma c = log\left(\frac{1 + P^{CAH}(\Omega_t, j, x)}{1 - P^{CAH}(\Omega_t, j, x)}\right). \tag{15}$$

Noting that the right side of (15) can be approximated by the data, as in (14), one can again construct a term in Ψ that accounts for the cost of conversion, c. One can redefine Ψ to have it be a function of P^{CAH} rather than c, as P^{CAH} is really what is observed in the data.

Using these formulations, our vector Ψ has the following components:

$$\begin{aligned}
&\Psi((x, P^{CAH}), (\Omega_t, j), \varepsilon) = (\Pi(\Omega_t, j), \\
&\quad 1\{own_j = NFP\}EVol(\Omega_t, j), 1\{own_j = NFP\}1\{beds_{jt} > 0\}, \\
&\quad 1\{own_j = Gov\}EVol(\Omega_t, j), 1\{own_j = Gov\}1\{beds_{jt} > 0\}, \\
&\quad -1\{x > 0\}, -1\{x > 0\}x, -1\{x > 0\}x^2, -1\{x < 0\}, -1\{x < 0\}x, \\
&\quad -1\{x < 0\}x^2, -1\{x < 0\}x\Phi^{-1}(1 - F_{\Omega_t,j}(x)), -1\{x > 0\}x\Phi^{-1}(1 - F_{\Omega_t,j}(x)), \\
&\quad -log[(1 + P^{CAH}(\Omega_t, j, x))/(1 - P^{CAH}(\Omega_t, j, x))]).
\end{aligned} \tag{16}$$

The corresponding vector θ is:

$$\theta = (1, \alpha_v^{NFP}, \alpha_p^{NFP}, \alpha_v^{Gov}, \alpha_p^{Gov}, \delta_1, \delta_2, \delta_3, \delta_4, \delta_5, \delta_6, \delta_7\sigma, \sigma, 1/\gamma).$$

It is easy to verify that the resulting dot product is equal to $TR((x, c), (\Omega_t, j), \varepsilon)$.

Using the approximations for W and $\hat{W}^p$, we use the same one-sided non-linear least squares approach as in BBL. Specifically, we choose our parameter estimates to minimize:

$$\sum_{p=1}^{P} \sum_{t,j \in \text{sample}} 1\{\hat{W}^p(\Omega_t, j) \cdot \theta > W(\Omega_t, j) \cdot \theta\}(\hat{W}^p(\Omega_t, j) \cdot \theta - W(\Omega_t, j) \cdot \theta)^2.$$

We obtain standard errors for the coefficients by bootstrapping the above four-step process.

4.5 Estimation of dynamic firm parameters

Our estimation algorithm depends on many necessary specifications and approximations that we list here. Most importantly, the state space of this problem, (Ω_t, j), is too large for computational purposes, as it includes the characteristics of all hospitals and patients in the market. Thus, we approximate the state space by summarizing it in relatively few dimensions. The important attributes that define the state for a hospital include its characteristics, some weighted sum of the characteristics of its competitors based on how close competitors they are, the level of competition, and the size of the market surrounding it.

For a given hospital, three of the characteristics noted in $hospchar_{jt}$ enter directly: CAH_{jt}, $beds_{jt}$ and own_j. The final characteristics are fixed and marginal costs. We estimate a hospital-specific productivity level, $\widehat{cost}_j$ to capture the fixed and marginal costs of a hospital. We estimate this value for each hospital as the hospital fixed effect from a regression of profits on characteristics, using data from before the start of our sample, from 1995 to 1997. Because $\widehat{cost}_j$ must capture variations in both fixed and marginal costs, we put in polynomial terms and interactions of it with other state variables in the regression of profits on states.

We also need to summarize the characteristics of patients and other hospitals in the surrounding market for any hospital. We measure these with three state variables for any hospital: summary measures of the number of Medicare and non-Medicare patients who are likely to be treated at any hospital, a measure of competition and the weighted CAH status of other hospitals. These terms together capture the size of the market and the degree of competitiveness of the market. We calculate the expected number of patients by estimating the Medicare utility function[17] $u_{ijt}^{Med} = \bar{u}_{ijt} + e_{ijt}$, where

$$\bar{u}_{ij}^{Med} = h^{Med}(dist_{ij}, closest_{ij}, beds_j, CAH_j, teach_j) \quad (17)$$

Here e_{ijt} is a type I extreme value residual and $distance_{ij}$ denotes the straight-line geographic distance between patient i and hospital j, $closest_{ijt}$ is a dummy for the hospital being the closest to the patient at time t and $teach_j$ is a dummy taking the value of one if the hospital

[17] For non-Medicare patients, we also use this function which is equivalent to assuming that the prices faced by these patients are the same across hospitals.

is a teaching institution.[18]

We then use estimtates these to calculate the probability P_{ijt} of patient i visiting hospital j in period t. Similarly, the expected volume for the hospital can be expressed as

$$EVol_{jt} = \sum_{i=1}^{I} Pr_{ijt}. \tag{18}$$

We calculate expected volume by insurance type: $EVol_{jt}^{Med}$ and $EVol_{j,t}^{Non-Med}(\Omega_j, t)$, analogously to $EVol_{jt}$ in (18).

In order to measure the level of competition in the market, we could potentially use a variety of measures related to the number of other hospitals nearby. A Herfindahl index is a convenient summary statistic from among these. Rather than arbitrarily defining a market over which to calculate a Herfindahl index, we follow the literature on the hospital industry (e.g., Kessler and McClellan, 2000) and define a patient-weighted Herfindahl index. Specifically, we start by defining

$$H_{it} = \sum_{j} Pr_{ijt}^2.$$

We then weight the Herfindahl index for each patient by the probability that they choose a given hospital. This gives us the measure that we use in our state space, the patient-weighted Herfindahl index:

$$HHI_{jt} = \frac{\sum_i Pr_{ijt} H_{it}}{EVol_{jt}},$$

which provides a summary statistic for the level of competition faced by each hospital.

Similarly, we define the CAH status of a hospitals' competitors, CAH_comp_{jt} as the patient-weighted sum of the CAH status of competitor hospitals. For each patient, the CAH status of competitor hospitals is defined by the weighted sum of the CAH status for competitor hospitals to j, weighted by the probability that the patient seeks care at any of these hospitals. Thus,

$$CAH\_comp_{jt} = \left(\sum_{i} Pr_{ijt} \frac{\sum_{k \neq j} Pr_{ikt} CAH_{kt}}{\sum_{k \neq j} P_{ikt}} \right) / EVol_{jt}. \tag{19}$$

[18] A teaching hospital is defined as having at least .25 residents per bed

Combining all these variables, the state space that we use in the analysis is $\Omega = (beds, CAH, \widehat{cost}, own, EVol^{Med}, EVol^{Non-Med}, HHI, CAH\_comp)$.

We now discuss how we solve for the first-stage static profit functions and actions and the low of motion at each state. Ideally, we would solve non-parametrically for these functions. However, this is not possible because of the large dimensionality of the problem. Since the state space is continuous, we solve for these functions with regressions. Specifically, group together the state vector and interactions and polynomials of the states as $r(\Omega)$. Then, we perform a linear regression of profits on $r(\Omega)$, where the exact specification is given in the results section.

In our model, CAH status is an absorbing state. Thus, we require an estimate of the hazard for $P^{CAH}(\Omega_t, j, x)$, the probability of successful conversion to CAH between time t and time $t+1$ at any state for which $CAH = 0$. We specify this hazard as a logit, and estimate it via maximum likelihood for non-CAH hospitals, of CAH approval on interactions of $r(\Omega)$ and investment, which we denote $\hat{r}(\Omega, x)$. Note that, given our model, it is appropriate to include investment as a regressor in this specification, unlike for the profit regression.

The specification for investment, $x_{jt}(\Omega)$, is more complicated to design. The majority of years, hospitals do not change their number of beds, or equivalently, they invest nothing. It is important to capture this feature of the data, because the fixed costs of investment will be identified by the extent to which firms choose to invest in lumpy amounts. Yet, a linear regression cannot model this type of mass-point. This suggests a latent variable model with a mass-point at zero. We estimate the following specification:

$$\begin{aligned} x^*_{jt}(\Omega) &= r(\Omega)b + e_{jt}, \text{ where:} \\ x_{jt} &= x^*_{jt} \text{ if } x^*_{jt} < 0, \\ x_{jt} &= 0 \text{ if } 0 \leq x^*_{jt} < \bar{x}, \\ x_{jt} &= x^*_{jt} - \bar{x} \text{ if } x^*_{jt} \geq \bar{x}, \text{ and} \\ e_{jt} &\sim N(0, \sigma_x^2). \end{aligned} \tag{20}$$

We estimate the parameters of (20), b, $\bar{x}$ and σ_x^2, using maximum likelihood. Note that our specification is similar to a Tobit model, but different in that the mass-point is in the middle, not on one end.

The state vector also contains four other variables that evolve over time as a function of the strategies of a hospital and its competitors. We estimate the transition for three of them, $EVol^{Med}$, $EVol^{Non-Med}$, and HHI as linear regressions where the difference between the value at time $t+1$ and t is regressed on $\hat{r}(\Omega, x)$ for time t. For CAH_comp_{jt}, investment does not enter since it is not a function of firm j's decision. Thus, we specify the transition for this variable to include only $r(\Omega)$.

Using these specifications, we implement the second-stage forward simulation process to compute W and W^p. We perform this process as follows, for each state. We first draw a value for e_{jt} and use this value to evaluate the simulated investment level. We then use $r(\Omega)$ or $\hat{r}(\Omega, x)$ (as appropriate) to simulate the CAH probability and the other laws of motion. If the value of any of these variables falls below 0 we set it to 0. Similarly, if the value of HHI of CAH_comp rises above 1 we set it to 1.

This process requires simulating unobservables for each of the equations. To simulate CAH approval, we estimate the approval probability for each state and then simulate with this probability. We simulate from the regressions for the linear transitions non-parametrically: we recover the distribution of the fitted residuals from the transition regressions and draw from this distribution. We cannot simulate non-parametrically for investment, since we do not observe the exact residual when investment is 0, which occurs when $x^*_{jt} \in [0, \bar{x})$. For values in this interval, we use the estimated normal density, while we estimate the residuals non-parametrically for values outside this interval.

4.6 Estimation of patient utility parameters

We estimate the parameters of the indirect utility function characterized in (17) for Medicare and non-Medicare patients using a maximum likelihood procedure. Specifically, we use the California OSHPD data on a subsample of California patients. For each patient we match latitude and longitude information to their reported home ZIP code and calculate straight-line distances to each hospital in their choice set. We limit the choice set to all hospitals within 150km circle of the patient's ZIP code. We also allow for the possibility of an outside good which is admittance to a hospital outside of the 150km circle.

The estimates from the patient flow model do not directly enter into the estimation. Rather, we use the estimated parameters from (17) together with locations of patients and hospitals to calculate the characteristics of the hospital's state space, specifically $EVol_{jt}^{Med}$, $EVol_{jt}^{Non-Med}$, HHI_{jt}, and CAH_Comp_{jt}. To perform this calculation, we need locations nationally and not just for California. Thus, we use Census data as our patient sample for this prediction. For each person in the relevant patient category we draw a 150km circle about the tract and calcuate Pr_{ijt} for each person in that tract. Once this calculation is made it is straightforward to calculate all of the state space variables for all hospitals in our sample.

4.7 Identification

Although we have specified a relatively intricate dynamic model of interaction between hospitals, the forces that will identify the parameters of interest are reasonably straightforward. The τ consumer utility parameters will be identified from the extent to which consumers choose hospitals based on characteristics such as location, severity of illness and hospital size.

The parameters in θ are identified by revealed preferences applied to our dynamic oligopoly model. Specifically, optimal behavior implies balancing the costs of investment, CAH conversion costs and fixed costs against the benefits in the form of profits and other returns. Different values of θ will imply different trade-offs, and the data will reflect particular trade-offs and hence particular values of θ. Since we use the accounting data on profits in our estimation, much of the identification derives from the shape of the gross profit function and the pattern of exit with respect to different states.

In particular, the bed investment cost parameters δ are identified by the impact of changing beds on the profit function. Heuristically, optimal investment levels will be higher if gross profits are more steeply sloped in beds, all else being equal. Since investment levels and the shape of profits with respect to beds are observed in the data, the relation between investment and the slope of profits in beds will identify the value of the investment cost parameters. The γ parameter on the cost of CAH conversion is similarly identified by the extent to which hospitals obtain CAH status at states where it is profitable to have achieved that status. For instance, if hospitals rarely achieve CAH status even when profitable, this suggests that a small γ is making the CAH conversion process very costly.

These arguments are heuristic rather than formally true because of the dynamic oligopoly that is built into our model: an investment in beds will not just change beds, but will potentially change the expected future value of all the state variables, through the interactions that occur between firms. For instance, an increase in beds may cause other firms to reduce their beds in expectation, in which case this positive strategic effect would need to be added to the direct effect of beds on profits. Moreover, firms must jointly decide on the decisions for investment in beds and CAH status. Nonetheless, a simple heuristic benchmark estimate for our investment parameters can be derived by evaluating the average impact of beds on profits, where profits are weighted by $1-\beta$, and estimating the optimal level of investment given this simple model.

Note that there are seven different δ parameters. The first six of these parameters relate to the different mean fixed and marginal costs of positive and negative investment. These parameters can all be separately identified by the relative extents of strictly positive and negative investments in beds and the extent of non-zero investment. In particular, the fact that most periods firms rarely invest suggests a large positive fixed cost of investment.

The two other parameters in the bed investment equation (2), δ_7 and σ relate to the distribution of investment for any state. The larger the variance of investment outcomes for a given state, the larger will be σ. Here, we estimate a distribution with two parameters, essentially two halves of two normal densities that intersect at 0. The δ_7 parameter is then identified by the relative variance of outcomes for negative investment to positive investment.

The final parameters that we estimate via the dynamic model relate to the objective functions by ownership type. These parameters can be identified by the pattern of exit in the market and the relation of exit to profits. For instance, if NFPs often do not exit even when the expected future profit path is negative, this suggests that they value the provision of service and/or patient volume. If it further turns out that in unprofitable markets, NFP hospitals remain in operation only when their expected volume is high, this suggests that NFPs value expected volume rather than simply the provision of service. Again, expected profits and expected volume are a function of the dynamic oligopoly behavior between firms. Yet, one can heuristically benchmark these parameters by examining the exit behavior by types as a function of current profits.

5 Results

5.1 Evidence on the Impact of the CAH Program

We present some evidence of the impact of the CAH program on the rural hospital performance and market structure. First, summary statistics of our sample of small rural hospitals at risk for CAH conversion are presented in Table 3. Our sample is 51% NFP. Local government hospitals comprise 39% of the sample and 11% of the sample are for-profit hospitals. The typical hospital faces some measured competition with an HHI is .42. Over the sample period the rural hospitals on average reduced their beds by 1.78. The closure rate is .008.

Table 4 compares CAH and non-CAH hospitals in the same sample for 2005. The table shows that CAHs are substantially smaller than non-CAH hospitals, which is to be expected given the regulatory framework they face. The average number of beds for CAHs is 22.47, very close to the upper bound of 25 beds. In Figure 3 we present the histograms of bed size for rural hospitals for 1996 and 2005. From this picture it is clear that the CAH program had large effects on the size distribution of rural hospitals. Figure 4 presents the bed size histograms for hospitals that ultimately converted to CAH status in 1996 and in 2004. Not surprisingly, CAH conversion dramatically altered the distribution of the number of beds per hospital. Furthermore, the large mass point at 25 beds suggests that the 25 bed limit is a binding constraint, i.e. CAHs would increase their bed size if the regulations allowed it.

With respect to ownership of CAHs, there is very little participation of for-profit organizations (4%), and large participation of government-owned hospitals (46%). In markets where CAHs are present, the percentage of Medicare-eligible residents averages 16% (shown in Table 4) and it is statistically significantly bigger (t=11.22) than the percentage of Medicare eligibles in areas where non-CAHs are present. This suggests that hospitals are responding to the incentives of the program, which is available only for Medicare reimbursement. In Figure 5 we present the time series of accounting profit (net income) margins, $\frac{\text{Profits}}{\text{Total Revenue}}$, for hospitals with less than 225 beds in 1995 by rural status. The time series pattern for profit margins is striking. Prior to the passage of the BBA which initiated the CAH program, profit margins in rural and non-rural hospitals were very similar. With the passage of the BBA, hospital in non-rural areas saw a dramatic decline in margins as the BBA dramatically cut Medicare payments to non-CAH hospitals.[19] However, hospitals in rural areas saw little decline in their profit margins following the passage of the BBA. This simple graph is consistent with the findings of MedPAC (2005) and Stensland et al. (2003) where they found that hospitals that coverted to CAH increased their margins significantly more than a sample of non-converting hospitals. Figure 6 shows that the exit rates of urban and rural hospitals move together during the period we study, and the difference in exit rates between rural and urban hospitals is amplified after the passing of the legislation.

5.2 First Stage Estimates

In the first stage we recover the parameters from patients' demand, hospitals' profits, and the policy functions for CAH conversion, investment and exit. The goal is to characterize accurately the behavior of the hospitals at every state, which is necessary for the second stage estimation of the dynamic parameters. Consumers' preferences for hospitals were estimated by means of a multinomial logit model, where hospitals were represented as a bundle of attributes including distance from the patient's census tract, whether the hospital is the closest to the patient, capacity measured by beds, CAH status, and teaching status. We estimate the preferences for both Medicare and private patients using discharge data from

[19] The rise of HMOs, which did not significantly impact rural areas, peaked around 1997 and may also explain some of the decline in profit margins for non-rural hospitals in the late 1990s.

the California OSHPD.[20] The probabilities generated by this model are the ones used to compute the expected volumes described in the model section of the paper. The estimates of the preference parameters are presented in Table 5. It can be seen that Medicare patients present a larger disutility from hospital distance relative to the younger population. The preferences for the rest of the attributes are very similar between the two groups.

The results from the regression of profits on states are presented in Table 6. Due to the large number of interactions included in the regression, we summarize the important results in Figure 7. As it is shown in the figure, the benefits from CAH conversion are larger for the hospitals that actually converted than to the non-converters had they converted at every level of productivity. In addition, it can be seen that the low performing hospitals are the ones that benefit the most from conversion. For a hospital with average productivity, conversion to CAH status implies an increase in profits of about \$260,000 per year, and almost twice as much for a hospital at the bottom 10th percentile.

Table 7 presents the estimates of the CAH conversion policy function, estimated with a probit model. The probability of converting is larger for NFP and government hospitals relative to for-profit hospitals. Larger hospitals and more productive hospitals are less likely to convert, as are the hospitals that show positive investment in capacity. Table 8 presents the results from our tobit-like regression for investment, where the parameters b, $\bar{x}$ and σ_x are estimated. In addition to the policy regressions, we estimate the laws of motion for the state variables HHI, $EVol^{Med}$, $EVol^{Non-Med}$, HHI and CAH_comp_{jt}, as linear regressions where the differences between the value at time $t+1$ and t are regressed on polynomials of the state variables. These results are available upon request.

5.3 Dynamic Parameter Estimates

The parameter estimates of the second stage are presented in Table 9. These are the parameters of the hospitals' objective function, investment cost, and CAH investment that rationalize the policy functions estimated in the previous section in a Markovian equilib-

[20] Future work will incorporate states that we believe are more representative of the rural population such as Iowa and Washington, and will include pre-policy and post-policy data.

rium. Overall the estimates are sensible. The first four parameters indicate that non-profit and government hospitals value patient volume and operating in addition to monetary profits. Our estimates of the parameters α_p^{NFP} and α_v^{NFP} imply that non-profit hospitals are indifferent between losing \$468,000 in profits and treating 1,000 patients and remaining open. Government hospitals value volume and remaining operating even more. The esimtates of α_p^{Gov} and α_v^{Gov} mean they are indifferent between losing \$2,393,000 in profits and treating 1,000 patients and remaining open.

The estimates of the parameters of the investment cost function, $\delta_1, \ldots \delta_7$, show that the costs of positive investment are much larger than the costs of disinvesting in beds, which is consistent with what we would expect given that additional beds need staff and physical space. The cost of increasing capacity by 10 beds is about \$7.5 million, and the cost of decreasing capacity by 10 beds is about \$0.80 million. The parameters also indicate that costs are increasing at an increasing rate. The last parameter in Table 9, γ^{-1} is the CAH approval process parameter. If a hospital invests \$1,000 in acquiring CAH status, it has a probability of 0.12 of being approved. If the hospital effort is \$150,000, the probability of approval increases to 0.95. This latter figure of \$150,000 corresponds to about one third of the average CAH hospital annual accounting profit.

6 Policy Experiments

In this section we provide the results from a counterfactual experiment that aims at finding the impact of the CAH program. We do this by simulating the equilibrium under the counterfactual scenario that CAH conversion is not available. To achieve the goal, we solve for the Markov Perfect Equilibrium along the lines of Ericson and Pakes (1995) using the structural parameters estimated above. Our first policy experiment includes 183 "monopoly" hospitals, defined as those that have a patient weighted Herfindahl Index $HHI \geq 0.75$. We simulate the outcomes of the equilibrium for a baseline and compare them to the counterfactual where conversion to CAH is not an option. Figure 8 shows the exit probabilities for the hospitals that converted, had they not converted to CAH over a 20-year period. In a period of 20 years, only 5% of those hospitals would have exited the market. As expected, the program also affected hospitals' capacity as shown in Figure 9. When CAH is not an option, hospitals keep their capacity fairly constant and above the proscribed level of 25 beds over the 20-year period of our simulation. In contrast, when CAH is an option the average size of converting hospitals declines to approximately 21 beds. We alos find that the program's effect on hospital value is the largest for smaller hospitals. For a 25-bed hospital the program doubles its value.

7 Conclusions

In this paper we seek to understand the impact of the CAH program on the rural hospital industry market structure. To evaluate the impact of the program we estimate a dynamic oligopoly game, where hospitals take into account the effect of their decisions on rivals. The estimation is performed using the recent two-step BBL procedure, which we modify by introducing private information in the investment cost function. The CAH program has dramatically transformed the rural hospital landscape. Incentives provided in the program radically reduced the average bed size of rural hospitals. Furthermore, our initial estimates suggest that the CAH program increased profits for converting hospitals, and disproportionally so for poor performing rural hospitals. That is, insofar as the program's intent was to provide extra assistance to hospitals that were at risk of failing, it achieved that goal. Our initial estimates are sensible and have several interesting implications. Non-profit and government hospitals intrinsically value treating patients and remaining open in addition to profits. Hospitals' cost of investment is asymmetric for bed investment and disinvestment. Simulations in monopoly markets show that the program prevented only 5% of closures had the program not been implemented. Our work contributes to a recent and fast growing literature that uses the results from the estimation of dynamic games to perform policy evaluations. It should be noted that these results are very preliminary and subject to evolution. Future work will include multi-agent simulations and welfare calculations to provide an overall assessment of the program.

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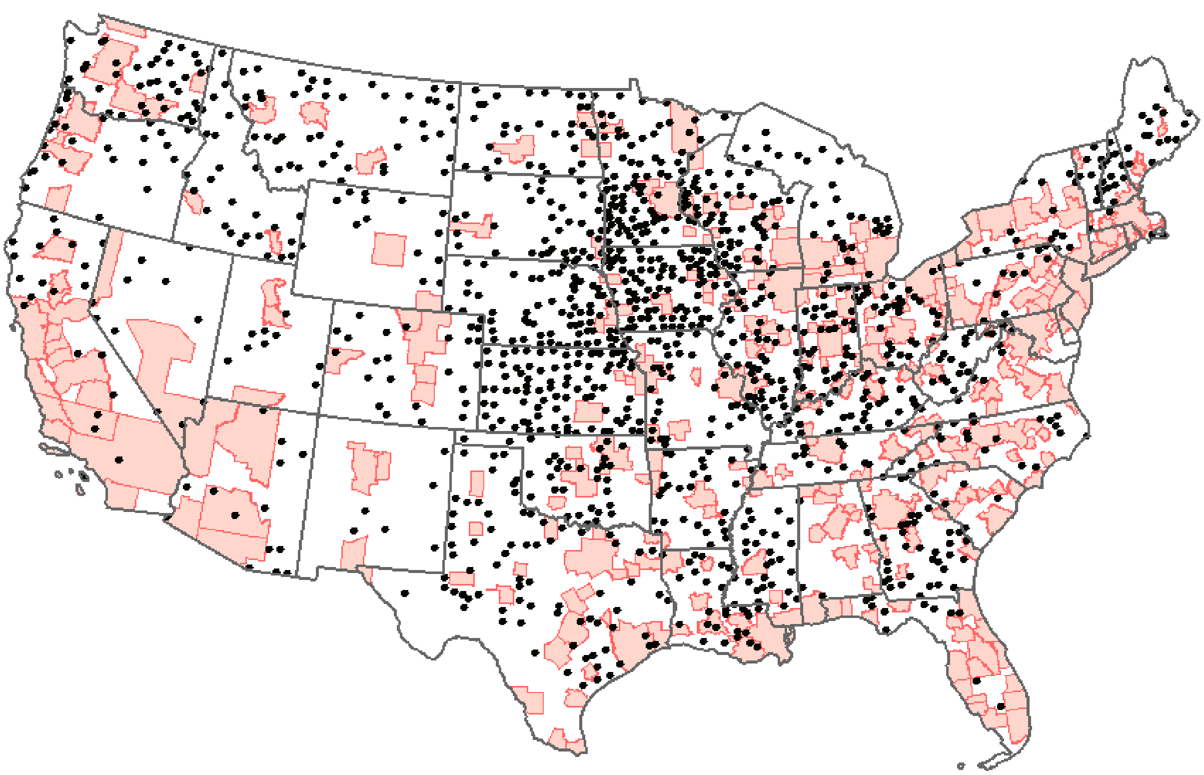

Figure 1: Spatial distribution of CAH. Dots represent CAH, polygons represent MHAs

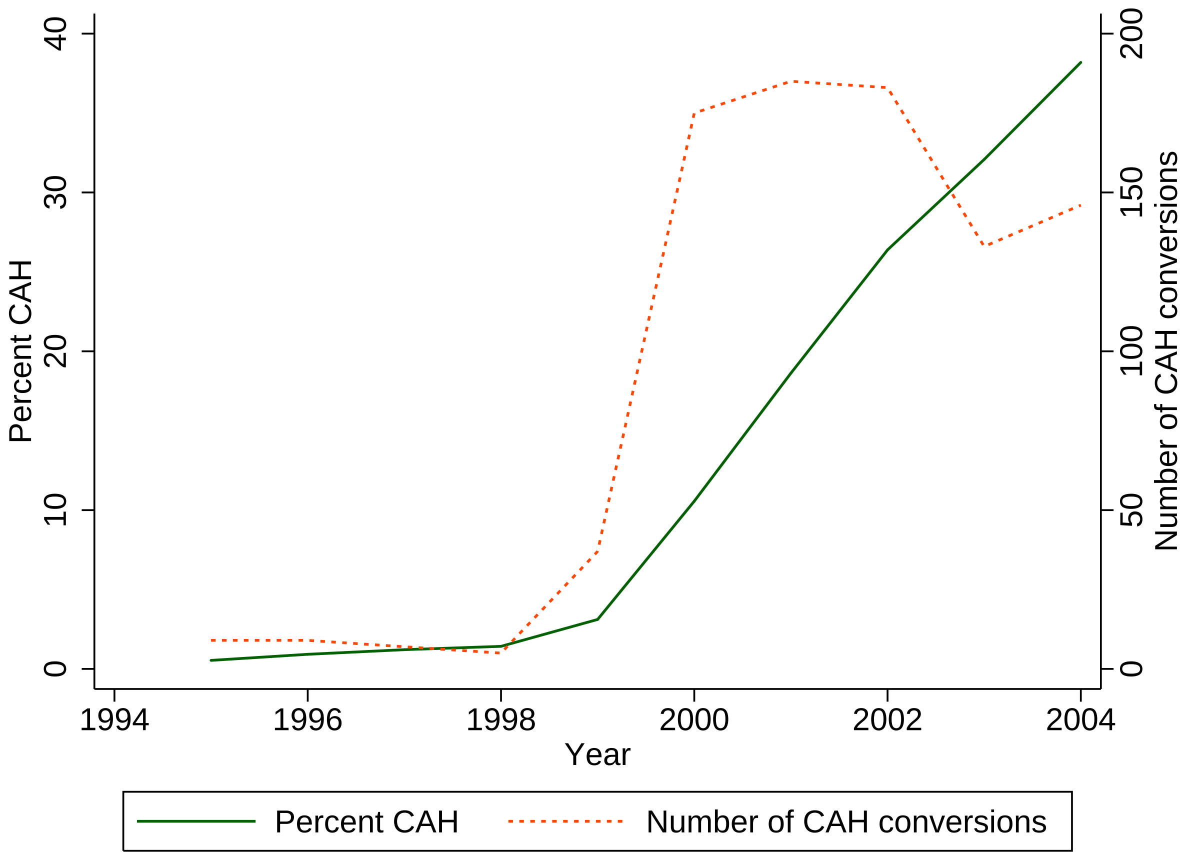

Figure 2: Conversion rates and percent CAH among U.S. rural hospitals

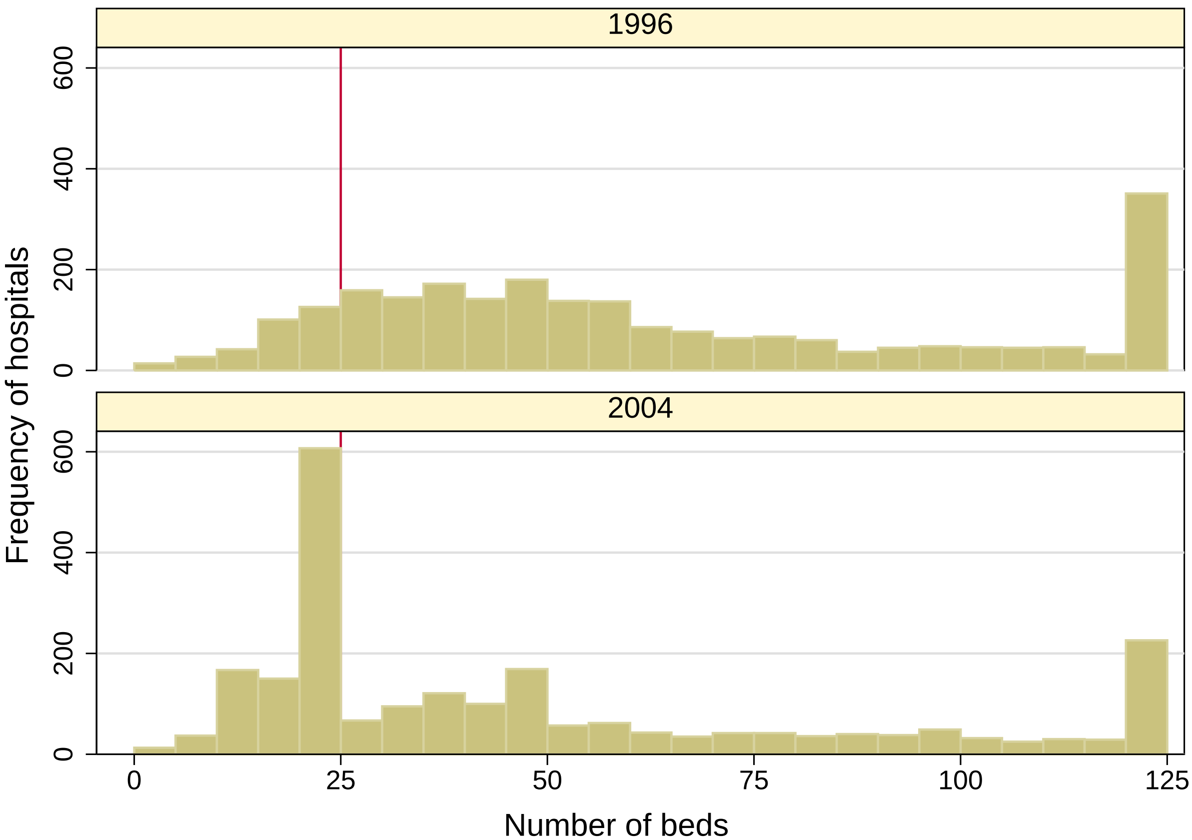

Figure 3: Size of rural hospitals, 1996 and 2004

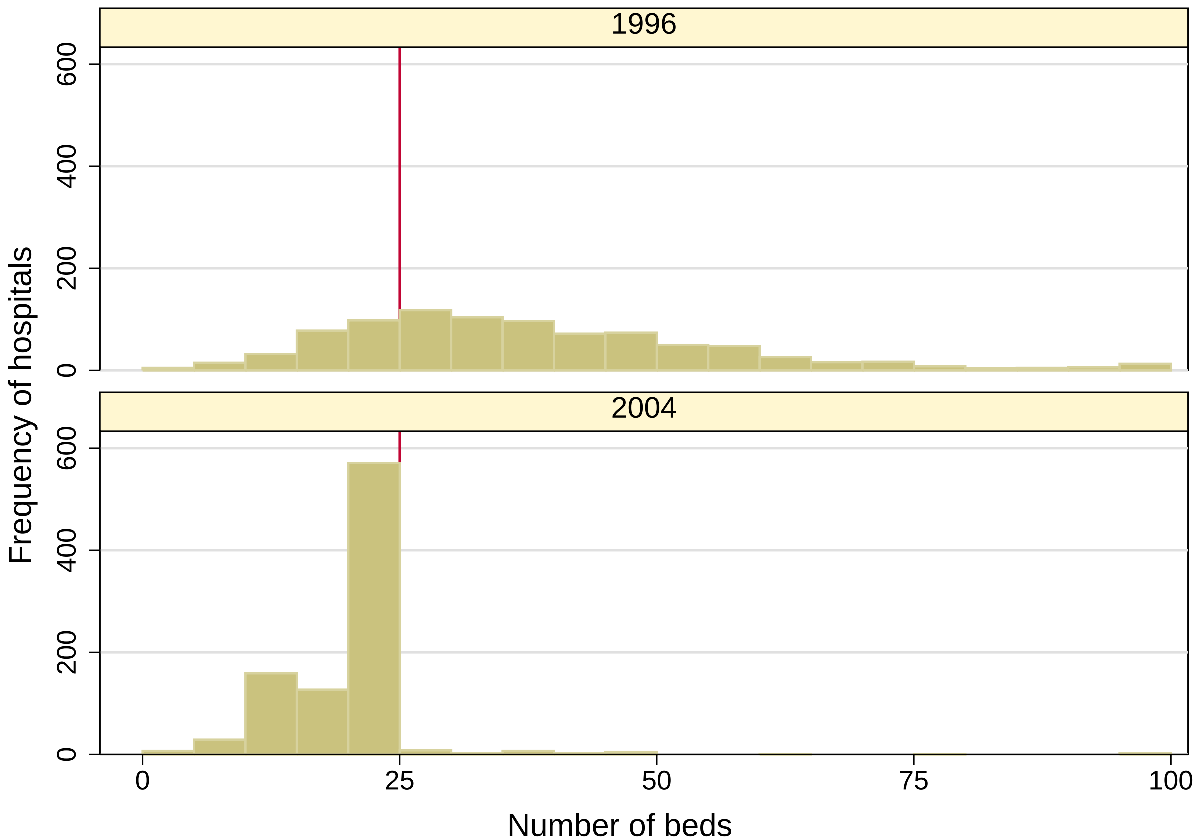

Figure 4: Size of hospitals that are CAH in 2004

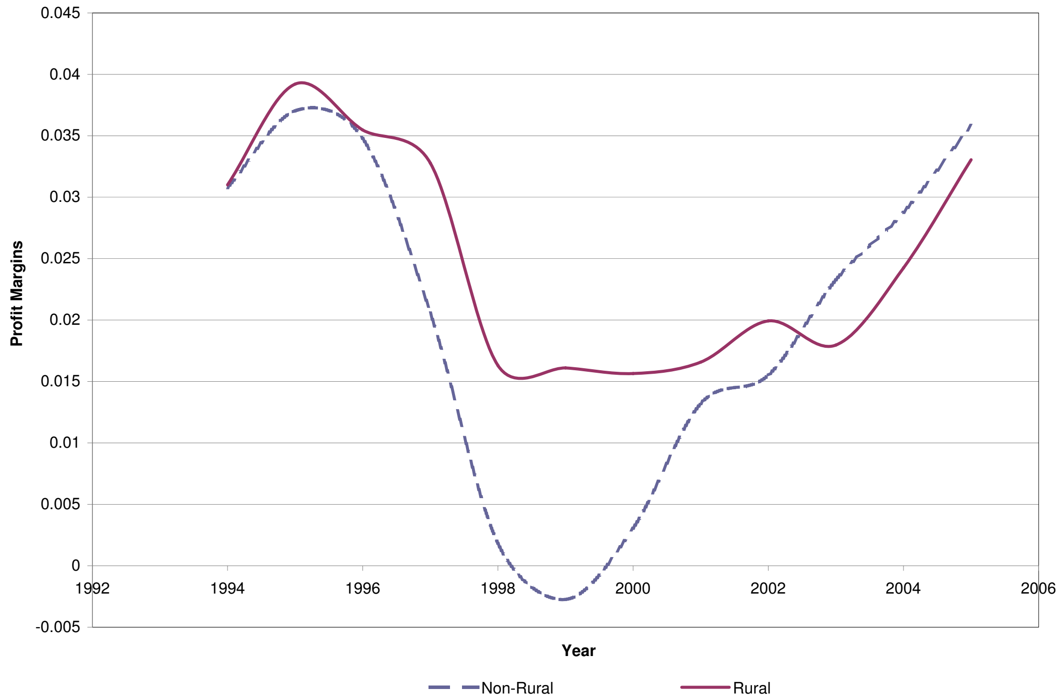

Figure 5: Mean profit margins for hospitals with less than 225 beds in 1995.

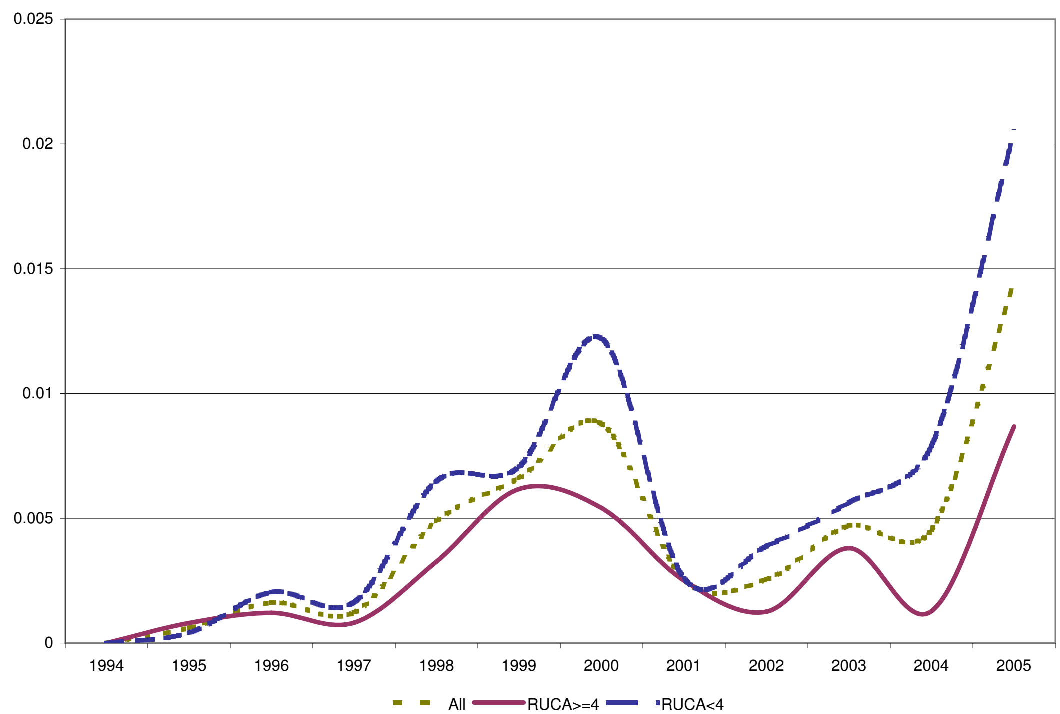

Figure 6: Exit rates for Rural, Urban and All U.S. Hospitals

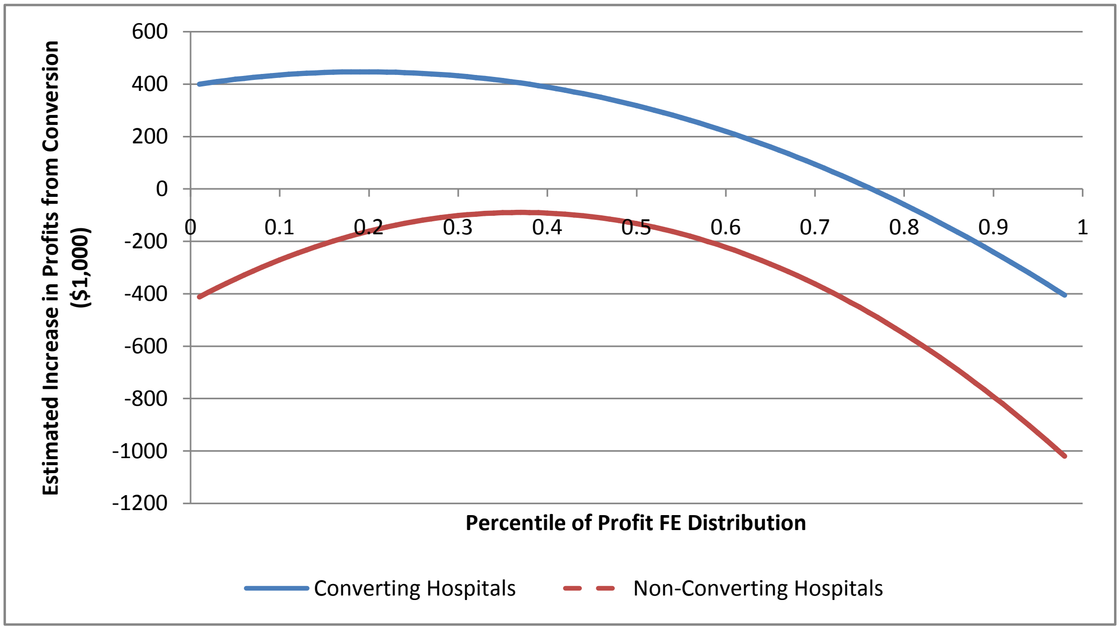

Figure 7: Change in profit from CAH conversion by CAH status and productivity($1,000)

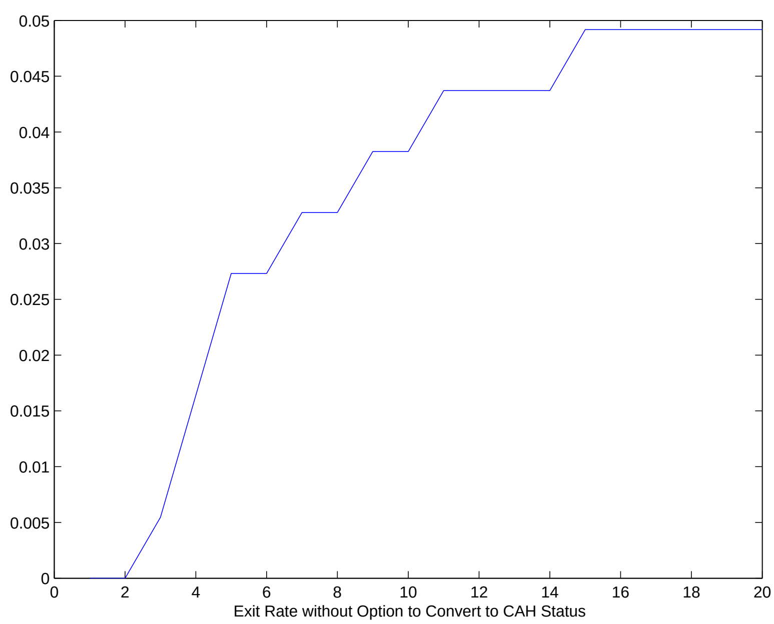

Figure 8: Impact of CAH program on exits

Figure 9: Impact of CAH program on size distribution

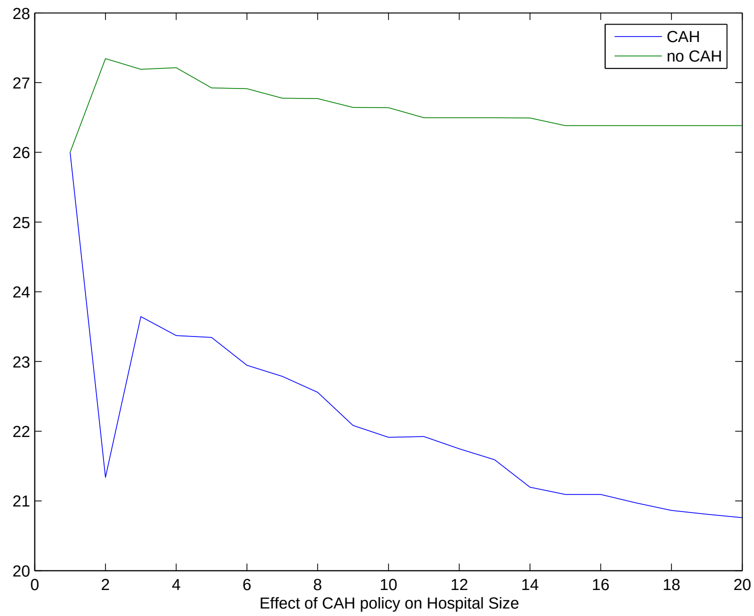

Table 1: Relevant Policy Changes for CAH

Legislation	Key Aspects of CAH Legislation and Regulation
BBA 1997	• CAH Program established. • Hospitals should operate no more than 15 acute beds and no more than 25 total beds, including swing beds. • All patients' LOS limited to 4 days. • Only government and NFP hospitals qualify. • Hospitals must be distant from nearest neighboring hospital, at least 35 miles by primary road and 15 by secondary road. • States can waive the distance requirement by designating "necessary providers".
BBRA 1999	• LOS restriction changes to an average of 4 days. • States can designate any hospital to be "rural" allowing CAHs to exist in MSAs. • FP hospitals allowed to participate.
BIPA 2000	• Payments for MDs "on call" are included in cost-based payments. • Cost-based payments for post-acute patiente in swing beds.
MMA 2003	• Inpatient limit increased from 15 to 25 patients. • Psychiatric an rehabilitation units are allowed and do not count against the 25 bed limit. • Payments are increased to 101 percent of cost. • Starting in 2006, states can no longer waive the distance requirement.

LOS: Length of Stay

Source: MedPac(2005)

Table 2: Definitions of Rural-Urban Commuting Area Codes

Code	Description
1	Metropolitan area core: primary flow within an Urbanized Area (UA)
2	Metropolitan area high commuting: primary flow 30% or more to UA
3	Metropolitan area low commuting: primary flow 10% to 30% to UA
4	Micropolitan area core: primary flow within an Urban Cluster of 10,000 through 49,999
5	Micropolitan high commuting: primary flow 30% or more to a large UC
6	Micropolitan low commuting: primary flow 10% to 30% to a large UC
7	Small town core: primary flow within UC of 2,500 through 9,999
8	Small town high commuting: primary flow 30% or more to a small UC
9	Small town low commuting: primary flow 10% through 29% to a small UC
10	Rural areas: primary flow to tract outside a UA or UC (including self)

Each code has up to 6 subcodes that classify the zip code depending on their precentage flow to Urbanized Areas or Urban Clusters

Table 3: Summary Statistics – Analysis Sample

	Mean	Std. Dev.
Profits ($1,000)	923.13	2,679.44
CAH Status	.22	.42
Not-For-Profit	.51	.50
Government	.39	.48
For-Profit	.11	.31
Beds	52.19	37.60
$\hat{f}$	41.04	1,884.36
HHI	.42	.19
CAH_Comp	.00028	.0014
$EVol^{Non-Med}$	15,176.7	13,700.17
$EVol^{Med}$	2,817.2	2,256.49
Investment (Δ Beds)	-1.78	8.50
Closure	.0081	.090
N	16,609	
Number of Hospitals	2,236	

Table 4: Summary Statistics in 2005 by CAH Status

	CAH	Non-CAH
Profits ($1,000)	448.67	1,835.1
Not-For-Profit	.47	.52
Government	.49	.32
For-Profit	.036	.16
Beds	22.47	70.17
$\hat{f}$	-483.31	590.83
HHI	.3587	.4485
CAH_Comp	.00074	.00032
$EVol^{Non-Med}$	2,247	13,700.17
$EVol^{Med}$	990.0	4,284.6
Investment (Beds)	-2.03	-.36
Closure	.0066	.0081
N	916	984

Table 5: Estimates from MNL Model of Hospital Choice

Variable	Medicare	S.E.	Private	S.E.
$Distance$	-.022	.0024	-.043	.0026
$Distance^2/100$	-1.48	.22	-.12	.22
$Dist \times Urban$	-.035	.0025	-.031	.0026
$Dist^2 \times Urban$	2.96	.22	2.69	.22
$Closest$	2.61	.067	2.08	.072
$Closest \times Beds$	-.0025	.00016	-.0017	.00017
$Closest \times Urban$	-.49	.061	-.61	.065
CAH	-14.68	4.12	-40.71	4464
$CAH \times Closest$	12.36	3.85	36.37	4464
$CAH \times Dist$	2.61	.067	.18	.066
$Beds$	.011	.00014	.012	.00013
$Beds^2$	-.00076	.0000020	-.00077	.000018
$Teaching$	-1.31	.040	-1.31	.039
$Closest \times Dist$	-.032	.00019	-.032	.0019
$Teach \times Dist$	.0092	.00089	.0098	.00082
$Beds \times Dist$	-.000018	1.86×10^{-6}	-.000021	1.81×10^{-6}
N	29,536		26,365	
Likelihood	-86,427		-72,765	

Table 6: First-Stage Regresion: Profits ($1,000)

Variable	Estimate	Robust s.e.	t
CAH status	471.42	164.60	2.86
Beds	19.14	7.58	2.52
$\hat{f}$	.51	.076	6.61
$\hat{f}^2$	.000036	.000015	2.61
$\hat{f}^3$	$-3.15x10^{-9}$	$1.67x10^{-9}$	-1.89
HHI	-2278.60	869.22	-2.62
HHI^2	1928.04	9.03	2.13
$\hat{f} * CAH$	.095	.19	.54
Vol. Under 65	045	0.0011	3.92
Vol. Over 65	-.081	0.072	-1.12
CAH_comp	-23,035.20	10,000.12	-2.30
CAH_comp*CAH	27,279.48	17,688.6	1.54
R^2	0.29		
N	16,609		

Standard errors clustered at the hospital level

Table 7: First-Stage Regresion: CAH Conversion

Variable	Estimate	Robust s.e.	z
NFP	.90	.23	3.84
Gov	.78	.23	3.32
$Beds$	.015	.014	1.12
$Beds^2$	-.0022	.0002	-10.78
$\hat{f}$	-.17	.33	-.53
$\hat{f}^2$	-.054	.025	-2.19
$\hat{f}^3$	.002	.002	0.98
HHI	.45	1.61	.28
$\hat{f} * HHI$	1.42	1.27	1.11
$\hat{f} * Beds$	-.0093	.0041	-2.27
Vol. Under 65	0.000049	0.000016	3.43
Vol. Over 65	-.00028	0.000097	-2.85
CAH_Comp	27.0	16.94	1.59
x	-.25	0.0083	-30.48
Constant	-1.34	.54	-2.47
Log Likelihood	-1,895.5		
N	11,155		

Standard errors clustered at the hospital level

Table 8: First-Stage Regression: Investment

Variable	Estimate	Robust s.e.	z
NFP	.90	.23	3.84
Gov	.78	.23	3.32
CAH status	-.072	.015	-4.59
CAH status*$Beds$	1.88	.46	4.07
$Beds$	-.0039	.0054	-.71
$Beds^2$	-.000026	.000027	-.96
$\hat{f}$	-.045	.18	-.25
$\hat{f}^2$	.0041	.58	.71
$\hat{f}^3$	-.00027	.00047	-0.58
HHI	-.46	1.27	-.37
$\hat{f} * HHI$	.16	.73	.22
$\hat{f} * Beds$	.00047	.00097	.48
Vol. Under 65	0.000016	0.000013	1.27
Vol. Over 65	-.000023	0.000084	-.28
CAH_Comp	8.63	46.86	.18
Constant	-1.34	.54	-2.47
$\bar{x}$	6.06	.15	85.08
σ_x	19.10	.22	40.48
Log Likelihood	-16,327.6		
N	14,028		

Table 9: Parameter Estimates Dynamic Oligopoly Equilibrium

Variable	Estimate	Bootstrapped s.e.
α_v^{NFP}	-76	(26)
α_p^{NFP}	2984	(1616)
α_v^{Gov}	-70	(22)
α_p^{Gov}	2622	(1274)
$1\{x > 0\}$	-200	(100)
$1\{x > 0\}x$	3414	(1105)
$1\{x > 0\}x^2$	.480	(.311)
$1\{x < 0\}$	1.803	(.872)
$1\{x < 0\}x$	-2363	(717)
$1\{x < 0\}x^2$	20.5	(15.3)
$1\{x < 0\}x\varepsilon$	1558	(561)
σ	1090	(377)
γ^{-1}	99	(90)