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

Gautam Gowrisankaran* Claudio Lucarelli† Philipp Schmidt-Dengler‡
Robert Town§

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Abstract

Many government policies either target the underlying supply infrastructure or have indirect effects on market structure. In this paper we seek to understand the impact of the Critical Access Hospital (CAH) program on the U.S. rural hospital infrastructure and societal welfare. This program provides generous reimbursement to hospitals in exchange for size and service limitations. We specify and estimate a model of the rural hospital industry in which hospitals choose investment, exit, prices and conversion to CAH status. Because these choices have dynamic impacts and even rural hospitals have geographically close competitors, we model hospitals as a dynamic oligopoly. We estimate the structural parameters from this model using a two-step inference method and assess the structural and welfare impacts of the CAH program. Our methods extend current estimation techniques for dynamic oligopoly models to allow for investment behaviors that are more consistent with the data. Our estimated parameters on investment costs and the costs of CAH conversion appear reasonable in magnitude. Preliminary results reveal that the CAH program increases the profits of converting hospitals by $260,000 and decreases exits by 5%.

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*University of Arizona and NBER

†Cornell University

‡London School of Economics

§University of Minnesota and NBER

1 Introduction

Governments often enact policies that target the underlying supply infrastructure, either directly or indirectly. 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. However, assessing the impact of these programs on welfare and other outcomes is often a difficult task. These programs affect the returns to market participation; thus their impact will be a direct consequence of entry, exit and investment decisions by a potentially large number of organizations. Assessing the impact of these programs requires measuring the impact on dynamic equilibrium outcomes (both discrete and continuous) of forward-looking agents. Until recently the estimation of the underlying "deep" parameters necessary to calculate the impact of these programs on industry market structure was computationally burdensome. However, recent advances in the estimation of dynamic games has made such estimation feasible.

In this paper we seek to understand the impact of the Critical Access Hospital (CAH) program on the U.S. rural hospital infrastructure and societal welfare. The overarching purpose of this program is to improve the access to care of the rural population by keeping open hospitals that would otherwise close. The CAH initiative is a voluntary program in which hospitals limit their capacity, measured by beds, and services 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. The program was initiated in 1997 as a provision of the Balanced Budget Act of 1997 and since then over 1,100 rural hospitals (roughly 25% of all US hospitals) have converted to CAH status. In 2006, CAH hospitals were expected to receive $5 billion in cost-based reimbursements, $1.3 billion more than what they would have received under PPS (MedPAC 2005). Not only is the program interesting from an economics perspective – it affects organizational incentives

along multiple dimensions; but the magnitude of the expenditures imply that a CAH program evaluation is of independent interest.

To evaluate the impact of the CAH program, we estimate a dynamic model of rural hospital exit, investment and CAH status.[1] The CAH program affects both the level of Medicare payments as well as the hospital's incentives to cost-minimize. Our framework allows average costs to be a function of these incentives. In our framework hospitals seek to maximize an objective function that includes both profits and volume, in the case of not-for-profit hospitals. As most rural hospitals are not-for-profit organizations, we follow a long tradition in health economics in allowing this deviation from pure profit maximization.[2] Each period, hospitals endogenously select their size (as measured by number of beds), decide whether to exit and post-1997 select whether or not to invest in becoming a CAH. The decisions are made in dynamic equilibrium, where hospitals take account of the effect of their decisions on rivals. Our model is a function of unknown parameters that pertain to the objective function for not-for-profits, the cost function for investing or disinvesting in beds, and the costs of obtaining CAH status.

Following the dynamic decisions, hospitals engage in static production. First, they decide on prices to charge to non-Medicare patients. Individuals then fall ill and decide at which hospital to seek treatment. They make their decisions based on their distance to each hospital, their own diagnosis, and characteristics of the hospital, such as beds. Non-Medicare patients also incorporate prices into their decisions. Hospitals that have limited their size, for instance to participate in the CAH program, will likely see reduced demand because of this.

To estimate the dynamic parameters, we build upon the approach of Bajari et al. (2007) (henceforth BBL). BBL's insight is that the observed strategies conditional upon the states and transitions between states in a dynamic game can be used as "data" in an estimation algorithm thereby averting the computational burden of solving for the fixed-point of the game for every evaluation of the parameter vector.[3] Pakes et al. (2007), Aguirregabiria and

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

[2] See, for example, Newhouse (1970), Pauly (1978), Lakdawalla and Philipson (1998) and Sloan (2000).

[3] Hotz and Miller (1993) first proposed a similar two-step approach to estimate the parameters of a single-agent dynamic decision making process.

Mira (2007) and Pesendorfer and Schmidt-Dengler (2007) have also suggested approaches to estimate parameters of dynamic games that rely on similar ideas. While BBL suggested the possibility of allowing for private information in the investment process, this is the first paper that introduces private information in the investment process. This allows firms' investment decisions to differ conditional on state. We develop a version of the BBL algorithm that allows for this extension.[4] Using this estimation algorithm, we recover the dynamic parameters noted above. We also recover static parameters of the consumer utility function. This then allows us to use those parameters to solve for the equilibrium under different counterfactual scenarios.

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 poorly 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 estimates of the dynamic parameters are sensible and have several interesting implications. First, not-for-profit and government hospitals intrinsically value treating patients and operating in addition to profits. Second, hospital cost of investment is non-convex and asymmetric. Third, our initial simulation on one hospital suggests that the CAH program does not dramatically impact exit probabilities.

Our work contributes to a recent and fast growing literature that uses the results from the estimation of dynamic games to perform policy evaluations, such as Gowrisankaran and Town (1997), Benkard (2004), Jofre-Bonet and Pesendorfer (2003), Ryan (2006) and Collard-Wexler (2006). In the following section we provide institutional background of the CAH program and review the literature. Section 3 describes our data, section 6 provides further descriptions through a reduced form analysis. Our model is presented in section 4, and section 5 describes our estimation method. The results and policy experiments are presented in sections 7 and 8 respectively, and section 9 concludes.

[4]The details of this estimation approach are described in a companion paper.

2 The Critical Access Hospital Program

2.1 Background

The CAH program was enacted in the Balanced Budget Act (BBA) of 1997.[5] 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 recently, the distance requirement does not appear to be binding. Most CAHs are less than 25 miles from a neighboring hospital.[6] 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. In the 1997 legislation the maximum size of a hospital is 15 beds and the length of stay is limited to 4 days for all patients.

CAH hospitals are required to provide inpatient, laboratory, emergency care and radiology services. A CAH must 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.

The program's rules have been modified several times since its inception. Table 1 summarizes the important legislative and regulator changes in the program. The most important of these changes are: 1) The Balanced Budget Reconciliation Act (BBRA) of 1999 changed the length of stay requirement and allowed states to declare hospitals in Metropolitan Statistical Areas to be designated 'rural' for the purposes of CAH designation; 2) The Medicare Prescription Drug, Improvement and Modernization Act (MMA) of 2003 increased the acute inpatient limit from 15 to 25 acute patients and increased the payments from 100 to 101

[5] Much of the information in the section is culled from MedPAC (2005). Readers desiring more information about the CAH program are encouraged to consult this source.

[6] MedPAC (2005).

percent of costs. These program changes provide variation in payoffs to becoming a CAH across both time and hospitals and thus help identify the parameters of interest. The variation also allows us to estimate the model on a subset of the data and forecast the impact of programmatic changes on hospital behavior and industry evolution. We can then examine the validity of our model by comparing these forecasts to policy realized hospital behavior.

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. Thus, the commonly made assumption that organizations make rational forecasts of future profit paths appears to be reasonable in our application.

Figure 1 shows that the rate of conversion to CAH remains very low until 1998. In 1999 the number of CAHs doubles and keeps growing at a fairly constant rate of about 4% per year until the end of our sample period. We believe that the delay between the enactment of BBA in 1997 and the timing of conversion is due to the application process, which requires large amount of paperwork, inspection visits and CMS approval.[7] By 2005, 25% of the hospitals in our sample have adopted the CAH status. It is said that conversion rates should decline after 2006, when the minimum distance requirement will be enforced (MedPAC 2005). We use our model to evaluate that out-of-sample prediction.

The spatial distribution of CAHs is shown in Figure 2. 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 Mid-West, and are mostly outside of MSAs.

2.2 Previous Research

There have been a number of contributions in the economics literature that relate to our study. There is an extensive literature on hospital closures, which have provided evidence on the characteristics of hospitals that make them more likely to exit the market. For example,

[7] 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

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 have studied a particular aspect of welfare, and have not taken into account how efficiency and access to care interplay, being this another contribution of our paper. In addition, all the papers mentioned above document the period before 1998, that is before hospitals were effectively converting into CAH.

Several researchers have previously studied detailed aspects of the impact of the CAH program. Many of these papers study the effects of the program from the point of view of the hospital that converted. The financial effects of CAH conversion are studied by Stensland et al. (2003). Comparing hospitals converting in 1999 pre-conversion and post-conversion data, and to other small rural hospitals they find a significant association of CAH conversion with increases in Medicare revenue (which is to be expected given that hospitals choose to convert), increases in hospital profit margins from -4.1% to 1.0%, and increases in costs per discharge of 17%. They state that increased Medicare payments are borne by federal taxpay-

ers, but local patients and CAH employees benefit from the improved financial conditions, however, they do not calculate whether the benefits are worth their cost. Stensland et al. (2004) re-do their analysis for hospitals converting in 1999 and 2000, reaching similar conclusions. Other papers such as Casey and Moscovice (2004) study the quality improvement initiatives of two CAH 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.

In contrast with the literature mentioned above, our paper studies the welfare impact of the CAH program on both consumers and producers, taking explicitly into account the strategic interactions between converters and non-converters, and being able to provide an overall assessment of the impact of the program. We list the channels by which welfare can be affected by the policy in the next subsection.

2.3 Possible Welfare Consequences of the CAH Program

The CAH program affects hospitals' incentives along a number of dimensions, and induces behavior whose aggregate welfare effects are unclear. The program affects rural hospitals' exit probabilities, keeping open hospitals that would otherwise close. This may be welfare improving for the residents of rural areas that would have to travel longer distances to receive medical care had the hospital exited the market. On the other hand, the program may be causing an inefficient allocation of capital by preventing its flow to higher return alternatives. If less productive hospitals are more attracted to adopt the CAH status, the program will interfere with an evolutionary improvement of the industry as in Jovanovic (1982).

In addition, if a hospital stays open, it may affect the patient volume of its competitors, and therefore, their profits. Because states could waive the distance requirement, there are hospitals receiving cost-based reimbursement, even though they are not critical for people's access to care, which would be welfare reducing.

The cost-based payments enable hospitals to invest in quality improvement as noted by Casey and Moscovice (2004), however, it reduces the incentives to cost minimize, although

it does not eliminate them, because non-Medicare patients' expenditures are still reimbursed in a prospective fashion.

As discussed in this section, to assess the overall welfare impact of the CAH program is a complicated task that requires consideration of dynamic equilibrium outcomes. By means of a dynamic oligopoly model we measure the overall welfare of the program, and provide a sense of how efficient are the current outcomes by comparing them to the planner's solution. In the remaining part of the paper we describe our strategy to achieve this goal.

3 Data

Our data is constructed by pooling information from various sources. The primary source of data are the publicly available Hospitals Cost Reports Information System (HCRIS) from the Centers for Medicare and Medicaid Services (CMS), 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. Each observation represents a hospital in a given year, and hospitals are repeatedly observed generating an unbalanced panel. Each hospital is identified over time by a unique provider number assigned by CMS. Given our focus on the impact of introducing the CAH reimbursement policy and the fact that the cost reports are subject to annual audits by fiscal intermediaries, the HCRIS provide useful data for our purposes.[8] It records information on hospitals' location, number of beds, inpatient discharges, inpatient and outpatient revenues, salaries, and accounting information such as inpatient and outpatient costs, depreciation, asset values and profits.[9] The sample we use in the estimation contains the 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.[10] When hospitals convert into CAH, a new provider

[8]This data is also used by the Prospective Payment Assessment Commission to recommend PPS changes to Congress.

[9]In the data, hospitals' reporting periods differ in terms of their length, and dates of beginning and end of report. This caused many hospitals to have multiple observations by year, and the information to be misaligned across hospitals in a temporal sense. We disaggregated the data at the quarter level and aggregated it back with a consistent length (one year) and a consistent beginning and ending period.

[10]The Flex Monitoring Team is a collaborative effort of the Rural Health Centers at the Universities of

number is issued by CMS, even if ownership does not change. By using data from Flex, we were able to link the new and old provider numbers, which allowed us to construct the pre-conversion history that led the CAHs to convert. For our purposes this was an important step, because otherwise our data would look as if CAH conversions were new entries, when in fact, mostly existing facilities were converting to a new status. According to this data source 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. The location of hospitals was completed with latitude and longitude data from the American Hospital Association Annual Survey (AHA). The AHA and HCRIS data sets are easily linkable by the CMS provider number which is present in both data sets. We use latitude and longitude to compute distances to define the markets and to link the hospitals' data to Census tract level information on population characteristics – primarily focusing upon the size of the under and over 65 year old population.

In order to calculate geographically varying demand and supply side variables which potentially affect the profitability of CAH conversion as well as the profitability of remaining in operation as an acute care facility we first define a 150 km circle about the hospital. In this circle all hospitals are potential competitors with hospitals that are further away having less strategic impact than nearby hospitals. Potential patients are all the residents of the census tracts within a radius of 150 Km. Given this circle and the distribution of patients and hospitals, we then specify a model of hospital choice where patient preferences for a particular hospital will depend upon distance to the hospital, bed size and teaching status. The census tract information is used to calculate the expected volume of Medicare and non-Medicare patients.[11]

Because the policy's stated objective is to maintain access to emergency and inpatient care for rural residents, we characterize rurality using the Rural-Urban Commuting Area

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), being one of its objectives to improve the financial performance of CAH.

[11] We assume Medicare enrollment is equivalent to being age 65 or older.

Codes (RUCA), version 2.0.[12] These measures of rurality are 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. The RUCAs are available at the Census tract and zip code levels. In general CMS considers rural all census tracts that have RUCA greater or equal than 4, and we adopt the same criterion in this paper. [13] The definitions of the RUCAs are shown in Table 2.

We complete our data construction 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.

4 Model

4.1 General setup

We specify a dynamic oligopoly model of interaction between hospitals where the decisions of hospitals reflect a Markov Perfect equilibrium. This model follows in the spirit of dynamic oligopoly models developed by Ericson and Pakes (1995) and first applied to the hospital industry by Gowrisankaran and Town (1997). The specifics of our model follow more recent work on estimation of dynamic oligopoly models, such as Ryan (2006) and Collard-Wexler (2006), and build on these works by incorporating functional forms for investment that are more consistent with the data and specifics of the small hospital sector. In comparison to

[12] 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.

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

Gowrisankaran and Town (1997), our current work incorporates a richer model of the hospital sector – that allows for variation in geography, size and hospital characteristics – and can be estimated using recently available micro-level data and estimation techniques for dynamic models (see Bajari et al. (2007)).

The unit of observation in our model is a market, generally a rural area. At any point in time, each market contains a set of hospitals $1, \ldots, J_t$, who are strategic, forward-looking players. Each period, there is an identical set of consumers $1, \ldots, I$, who seek treatment for their illness. Hospitals are differentiated by their location, CAH status, size, ownership structure and productivity, while consumers are differentiated by their location and illness cost. Time is discrete with a period corresponding to a year and hospitals discount the future with the same discount factor β. In our model, dynamic considerations are relevant for hospitals because hospitals' characteristics are persistent from year to year.

We specify that any hospital with 225 beds or less located in a RUCA zip code of four or higher is a strategic player of our game. We limit our sample to these hospitals because large or urban hospitals will have different objectives, 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. Nonetheless, patients may choose these large hospitals. For instance, patients in a rural county may travel to a big-city hospital located relatively nearby to them. Indeed, regulations require CAH hospitals to develop referral agreements with a larger hospital. For this reason, we let all other hospitals in the U.S. be modeled as non-strategic players whose characteristics evolve exogenously.

Each period, we model a game with four stages. First, nature moves and provides each hospital with a period-specific investment cost shock. Second, knowing the value of their individual shocks, hospitals in the market simultaneously choose their strategies for investing in beds, exiting and obtaining CAH status. Third, hospitals choose prices for non-Medicare patients. Finally, each patient selects a hospital based on their insurance status and other characteristics. Note that we do not allow hospitals to change their locations, productivity or ownership status.

We do not model entry since entry is very rare 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, we believe that entry is not a huge feature of this market. Of course, given that our model is dynamic, we might expect more entry in the long run, as current firms exit due to random shocks. However, it would be hard to credibly identify the parameters on the entry distribution given the paucity of entry in the data.

Hospitals make their investment, exit, CAH conversion and production decisions in order to maximize the expected discounted values of their net future returns, which depend on their onwership type own_j. We model three ownership types: for-profit (FP), not-for-profit (NFP) and government (Gov). In our model, a hospital's ownership type is fixed and cannot be changed.

For a FP hospital, returns are synonymous with profits, while for NFP and government hospitals, returns are a weighted sum of profits, expected patient volume and the provision of service, which we denote as having a positive number of beds.

Specifically, let $beds_{jt}$ denote the number of beds, $E\Pi_{jt}$ expected profits net of investment expenses and $EVol_{jt}$ expected volume, all for hospital j at time t. Then, at any time τ, FP hospitals seek to maximize

$$E_\tau \left[\sum_{t=\tau}^{\infty} \beta^{t-\tau} E\Pi_{jt} \right],$$

while NFPs seek to maximize

$$E_\tau \left[\sum_{t=\tau}^{\infty} \beta^{t-\tau} (E\Pi_{jt} + \alpha_v^{NFP} EVol_{jt} + \alpha_p^{NFP} 1\{beds_{jt} > 0\}) \right], \tag{1}$$

where α_v^{NFP} and α_p^{NFP} are parameters to estimate.

Note that a weight term on expected net profits for NFPs is not identified: if we included such a term in (1), we could then multiply the three α terms by a constant and all observable predictions of the model would be the same, as this would effectively just change the units of NFP utility. Hence, in (1), we normalize the weight on expected net profits to be one. We assume that government hospitals maximize a similar objective function to (1), but with weights α_v^{Gov} and α_p^{Gov}.

4.2 Investment in beds and CAH status

We now detail the specifics of the investment processes that determine changes in the number of beds and in CAH status and through this in industry structure. Let CAH_{jt} denote CAH status for hospital j at time t. At the start of each period t, each hospital j faces a mean cost of investment that is common across hospitals and an *i.i.d.* shock to its investment cost, ϵ_{jt}. We assume that hospital j knows the value of ϵ_{jt} prior to making its time t investment decision but that it does not know the value of other firms' shocks, and we let ϵ_{jt} be distributed $N(0, \sigma^2)$, where σ is a parameter that we estimate.

Knowing ϵ_{jt}, each hospital simultaneously chooses a level of investment x which denotes the number of beds to be added. We allow x to be positive, negative or zero. The investment in beds is realized at the start of the following period. We use the following functional form for investment:

$$\begin{aligned} InvCost(x, \epsilon) = {} & 1\{x > 0\}\delta_1 + 1\{x > 0\}\delta_2 x + 1\{x > 0\}\delta_3 x^2 \\ & + 1\{x < 0\}\delta_4 + 1\{x < 0\}\delta_5 x + 1\{x < 0\}\delta_6 x^2 \\ & + (1\{x < 0\}\delta_7 + 1\{x > 0\})x\epsilon. \end{aligned} \tag{2}$$

Our investment choice is motivated by several important factors. In our data, hospitals do not alter their investment level for the vast majority of years. This suggests that there are substantial fixed costs for investment. In addition, the marginal costs of positive investment are likely to be very different than the marginal costs of negative investment. A positive investment involves building a new physical facility and providing medical equipment for that facility. Given the specificity of this investment, the scrap value of selling that facility is likely less than the cost of building it. Thus, we use a quadratic adjustment cost of investment with the cost of investment allowed to be different for positive or negative changes in the number of beds. This specification is similar to that of Ryan (2007) and a long literature that he cites.

Our investment process deviates from the literature in that we allow for the *i.i.d.* investment cost shock ϵ_{jt}. The use of an investment cost shock allows us to have a model where investment levels can vary for a hospital at a given state, as we find in the data. We let the

effect of this shock vary for a positive or negative investment level, through the parameter δ_7. We restrict δ_7 to be positive. Note that variations in ϵ will generate variations in investment levels for any state. In particular, a higher value of ϵ means a higher increment in cost for higher x. This implies that investment is weakly decreasing in ϵ for any state for reasonable profit functions. We impose this weak monotonicity property as an assumption. As we discuss in Section 5 below, the monotonicity assumption allows us to estimate our model with an adaptation of the techniques of Bajari et al. (2007).

A hospital can exit the industry by disinvesting in beds until it has none left. Once a hospital has no beds it is assume to have *permanently* exited the industry. It can no longer build beds or otherwise earn profits. Like other investment realizations, exits occurs at the start of the following period.

Concurrently with the investment decision, each non-CAH hospital simultaneously decides whether it wants to convert to CAH status. The hospital pays a fee $c^{CAH} \geq 0$ in order to attempt to convert to CAH status in the following period. Conversions to CAH status must be approved by the government and this approval process is lengthy, potentially costly, and uncertain. Hence, we model the CAH approval process as stochastic, with the outcome occurring at the start of the next period. We assume that firms can choose the CAH fee, and that a greater fee results in a greater chance of successful approval of CAH status. Specifically, we let

$$Pr(\text{CAH approval}|c^{CAH}) = 2exp(\gamma c^{CAH})/(1 + exp(\gamma c^{CAH})) - 1, \tag{3}$$

where γ is a parameter to estimate. Note that the specification is designed to be similar to a logistic model but different in that a firm that pays c^{CAH} of 0 has a zero probability of becoming a CAH hospital.

In our model, CAH hospitals are not allowed to revert to non-CAH status. We define $Pr(\text{CAH approval}) = 0$ for CAH hospitals. Also, we assume that any CAH hospital with more than 25 beds has any beds over 25 removed. We assume that the cost of this elimination of beds is zero. We make this assumption to be consistent with the regulations that specify that CAH hospitals are not allowed to have more than 25 beds.

4.3 Hospital production process

After investment, the hospital production process occurs. Hospitals incur both fixed costs, FC_{jt} and marginal costs mc_{ijt} from treating patient i. These costs are known at the start of the third stage. We assume that fixed costs consist of an aggregate term and a hospital-specific term,

$$FC_{jt} = \overline{FC} + \widehat{FC}_j.$$

Similarly, we assume that marginal costs consist of a patient specific term and a hospital efficiency term,

$$mc_{ijt} = sev_i + \widehat{mc}_j.$$

We let sev_i denote the patient's severity of illness, and allow marginal costs to vary based on severity of illness. Severity of illness, in turn, is a function of DRGs and other observable characteristics.

Patients are also differentiated by their insurance ins_{it} which can be Medicare (Med) or non-Medicare (NM). Knowing their cost structure, hospitals simultaneously set the base price for non-Medicare patients, which we call p_{jt}. The price p_{jt} is adjusted based on patient severity of illness, so that the total bill for a patient with base severity sev_i is $p_{jt}sev_i$. Patients, in combination with their insurance companies, will pay the hospital this price upon treatment.

CAH hospitals submit a bill to Medicare for their cost of treating Medicare patients that is based on *average cost*, which we denote ac_{ijt}. Note that

$$ac_{ijt} = \frac{FC_{jt} + \sum_{i=1}^{I} mc_{ijt}}{I}$$

Medicare reimburses the hospital as a fixed percentage, r^{CAH}, of average costs. In contrast, non-CAH hospitals submit sev_i (essentially DRGs) to Medicare, and are reimbursed some fixed percentage r^M of sev_i.

Let Pr_{ijt} denote the probability that patient i chooses hospital j. Then, we can express expected hospital profits $E\Pi_{jt}$ for CAH hospitals as:

$$E\Pi_{jt}^{CAH} = \sum_{ins_i=Med} Pr_{ijt} r^{CAH} ac_{ijt} + \sum_{ins_i=NM} Pr_{ijt}(p_{jt} - \widehat{mc}_j) sev_i - FC_{jt}, \tag{4}$$

while for non-CAH hospitals, the term in the first sum of the equation analogous to (4) would be $Pr_{ijt}r^M sev_i$.

The final stage is for patients to choose the hospital at which to seek treatment. Each patient makes a discrete choice of one of the hospitals in the market, where the set includes the large, urban hospitals whose decisions we treat as exogenous. An important determinant of hospital choice is distance. Let *location* denote geographic location (of a hospital or patient), $distance_{ij}$ denote the straight-line geographic distance between patient i and hospital j, $closest_{ijt}$ be 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 is a teaching institution.[14]

Let us first consider Medicare patients. These patients pay only a fixed deductible for the hospital treatment. Since we assume that patients are constrained to choose some hospital, we can ignore this deductible. We can write the utility function for Medicare patients as $u_{ijt}^{Med} = \bar{u}_{ijt} + e_{ijt}$, where

$$\bar{u}_{ij}^{Med} = h^{Med}(dist_{ij}, closest_{ij}, beds_j, CAH_j, teach_j) \tag{5}$$

and e_{ijt} is a type I extreme value residual. Note that our model of patient utility allows for the fact that patients with a high severity of illness may prefer bigger hospitals, and allows for CAH status to directly influence the utility of patients.

Let us now consider non-Medicare patients. Non-Medicare patients will pay a coinsurance, which amounts to a fixed percentage of the cost of their care, *copay*. Thus, the price faced by non-Medicare patient i is $copay \cdot p_{jt}$. The utility function for non-Medicare patients is identical to (5) except for the addition of a new arguents, *copay* and p_{jt} to their expected utlity $h^{NM}(dist_{ij}, closest_{ij}, beds_j, CAH_j, teach_j, p_{jt})$.

Given the type I extreme value error assumption, we can use (**??**) to write the choice probability for Medicare patients as

$$Pr_{ijt} = \frac{exp(\bar{u}_{ijt}^{Med})}{1 + exp(\bar{u}_{ijt}^{Med})}$$

with an analogous expression for non-Medicare patients. Similarly, the expected volume for

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

the hospital can be expressed as

$$EVol_{jt} = \sum_{i=1}^{I} Pr_{ijt}. \tag{6}$$

4.4 Firm optimization and equilibrium

Using the industry structure and preferences that we have described above, we can define the optimization problem for the firm and use this to characterize the Markov Perfect equilibrium of the industry. We start by defining the state space as the set of payoff relevant state variables, consistent with the definition of Markov Perfect equilibrium.

The state for a given hospital consists of its characteristics and the characteristics of the expected consumers and firms near it. We can group a hospital's characteristics together as $hospchar_{jt} = (beds_{jt}, CAH_{jt}, \widehat{mc}_j, \widehat{FC}_j, own_j, location_j)$ and the characteristics for a patient together as $patchar_i = (sev_i, ins_i, location_i)$. We further group together the aggregate industry state at time t as $\Omega_t = (hospchar_{1t}, \ldots hospchar_{J_t t}, patchar_1, \ldots, patchar_I)$. Hospital j's state can then be described as the industry state and the hospital's position within this state, (Ω_t, j).

Using this definition of the state space, we can write the single-agent decision problem for the firm and use this to exposit the properties that must hold in a Markov Perfect equilibrium. We start by analyzing the per-period return. At any period, a firm will earn a return that is a function of its state, action (x, c^{CAH}) and unobservable ϵ. Let this function be denoted $TR((x, c^{CAH}), (\Omega_t, j), \epsilon)$. We can write this vector as:

$$\begin{aligned} TR((x, c^{CAH}), (\Omega_t, j), \epsilon) &= E\Pi(\Omega_t, j) + \alpha_p^{Gov} - InvCost(x, \epsilon) - c^{CAH} \\ &+ 1\{own_j = NFP\} \left(\alpha_v^{NFP} EVol_{jt} + \alpha_p^{NFP} \cdot 1\{beds_{jt} > 0\}\right) \\ &+ 1\{own_j = Gov\} \left(\alpha_v^{Gov} EVol_{jt} + \alpha_p^{Gov} \cdot 1\{beds_{jt} > 0\}\right). \end{aligned} \tag{7}$$

Note that TR is different than just net profit maximization because NFPs and government hospitals maximize a weighted sum, not just profits.

Using (7), we can define the net expected total returns to firm j at the start of any period

t as $V(\Omega_t, j)$ and express $V(\Omega_t, j)$ recursively as the following Bellman equation:

$$V(\Omega_t, j) = \int_{\epsilon} max_{x,c^{CAH}} \left\{ TR((x, c^{CAH}), (\Omega_t, j), \epsilon) + \right. \\ \left. 1\{beds_{jt} + x > 0\} \beta E \left[V\left(\Omega_{t+1}, j\right) | (\Omega_t, j), (x, c^{CAH}) \right] \right\} dP(\epsilon), \tag{8}$$

where the law of motion for the jth component of Ω_t, is

$$beds_{j,t+1} = beds_{jt} + x \text{ and} \\ CAH_{j,t+1} = CAH_{jt} + Pr(\text{CAH approval}|c^{CAH}). \tag{9}$$

The Bellman equation (8) reflects the fact that if firm j exits, it receives no further returns. If firm j does not exit, then its returns depend on the law mof motion for the non-j components. Firm j takes these as given and never as a function of x or c^{CAH}. Standard arguments show that the Bellman equation (8) has a unique fixed point provided that $\beta < 1$ and profits are bounded.

Using the definition of the Bellman equation, we can now define a Markov Perfect equilibrium. The Markov Perfect equilibrium is a set of investment strategies for every state and shock, $\hat{x}(\Omega_t, j, \epsilon)$ and $\hat{c}^{CAH}(\Omega_t, j, \epsilon)$, for which the following property holds: for each firm j, $\hat{x}$ and $\hat{c}^{CAH}$ satisfy the Bellman equation (8) given that the law of motion for other firms is derived from $\hat{x}$ and $\hat{c}^{CAH}$ applied to an analogous equation to (9). This condition ensures that no unilateral deviation is profitable at any state.

5 Inference

5.1 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 **?** and applied to the dynamic oligopoly setting by Gowrisankaran and Town (1997). 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, $TR((x, c^{CAH}), (\Omega_t, j), \epsilon)$ 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

$$E\left[TR((x, c^{CAH}), (\Omega_t, j), \epsilon)\right] = \Psi((x, c^{CAH}), (\Omega_t, j), \epsilon) \cdot \theta, \tag{10}$$

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 (10) to exposit the value function similarly as:

$$V(\Omega_t, j) = E_t\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \Psi((\hat{x}(\Omega_t, j, \epsilon), \hat{c}^{CAH}(\Omega_t, j, \epsilon)), (\Omega_t, j), \epsilon)\right] \cdot \theta, \tag{11}$$

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 (11).

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 (11), 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 (10), 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 $\hat{x}(\Omega_t, j, \epsilon)$ 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 $\Psi((x, c^{CAH}), (\Omega_t, j), \epsilon)$.

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 (10). 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 inverse c.d.f. for investment at state (Ω_t, j). Then, for any observed investment level x, in equilibrium,

$$\epsilon_{j,t} = \sigma\Phi^{-1}(1 - F_{\Omega_t,j}(x)), \tag{12}$$

where Φ^{-1} is the inverse of the standard normal c.d.f. Since the only component of (12) that is unobservable is σ and σ enters linearly in (12), 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),

$$\gamma c^{CAH} = log\left(\frac{1 + P^{CAH}(\Omega_t, j, x)}{1 - P^{CAH}(\Omega_t, j, x)}\right). \tag{13}$$

Noting that the right side of (13) can be approximated by the data, as in (12), one can again

construct a term in Ψ that accounts for the cost of conversion, c^{CAH}. One can redefine Ψ to have it be a function of P^{CAH} rather than c^{CAH}, as P^{CAH} is really what is observed in the data.

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

$$\begin{aligned}
&\Psi((x, P^{CAH}), (\Omega_t, j), \epsilon) = (\Pi(\Omega_t, j), \\
&\quad 1\{own_j = NFP\}EVol(\Omega_t, j), 1\{own_j = NFP\}1\{beds_{jt} > 0\}, \\
&\quad 1\{own_j = Gov\}EVol(\Omega_t, j), 1\{own_j = Gov\}1\{beds_{jt} > 0\}, \\
&\quad - 1\{x > 0\}, -1\{x > 0\}x, -1\{x > 0\}x^2, -1\{x < 0\}, -1\{x < 0\}x, \\
&\quad - 1\{x < 0\}x^2, -1\{x < 0\}x\Phi^{-1}(1 - F_{\Omega_t,j}(x)), -1\{x > 0\}x\Phi^{-1}(1 - F_{\Omega_t,j}(x)), \\
&\quad - log[(1 + P^{CAH}(\Omega_t, j, x))/(1 - P^{CAH}(\Omega_t, j, x))]).
\end{aligned} \tag{14}$$

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 $TR((x, c^{CAH}), (\Omega_t, j), \epsilon)$.

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.

5.2 Details of specifications and approximations

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 (5).[15] We then use these to calculate expected volume by insurance type, $EVol_{jt}^{Med}$ and $EVol_{j,t}^{Non-Med}(\Omega_j, t)$, analogously to $EVol_{jt}$ in (6).

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

[15] 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.

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,

$$CAH_comp_{jt} = \left(\sum_i Pr_{ijt} \frac{\sum_{k \neq j} Pr_{ikt} CAH_{kt}}{\sum_{k \neq j} P_{ikt}} \right) / EVol_{jt}. \tag{15}$$

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:

$$\begin{aligned} x^*_{jt}(\Omega) &= r(\Omega)b + e_{jt}, \text{ where:} \\ x_{jt} &= x^*_{jt} \text{ if } x^*_{jt} < 0, \\ x_{jt} &= 0 \text{ if } 0 \leq x^*_{jt} < \bar{x}, \\ x_{jt} &= x^*_{jt} - \bar{x} \text{ if } x^*_{jt} \geq \bar{x}, \text{ and} \\ e_{jt} &\sim N(0, \sigma^2_x). \end{aligned} \tag{16}$$

We estimate the parameters of (16), b, $\bar{x}$ and σ^2_x, 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 ϵ 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.

5.2.1 Estimation of Utility Parameters

Our approximation of the state space requires construction of several variables are functions of patient choice probabilities. To generate these probabilities we estimated utility parameters associated with hospital admission. Specifically, we estimate the parameters of the indirect utility function characterized in (5) for Medicare and non-Medicare patients. We approximate the expected utility functions $h^{Med}(\cdot)$ and $h^{NM}(\cdot)$ by higher order and interaction terms of its arguments. To estimate the utility parameters we use hospital discharge data from 2003 from California's Office of Statewide Health Planning and Development (OSHPD). We draw two random samples of Medicare and non-Medicare, private, non-HMO enrollees and estimate the parameters of the model seperately for each population. 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. In the implimentation 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 admittence to a hospital outside of the 150km circle.

The parameter estimates from (5) together with locations of patients and hospitals allows us to calculate Pr_{ijt}, the probability that a given patient goes to a given hospital seperately for Medicare and the non-Medicare populations. To calculate the variables in the state space, $EVol_{jt}^{Med}$, $EVol_{jt}^{Non-Med}$, HHI_{jt}, and CAH_Comp_{jt} we use the expected utility estimates applied to Census tract data. 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 straight-forward to calculate all of the state space variables for all hospitals in our sample.

5.3 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.

6 Evidence on the Impact of the CAH Program

In this section we present some evidence of the impact of the CAH program on the rural hospital infrastructure. From our earlier discussion, the CAH program was signed into law

in 1997 and went into effect in 1999. In this section we provide some simple descriptions of the impact of the CAH program on rural hospital performance and market structure. From our previous discussion, the purpose of the CAH program is to maintain access to inpatient and emergency care for rural residents. It does this by providing more generous Medicare reimbursement while requiring participating hospitals to limit their capacity to 25 beds and restricting their behavior along several other dimensions.

In this section we document the impact of the CAH program along three dimensions. First, we examine its impact on the distribution of hospital bed size. Second, we analyze the impact of the program on profitability. Third we explore the impact on hospital closures. We perform these analyses in two steps. We present simple time series graphs of trends in the hospital industry broken down by rural and non-rural status.

6.1 Summary Statistics

Summary statistics of the analysis sample are presented in Table 3. Our sample of rural hospitals is predominantly not-for-profit organizations – 51% of the sample is NFP. Local government hospitals comprise 39% of the sample and 11% of the sample are for-profit hospitals. The typical hospital faces little measured competition. The 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 presents the summary statistics seperately for CAH and non-converting hospitals for 2005. Table 4 compares hospitals that have adopted the CAH status to other hospitals in rural areas. 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 Figures 3 to 4 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. Figures 5 and 6 present the bed size histograms for hospitals that ultimately converted to CAH status in 1996 and in 2005. 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 7 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.[16] 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 8 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. We provide further data analysis in the next section.

[16]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.

7 Estimation Results

7.1 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 be able to describe the behavior of the hospitals at every state, and therefore, in the second stage to be able to find the dynamic parameters that make this behavior optimal. 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 the California OSHPD.[17] 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 9. 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

[17] 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.

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.

7.2 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 make the policy functions estimated in the previous section optimal. Overall the estimates are sensible. Non-profit and government hospitals value patient volume and operating in addition to monetary profits. The parameter estimated 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. 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, show that the cost of positive investment are much larger than the cost 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 last parameter in Table 9, is the CAH approval process parameter. If a hospital invest $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.

8 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 a la Ericson and Pakes using the structural parameters estimated above. Our first policy experiment includes 183 "monopoly" hospitals, defined as those that have a $HHI \geq 0.75$. 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 10 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 11. 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. In Figure 12 we plot the effect of the CAH program on hospitals' value. We 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.

9 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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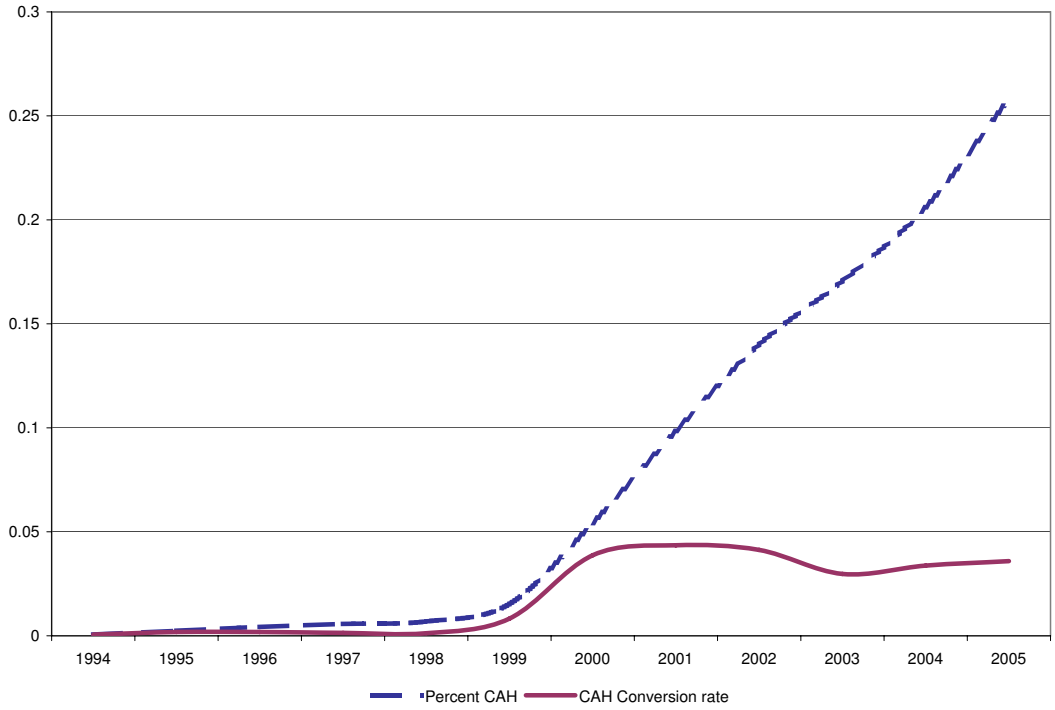

Figure 1: Conversion rates and Percentage of CAH Hospitals in the U.S.

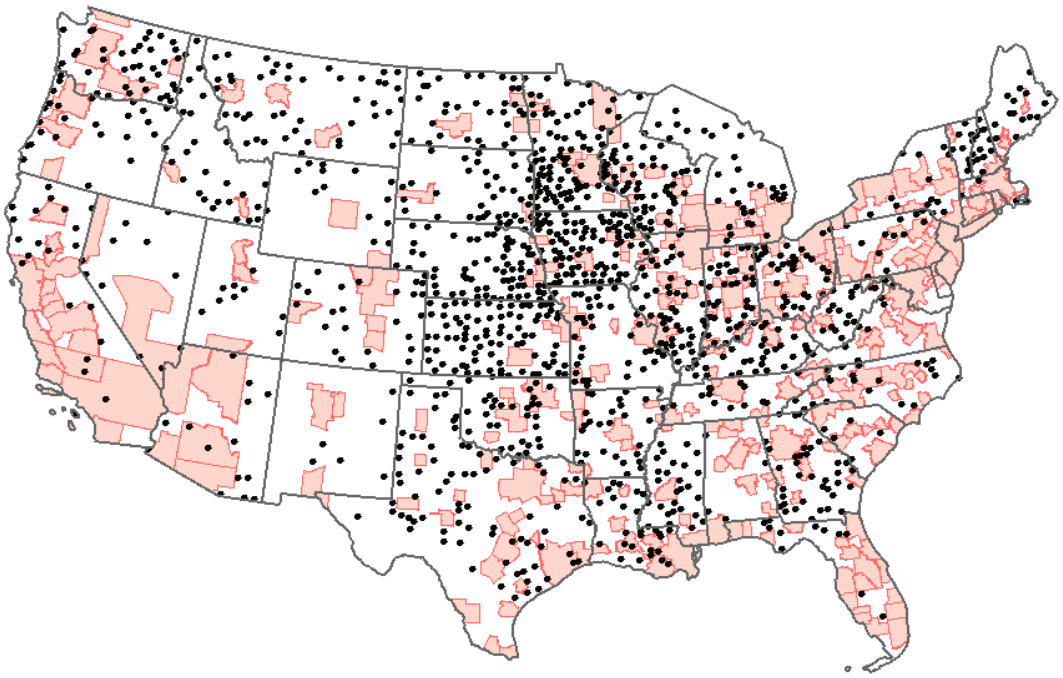

Figure 2: Spatial distribution of CAH. Dots represent CAH, polygons represent MHAs

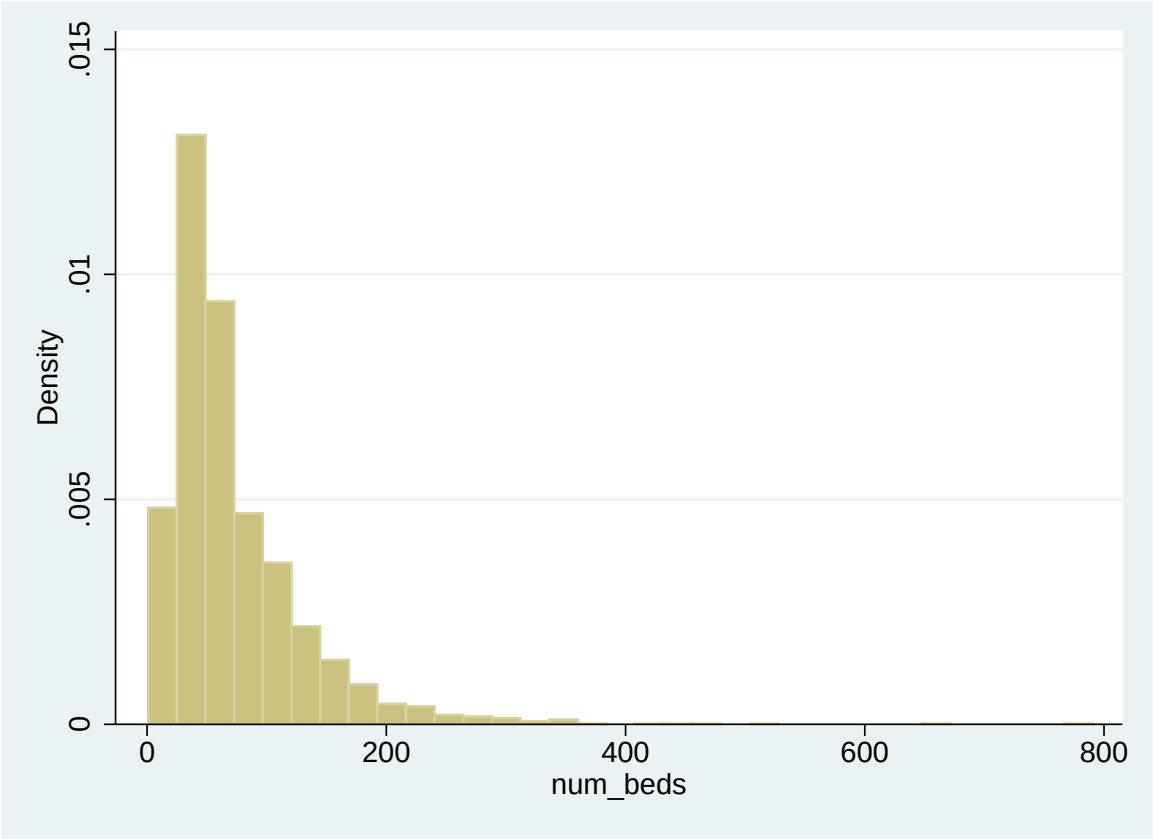

Figure 3: Histogram of bed size, rural hospitals, 1996

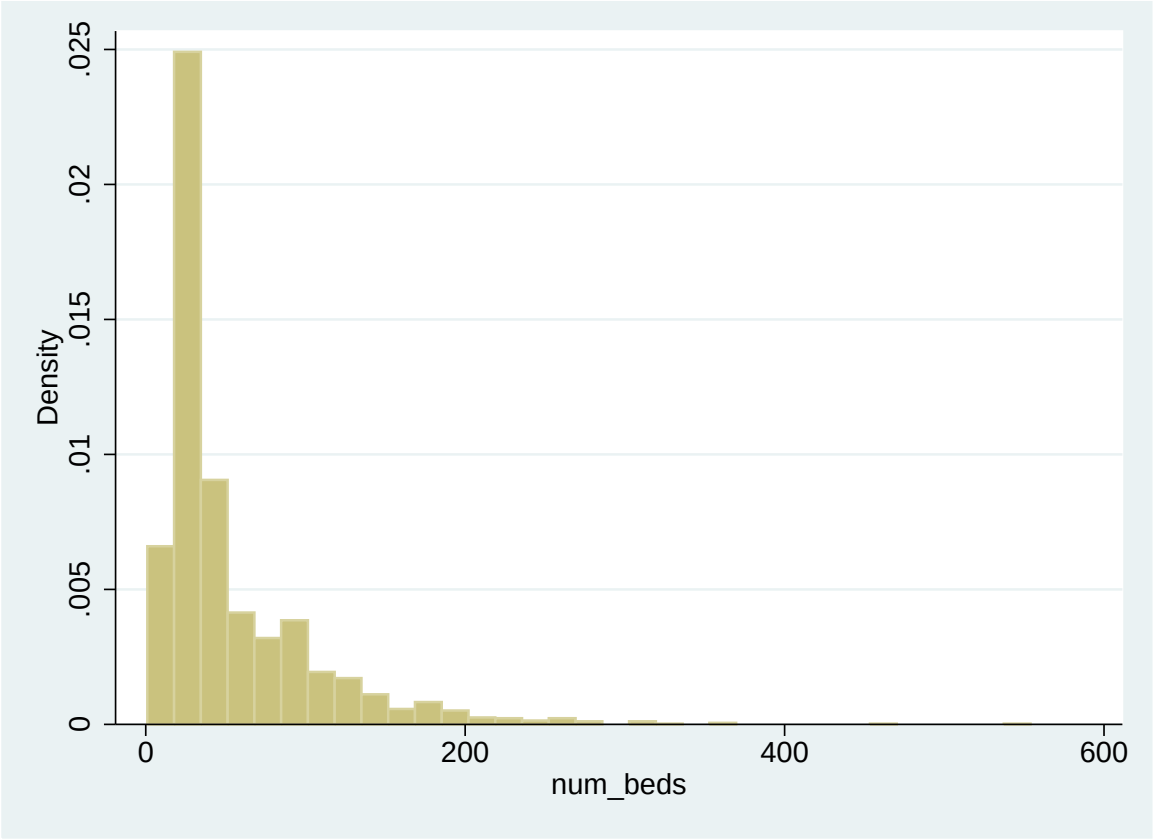

Figure 4: Histogram of bed size, rural hospitals, 2005

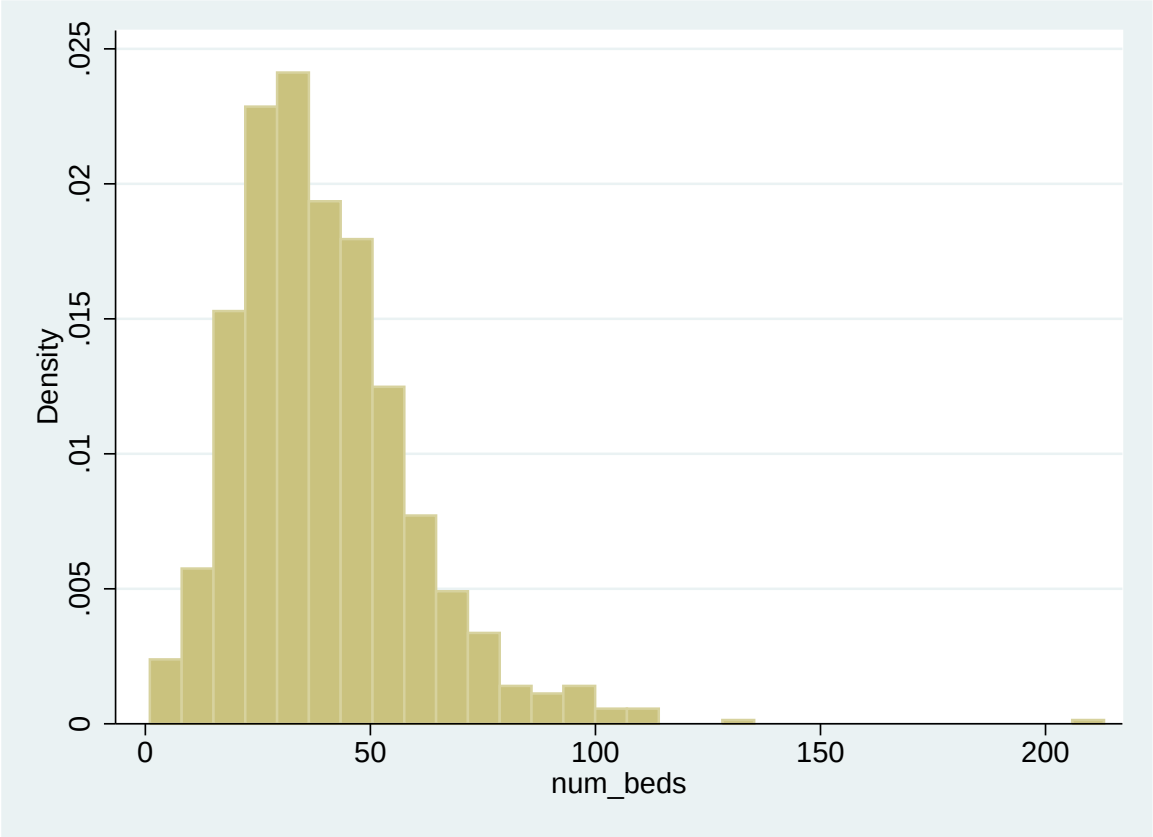

Figure 5: Histogram of CAH converters, 1996

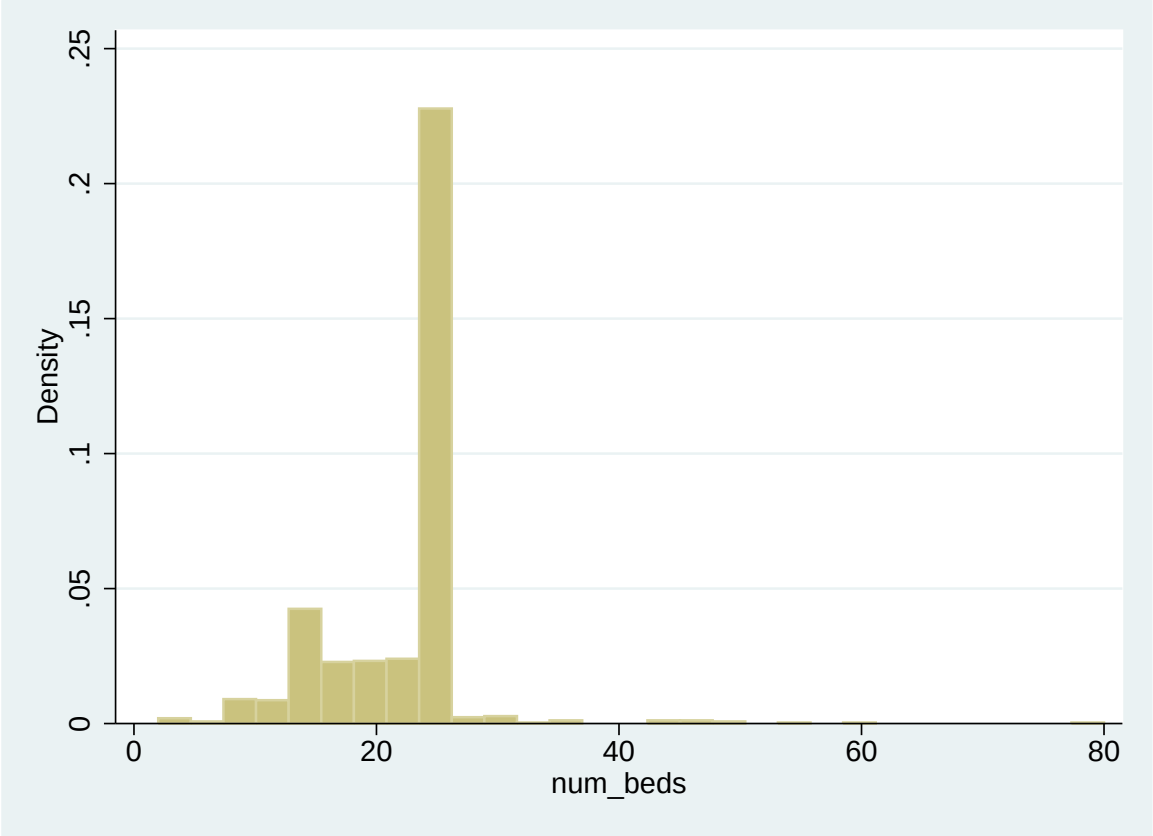

Figure 6: Histogram of CAH converters, 2005

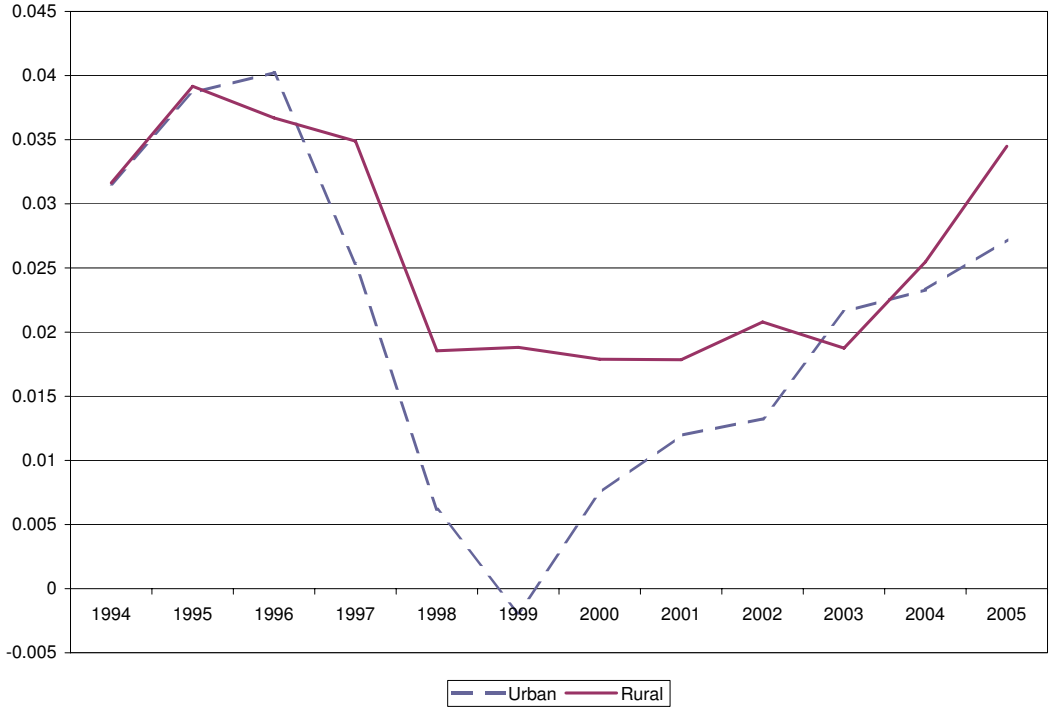

Figure 7: Mean profit margins for hospitals with less than 225 beds in 1995.

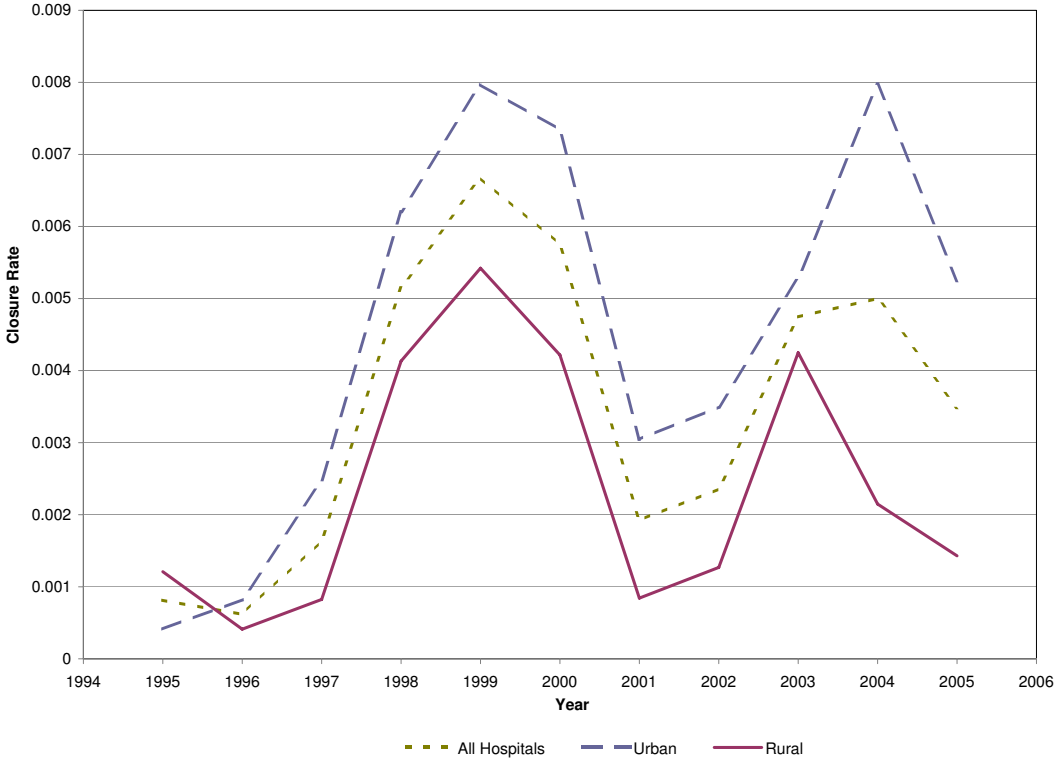

Figure 8: Exit rates for Rural, Urban and All U.S. Hospitals

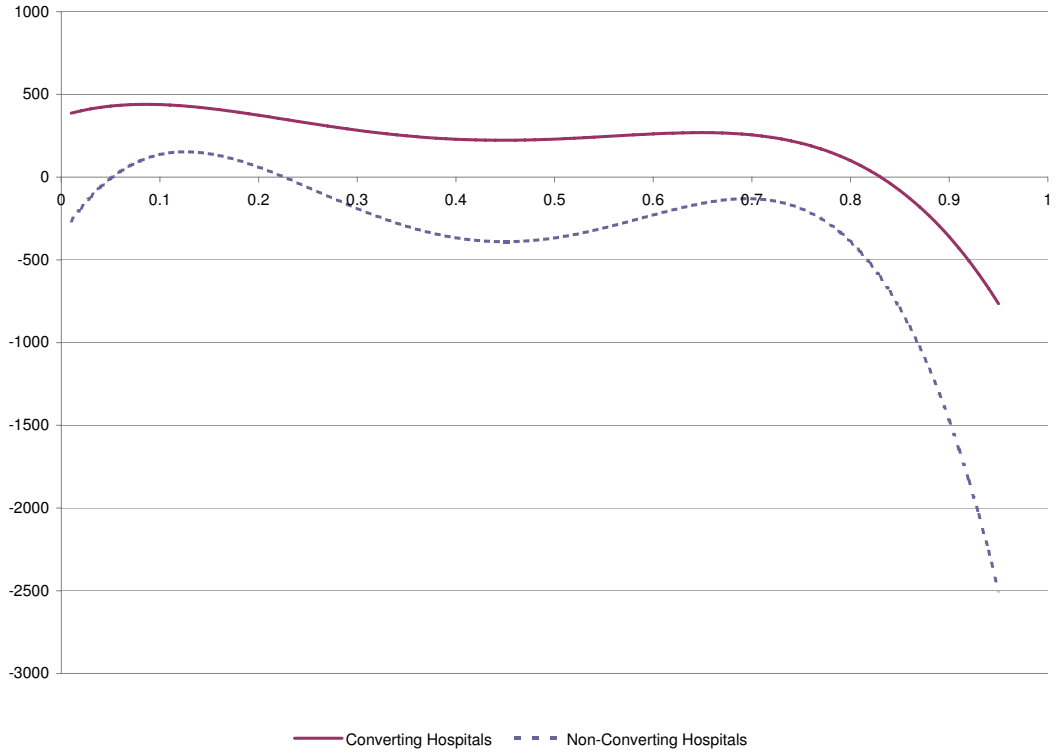

Figure 9: Change in profit from CAH conversion by CAH status and productivity($1,000)

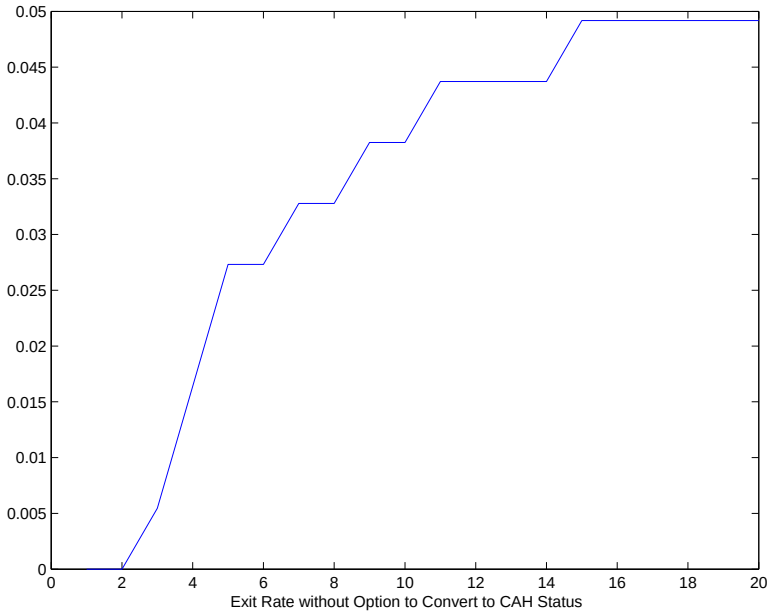

Figure 10: Impact of CAH program on exits

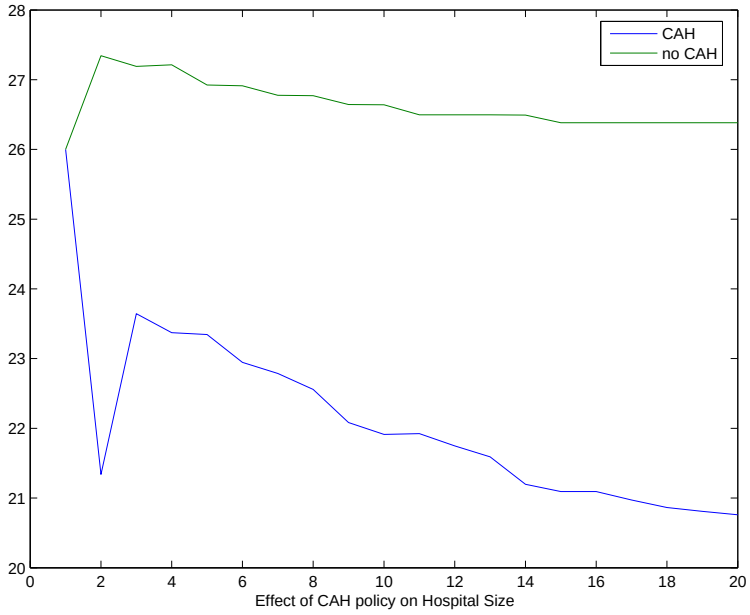

Figure 11: Impact of CAH program on size distribution

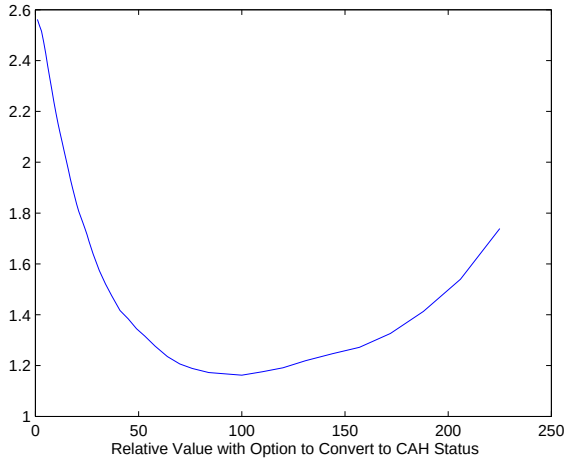

Figure 12: Impact of CAH program on hospital value by number of beds

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	Robust s.e.
α_v^{NFP}	.41	
α_p^{NFP}	58.00	
α_v^{Gov}	2.20	
α_p^{Gov}	193.09	
$1\{x > 0\}$	$1.46x10^3$	
$1\{x > 0\}x$	605.40	
$1\{x > 0\}x^2$	.089	
$1\{x < 0\}$	-102.3	
$1\{x < 0\}x$	-80.88	
$1\{x < 0\}x^2$	1.07	
$1\{x < 0\}x\epsilon$	10.02	
σ	5.17	
γ^{-1}	41.57	