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 (Flex) Program. The goal of this program is to maintain access to hospital care for rural residents. Like many other government policies, the Flex program targets the underlying supply infrastructure, in this case by providing more generous cost-plus reimbursement to rural hospitals in exchange for capacity and service limitations. The program created a new class of hospital, the Critical Access Hospital (CAH), to which rural hospitals can convert. 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 efficiently estimate the structural parameters and compute counterfactual equilibria. We use the methods to estimate the impact of eliminating and modifying the Flex program on access to hospitals and patient welfare. We find that without the Flex program 5% of currently operating hospitals would have closed. Although the minimum distance to a hospital is reduced by the program, the actual average distance traveled to receive care increased. We find that overall consumer surplus has decreased as a result of the Flex Program. 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 Balanced Budget Act of 1997, the U.S. government passed the Medicare Rural Hospital Flexibility (Flex) Program, whose overarching goal was 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. Participating hospitals opt out of the standard Prospective Payment System (PPS) and instead receive cost-based reimbursements from Medicare that were generally relatively generous. In return, they must comply with a number of restrictions, principally, limits on their capacity to 25 beds or less and patient length-of-stay to 96 hours or less. By 2006, 25% of all general acute care U.S. hospitals had converted to CAH status and Medicare's payments to converting hospitals are estimated to have increased by 35%, to $5 billion (MedPAC, 2005).

Although the Flex program was designed for small, rural hospitals, 98% of hospitals that converted by 2006 had more than 25 beds in 1996, and the mean beds for converters decreased from 42 in 1996 to 22 in 2006. The fact that some hospitals lowered their size in order to qualify for the program was an important consequence of the Flex program given the dimensions of the capacity changes, but one that was very separate from the main policy intent of "access." Yet, the types of policy consequences embodied in the Flex program are not unique. Many other government policies seek to achieve their goals by affecting the returns to entry, exit and investment and thus may have important consequences on industry structure and through that consumer welfare and firm profits. Examples abound and span countries and industries. Education vouchers and the charter school option affect the number and size distribution of private schools. Greenhouse gas policies affect the installation, expansion and scrapping decisions for power plants.

The goal of this paper is to understand the impact of the Flex program on hospital care for the rural U.S. population, incorporating the endogenous response of hospital characteristics to the program and the resulting consequences on industry structure. By providing generous and cost-based reimbursements, the program likely forestalled rural hospital exit, thereby increasing access to rural residents, its main policy goal. However, by limiting beds and services, the program also likely caused hospitals to lower their capacity and not offered the range or quantity of services that they did pre-conversion. The extent to which the program benefitted consumers depends on the extent to which the option to convert to CAH status forestalled exit and spurred reductions in bed size.

Given appropriate data, one might use reduced-form regressions of hospital exit and investment on exposure to the Flex program to estimate the policy impact of the program. Unfortunately, there is no control group of hospitals that are not exposed to the Flex program. Thus, we proceed with a structural approach: we specify a model of hospital and consumer decisions, estimate the fundamental parameters underlying these decisions, use the estimated parameters to compute industry structure under counterfactual policy environments, and use the industry structure to compute welfare. Because entry, exit and investment affect future returns in a strategic environment, the structural approach requires solving and estimating a dynamic oligopoly model where firms can choose CAH status and capacity through investment. We develop new methods to compute and estimate models of dynamic oligopoly capacity games that might also be useful to analyze these types of industries.

In our model, each period hospitals select their investment or disinvestment in beds, whether to exit, and, for eligible hospitals, whether or not to convert to CAH status.[1] We model sequential random private information cost shocks for beds investment and CAH status. We allow for non-linear adjustment costs in beds. The private information shock and stochastic CAH outcome generate randomness in the outcomes of the model, necessary for the existence of a pure strategy equilibrium and a well-defined likelihood function. Following the hospital decisions, each period individuals fall ill and make a static discrete choice of hospital. Patient utility from a hospital includes hospital characteristics, distance to the hospital and interactions plus an unobservable component that follows a nested-logit structure. We allow for unobserved heterogeneity in the impact of CAH status on profits, based on the cost structure of each hospital. We recover hospital cost fixed effects using panel data from 1994-8, before the implementation of the program.

Hospitals earn profits from the patients that they treat. For-profit (FP) hospitals seek to

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

maximize the expected discounted sum of current and future profits. Not-for-profit (NFP) and government hospitals seek to maximize a weighted average of the expected discounted sums of profits and the provision of service. 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 determinants of profits, the objective functions for NFP and government hospitals, the cost function for investing or disinvesting in capacity and exit, the costs of CAH conversion, the size of random cost shocks and consumer utility parameters.

The structural parameters of our model are identified in a reasonably transparent and intuitive manner. The heterogeneous treatment impact of CAH policy on hospital profits is identified by using the pre-treatment period to determine a hospital's type, as in the labor literature (see Todd and Wolpin, 2006). The costs of investment in beds or CAH status are identified by the ratio of the extent to which gross profits change following the change in state variable to the likelihood of choosing that policy. If CAH status increases profits for certain hospitals significantly but those hospitals rarely convert, our model infers that conversion is very costly. Note in particular that our model has few parameters to identify relative to a reduced-form approach. This is because theory provides guidance as to the structure of the problem, allowing us to predict counterfactual policies from the limited set of parameters noted above.

A number of recent papers have developed methods to structurally estimate the parameters of dynamic oligopoly models and our paper builds on this literature. First proposed by Hotz and Miller (1993) and Hotz et al. (1994) in the context of dynamic single-agent models with discrete choices, the idea is to use the data in place of optimizing behavior to simulate the state forward for a given choice. This avoids 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 by Bajari et al. (2007) (henceforth BBL), Pakes et al. (2007) (POB), Aguirregabiria and Mira (2007) (AM) and Pesendorfer and Schmidt-Dengler (2007).

Our estimator is based on insights developed by BBL applied in a quasi-maximum likelihood framework. AM also develop a quasi-maximum likelihood estimator for discrete choice models such as entry games where one can forward simulate to solve for values conditional on choice. A direct application of POB would not be computationally feasible in our context because the forward simulation is very computationally costly. BBL show that the forward simulation need only be done once if the value function can be written linearly in the structural parameters. BBL propose estimating the parameters using an inequality approach, based on the fact that the value of the observed choices must be bigger than the value of counterfactual firm policies. The advantage of the BBL approach is that it is computationally feasible to use for models with many or continuous choices and states, such as ours. However, the efficiency properties of the inequality approach are unknown and may depend on how many inequalities are chosen and how the inequalities are sampled.[2]

We develop a computationally efficient quasi-maximum likelihood estimator. We do this by writing the choice-specific value function linearly in the structural parameters (essentially applying the insight of BBL to a slightly different context) and by developing a method for rapidly computing the probability of each choice given choice-specific value functions. We also develop methods to solve for the equilibria of our model for counterfactual policies that are based on our method for computing the probability of each choice. To our knowledge, no methods exist to compute equilibria of dynamic oligopoly capacity games.[3] Simulation approximation methods, which are the most commonly used, generally result in non-existence of equilibrium for this type of game.

The estimation of the parameters of dynamic discrete games dates to Gowrisankaran and Town (1997) where they studied the dynamics of the hospital industry, and Benkard (2004) modeled the dynamics of the airline manufacturing industry in a learning-by-doing environment. The introduction of these new methods have allowed researchers to more easily estimate parameters of dynamic discrete games. Not surprisingly, there has been a recent increase in the number of papers constructing and estimating the parameters of rich models

[2]BBL also suggest a GMM approach such as POB as an alternative.

[3]Most recent computable dynamic oligopoly models are based on the Pakes and McGuire (1994) model and specify quality ladder games with a stochastic and discrete, typically binary, investment realization.

of firm dynamics in oligopolistic settings. For example, Ryan (2006) studies the impact of environmental regulations on cement manufacturing market structure, Collard-Wexler (2006) studies the role of demand fluctuations in ready-mix concrete, Snider (2008) estimates the use of capacity choice in a predatory pricing setting and Dunne et al. (2008) uses the methods of POB to estimate the role of entry and fixed costs in affecting market structure for dentists and chiropractors.

The remainder of this paper is divided as follows. Section 2 provides the institutional background of the Flex program. Section 3 describes our data. Our model is presented in Section 4 and Section 5 describes our estimation method. The results and policy experiments are presented in Sections 6 and 7 respectively, and Section 8 concludes.

2 The Critical Access Hospital Program

2.1 Background

The Flex program was enacted in the Balanced Budget Act (BBA) of 1997.[4] 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.[5] 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. 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

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

[5]In 2006, the legislation was passed that prevents states from waiving the distance requirement.

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. Last, the CAH legislation provides resources for hospitals to hire consultants to project revenues and costs under the Flex program and determine which strategy is best for the hospital given its 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 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 limit from 15 to 25 acute patients and increased the payments from 100 to 101 percent of costs.

Figure 1 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. 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 amounts of paperwork, inspection visits and CMS approval.[6] By 2005, over 20% of hospitals have adopted CAH status. It is said that conversion rates should decline after 2006, when the minimum distance requirement will be enforced (MedPAC (2005)).

The 2005 spatial distribution of CAHs within the 48 continental United States is shown in Figure 2. By 2005, CAHs are present in most states, but New Jersey, Delaware, Rhode Island, Connecticut and Maryland do not participate in the program. CAHs concentrate in the Midwest, and are mostly outside of MSAs. The State of Alabama has unusually few CAHs, and from our discussions with industry experts, we believe that the responsible state office did not facilitate CAH conversions.

[6] 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

2.2 Previous Research on Hospital Exit

A number of studies examine hospital exit and thus relate to the Flex program . 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, while secular nonprofits responded the least.

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 hospital closures on consumer 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 year-1988 dollars 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 Flex 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) study 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 greatly enhanced our understanding of hospital exits and the Flex program, it does not attempt to model the impact of the CAH policy on hospital investment and exit. Thus, it cannot be used to analyze the impact of different rural hospital policies on industry structure and welfare. Gowrisankaran and Town (1997) also examined a dynamic model of the hospital industry. In comparison to that paper, our work incorporates a richer model of the hospital sector that allows for variation in geography, size and hospital characteristics. The model is also identified with much richer data than was used in that paper.

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, 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

[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 day level and then aggregating 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.

as 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 Registered Deletions section of the AHA Survey for years 1994-2005. These reports contain a list of the hospitals that exited the market during the year.

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 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

[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.

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] Very few medium to large size hospitals convert to CAH status, so we allow only hospitals with 160 beds or less to be candidates for CAH conversion. Consistent with the timing of the law, we consider conversions over the period 1999-2005 for NFP and government hospitals and 2001-05 for FP hospitals. We also eliminate non-participating states and Alabama. These four criteria determine our sample for 'at-risk' hospitals.

4 Model and equilibrium

4.1 Model

We specify a dynamic oligopoly model for a geographic area where the strategic players are the 'at-risk' hospitals defined above. 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, fixed demand attractiveness $\bar{\xi}_j$ and fixed cost level FE_j. 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 strategies for capacity investment, 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 time-invariant, we suppress it when not necessary to economize on notation, and write the environment for hospital j as (Ω, j).

Hospitals choose actions in order to maximize the expected discounted values of their net

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

future returns where returns depend on own_j. We model three ownership types: for-profit (FP), not-for-profit (NFP) and government. For a FP hospital, returns in any period are synonymous with profits, while for NFP and government hospitals, returns are a weighted sum of profits and the provision of service.[11] We denote the weight on the provision of service as α_p^{NFP} and α_p^{Gov} for NFP and government hospitals respectively, 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 ϕ 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 at state (Ω, j). 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 150. We

[11] 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 (2006) 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 Philiipson (2006) 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

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

where ϕ is the scrap value and $\delta_1,\ldots,\delta_6$ are investment 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

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

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 (2006) and a long literature that he cites but is different from earlier quality-ladder dynamic oligopoly models[12] 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 (9) is, to our knowledge, new, but we believe that it is intuitive given $MeanInvCost$.

After the investment decision, each eligible non-CAH hospital simultaneously decides whether it wants to convert to CAH status. At this point, each eligible hospital receives a private, iid cost of conversion draw $\varepsilon^c_{jt}\sim N(\mu^c,\sigma^c)$. If the hospital converts in period t, it incurs a one-time cost of ε^c_{jt}. We denote the CAH status of the hospital by $c_{jt}\in\{0,1\}$ where $c_{jt}=1$ denotes a converted hospital and $c_{jt}=0$ denotes a non-CAH. Consistent with government limitations, we define eligibility for conversion at time t as having beds after investment $x_{jt}\le 25$. Having already converted, CAH hospitals are not allowed to revert to

[12] See Ericson and Pakes (1995), Pakes and McGuire (1994) and Gowrisankaran and Town (1997).

non-CAH status. 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 in 1999. 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 model production as follows. Each period t, there is a set of patients $1, \ldots, I_t$ who seek treatment for their illnesses. Patients are geographically dispersed and select a hospital for their care based on its distance and the characteristics of the hospital. Each patient makes a discrete choice among all available hospitals in that period that are within 150 KM of her location or the outside option, which corresponds to choosing a hospital outside of this radius. More precisely, the patient's utility function of an inpatient admission is given by

$$u_{ijt} = \bar{\xi}_j + w_{ijt}\beta^c + \xi_{jt} + \upsilon_{ijt}. \tag{3}$$

Here w_{ijt} is a vector of hospital/patient characteristics including an indicator whether the hospital has converted to CAH status, the straight-line distance from the patient's ZIP code to the hospital, distances squared, an indicator for the closest hospital, hospital bed size, and interactions of these variables. Also included in w_{ijt} are indicators for rural residents interacted with distance and CAH status. Unobserved time-varying hospital desirability is captured by ξ_{jt}. We assume that this factor is *i.i.d.* across time and that ξ_{jt} is known only at time t. Hence, its realization does not affect dynamic firm decisions but does affect consumer decisions. The utility shock υ_{ijt} is a mean zero shock. We assume that it takes on a nested logit structure; it is composed of two terms, an *i.i.d.* type 1 extreme value term multiplied by a parameter ρ and a part that is common across hospitals within a type, distributed $C(\rho)$. We model three types of hospitals: CAHs, non-CAHs and the outside option.

We do not model the price of the hospital in our patient utility model. There are two reasons for this. First, it is very difficult to observe prices. Second, the vast majority of rural patients are covered by Medicare and do not face any price variation. Among patients who do not have Medicare, the majority of rural patients have fee-for-service (FFS) insurance that also does not have price variation.

We observe locations of consumers at the ZIP code level for each year. We assume that there are enough patients in every ZIP code that hospital shares at the ZIP code level are observed without error. This allows us to treat ξ_{jt} as an econometric residual and estimate the demand parameter using the instrumental variables method of Berry (1994). A "market" in this framework corresponds to a ZIP code and year combination. We use the mean number of beds, mean distance and mean number of firms within group as instruments for log within-group share.

Using the estimated demand model, we compute expected profits for a hospital as a function of the state, $\Pi(\overline{\Omega}, \Omega, j)$, which is then used as an input in the dynamic model. The traditional way to compute profits (see Benkard, 2004, for instance) would be to multiply demand by price and subtract costs. However, in our case, we observe profits directly in the data, allowing us to bypass this step and compute expected profits as a regression of the observed profits on the state variable. This allows us to estimate a profit function that is consistent with competition, CAH status and location affecting profits in a more flexible way than if we had specified marginal costs linearly, as is typical.

We assume that profits in the years before the Flex program implementation are a function of beds, ownership and other measures that are interactions between $\overline{\Omega}$ and (Ω, j); specifically, the effective number of hospitals in the market, the expected volume of Medicare and under 65 year old patients and interactions of these variables as well as a hospital cost fixed effect FE_j that enters linearly. In the post-Flex period, profits depend further upon all the pre-implementation variables interacted with CAH status and the CAH status of competitors. In particular, FE interacts with CAH status even though it enter linearly in the pre-implementation period. The reason for this is that the Flex program pays on a cost basis while traditional Medicare pays a fixed rate. Thus, hospitals with low cost (low FE) will have relatively less gain from CAH status all else equal. Our specification for FE borrows from a long literature in labor economics, which similarly considers models with heterogeneity in the impact of the 'treatment' (CAH status in our case) based on 'type' (FE in our case), and endogenous selection into treatment. A typical assumption in this literature, that the pre-treatment period can be used to identify the type (see Todd and Wolpin, 2006), is identical to our assumption.

4.2 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 (Maskin and Tirole, 1988, see). 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 a hospital j with $B_j > 0$ (i.e., that has not closed down) as:

$$EGR(\Omega, j) = E\left[\Pi(\Omega, j) + 1\{own_j = NFP\}\alpha_p^{NFP} + 1\{own_j = Gov\}\alpha_p^{Gov}\right], \tag{4}$$

where we are implicitly letting B and own 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 realization of ε_j as $EV(\Omega, j)$. Let $ConCost(x_j, \Omega)$ denote the expected cost of conversion given prior to the realization of Let (x_{-j}, c_{-j}) denote the actions of all firms other than firm j; let $p(x_{-j}, c_{-j}|\Omega)$ denote 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:

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

We now further exposit the optimal choices of investment necessary to compute and estimate the model. Recall that firm j chooses x_j and then receives its CAH investment cost draw and chooses its CAH status. Let us now consider the decision to convert, 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 $x_j \in \{1, \ldots, 25\}$, the optimal choice, which we denote $\hat{c}(\Omega, j|x_j)$, satisfies

$$\hat{c}(\Omega, j, \varepsilon_j^c|x_j) = \underset{c_j \in \{0,1\}}{\operatorname{argmax}} \left\{ -c_j\varepsilon_j^c + \beta \int \sum_{\Omega'} EV(\Omega', j) g(\Omega'|x_j, c_j, x_-j, c_{-j}, \Omega) dp(x_{-j}, c_{-j}|\Omega) \right\}; \tag{6}$$

for other values of x_j, $\hat{c} = 0$.

We now 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, ex ante to the realization of ε_j^c. Specifically,

$$\overline{V}(\Omega, j, x_j) = -MeanInvCost(B(\Omega, j), x_j) + \int max_{c_j}[-c_j\varepsilon_j^c + \beta 1\{x_j > 0\} \int \sum_{\Omega'} EV(\Omega', j) g(\Omega'|\cdot) dp(x_{-j}, c_{-j}|\cdot)] dp(\varepsilon_j^c). \tag{7}$$

Finally, we define the optimal level of investment as

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

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 $\hat{c}(\Omega, j, \varepsilon_j^c|x_j)$, for which the following holds: for each state $(\Omega, j, \varepsilon_j)$, $\hat{x}(\Omega, j, \varepsilon)$ and $\hat{c}(\Omega, j, \varepsilon_j^c|x_j)$ 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).[13] Let $o(x)$ denote the dimensionality of x and let Δ^N denote the N-dimensional simplex. We

[13]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.

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 (9) 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 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. ∎

4.3 Computing Equilibria

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 $\hat{x}(\Omega, j, \varepsilon)$ and $\hat{c}(\Omega, j, \varepsilon_j^c | x_j)$. 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)

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

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) $\underline{\underline{\varepsilon}}(x) < \overline{\overline{\varepsilon}}(x) \iff x \in CE(X)$.*

Denote the set of $x \in CE(X)$ as $x_1^{CE}, \ldots, x_L^{CE}$. 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. $\overline{\varepsilon}_{x_{\ell-1}^{CE}, x_\ell^{CE}} < \overline{\varepsilon}_{x_{\ell-2}^{CE}, x_{\ell-1}^{CE}}$ *for all $\ell = 3, .., L$.*

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_L^{CE} is chosen in the range $(-\infty, \overline{\varepsilon}_{x_{L-1}^{CE}, x_L^{CE}}]$, x_{L-1}^{CE} is chosen in the range $[\overline{\varepsilon}_{x_{L-1}^{CE}, x_L^{CE}}, \overline{\varepsilon}_{x_{L-2}^{CE}, x_{L-1}^{CE}})$, all the way to x_1^{CE}, which is chosen in the range $[\overline{\varepsilon}_{x_1^{CE}, x_2^{CE}}, \infty)$.[14]

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

5 Estimation and identification

5.1 Overview

The structural parameters of our model are the α objective function parameters, the δ and σ investment cost parameters, the discount factor β, the CAH conversion cost parameter γ, the β^c and FE parameters from the consumer utility function and the parameters from the profit function. We estimate the consumer utility parameters β^c using the 2SLS linear regression proposed by Berry (1994), as the consumer does not face a dynamic problem. We estimate profits as a function of the state variables using a linear regression. It is difficult to identify

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

the discount factor and hence we set it to $\beta = .95$. Define the remaining parameters as $\theta = (\alpha, \delta, \sigma, \gamma)$. We estimate θ using structural methods that impose the dynamic oligopoly model.

A method for estimating the structural parameters of dynamic models was developed by Rust (1987) 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: they require solving the Markov Perfect equilibrium repeatedly, which is very time-consuming.

More recently, authors have developed two-step methods to estimate dynamic models 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 develop an estimation algorithm for these remaining parameters based on the ideas of two of these works, Bajari et al. (2007) and Pakes et al. (2007). BBL 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. The structure of our model allows us to do this, as we show in Section 5.2 below.

BBL also show that one can estimate the structural parameters with an inequality approach that finds parameters such that the policies are as close to optimal as possible against a finite set of alternate policies. A 'policy' here is defined as a mapping from state variables and unobservables to actions. This method is particularly useful for models with continuous or many actions as otherwise, solving for optimal decisions is computationally difficult. BBL do not address the efficiency of the inequalities estimator, nor do they discuss a procedure for choosing the right set of alternate policies.

BBL also suggest a GMM estimation method similar to POB. The idea of this method is to use forward simulation to compute choice-specific value functions, to use the choice-specific value functions to solve for the probability of each action, and to create moment conditions based on the difference between observed action and action probability. With GMM estimators, one can estimate the optimal weighting matrix to develop asymptotically efficient estimators conditional on the set of moments.

Our algorithm is GMM. We adapt the POB algorithm in two ways that allow us to vastly reduce the computational time. First, we perform our forward simulation for all current choices using the linearity idea developed by BBL. Second, we use our computational method to solve for the probability of each action given choice-specific value functions. We discretize the choice of beds and CAH status into 27 possibilities and thus our method requires forward simulating 27 choices for each state. This is computationally much quicker than an inequality approach, in part because it takes advantage of the fact that we can compute the probability of each choice rapidly and without simulation error.[15]

5.2 Estimation algorithm

We estimate the parameters using a quasi-likelilood approach. For any observation, our likelihood function is based on the difference between the realized state transition (in terms of beds and CAH status) and the probability of the realized state transition given the parameter vector and optimizing behavior, interacted with exogenous state variables. The randomness is due to ε_j and ε_j^c.

To understand the computation of our estimator, define first $\overline{\overline{V}}(\Omega_t, j, B_{j,t+1}, CAH_{j,t+1})$ to

[15] The large number of choices, private information and large state space may increase the variance of the inequality criterion function and hence imply that the number of inequalities necessary for a consistent estimator will be large.

be the value for a given realization of beds and CAH status next period, gross of the costs of CAH conversion and of the ε term. Given $\overline{\overline{V}}$ and the parameters μ^c and γ^c, we solve for the probability CAH conversion and the expected associated cost.[16] Using the optimal CAH conversion policy $\hat{c}$, we then calculate the choice-specific value function $\overline{V}(\Omega_t, j, x_{jt})$ (defined by (7)) for each level of beds investment. Using our efficient computational algorithm, we then evaluate the probability of each capacity choice and through that the probability of each capacity choice and CAH state transition cell, which are used to form moment conditions as noted above.

The remaining difficulty is in constructing $\overline{\overline{V}}$ such that the time-intensive part of the computation need not be done for each parameter vector. Similarly to BBL, we would like to find some function of states and actions, $\Psi((\Omega, j), (x, c))$, such that the dot product of Ψ and a function of the structural parameters $f(\theta)$ will yield the net returns in any period,

$$ENR\left((\Omega, j), (x_j, c_j)\right) = \Psi((\Omega, j), (x_j, c_j)) \cdot f(\theta), \tag{12}$$

where ENR are expected net total revenues. We can then forward simulate Ψ in order to express $\overline{\overline{V}}$ as a linear combination of the structural parameters and some forward simulation function:

$$\begin{aligned} &\overline{\overline{V}}(\Omega_t, j, B_{j,t+1}, CAH_{j,t+1}) = -MeanInvCost(B(\Omega_t, j), B_{j,t+1}) + \\ &E_t\left[\sum_{\tau=t+1}^{\infty} \beta^{\tau-t}\Psi\left((\Omega_\tau, j), (x_{j\tau}, c_{j\tau})\right) \middle| B_{j,t+1}, CAH_{j,t+1}\right] \cdot f(\theta), \end{aligned} \tag{13}$$

where the expectation implicitly assumes that next period's state for firm j is given by $B_{j,t+1}, CAH_{j,t+1}$ and that future actions for firm j and all actions for other firms follow the equilibrium as reflected by the data.

Many elements of Ψ and $f(\theta)$ are straightforward to design. For instance, gross revenues enters Ψ and is multiplied by 1, the presence of positive investment enters and is multiplied by δ_1, the level of positive investment enters and is multiplied by δ_2, etc. The most difficult parts to design concern the unobservables. In calculating net revenues using (12), one must

[16] For firms for which $x_j > 25$ or which already have CAH status, only one realization of $CAH_{j,t+1}$ is possible and the CAH investment cost is always zero.

take into account the correlation between the investment level and ε in order to recover accurately the cost of investment.[17] To see this, recall from Corollary 4.4 that investment is monotonic in ε. If one instead assumed that the distributions of investment and cost shocks were uncorrelated, one would overstate the costs of investment.

Fortunately, the monotonicity leads to a method to infer ε from the investment choice: a firm that chooses a next period capacity level in the ath percentile of the capacity level distribution must have obtained a draw of ε that is in the $1-a$th percentile of the ε distribution. Let $\hat{F}_{\Omega,j}(x)$ denote the c.d.f. of capacity levels at state (Ω, j) estimated from the data and Φ and ϕ denote the distribution function and density of ε respectively. Then, a given capacity choice of $x_j > 0$[18] will occur if and only if

$$\begin{aligned}
& \varepsilon_j \in \left[\Phi^{-1}(1-\hat{F}_{\Omega,j}(x_j)), \Phi^{-1}(1-\hat{F}_{\Omega,j}(x_j-1))\right) \\
\implies \quad & E[\varepsilon_j|(\Omega,j),x_j] = E\left[\varepsilon_j|\varepsilon_j \in \left[\Phi^{-1}(1-\hat{F}_{\Omega,j}(x_j)), \Phi^{-1}(1-\hat{F}_{\Omega,j}(x_j-1))\right)\right] \qquad (14) \\
\implies \quad & E[\varepsilon_j|(\Omega,j),x_j] = \frac{\phi\left(\Phi^{-1}(\hat{F}_{\Omega,j}(x_j))\right) - \phi\left(\Phi^{-1}(\hat{F}_{\Omega,j}(x_j-1))\right)}{\hat{F}_{\Omega,j}(x_j) - \hat{F}_{\Omega,j}(x_j-1)}.
\end{aligned}$$

Equation (14) shows that the random costs of investment can be written as a term that does not depend on θ, $E[\varepsilon_j|(\Omega,j),x_j]$, multiplied by the σ parameters.

A similar line of logic gives a closed form expression for the CAH investment shock conditional on converting as $E[\varepsilon_j^c|(\Omega,j),c_j=1] = -\Phi(\bar{\varepsilon_j^c})$. Then, the expected cost incurred from conversion is $E[\varepsilon_j^c|(\Omega,j),x_j,c_j]\sigma^c$.

[17] Other recent empirical dynamic oligopoly papers, such as Ryan (2006), typically do not allow for private information shocks to investment or other choice variables that affect the state.

[18] We omit the derivation of the $x_j = 0$ case, which is similar.

Using these formulations, we define:

$$
\begin{aligned}
&\Psi((\Omega, j), (x_j, c_j)) \\
&\quad = [EGR(\Omega, j), 1\{own_j = NFP\}1\{B_j > 0\}, 1\{own_j = Gov\}1\{B_j > 0\}, \\
&\quad - 1\{x_j > B_j\}, -1\{x_j > B_j\}(x_j - B_j), -1\{x_j > B_j\}(x_j - B_j)^2, \\
&\quad - 1\{x_j < B_j\}, -1\{x_j < B_j\}(x_j - B_j), -1\{x_j < B_j\}(x_j - B_j)^2, \qquad (15) \\
&\quad - 1\{x_j = 0 \text{ and } B_j > 0\}, -1\{x_j > B_j\}E[\varepsilon_j|(\Omega, j), x_j], -1\{x_j < B_j\}E[\varepsilon_j|(\Omega, j), x_j], \\
&\quad - \hat{P}^{CAH}_{(\Omega,j),x_j}, \hat{P}^{CAH}_{(\Omega,j),x_j} E[(\varepsilon^c_j|c_j = 1)].
\end{aligned}
$$

Using $f(\theta) = (1, \alpha^{NFP}, \alpha^{Gov}, \delta_1, \ldots, \delta_6, \phi, \sigma_1, \sigma_2, \mu^c, \sigma^c)$, it is easy to verify that $\Psi((\Omega, j), (x_j, c_j)) \cdot f(\theta)$ satisfies (12).

Knowledge of $\overline{\overline{V}}(\Omega_t, j, B_{j,t+1}, CAH_{j,t+1})$ allows for a given θ then allows us to compute the optimal probability of conversion and the corresponding expected cost of conversion. This then yields the corresponding choice-specific value function $\overline{V}(\Omega_t, j, x_{jt})$. Our algorithm developed in Section 4.3 allows us to compute the probability of each capacity choice $P_{(\Omega,j),x_j}(\theta)$ as a function of the model parameters as well as the probability $P^{CAH}_{(\Omega,j),x_j}(\theta)$ of conversion in each state. Let $\mathbf{P}(\theta,\Omega, j) = [P_{(\Omega,j),x_j}(\theta); P^{CAH}_{(\Omega,j),x_j}(\theta)]$ be the vector that contains the stacked probabilities of capacity level choices and conversion probabilities of hospital j in state Ω. Similarly $\hat{\mathbf{P}}(\Omega, j) = [\ \hat{P}_{(\Omega,j),x_j}; \hat{P}^{CAH}_{(\Omega,j),x_j}]$ is the vector of capacity choice and conversion probabilities estimated from the data. Our estimator $\hat{\theta}$ minimizes sets the sample moment condition of choice probabilities generated by the model computed using our algorithm at a specific parameter vector θ and the choice probabilities observed in the data

$$
\sum_{j=1}^{J} \sum_{\Omega \in \mathbf{\Omega}} \mathbf{Z}(\Omega, j) \otimes \Big(\mathbf{P}(\theta,\Omega, j) - \hat{\mathbf{P}}(\Omega, j)\Big)
$$

as close as possible to zero, where $\mathbf{Z}(\Omega, j)$ is a vector of instruments containing state variables. This GMM estimator is also an asymptotic least squares estimator in the sense of Pesendorfer and Schmidt-Dengler (2007) with weights determined by the choice of $\mathbf{Z}(\Omega, j)$. It exploits BBL's idea of linearity in the parameters to facilitate forward simulation. The algorithm developed in this paper enables the computation of choice probabilities so that moment conditions similar to POB can created to form the asymptotic least squares estimator.

5.3 Parametrization of first-stage

We now discuss how we estimate the static profit functions, the actions and the low of motion at each state. Ideally, we would solve non-parametrically for these functions. However, non-parametric estimation is not possible because of the large dimensionality of the problem. The state space, $(\overline{\Omega}, \Omega_t, j)$ includes the characteristics of all hospitals and patients in the market. Although the dimensionality of Ω_t is relatively small, the transition of Ω_t depends on $\overline{\Omega}$. For instance, if a market is overserved by beds relative to the number of consumers, profits are likely to be low and firms are likely to disinvest.

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, a 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.

We include CAH_{jt}, B_{jt}, own_j and ξ_j as a hospital's characteristics. In order to capture unobserved cost differences, we regress profits on state variables and time dummies using data prior to the start of our sample, from 1994 to 1997. We then use the fixed effect from this regression, $\hat{FE}$ as an additional time-invariant state variable, to capture differences in profits that may affect investment, closure and CAH conversion decisions.

We use five state variables to summarize the characteristics of patients and other hospitals in the surrounding market for any hospital: the expected number of Medicare ($EVol^{med}$) and under 65 year old patients ($EVol^{under65}$)treated at any hospital, a measure of competition for Medicare and under 65 year old patients and the weighted CAH status of other hospitals. These terms are meant to capture the size and degree of competitiveness of the market.

We use the estimated utility parameters (3) to predict patient choice and from that, Medicare patient volume. We also calculate the expected hospital volume of the under 65 year old population by using the same choice model but multiplying by probability of admission by the size of the under 65 year old population above poverty in the ZIP code times the relative rate of hospitalization.

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., see Kessler and McClellan (2000)) and define a patient-weighted Herfindahl index. Specifically, we first define a zip-code/year level Herfindahl index using the estimated choice probabilities from the patient choice model. We then define the Herfindahl index for a hospital/year as the weighted sum of Herfindahl indices over zip-codes, weighted by the probability that a person in that ZIP codes chooses the given hospital. Similarly, we define CAH_comp, the CAH status of a hospitals' competitors, as the patient-weighted sum of the CAH status of competitor hospitals.

We estimate profits with a linear regression. The regressors includes the state variables noted above, and interactions and higher-order terms of the state variables.

To simulate forward, we need to define the policy function and the transition for other state variables. We model the CAH evolution $P((\Omega, j), x)$ as a logit. We use as regressors the state variables and interactions noted above, omitting CAH status, and the firm's own investment policy x_j. We estimate this model via maximum likelihood for non-CAH hospitals for whom $x_j \leq 25$.

Estimating the transition for beds, $x(\Omega, j)$, is the most challenging. In about 70% of time periods, hospitals do not change their number of beds. 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. When hospitals do change their number of beds, they disproportionately change them to 25 beds, likely to be able to obtain CAH status. It is important to accurately predict the probability of a hospital dropping to 25 beds or less. Thus, we model a two-step process. The first step is a logit model which predicts whether the hospital changes its beds. The second step is an ordered probit model which predicts the number of new beds given that the hospital changes its beds. We estimate these models separately for CAH and non-CAH hospitals. We discretize the number of beds for the ordered probit to intervals of 5, and omit the own bed choice. Thus, a hospital with 10 beds has choices 0, 1, 2, 3, etc. corresponding to 0, 5, 15, 20, etc. beds, respectively. We estimate the parameters of these four models using maximum likelihood.

Last, we need to estimate the transitions for other state variables, namely the Medicare and the under 65 year old volumes, the Medicare and under 65 year old HHIs and CAH_comp. We estimate these transitions with linear regressions, where the forward difference is regressed on current state variables, interactions, and beds investment.

One issue is that these state variables can sometimes diverge far from realistic values for a few observations. We limit them to reasonable bounds: we limit the HHI measures and CAH_comp to lie between 0 and 1; we also limit volume to be between 0 and some multiple of beds. If any of these variables is out of bounds during the simulation we restrict it to the bounding value.

5.4 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 β^c consumer utility parameters will be identified from the extent to which consumers choose hospitals based on characteristics such as location, CAH status and hospital size. Because we allow for hospital fixed-effects, the effects of CAH status and bed size changes will be identified from the difference-in-difference: we will examine how the attractiveness of hospitals that convert to CAH status or change their number of beds change following their transformations.

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. Since we use the accounting data on profits in our estimation, much of the identification derives from the shape of the gross profit function in different states.

In particular, the bed investment cost parameters δ are identified by the impact of changing beds on the profit function. Optimal investment levels will be higher if gross profits are more steeply sloped in beds, all else being equal. 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. For instance, the fact that most periods firms rarely invest suggests a large positive fixed cost of investment. The ψ parameter is similarly identified by the extent to which firms exit when faced with low current profits. The γ parameter is similarly identified by the extent to which hospitals obtain CAH status at states where it is profitable to have achieved that status.

The σ parameters are identified by the distribution of investment for any state. The larger the variance of investment outcomes for a given state, the larger will be σ. We estimate a distribution with two parameters, which allows for different relative variance of outcomes for negative investment and positive investment. Finally, the objective function parameters can be identified by the relation of the pattern 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.

These arguments are all approximate because of the fact that our model is a dynamic oligopoly, implying that investments result in an option to invest again in the future and may result in a change in competitors' actions. For instance, an increase in beds may cause competitors to reduce their beds, thereby implying a positive strategic effect that was not in our explanation above.

6 Results

6.1 Evidence on the Impact of the CAH Program

We present some evidence of the impact of the Flex 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 2. 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 3 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 Flex program had a large impact 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%). Relative to the under-65 population, Medicare patients comprise a greater proportion of the patients for CAH hospitals relative to non-CAH hospitals (shown in Table 3). 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 160 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 Flex 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.

[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.

6.2 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 accurately characterize the behavior of the hospitals at every state, which is necessary for the second stage estimation of the dynamic parameters. Table 4 presents the IV-fixed effects, nested logit estimates of the parameters of the utility function, equation (3). The probabilities generated by this model are the ones used to compute the expected volumes and the Herfindahl indices described above. The parameters all are sensible and precisely estimated. All else equal, patients prefer hospitals that are closer and larger and the reduction in rural residents utility from traveling further is less than urban residents. Importantly, CAH conversion reduces the desirability of the hospital. Hospitals that seek to convert face a trade-off. If they convert, they receive high revenue per discharge, however CAH conversions also result in fewer admissions. The estimate indicate that there is significant within CAH class correlation in the errors – the estimate of ρ is .70 and it is very precisely estimated.

The results from the regression of profits on states are presented in Table 5. Hospital profits are increasing in $F\hat{E}_j$ and the under-65 year old HHI. An under-65 admission is significantly more profitable than a Medicare admission. Profits are concave in bed size with the point at which profits are maximized as a function of beds is increasing in $F\hat{E}_j$. At mean values of the variables predicted hospital profits are maximized at approximately 101 beds. However, hospitals with lower values of $F\hat{E}_j$ maximize predicted profits at lower bed size levels. A one standard deviation reduction in $F\hat{E}_j$ lowers the predicted optimal bed size to approximately 80 beds.

An important output from the profit regression that feeds into the second stage is the expected change in profits from converting to a CAH. As CAH is interacted with a number of variables it is difficult to get a sense of that predicted value from examining the coefficient estimates. To give a sense of the variation in the predicted profits from conversion we graph the predicted profits from conversion as a function of $F\hat{E}_j$ in Figure 7. The predicted benefits from CAH conversion are positive for low levels of $F\hat{E}_j$ and as $F\hat{E}_j$ increases, converting is predicted to lead to a decrease in profits. That is, low profitability hospitals are the ones that benefit the most from conversion. For a hospital with a $\hat{FE}_j$ (approximately one standard deviation below the mean) conversion to CAH status implies an increase in profits of about \$884,000 per year. The parameter estimates imply CAH conversion increases profits for approximately 24% of hospitals in our sample. Conditional on an expected positive profit from conversion, the mean predicted profit from conversion is \$728,000. Importantly, the estimated expected increase in profits predicts CAH conversion. A simple logit regression of CAH conversion on predicted profitability of conversion yields a positive and signifiant (z-statistic = 12.9) coefficient. Using a hit/miss criteria to assess the fit shows that the predicted profitability is a good predictor of CAH conversion. In 2005, the predicted probability of CAH conversion of greater than .5 predicts 65% of the actual conversions and predicted probability less than .5 predicts 72% of the actual non-conversions correctly (approximately 51% of the hospitals in our sample converted by 2005).

Table 6 presents the first-stage policy function estimates of the probability of CAH conversion in period $t+1$ conditional on $Beds_{t+1} \leq 25$. The probability of converting is larger for not-for-profit and government hospitals relative to for-profit hospitals. Larger hospitals and hospitals with larger $\hat{FE}$ are less likely to convert, as are the hospitals that show positive investment in capacity. Table 7 presents the results from the first-stage in our two stage investment model, the predicted probability of positive investment. We estimate the parameters separately for CAH and non-CAHs. CAHs are much less likely to change their bed size. For CAH hospitals, the probability of investment is declining in bed size and ξ_j (up to 22 beds). For non-CAHs, for-profit and smaller hospitals and those with lower expected volumes are less likely to invest. The conditional investment parameter estimates are presented in Table 8. Again, the parameters are estimated separately for CAHs and non-CAHs. For CAHs, the conditional investment is increasing in the bed size of the hospital, $\hat{FE}$ and the expected volume of Medicare and the under-65 population. For non-CAHs, investment is increasing in for-profit status, bed size, total admissions and ξ_j.

In addition to the policy regressions, we estimate the laws of motion for the state variables HHI, $EVol^{Med}$, $EVol^{under65}$, Medicare 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.

6.3 Dynamic Parameter Estimates

The structural parameter estimates of the dynamic oligopoly model are presented in Table 9. These parameters correspond to the hospitals objective function, investment cost, and CAH investment and rationalize the first stage policy functions in a Markovian equilibrium. The first two parameters, α_p^{NFP} and α_p^{Gov} indicate that non-profit and government hospitals value remaining open and providing service at about \$450,000 per year. The investment cost parameters show large and asymmetric costs of changing capacity. The expected cost of the first bed added is about \$2.6 million and the expected cost of the first bed disposed is about \$150,000. Each additional bed added has an expected cost of about \$3.3 million, and each additional bed disposed has an expected cost of about \$1.6 million. As expected, investing in beds is more costly than disinvesting in beds as adding beds requires additional staff, equipment and space. The large mean investment and disinvestment costs obtained are consistent with the patterns observed in the data. These estimates are consistent with the fact that hospitals do not change capacity often. The lack of investment implies there must be, on average, large costs to changing capacity. It should be noted that the values shown above are obtained at the mean levels, however, the realized investment cost will depend on the realization of the privately observed investment cost shock. In Table 9, the standard deviations of the cost shock for positive and negative investment, σ_1 and σ_2 respectively, indicate that the cost shocks are important in determining a hospital's investment cost. We graphically show in Figure 9 that there is substantial variation in the investment and disinvestment costs, hospitals receiving a shock 2 standard deviations above the mean exhibit substantially higher costs than those receiving a shock 2 standard deviations below the mean. Conditional on investment, the investment cost is probably at the low end of the distribution. The parameter ϕ indicates that when the hospital exits it receives a scrap value of \$2.6 million. The parameters of the distribution of the CAH conversion cost indicate that this cost is low, but shows substantial variance.

In Figure 8 we summarize the fit of our model by comparing the market structure observed in our data to the predictions of our model. The predictions of our model using the dynamic parameters in Table 9 closely match the observed market structure.

7 Policy Experiments

In this section we provide the results from counterfactual experiments that seek to understand the impact of the Flex Program and the impact of alternative programs. In all counterfactuals we explicitly solve for the Markov Perfect Equilibrium of the game using our algorithm described in section 4.3. We use the structural parameters estimated above, and obtain a prediction of the market structure under the baseline situation (with CAH), and under three alternative scenarios. In the first counterfactual experiment we compute the equilibrium in the absence of the Flex Program. The difference between this scenario and the baseline will be informative of the impact of the Flex Program. When CAH is not an option, rural hospitals in monopoly and duopoly markets would have kept larger capacity levels (about 10 more beds), as shown in Figure 11. In Figure 10 we show the impact of the program on exits in monopoly and duopoly markets, and we find that in twenty years the program prevented the exit of 6% of currently operating hospitals. By keeping hospitals open the minimum distance to a hospital remains fairly constant at about 7.4 kilometers over the 20-year period of our simulation, this distance would have increased by about 0.2 kilometers had the Flex Program not been introduced (see Figure 12). Interestingly, with the Flex Program the average distance traveled to receive care increased by about 0.5 Kilometers as shown in Figure 13. The evidence presented our first counterfactual reveals an interesting policy tension: rural residents value access to care, but also value large and complex facilities. Our results suggest that the Flex Program has promoted the first, but discouraged the second, with an overall loss for patients in rural areas as shown in Figure 15, where we compare the consumer surplus of the baseline with the scenario without the Flex Program.

In our second counterfactual, we study the impact of implementing the Flex Program but with a larger capacity limit of 35 beds. In Figure 14 we see that more hospitals convert to Critical Access Hospital status with the larger bed limit. Although this modification of the program results in slightly larger facilities, consumer surplus decreases compared to the baseline situation with the 25-bed limit. There is a large utility loss from seeking care at a CAH as shown in Table 4 above and beyond the reduction in capacity. In a companion paper using individual-level data, we have found that patients tend to bypass these facilities and seek care in larger and more complex hospitals. On the other hand, among all the counterfactuals we study, this modified policy is the most effective in terms of keeping hospitals open and at short distances as shown in Figures 10 and 12.

Our third counterfactual simulation replaces the Flex Program by a lump-sum transfer of $250,000, without capacity constraints. We find that this alternative policy would have induced 3.8% of currently operating hospitals to exit, a smaller effect than having no intervention. The impact of this alternative policy after 20 years is hospitals holding about 11 more beds than under the current situation. Because this policy does not induce hospitals to decrease capacity, does not require hospitals to adopt CAH status, and prevents some exits, the average distance traveled to receive care is the lowest of all our counterfactual scenarios. In Figure 15 we can see that the consumer surplus is the largest among all our counterfactual scenarios.

8 Conclusions

In this paper we seek to understand the impact of the Flex 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 inspired in recent two-step methods for the estimation of dynamic games, which we modify by introducing private information in the investment cost function and by developing an efficient computational algorithm to find the equilibrium of the game and make it feasible to be estimated via quasi-maximum likelihood. The Flex 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 and duopoly markets show that the program prevented 5% of closures had the program not been implemented. In addition, although the minimum distance to a hospital is reduced by the program, the actual average distance traveled to receive care increased. We find that overall consumer surplus has decreased as a result of the Flex Program. We find that an alternative policy that offers lump-sum transfers to rural hospitals without capacity limits would have handled the policy tension between access and size of hospitals better, leading to improved patient welfare. Our work contributes to a recent and fast growing literature that uses the results from the estimation of dynamic games to perform policy evaluations. The methods we develop may be more broadly useful in estimating and computing dynamic oligopoly games with investment in capacity.

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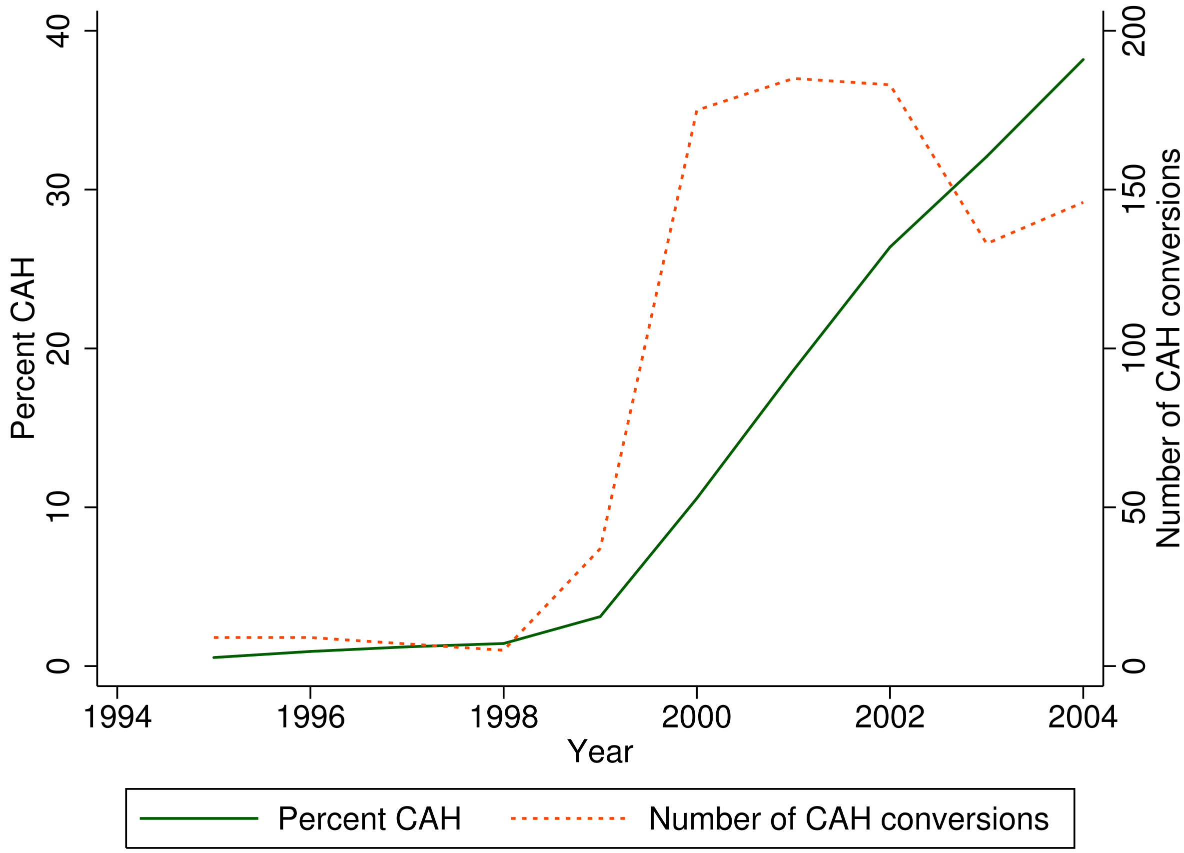

Figure 1: Number of conversions and percent CAH among U.S. rural hospitals

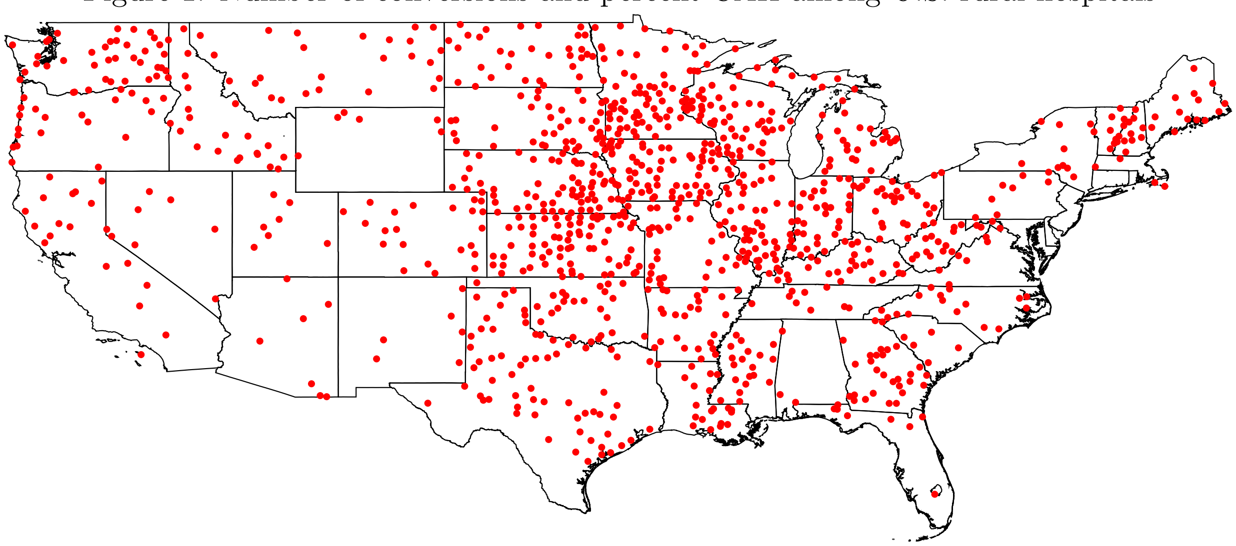

Figure 2: Spatial distribution of CAH. Dots represent CAHs

Figure 3: Size of rural hospitals, 1996 and 2004

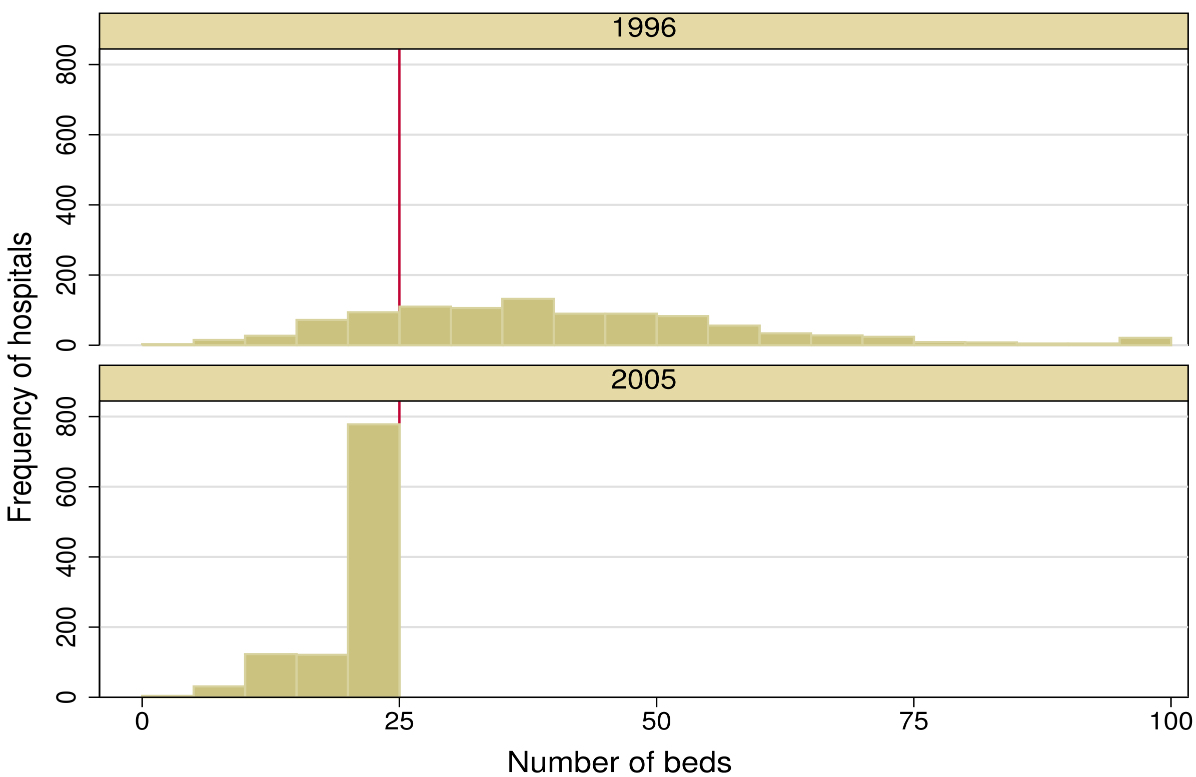

Figure 4: Size of hospitals that are CAH in 2004

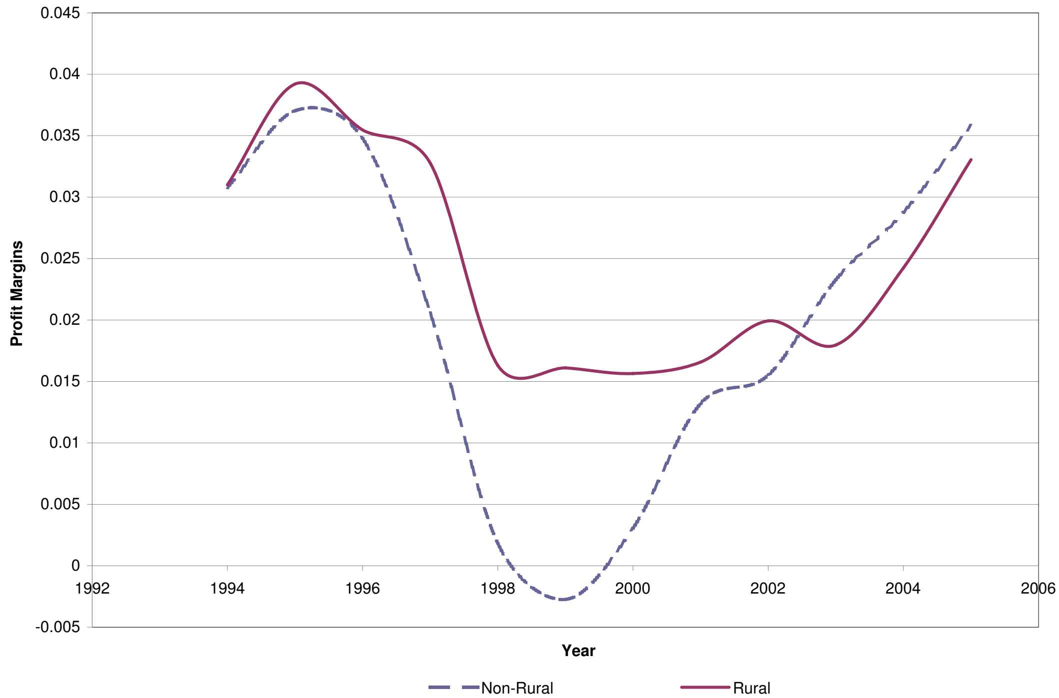

Figure 5: Mean profit margins for hospitals with less than 160 beds in 1995.

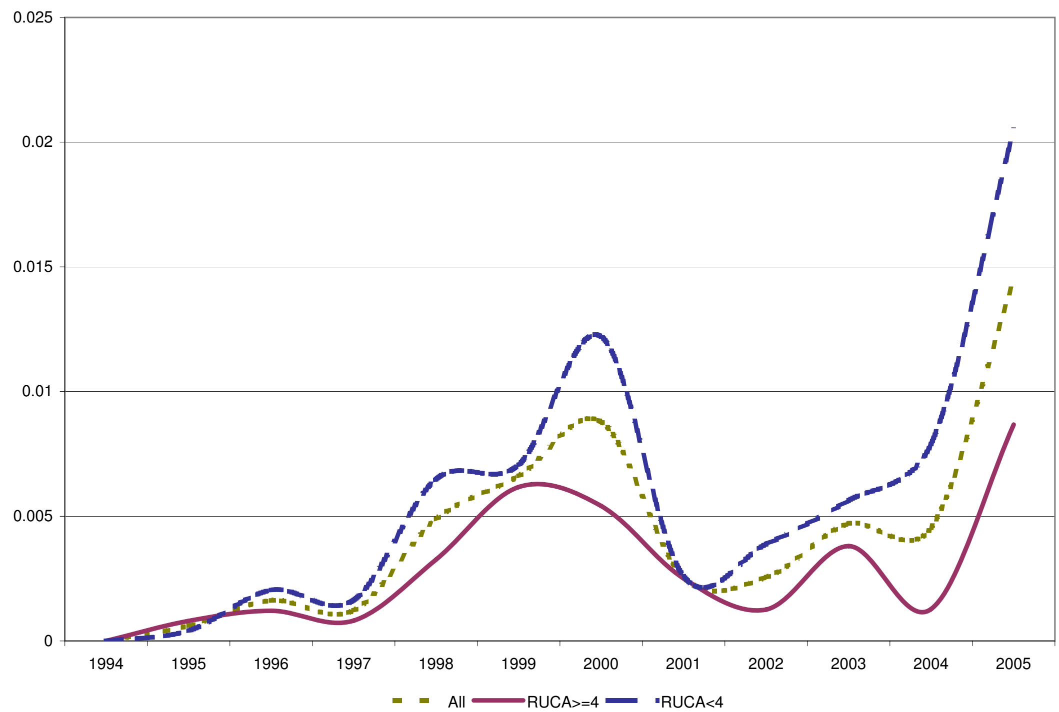

Figure 6: Exit rates for Rural, Urban and All U.S. Hospitals

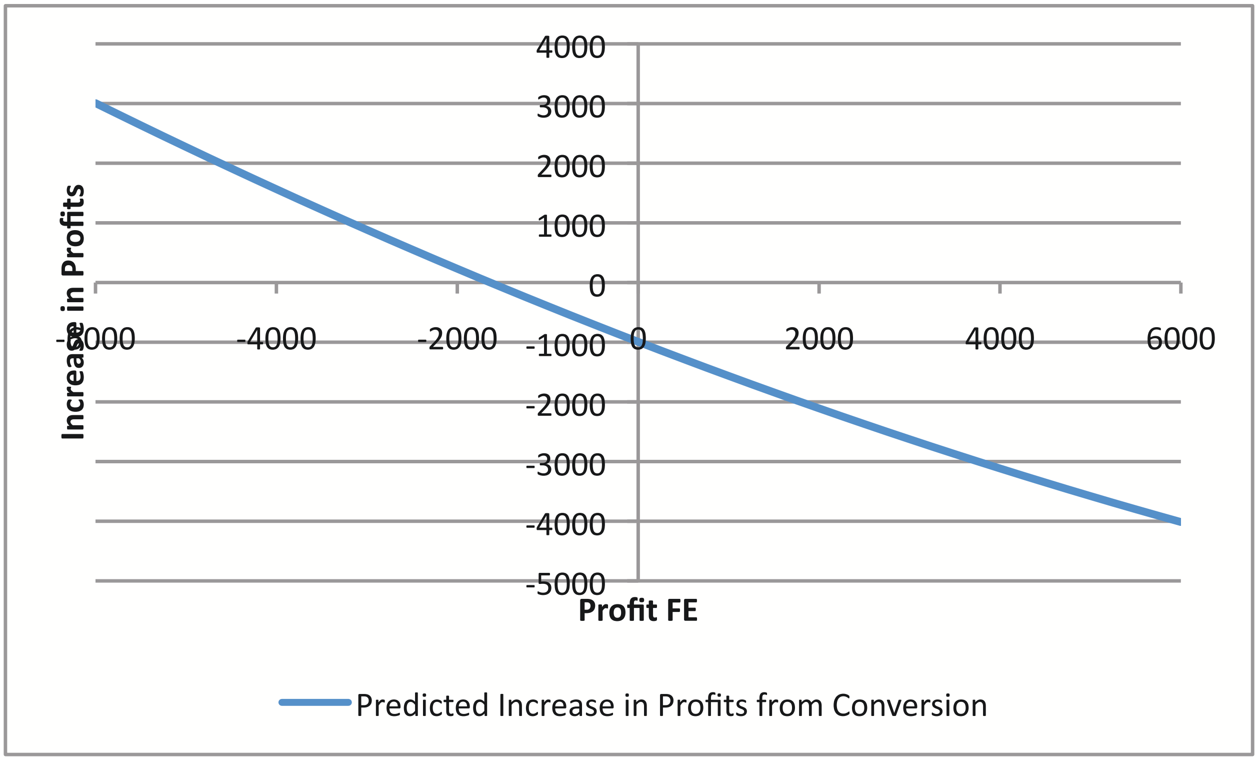

Figure 7: Change in profit from CAH conversion by CAH status and Profit FE ($1,000)

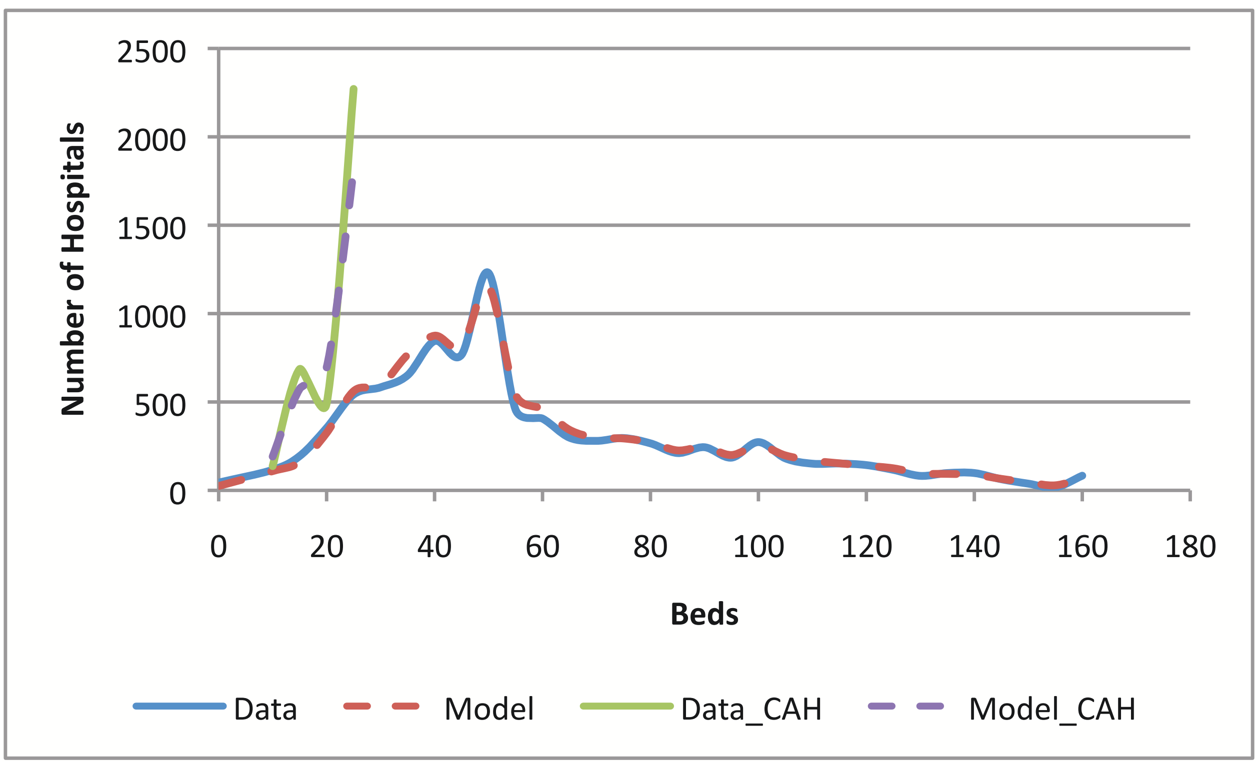

Figure 8: Fit of the dynamic model

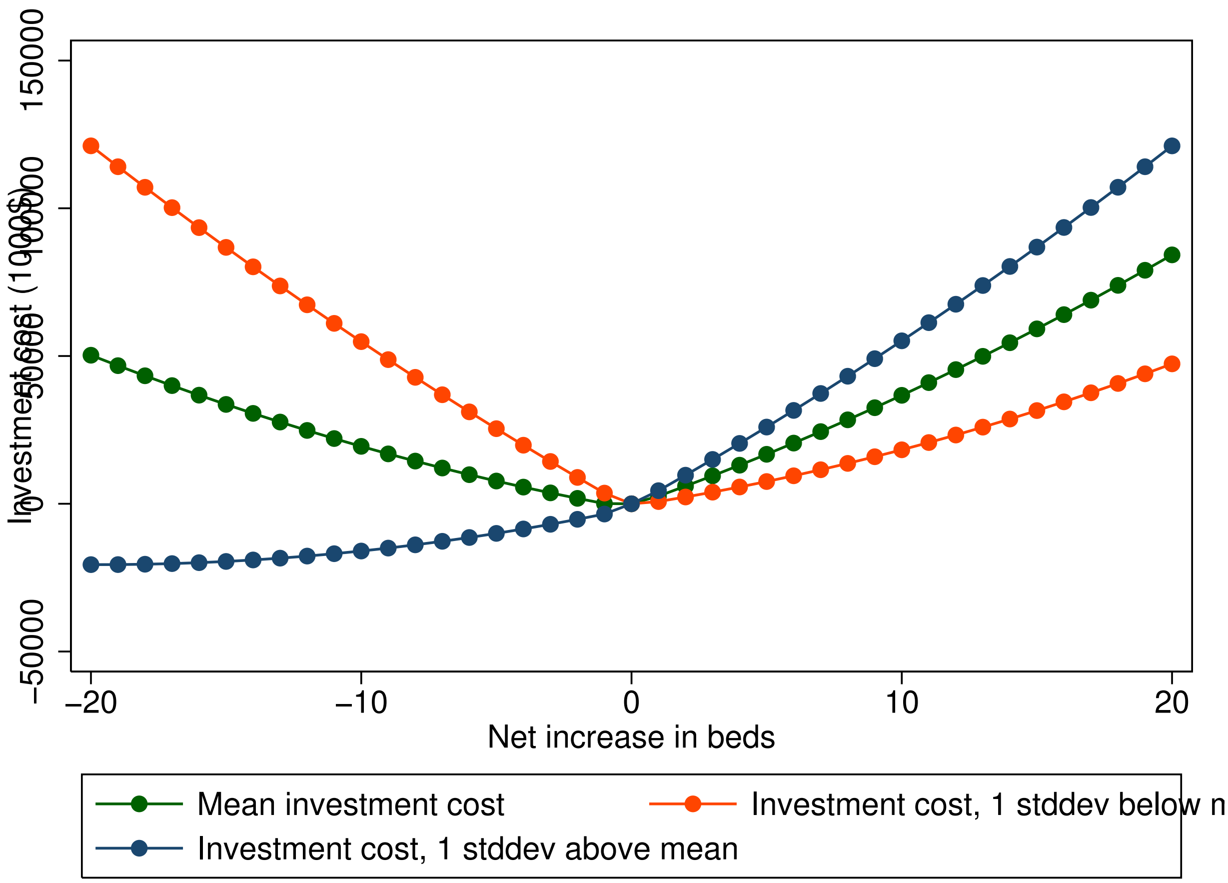

Figure 9: Estimated implied investment costs

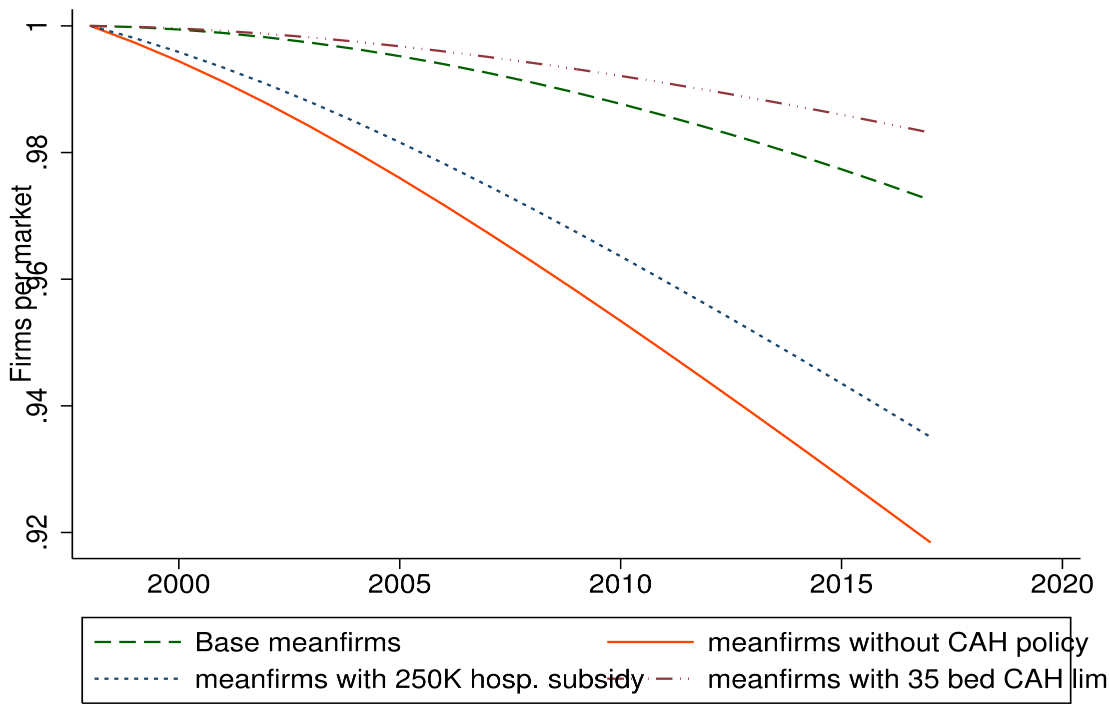

Figure 10: Impact of the program and alternative programs on number of firms.

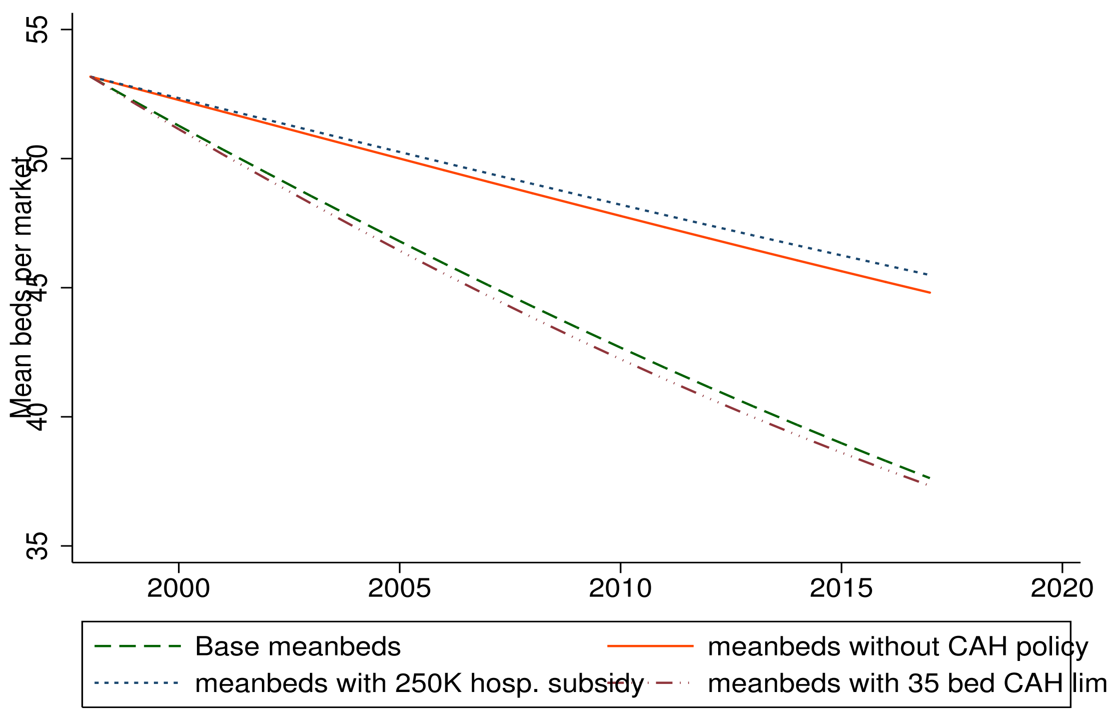

Figure 11: Impact of the program and alternative programs on number of beds

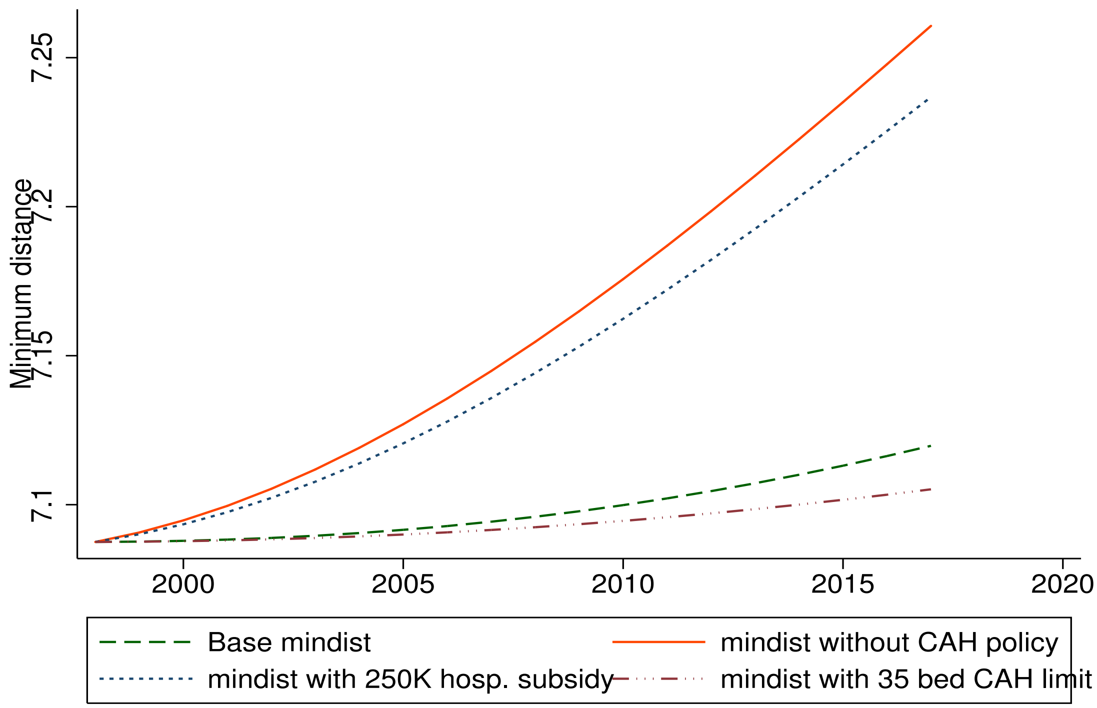

Figure 12: Impact of the program and alternative programs on min. distance to a hospital.

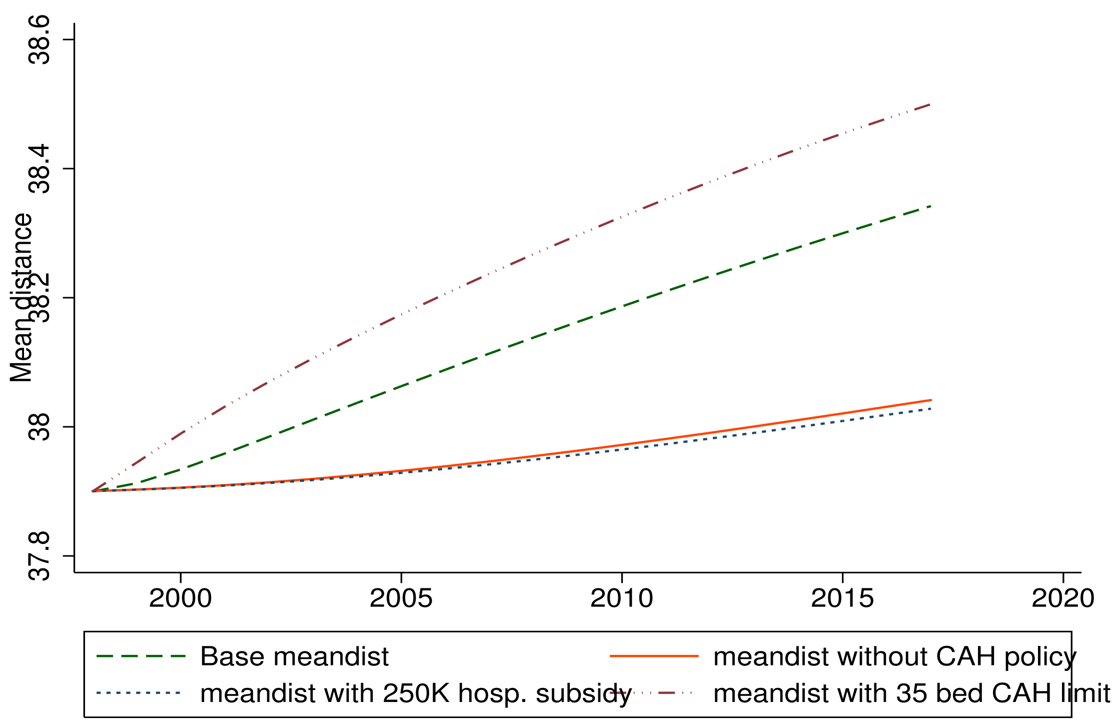

Figure 13: Impact of the program and alternative programs on average distance traveled

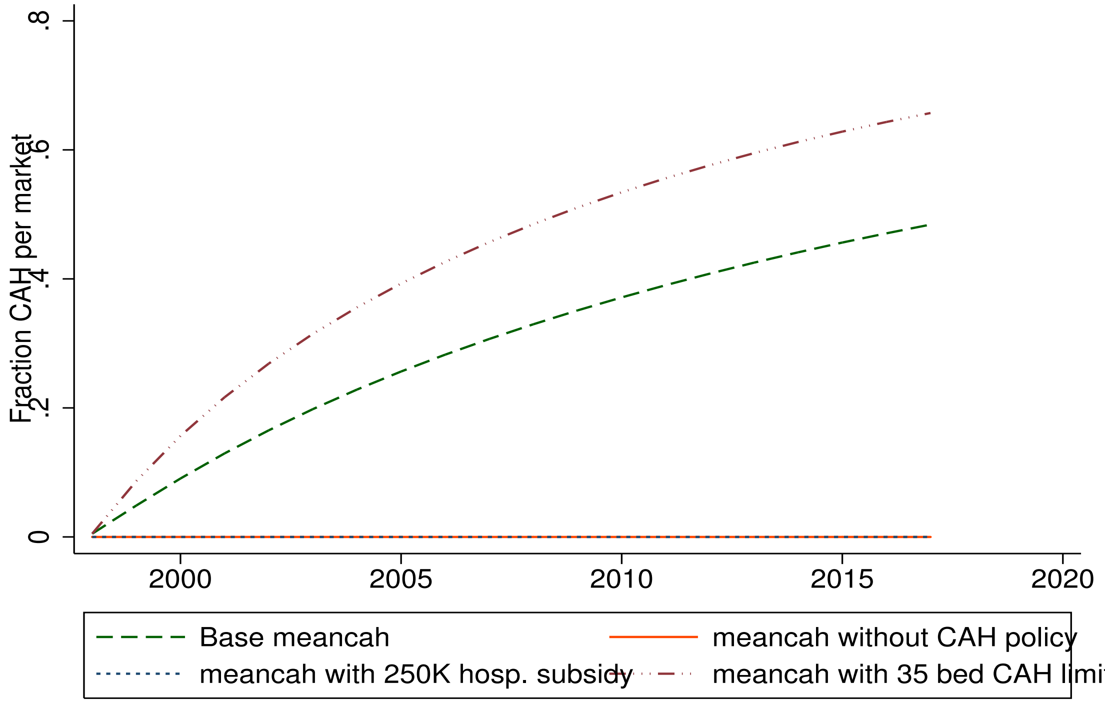

Figure 14: Impact of the program and alternative programs on fraction of CAH per market.

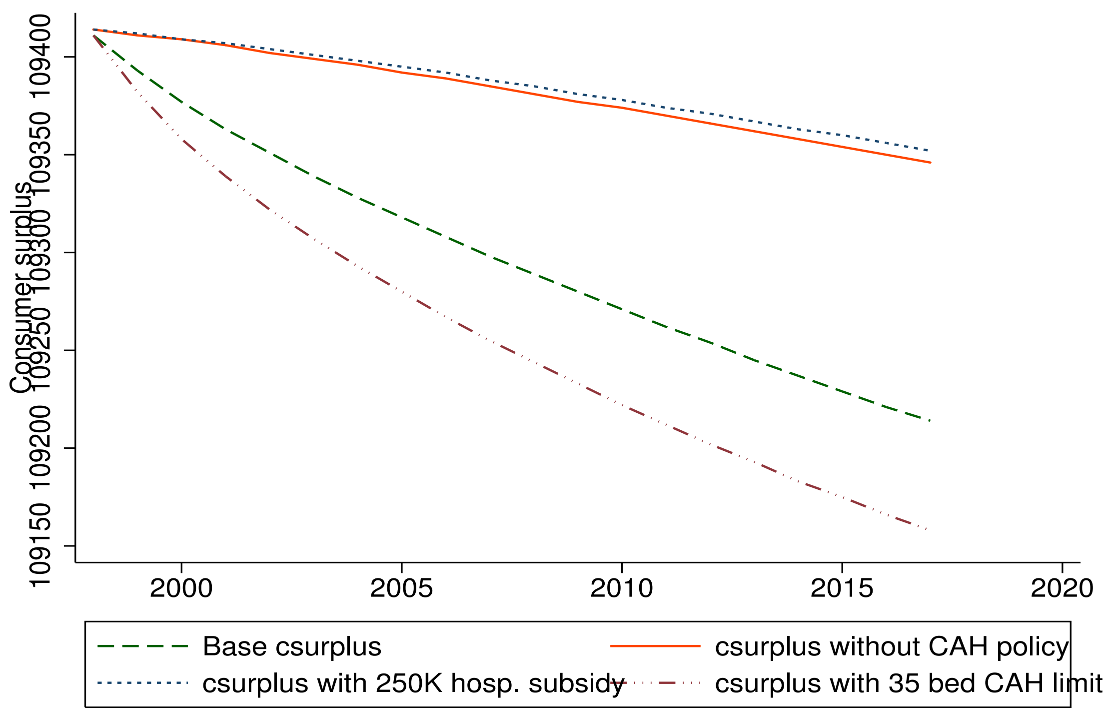

Figure 15: Impact of the program and alternative programs on consumer surplus

Table 1: Relevant Policy Changes for CAH

Legislation	Key Aspects of CAH Legislation and Regulation
BBA 1997	• Flex 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: Summary Statistics – Analysis Sample

	Mean	Std. Dev.
Profits ($1,000)	951.25	2,712.4
CAH Status	.25	.43
Not-For-Profit	.53	.50
Government	.40	.49
For-Profit	.11	.31
Beds	48.6	33.5
$\hat{FE}$	-92.1	2,960.3
$\hat{\xi}_j$	-.73	.93
Medicare HHI	.20	.10
Under 65 HHI	.20	.10
CAH_Comp	.016	.034
$EVol^{under65}$	475.7	597.5
$EVol^{Med}$	282.7	411.8
Investment (Δ Beds)	-1.76	7.73
Closure	.0029	.053
N	15,258	
Number of Hospitals	2,121	

Table 3: Summary Statistics in 2005 by CAH Status

	CAH	Non-CAH
Profits ($1,000)	662.9	2,290.6
Not-For-Profit	.51	.51
Government	.44	.29
For-Profit	.044	.19
Beds	22.12	68.49
$\hat{FE}$	-878.7	893.6
$\hat{\xi}_j$	-.98	-.41
Medicare HHI	.20	.18
Under 65 HHI	.21	.18
CAH_Comp	.0093	.041
$EVol^{under65}$	70.2	420.18
$EVol^{Med}$	286.8	584.56
N	998	972

Table 4: Estimates from Nested Logit Model of Hospital Choice

Variable	Coefficient	S.E.
Distance	-.023	.000078
Distance^2	.00011	4.2×10^{-7}
Closest	.48	.0035
Closest $\times$ Dist	-.0020	.00022
CAH	-3.05	.013
CAH $\times$ Closest	1.51	.017
CAH $\times$ Dist	-.0069	.00016
Beds	.00027	.000010
Beds $\times$ Dist	-2.72×10^{-6}	5.93×10^{-8}
Rural $\times$ Beds	.00077	.000012
Rural $\times$ Dist	.0070	.000067
Rural $\times$ Dist^2	-.000069	5.74×10^{-7}
Rural $\times$ Closest	.0070	.000066
Rural $\times$ CAH	1.36	.015
Rural $\times$ CAH $\times$ Dist	-.0069	.00016
Rural $\times$ CAH $\times$ Closest	-.84	.018
Rural $\times$ CAH $\times$ Dist $\times$ Closest	-.010	.00025
$Log(s_{j\|CAH})(\rho)$	.71	.00074
Constant	2.68	.0036
N	2,743,114	

Table 5: First-Stage Regression: Profits ($1,000)

Variable	Estimate	Robust s.e.	t-statistic
CAH status	1,440.7	1,389.8	1.04
For-Profit	,1857.7	452.4	4.11
Not-For-Profit	244.9	136.2	1.80
For-profit × CAH	-1,040.1	1,333.9	-.78
Beds	-18.3	14.5	-1.27
Beds^2	.49	.16	3.10
Beds^3	-.0024	.00045	-5.42
$\hat{FE}$	-3,654.4	8,832.0	-.41
$\hat{FE}^2$	35,839.2	32895.9	1.09
$\hat{FE}^3$	-76,284.9	47,283.9	-1.61
$\hat{FE}^4$	49,965.8	23094.7	2.16
Medicare HHI	-3,286.6	3,954.9	-0.83
Under 65 HHI	3,171.0	4,015.7	0.79
$\hat{FE}\times$ CAH	-6,003.3	14,829.9	-0.40
$\hat{FE}^2\times$ CAH	-4,424.9	52,224.5	-0.08
$\hat{FE}^3\times$ CAH	6,392.5	72,749.0	0.50
$\hat{FE}^4\times$ CAH	-31,394.0	34869.0	-0.90
$EVol^{under65}$	.015	.0064	2.30
$EVol^{Med}$	-.18	.63	-0.29
$EVol^{under65}\times$ CAH	.59	1.24	0.48
$EVol^{Med}\times$ CAH	-.11	1.39	-0.08
CAH_comp	1,041.5	1,702.9	0.61
Constant	-46.3	831.7	-0.06
R^2	0.09		
N	15,258		

Standard errors clustered at the hospital level

Table 6: First-Stage Regression: $Prob[CAH(t+1) = 1 | CAH(t) = 0, Beds(t+1) \leq 25]$

Variable	Estimate	Robust s.e.	z
Beds_{t+1}	-.10	.020	-4.98
For-profit	-.88	.51	-1.73
Not-for-profit	-.14	.12	-1.18
Beds	.18	.041	4.39
Beds^2	-.0013	.00044	-2.96
$\hat{FE}$	-0.000035	.000076	-.46
$\hat{FE} \times$ Beds	7.14×10^{-7}	3.12×10^{-6}	.23
$\hat{\xi}_j$	.53	.26	2.01
$\hat{\xi}_j \times$ Beds	.01	.0096	1.04
Medicare HHI	3.18	1.07	2.99
Under 65 HHI	-2.34	1.07	-2.18
$EVol^{under65}$	.0016	.00076	2.13
$EVol^{Med}$	.000095	0.00027	.36
Total Admits $\times$ Beds	-5.10×10^{-6}	.000012	-.44
CAH_comp	21.25	4.12	5.15
Constant	-1.09	.86	-1.27
Log Likelihood	-951.1		
N	2,121		

Table 7: First-Stage Regression: Prob. Non-Zero Investment

Variable	CAH	Robust s.e.	Non-CAH	Robust s.e.
For-profit	.56	.41	-.45	.11
Not-for-profit	-.12	.15	-.033	.047
Beds	.29	.17	.011	.0042
Beds^2	-.13	.0042	-.000051	.000027
$\hat{FE}$	.00037	.000039	-.000044	.000021
$\hat{FE}\times$ Beds	-.000020	.000020	4.13×10^{-7}	2.32×10^{-7}
$\hat{\xi}_j$	1.43	.40	.22	.061
$\hat{\xi}_j\times$ Beds	-.067	.020	-.0058	.0011
Medicare HHI	1.55	2.03	2.54	.87
Under 65 HHI	-.98	2.09	-.000055	.000059
$EVol^{under65}$	-.00017	.0024	-.000055	.000059
$EVol^{Med}$	.00061	0.0012	.00044	.00012
Total Admits $\times$ Beds	-.000033	.000066	-1.49×10^{-6}	5.96×10^{-7}
CAH_comp	-2.37	5.14	-.97	.64
Constant	-2.31	1.81	-1.65	.17
Log Likelihood	-718.2		-5,950.9	
N	2,683		10,366	

Table 8: First-Stage Regression: Conditional Investment

Variable	CAH	Robust s.e.	Non-CAH	Robust s.e.
For-profit	-.89	.71	.89	.18
Not-for-profit	.38	.32	.067	.072
Beds	1.06	.31	.17	.0086
Beds^2	-.019	.0076	-.00029	.000052
$\hat{FE}$	-.0018	.0011	.000074	.000032
$\hat{FE}\times$ Beds	.00013	.000057	2.79×10^{-7}	3.75×10^{-7}
$\hat{\xi}_j$	-.55	.84	.48	.10
$\hat{\xi}_j\times$ Beds	.056	.043	-.0031	.0018
Medicare HHI	-2.21	4.66	.37	1.50
Under 65 HHI	.35	4.71	-1.58	1.53
$EVol^{under65}$	.015	.0048	.000046	.00010
$EVol^{Med}$	.015	0.0032	-.0010	.00018
Total Admits $\times$ Beds	-.00048	.00015	4.99×10^{-6}	9.23×10^{-7}
CAH_comp	-5.29	7.80	-6.45	1.00
Log Likelihood	-200.4		-5,759.6	
N	229		2,794	

Cut coefficients are not reported.

Table 9: Parameter Estimates Dynamic Oligopoly Equilibrium

Variable	Estimate	s.e.	
α_p^{NFP}	441.3	(123)	**
α_p^{Gov}	453.0	(114)	**
$1\{x > B\}$	-681.2	(240)	**
$1\{x > B\}(x - B)$	3,232	(84.5)	**
$1\{x > B\}(x - B)^2$	50.69	(1.64)	**
$1\{x < B\}$	-1,584	(81.9)	**
$1\{x < B\}(x - B)$	-1,612	(49.8)	**
$1\{x < B\}(x - B)^2$	49.05	(.866)	**
ϕ	-2,681	(1954)	
σ_1	1,844	(48.44)	**
σ_2	1,772	(26.84)	**
μ^c	-1931	(726)	**
σ^c	8,538	(435)	**