Regulation and Capacity Competition in Health Care: Evidence from U.S. Dialysis Markets*

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Abstract

This paper studies entry and capacity decisions by dialysis providers in the United States. We estimate a structural model where providers make continuous strategic choices of capacity based on their private information about own costs and knowledge of the distribution of competitors' private information. We evaluate the impact on the market structure and providers' profits under counterfactual regulatory policies that increase per capacity cost or reduce per capacity payment. We find that these policies reduce the market capacity as measured by dialysis stations. However, the downward sloping reaction curve shields some providers from negative profit shocks in certain markets. The paper also has a methodological contribution in that it proposes new estimators for Bayesian games with continuous actions.

JEL Classification: L11, L13, I11

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1 Introduction

Dialysis is the major treatment for more than 630,000 patients in the U.S. who suffer from End Stage Renal Disease (ESRD). Medicare, the monopolistic buyer of dialysis services, has spent 8.6 billion dollars in 2007 on the treatment and medication of dialysis patients. While Medicare pays a fixed rate to dialysis providers, rising dialysis expenditure motivates a recent Medicare reform that aims at reducing costs and maintaining the quality of care.[1] The core component of the reform is a new reimbursement system that incorporates the payments for multiple drugs and services furnished in a dialysis session into a single bundled rate. This effectively reduces the average per-treatment rate received by dialysis providers and subsequently lowers the per-patient margin. On the other hand, lowering dialysis reimbursement rate raises the concern of insufficient payments, which may eventually compromise dialysis accessibility. Dialysis capacity, as measured by the number of dialysis stations, is an important metric used by policy makers to evaluate the adequacy of dialysis payment policies. In this paper, we analyze the provision of dialysis capacity and evaluate the implications of counterfactual dialysis payment policies. Our results offer some insights about the conduct of health care providers and the effectiveness of fixed-price regulation.

We build a model of static Bayesian games with *continuous* actions to examine the strategic interactions between U.S. dialysis providers in their choices of capacity across Hospital Service Areas (HSA) in 2007. We focus on three types of providers on the market: FMC, DaVita and all other non-Chain providers.[2] We estimate how payoffs of these providers depend on exogenous market characteristics (such as sizes, and measures of ESRD risks, etc.) as well as the endogenous choices of capacity. We then use our estimates to predict the impact of payment policies that either raise or reduce the margin per capacity unit. In particular, we are interested in how different providers would respond to positive or negative adjustment in the reimbursement for dialysis treatment and whether high capacity helps dialysis providers to maintain their market presence with lower margins.

The impact of strategic choices of capacity on the market structure and on the intensity of competition has been studied in several theoretical papers (e.g. Dixit 1980, Gelman and Salop 1983, Kreps and Scheinkman 1983 etc.). On the other hand, the empirical literature has largely ignored the strategic incentives in the *continuous choices* of capacity. With little price and quality competition (as shown in Grieco and McDevitt 2013 and Cutler, Dafny and Ody 2012), these strategic incentives are

[1] The reform was proposed in 2008 and became effective in 2011. The full implementation of the policy is expected to complete in 2014.

[2] FMC and DaVita are the industry leaders with national footprints. They jointly own 2/3 of the dialysis facilities and treat more than 2/3 of all dialysis patients. All other non-FMC or non-DaVita providers are referred to as non-chain hereinafter. The scale of operation and the market penetration of each of these non-chain providers are not comparable to the two leaders.

important for dialysis providers.[3] In practice, a dialysis provider's margin decreases in the capacity of competitors. One explanation for this pattern is that additional capacity allows a provider to offer a more flexible treatment schedule, which is highly valued by patients.[4] Given the high operation and maintenance costs for each dialysis station, optimal capacity choices depend on the trade-off between the market demand, the capacity costs and the competitive interactions between dialysis providers.

We characterize providers' strategies in a Bayesian Nash equilibrium by the first-order conditions of their constrained maximization problems (subject to the constraints of non-negative capacity). We show that these conditions are similar to censored regressions, except that the expected capacity for competitors in equilibrium now enters as a "generated" regressor. We propose several estimators (two-stage, MLE and GMM) to infer the marginal effects of a provider's own capacity, the capacity of its competitors and the market conditions on its profits.

Our estimates conform to the empirical regularities that a dialysis provider's choice of capacity is decreasing in those of its competitors' (i.e. reaction curve is downward sloping) and that competition is more intense between competitors with high capacity. We find that, all else being equal, increasing a provider's expected capacity by one unit (a dialysis station) reduces a competitor's choice of capacity in equilibrium by an average of 0.2-0.4 units and decreases the competitor's entry probability by 3%-13%. This suggests that focusing on providers' binary entry decisions overlooks rather substantial strategic interactions between their choices of capacity. Our results are also robust to various sample selection criteria and the choice of methods in econometric implementation (such as two-stage, nested maximum-likelihood and GMM).

In our counterfactual analyses, we find that on average providers' capacity choices respond negatively to a reduction in the profit margin that results from a more stringent reimbursement policy. The effects are reversed under more generous reimbursement policies that increase the profit margin. More interestingly, the responses are heterogeneous across markets and providers. For example, FMC and non-chain independent providers respond most strongly to both negative and positive margin adjustments while DaVita reacts mildly in both cases. In some markets, DaVita reduces (increases) its capacity when the margin widens (shrinks) by the same portion as its competitors. Such a pattern is explained by the downward-sloping reaction curve in the Bayesian game of capacity choices, which incentivizes DaVita to decrease its capacity if the competitors expand and to increase capacity

[3] Both Grieco and McDevitt (2013) and Cultler, Dafny and Ody (2012) find little effect of competition on various measures of dialysis quality and patient outcomes.

[4] Given that a typical dialysis patient visits providers three times a week for a total of nine to twelve hours, the scheduling flexibility is found to be more important than survival in patient's dialysis choice (Johansen 2011). It's easier for patients to find their preferred appointments with the providers capable of performing multiple concurrent dialysis sessions.

if others scale down. Our results show that the effect of the reaction curve are large enough to offset the impact of positive (negative) adjustments in the profit margins in certain markets. This offers evidence that the shape of the reaction curve could potentially magnify a provider's response to small changes in the profit margin in some markets, and that it plays a crucial role in determining the effect of reimbursement policies.

Apart from its empirical motivation and findings, our paper also contributes to the methodological literature on the estimation of empirical games. We are not aware of any previous work structurally estimating Bayesian games with *continuous* actions. The bulk of existing literature studies competitive effects in games with *discrete* actions in various contexts such as entry games, where alternatives available to players are naturally finite (e.g. Aradillas-Lopez (2010), Bajari, Hong, Krainer and Nekipelov (2010), Berry and Tamer (2007), Davis (2006), Mazzeo (2002), Seim (2006) and Sweeting (2009)). In our application, binary entry decisions are closely associated with continuous choices of capacity, suggesting that even small incremental changes in capacity play an important role in determining the firms' payoffs and the market outcomes. One of the main messages of our paper is that overlooking the information revealed in the chosen level of capacity may compromise researchers' understanding of the market mechanism.

The rest of this paper is organized as follows. Section 2 introduces the background of the dialysis industry. Section 3 specifies the econometric model for our structural analysis. Section 4 discusses the identification and estimation of the model. Section 5 describes the data. Section 6 presents empirical findings and results from the counterfactual exercises. Section 7 concludes.

2 Background

2.1 Dialysis and Capacity

Chronic Kidney Disease (CKD) affects more than twenty million adults in the United States. The advanced stage of CKD is known as End Stage Renal Disease (ESRD) and is most commonly caused by diabetes and high blood pressure. The only treatment for ESRD is dialysis or a kidney transplant. Given the limited supply of donor organ and the surgical risk associated with comorbidities, many ESRD patients rely on routine dialysis as the major treatment.

Dialysis is a therapy that removes waste (such as urea) and excess water from the body as a replacement for lost kidney function. Hemodialysis is the most common treatment modality and accounts for about 90% of the dialysis population in the U.S.[5] In a hemodialysis session, a dialysis

[5] Alternatively, about 10% of the dialysis population chooses peritoneal dialysis which is usually performed everyday

machine pumps a patient's blood into the dialyzer, cleans it with dialysate (a solution that removes excess fluids and wastes) and injects the cleaned blood back into the patient's body. It is impossible to provide dialysis without those machines.

Acquiring and operating a dialysis machine is costly. A new dialysis machine costs between \$10,000 and \$15,000 with a life span of five to seven years. There are other associated costs, such as dialysis chairs, private screens, etc. The industry experts estimate a cost of \$100,000 to maintain and operate one dialysis station over its lifetime. The dialysis capacity in a given market (HSA), as measured by the number of dialysis stations operated, is practically a permanent decision for each dialysis provider, as data report little subsequent adjustment in capacity by providers following initial entry into a market. Grieco and McDevitt (2013) finds that dialysis capacity remains constant for over 90% of the dialysis facilities in the U.S. between 2004 and 2007.

2.2 Regulatory Background

The ESRD patients receive almost universal coverage under Medicare regardless of their age.[6] Around 80% of the dialysis population relies on Medicare as the primary payer (USRDS 2010). Under the old system, Medicare reimbursed three dialysis sessions per-week under a fixed rate (after adjusting for patient's case-mix, local wages and other factors associated with the cost of treatment). In addition, providers are also paid for separately billable services that are furnished during the in-center hemodialysis sessions (e.g. injectable drugs such as Epogen and diagnostic laboratory tests), which represent about 40 percent of total Medicare payments per dialysis treatment session. The generous reimbursement for separately billable services has raised the concern that it may create distorted profit incentives for drug over-utilization. For example, one of the separately billable drugs known as Epogen, primarily used for treating a common complication of ESRD, cost \$2.1 billion in 2008 and has become Medicare's largest drug expenditure. DaVita, one of the largest chain dialysis providers, was investigated for overbilling dialysis drugs.[7] Thamer et al. (2007) found that large profit-seeking chain facilities used larger dose of Epogen and suggested this is due to the profit incentives. The excessive use of drugs such as Epogen not only increases the Medicare expenditure, but also raises cardiovascular risk (e.g. heart attack, stroke etc.) and subsequently lowers the quality of life of ESRD patients.

In 2008, Medicare proposed a new payment system and eliminated the drug incentive by incorpo-

by patients at home.

[6] ESRD was recognized as disability under the Medicare Reform Act in 1972. The legislation was signed into law and became effective in 1973.

[7] In 2006, 25% of DaVita's revenue came from Epogen. The government decided not to pursue the case in 2011.

rating separate billable items into an expanded bundled payment.[8] Additionally, pay-for-performance quality incentives were introduced under the new system. Dialysis providers whose quality of service (as measured by patient's hemoglobin and urea levels) fails to meet standards could be penalized with a reduction in the rate of up to 2 percent. The new dialysis payment system became effective in 2011 and the full implementation is expected to take place in 2014.

The new Medicare reimbursement rule could have a significant impact on dialysis providers. The Government Accountability Office estimates an $880 million saving on dialysis payments.[9] Our counterfactual experiments are motivated by this reform and investigate how dialysis providers respond to different adjustments in the reimbursement rate.

2.3 Dialysis Market

The dialysis market in the U.S can be characterized as a duopoly. In 2007, DaVita and Fresenius Medical Care (FMC), the two largest national chains, jointly treated over 66% of dialysis patients (31% by DaVita vs. 35% by FMC) and owned around 66% of the dialysis facilities (30% by DaVita vs. 36% by FMC).[10] Both national chains grew significantly after a series of consolidations in the 2000s. In 2004, DaVita bought Gambro who owned over 550 facilities in 2005 and FMC bought Renal Care Group with more than 450 facilities.[11] Overall, the mergers between 2004 through 2006 consolidated the six largest chains into two. As of 2007, the market has been dominated by these two major chain providers.

We focus on three types of dialysis providers: FMC, DaVita and all other providers (referred to as non-chain providers). Given the proximity in the time frame between 2004 and 2006 when these major consolidations and subsequent market reorganization took place, we believe that the decisions of providers can be treated as made simultaneously. Using information on the capacity of dialysis providers between 2004 and 2009, we find that 1) both DaVita and FMC adjusted their choices of capacity in the acquired facilities immediately following the merger, and 2) capacity in the acquired facilities has hardly changed since 2007. These facts offer evidence that the providers' choices of capacity reported in data should be interpreted as equilibrium outcomes.

[8] For example, the Medicare base rate per dialysis session was $133.81 while it was $229.63 under the 2008 proposal. Note that the proposed base rate incorporates all separable billable services including lab test and injectable drugs.

[9] Source: http://www.ama-assn.org/amednews/2012/12/24/gvsd1226.htm

[10] Source: USRDS Atlas of ESRD 2009, Chapter 10.

[11] The merger between FMC and Renal Care Group was announced in May 2005 and completed in March 2006.

3 A Model of Capacity Choices with Private Information

We now specify a model of simultaneous Bayesian games with continuous actions. Consider a market that is served by N providers competing through the choices of capacity. A provider (firm) i's profit from choosing capacity K_i in a market m, as measured by the number of dialysis stations, is given by

$$\Pi_{i,m}(K_{i,m}, K_{-i,m}, X_m, \varepsilon_{i,m}) = K_{i,m}\pi_i(X_m, K_{-i,m}, \varepsilon_{i,m}) - c_i(K_{i,m}). \quad (1)$$

The function $\pi_i(X_m, K_{-i,m}, \varepsilon_{i,m})$ is the variable profit for i per unit in capacity (A provider's variable profit per unit in a market is defined as the ratio between its gross profits before subtracting the fixed costs in c_i and its total capacity in that market.) It depends on the vector of competitors' capacity $K_{-i,m} \equiv (K_{j,m})_{j\neq i}$, the market characteristics X_m, and an idiosyncratic profit component $\varepsilon_{i,m}$ which is i's private information. We assume $\varepsilon_{i,m}$ are independent across providers conditional on X_m. To simplify notation, we drop the subscript m below.

An implication of the specification above is that the gross variable profit for a provider is proportional to its choice of capacity. This is motivated by the observation that each dialysis machine receives a flat rate from Medicare for each treatment. A typical dialysis patient receives three treatments per week, each lasting for about four hours. An additional hour is needed for setting up and cleaning the machine per treatment. This sums to 15 hours per week. On average, a dialysis machine treats 3 to 5 patients per week. During a treatment, operating staff such as registered nurses and technicians need to overlook the patients and perform routine checks. Given the fixed rate for a dialysis treatment, it is plausible that a provider's variable profit is approximately proportional to its dialysis capacity, as measured by the number of dialysis stations.

We adopt a linear specification of per-unit variable profit π_i:

$$\pi_i(X, K_{-i}, \varepsilon_i) = X\beta_i + \textstyle\sum_{j\neq i}\gamma_{i,j}K_j - \varepsilon_i$$

where $\gamma_{i,j}$ are heterogeneous marginal effects of j's capacity on i's per unit variable profits. There are two reasons for this simplistic specification.

First, this linear specification for π_i can be interpreted as a practical reduced-form approximation (regression) of actual variable profit per unit in capacity in the data-generating process. Using this as a benchmark helps us to understand how strategic capacity choices determine market outcome and firms' profits. As we show in Section 6, this specification explains a large portion of the variation in capacity choices reported in data. It is worth noting that a provider's own capacity is not included in the specification for per capacity variable profits π_i. This means the gross variable profits are proportional rather than quadratic in a provider's own capacity. As explained above, such proportionality is mostly motivated by the inelastic market demand for dialysis treatment, and the fixed rates for dialysis treatment set by Medicare.

Second, focusing on this linear specification allows us to establish the identification of marginal effects of market characteristics on profits. In principle, we could extend our estimation algorithm in Section 4 below to a richer structural model (such as one with market-level unobserved heterogeneity) in order to fit the data better. Yet this is known to raise new challenges with the identification of structural parameters, in particular the marginal effects of capacity and market conditions on providers' profits.

The firm-specific fixed cost is given by:

$$c_i(K_i) = a_i K_i^2 + b_i K_i, \text{ where } a_i > 0.$$

We adopt a quadratic cost specification for the following reasons. First, the assumption of constant scale of economy (i.e. costs are linear in capacity) is not plausible in the dialysis industry. Adding a dialysis station not only involves significant investment, but also requires additional space, maintenance and personnel (e.g. technician and nurses) etc., whose supply is relatively inelastic. The quadratic form is helpful to capture such feature as well. Second, quadratic costs take a flexible nonlinear form and thus can be considered as a second-order polynomial approximation to more complicated cost structures. Our estimation algorithm below can be extended to allow for higher-order polynomials in the specification. Finally, that there is no constant term in the quadratic function is due to the need for a location normalization: i.e., profits from no entry ($K_i = 0$) need to be zero.

We assume choices of capacity in data are rationalized by providers' strategies in a pure-strategy Bayesian Nash equilibrium (PBNE). A pure strategy for a provider i is a mapping from its information set (X, ε_i) into the support for capacity ($\mathbb{R}_+$). A profile of pure-strategies $\{K_i^*(.)\}_{i \in N}$ forms a PBNE if:

$$K_i^*(X, \varepsilon_i) = \arg \max_{K_i \in \mathbb{R}_+} \mathbb{E}_{\varepsilon_{-i}} \left[\Pi_i(K_i, K_{-i}^*(X, \varepsilon_{-i}), X, \varepsilon_i) | X, \varepsilon_i \right] \tag{2}$$

where $K_{-i}^*(X, \varepsilon_{-i})$ is a shorthand for $\{K_j^*(X, \varepsilon_j) : j \neq i\}$. The case with $K_i = 0$ means provider i decides not to enter the market. Existence of PBNE in our model follows from Theorem 3 in Athey (2001) and the fact that the cross-derivatives of the ex post profit for i with respect to (K_i, K_j) and (K_i, ε_j) are constants.

Next, we derive the first-order condition for PBNE, which is the foundation for our estimators. We adopt a conventional regularity condition that ensures the order of differentiation and integration in $\frac{\partial}{\partial K_i}\mathbb{E}_{\varepsilon_{-i}}\left[\Pi_i(K_i, K_{-i}(X,\varepsilon_{-i}), X, \varepsilon_i)|X,\varepsilon_i\right]$ can be switched for all i and vectors of admissible strategies $K_{-i}(X,\varepsilon_{-i})$.

Proposition 1 *Under the model assumptions above,*

$$K_i^*(X,\varepsilon_i) = \max\left\{0, \frac{1}{2a_i}\left(X\beta_i + \sum_{j\neq i}\gamma_{i,j}\mathbb{E}_{\varepsilon_j}\left[K_j^*(X,\varepsilon_j)|X,\varepsilon_i\right] - b_i - \varepsilon_i\right)\right\} \tag{3}$$

in any PBNE.

This proposition has a couple of key implications for estimation. First, it implies the scale of $a_i, b_i, \beta_i, \gamma_{i,j}$ and the distribution of ε_i cannot be jointly recovered from (3). Hence without loss of generality we set $a_i = 1/2$ as a necessary scale normalization.[12] Second, the equilibrium condition in (3) is similar to a single-agent censored regression, except that a subvector of its regressors now consists of equilibrium objects $\{\mathbb{E}_{\varepsilon_j}[K_j^*|x,\varepsilon_i] : j \neq i\}$. Thus the model lends itself to standard maximum likelihood estimation of censored regressions with generated regressors.

We conclude this section with further justifications of our modeling choices, citing distinctive institutional features of the dialysis market. First, providers' choices of capacity are essentially continuous. Our data show such capacity choices for a provider in a market could range from 0 to almost 60. With such a large action space, it is practically infeasible to apply a typical multinomial choice framework to analyze capacity decisions.

Second, a dialysis provider rarely adjusts its capacity after its initial entry (Grieco and McDevitt 2013). This indicates that providers' market entry decisions are practically made simultaneously with their continuous choices of capacity. Both decisions are de facto permanent, based on providers' expectation about market profitability.

Finally, providers interact through a simultaneous game with incomplete information, because each dialysis provider has little information about components that affect its competitors' profits (e.g., randomness in their nephrologists' referral patterns and idiosyncratic elements in their operating and maintenance costs). Hence a provider's payoff depends on idiosyncratic information that is not known to others. An alternative assumption of complete information would have ignored such idiosyncrasies in a provider's private information set.

[12] The scale parameter a_i could be identified if additional data is available. For instance, if the average per-unit variable profits for each provider are reported in data, then they can be used to jointly identify the scale parameter along with other parameters in the profit functions.

4 Econometric Methods

We now discuss the identification of coefficients $\beta_i, \gamma_{i,j}, b_i$ in (3) using a typical two-step argument. First, under the assumption that private information is independent across players conditional on market characteristics, player i's expectation for a competitor js' capacity in (3) is a function of market characteristics X alone.[13] Provided that data is rationalized by a single profile of PBNE strategies $\{K_i^* : i \in N\}$, this function is identifiable as the expectation of K_j^* conditional on X. With the scale normalization $a_i = 1/2$, (3) becomes

$$K_i^*(X, \varepsilon_i) = \max\left\{0, X\beta_i + \textstyle\sum_{j\neq i} \gamma_{i,j}\varphi_j(X) - b_i - \varepsilon_i\right\} \tag{4}$$

for all i, where $\varphi_i(X) \equiv \mathbb{E}_{\varepsilon_j}[K_j^*(X, \varepsilon_j)|X]$ is directly identifiable if the data is generated from a single PBNE. With the distribution of ε_i parameterized (e.g. as a normal or a logistic distribution), the joint identification of $\beta_i, \gamma_{i,j}, b_i$ and parameters in the distribution of ε_i follows from typical arguments for parametric Tobit models, as long as the vector of X and $\{\varphi_j(X)\}_{j\neq i}$ under equilibrium demonstrates sufficient variation (i.e. their joint support satisfies a typical mild full-rank condition).[14]

This identification strategy leads to the following two-step estimator: In the *first* step, estimate the expectation of providers' equilibrium capacity choices $\hat{\varphi}_i(X)$. This could be done either using kernel estimators (with the local constant or the polynomial approach), or using sieves estimators with polynomial bases. We adopt the latter approach for the estimates reported in Section 6. That is,

$$\hat{\varphi}_j(x_g) \equiv \min_{\{\alpha_s\}_{0\leq s\leq S}} \tfrac{1}{G}\textstyle\sum_{g=1}^{G}\left[k_{g,j} - \textstyle\sum_{s=0}^{S}\alpha_s x_g^s\right]^2 \tag{5}$$

where g is an index for the G independent games (markets) observed in data; and $k_{g,j}, x_g$ are realizations of K_j, X in market g. We set the order S to four in estimation. Alternatively, to reduce computational costs in estimation, one may choose to replace these first-step nonparametric estimates with those from a reduced-form Poisson regression. A Poisson regression works well in practice when the shapes of the empirical distribution of dependent variables are close to some distributions from the exponential family. (See Cameron and Trivedi (1998) and Christensen (1997) for details.) In such cases, Poisson regressions are known to provide good approximations in terms of model fit, especially

[13] In case the actual data-generating process is such that the firms' private information are positively (or negatively) correlated, our estimates may understate (or overstate) the negative effects of competitors' capacity choices on a provider's profits.

[14] In fact, the identification of coefficients $\beta_i, \gamma_{i,j}, b_i$ can be shown for (4) under nonparametric stochastic restrictions on ε_i instead of parametric assumptions. Examples of these stochastic restrictions include: independence between ε_i and X as in Buckley and James (1979) and Horowitz (1986); conditional symmetry as in Powell (1986); and median independence in Powell (1984).

when the dependent variables are continuous or count data, as is the case in our application.

In the *second* step, use a maximum likelihood estimator where the distribution of ε_i is parameterized (e.g., $\varepsilon_i \tilde{} N(0,\sigma_i^2)$ for all i, where σ_i^2 is a parameter to be estimated). Specifically, let $\theta \equiv (\theta_i)_{i\in N}$ where $\theta_i \equiv (\beta_i, \{\gamma_{i,j}\}_{j\neq i}, b_i, \sigma_i)$. Our two-stage estimator is defined as

$$\hat{\theta}^{TS} \equiv \arg\max_\theta \tfrac{1}{G} \log \hat{L}_G(\theta)$$

where

$$\begin{aligned}
\hat{L}_G(\theta) \quad &\equiv \quad \textstyle\prod_{g\leq G} \prod_{i\in N} \hat{f}_i(k_{g,i} \mid x_g;\theta_i); \text{ and} \qquad (6)\\
\hat{f}_i(k_i \mid x;\theta_i) \equiv &\quad \left\{1-\Phi\left(\frac{x\beta_i + \sum_{j\neq i}\gamma_{i,j}\hat{\varphi}_j(x) - b_i}{\sigma_i}\right)\right\}^{1(k_i=0)} \left\{\frac{1}{\sigma_i}\phi\left(\frac{k_i - x\beta_i - \sum_{j\neq i}\gamma_{i,j}\hat{\varphi}_j(x) + b_i}{\sigma_i}\right)\right\}^{1(k_i>0)}.
\end{aligned}$$

With the number of bases used in the first-step polynomial estimation expanding at an appropriate rate as the sample size increases, the preliminary estimate $\hat{\varphi}_j(.)$ converges to the true function uniformly at a rate fast enough to maintain the root-n asymptotic normality of the second step MLE estimators.

Alternatively, one could also use another likelihood-based estimator, denoted $\hat{\theta}^{FL}$, which adopts a full nested fixed-point maximum-likelihood approach. This estimator amounts to replacing the first-step estimates $\hat{\varphi}_i$ in the two-stage estimator $\hat{\theta}^{TS}$ by $\tilde{\varphi}_i(x;\theta)$, which is defined as the solution for $\{\varphi_i(x)\}_{i\in N}$ in the following fixed-point equation: For all $i \in N$,

$$\varphi_i(X) \equiv \mathbb{E}_{\varepsilon_i}[K_i^*(X,\varepsilon_i)|X] = \mathbb{E}_{\varepsilon_i}\left[\max\left\{0\ ,\ X\beta_i + \textstyle\sum_{j\neq i}\gamma_{i,j}\varphi_j(X) - b_i - \varepsilon_i\right\}\Big| X\right]. \qquad (7)$$

Such an estimator is feasible under our specification of π_i and parameterization of the private information distribution.[15] The nested maximum-likelihood estimator used in our case is analogous to that applied widely to dynamic discrete choice models (e.g. Rust 1987).

It is possible to improve efficiency in estimation using a General-Method-of-Moment (GMM) framework that further exploits the fixed-point characterization of ex ante equilibrium capacities in the

[15] Under normality assumption of ε, (7) has a closed form

$$\varphi_i = \Phi\left(\frac{x\beta_i + \sum_{j\neq i}\gamma_{i,j}\varphi_j - b_i}{\sigma_i}\right) * \left\{x\beta_i + \sum_{j\neq i}\gamma_{i,j}\varphi_j - b_i + \sigma_i \frac{\phi\left(\frac{x\beta_i+\sum_{j\neq i}\gamma_{i,j}\varphi_j - b_i}{\sigma_i}\right)}{\Phi\left(\frac{x\beta_i+\sum_{j\neq i}\gamma_{i,j}\varphi_j - b_i}{\sigma_i}\right)}\right\}$$

for $i \in N$, where φ_i is the expectation of provider i's capacity in equilibrium.

second step of the two-stage estimator above. To this end, we propose a third, GMM estimator that incorporates the structural fixed-point equation (7) which characterizes the expected capacity for each provider in a PSBNE. More specifically, the GMM estimator is:

$$\hat{\theta}^{GM} \equiv \arg\min_{\theta} \hat{M}'_G(\theta)\hat{W}_G\hat{M}_G(\theta)$$

where the empirical moments are:

$$\hat{M}_G(\theta) \equiv \left[\tfrac{1}{G}\nabla_\theta \log \hat{L}_G(\theta) \quad ; \quad \tfrac{1}{G}\textstyle\sum_{g\leq G}\sum_{i\in N}\left[\tilde{\varphi}_i(x_g;\theta) - \hat{\varphi}_i(x_g)\right]^2\right] \tag{8}$$

where $\hat{L}_G(\theta)$ is defined in (6); $\hat{W}_G$ is a consistent estimator for the optimal GMM weight matrix; $\hat{\varphi}_i(x)$ is the first-stage non-parametric estimates for expected capacities in equilibrium (e.g. a polynomial approximation defined in (5)); and $\tilde{\varphi}_i(x;\theta)$ is a solution for $\{\varphi_i(x)\}_{i\in N}$ in (7) at $X = x$ given the vector of parameters θ. Alternatively, in order to reduce computational costs, one can also choose to replace $\hat{\varphi}_i(.)$ with the fitted values of expected capacities based on a reduced-form Poisson regression. We adopt this approach in our estimation later. In Section 6, we first obtain initial GMM estimates by setting the weight matrix to be the identity matrix. We then estimate the optimal weight matrix $\hat{W}_G$ using the initial estimates, and apply it to weighted GMM to improve estimation efficiency.

We conclude this section with several remarks regarding the issue of multiple equilibria and the comparison between the three estimators $\hat{\theta}^{TS}$, $\hat{\theta}^{FL}$ and $\hat{\theta}^{GM}$.

Remark 1. For any given market characteristics x and any vector of parameters θ, there could potentially be multiple solutions for $\{\varphi_i(x)\}_{i\in N}$ in (7). However, such multiplicity does not affect the validity of our two-stage estimator under the common assumption that the data is rationalized by a single Bayesian Nash equilibrium (BNE). This is because, under this single equilibrium assumption, a provider's expected capacity in the likelihood is directly identified from data, rather than solved for from (7).

On the other hand, the full nested fixed-point MLE estimator is susceptible to the issue of multiple equilibria. To deal with this, we do not directly apply the original nested fixed-point MLE, but instead adopt an alternative approach proposed by Judd and Su (2012). This approach, known as the "Mathematical Program with Equilibrium Constraints" (MPEC), reformulates the original problem into the maximization of likelihood over the space of structural parameters and strategies subject to a set of constraints that define PBNE. Hence it avoids the need to solve for the inner loop in the full nested fixed-point MLE. The MPEC algorithm implicitly deals with the multiplicity issue through an effective ad hoc procedure, which always picks an equilibrium that maximizes the likelihood. More detailed discussions are included in Section 5.3.

Remark 2. The afore-mentioned multiplicity also does not affect the validity (consistency) of our GMM estimator under the assumption of a single BNE in the data, as we have incorporated the following ad hoc procedure in the calculation of $\hat{\theta}^{GM}$. Suppose for some (x_g, θ) the system of equations in (7) admits multiple solutions of the vector $\tilde{\varphi}(x_g; \theta) \equiv \{\tilde{\varphi}_i(x_g; \theta)\}_{i \in N}$ (which are often picked up by experimenting with multiple initial points while solving the nonlinear fixed-point equation in (7)). In such cases, choose the vector of $\tilde{\varphi}(x_g; \theta)$ that minimizes the empirical moments in (8) while evaluating the objective function of GMM. To see how such a procedure maintains the consistency of $\hat{\theta}^{GM}$ under multiple equilibria, note the second set of moments in (8) takes a form similar to the objective function of a minimum-distance estimator. Thus, this procedure is effectively using the directly identifiable $\mathbb{E}[K_i^*(X, \varepsilon_i)|X]$ to guide our choices of equilibrium-implied expected capacities while implementing GMM.

Remark 3. The two-stage estimator $\hat{\theta}^{TS}$ and the full nested fixed-point ML estimator $\hat{\theta}^{FL}$ have respective advantages. As explained in Remark 1, $\hat{\theta}^{TS}$ is robust to the issue of multiple equilibria but does not explicitly use the structure in the fixed-point characterization of ex ante capacities in equilibrium (i.e. the φ_i's). In contrast, $\hat{\theta}^{FL}$ is explicit in exploiting this structural relation defining $\{\varphi_i\}_{i \in N}$, but is potentially susceptible to the issue of multiple equilibria.[16] Therefore, choices between the two should depend on researchers' judgment about the possibility of multiple equilibria in the data-generating process. The GMM estimator $\hat{\theta}^{GM}$, on the other hand, provides the benefits of both estimators. Due to the use of the second moments, the GMM estimator not only exploits the structural relations defining ex ante capacities, but also manages to deal with the issue of equilibrium multiplicity under the assumption that choices of capacity in data are rationalized by a single pure-strategy Bayesian Nash equilibrium.

5 Data Description

5.1 Construction of the Sample and the Definition of Markets

We construct our sample from the Dialysis Facility Compare Data published by the Center for Medicare and Medicaid Services in 2007. The CMS receives monthly updates about the characteristics of each facility (e.g. name, address, chain affiliation, number of dialysis stations, date of certification

[16] The full-maximum-likelihood estimator should be more efficient than the two-step estimator, provided the identification of parameters holds under the parameterization, and the model always admits a unique PBNE under all x and θ.

etc.) and posts them online every quarter. A similar dataset has been used by several recent studies on the dialysis market including Ramanarayanan and Snyder (2011), Grieco and McDevitt (2013), and Cutler, Dafny and Ody (2012). The key variable of interest is a provider's choice of capacity, or the number of dialysis stations.

The market for out-patient dialysis is local in nature. Dialysis patients usually receive three treatment sessions per week, each of which lasts for about four hours. They are in general unwilling (or unable) to travel too far. According to the Medicare Payment Advisory Commission (MedPAC), the median driving distance between patients and dialysis facility is six miles. Following several other studies on dialysis markets (e.g. Grieco and McDevitt 2013, Cutler, Dafny and Ody 2012), we use Hospital Service Area (HSA) to delineate the local market. HSA is compiled by the Dartmouth Atlas from Medicare data on patients' choices of hospitals. Such an area is relatively self-contained with respect to healthcare services.[17] The number of HSAs in the U.S. is roughly equal to the number of U.S. counties; however, their boundaries don't overlap in general. Unfortunately, demographics such as population, age and racial composition are not available at the HSA level. To obtain the market-level profit and the cost shifters, we assign each HSA to a county based on the population distribution within HSA.[18] Then we use county-level demographics data from U.S. Census (e.g. racial composition, age, income, poverty, size of business payroll etc.) to approximate the population characteristics within an HSA.

We supplement the demographics data from the census with hospital and physician capacity data from the Dartmouth Atlas. While the Dartmouth Atlas only reports this information for 2006, it provides a good approximation for 2007 because there were no major shifts in the industry environment between these two consecutive years. We use the age-adjusted prevalence rate of diabetes as proxies for ESRD risks. We also use hospital beds and the number of nephrologists to control for the base demand and intensity of health care. We include these variables because the market population alone does not accurately reflect the size of the customer base relevant to the dialysis service industry. By including the diabetic prevalence rates and other factors related to ERSD risks, we expect to obtain a better measure of the size of the customer base for dialysis treatment in each market. Hence our treatment of the market size differs slightly from the classical approach in entry games such as in Bresnahan and Reiss (1991), but is comparable to those in Jia (2008) and Ciliberto and Tamer (2009).

[17] Specifically, an HSA is defined by assigning ZIP codes to the hospital area where the greatest proportion of their Medicare residents (including those with ESRD) were hospitalized. In the absence of detailed patient-level information, HSA approximates geographic markets for dialysis more closely than alternative definitions (e.g., county, state or metropolitan statistical area).

[18] We decompose each HSA into a collection of zip codes and obtain the population for each zip from the Census. We assign HSA to a county if that county contains the largest proportion of HSA population.

Moreover, our estimation results below show these additional variables explain a significant portion of the variation in the capacity choice of dialysis providers.

Following Ford and Kaserman (1993), who showed the certificate of need (CON) regulation discouraged entry by requiring additional regulatory procedure for providers to establish their market presence, we construct a binary indicator for the state level CON regulation. Finally, we use the distance between an HSA and the headquarters of the chains as cost shifters.[19]

The distribution of dialysis capacity is highly skewed. For example, in a sample that includes almost all HSAs in the lower 48 states, the average market capacity in a given market is about 21, but the total dialysis capacity in some markets can be as high as 1309. The high capacity outliers usually lie in heavily populated cities such as Chicago, Los Angeles etc.. In these markets, chain providers often operate multiple branches in close proximity to each other. The nature of competitive interactions is clearly different from an average market. For our analysis, we choose to focus on areas with population between 40,000 and 800,000.[20] We exclude another 124 outliers with total market capacity greater than 60.[21] As a robustness check, we perform the analysis in larger samples that include almost all HSAs using the two-stage estimator. We obtain results very similar to what we report in the paper. These additional results are reported in Panel A Table A1 in the appendix. Our main results are also robust to alternative sample selection criterion as shown in Panel B and Panel C in Table A1.[22]

Our final sample contains 1320 HSA and 1287 facilities in the 48 contiguous states in 2007. Conditional on entry into these markets, chain dialysis providers usually open a single branch. One potential concern is that capacity decisions of chain providers are correlated across markets. However, such a concern is minimal for our analysis since our sample selection criterion ensures the markets are relatively isolated. A back-of-envelope spatial analysis shows that the average distance from an FMC

[19] We use the HSA boundary file from Dartmouth Atlas to pin point the centroid for the market. The distance from the geographical center of each HSA to the headquarters of either chain is calculated using the Haversine formula.

[20] This eliminates 1646 HSAs, most of which are sparsely populated rural areas and quite different from an average market. According to MedPAC, the median distance between a rural patient and a dialysis station is almost four times longer than for urban patients. Therefore patients in rural areas are more likely to seek outside options such as hospital units or home dialysis service. Nevertheless, we test the robustness of our results in panel (A) of Table A1 using an alternative sample selection criterion based on an enlarged sample with more than 3000 HSAs and get results very similar to our main specification. Besides, our sample selection criterion is in line with other studies in the literature (e.g., Bresnahan and Reiss (1991), Collard-Wexler (2013)).

[21] Our current cutoff is approximately the 90th percentile in the distribution of total capacity in a market. Our results are robust to alternative cutoff values (e.g. the 95th or the 85th percentile in capacity distribution). See panels B and C in Table A1 for details.

[22] There is no obvious evidence that the actual geographic market should be more disaggregated than HSA. If the actual market is more disaggregated than HSA, we would obtain very different results when large markets are excluded from the estimation sample. In an additional robustness check, we perform our analysis using the two-stage estimator after excluding market in areas with more than 200,000 residents. The estimates obtained using the smaller sample are similar to our main specification.

facility in the sample to its closest FMC neighbor is 12.5 miles while the statistic for DaVita is 12.3 miles.[23] Most of the facilities (287 out of 353 for DaVita and 242 out of 490 for FMC) are not within 10 miles radius of another facility of the same chain. Overall, there is no evidence that correlation between capacity decisions should be a concern for our analysis.

5.2 Descriptive Statistics

Table 1 summarizes the capacity choices of FMC, DaVita and non-chain providers. There are two significant empirical regularities. First, dialysis providers' capacity choices vary substantially over a wide support. For example, the average capacity of FMC is 6.4 followed by non-Chain and DaVita with the standard deviation ranging between 9.22 and 11.4. While one may estimate a multinomial choice model by grouping capacity levels into aggregate categories (such as low, medium and high capacity), this type of exercise would overlook the information contained in the rich variation in the choices of capacity. Furthermore, in our sample, the number of dialysis stations in a given facility ranges from 1 to 54. Thus, even after removing the outliers, the action space remains too large for a multinomial choice model. Therefore we analyze dialysis providers' capacity decisions as continuous choices. Second, there is a substantial number of markets in which some providers choose not to enter. FMC, the largest provider, enters about 31% of the markets (followed by non-Chain 28% and DaVita 23%). Thus the overall *unconditional* expectation of capacity is much smaller than the mean capacity *conditional on entry*.

The correlation between entry and capacity decisions in Table 2 presents descriptive evidence for strategic interactions. A provider's market presence and capacity choice are both negatively correlated with its competitors'. For example, the correlation between FMC and DaVita's entry decisions is –0.12, while the correlation between FMC's capacity and DaVita's entry decision is -0.14. This suggests DaVita and FMC generally enter different markets, and DaVita is even less likely to enter when FMC chooses a larger capacity.

However, we cannot infer from these aggregate correlation patterns alone that all providers' response curves to competitors' choices of capacity are downward sloping, for this would risk overlooking the heterogeneity in providers' profit and cost structures. The observed aggregate correlation pattern in Table 2 could be driven by a subset of providers or a subset of markets in data and thus may not be representative of the other providers or markets in general. Indeed, a key motivation for our structural analyses in Section 4 is the need to account for such heterogeneity in the reaction curve across providers.

[23] The calculation of distances is based on both in sample and out of sample facilities.

Table 3 presents summary statistics of the market demographics. An average market in our sample is populated by 75,531 residents, 1,030 miles away from FMC's headquarter and 1,100 miles away from Davita's headquarter. About 23 percent of the markets are located in the northeast region, 24 percent in the mid-west, 17 percent in the west and the remaining 31 percent in the south. The CON regulation is effective in 21 percent of the markets. We employ a parsimonious set of profit and cost shifters including percent of population over 65, racial composition etc. In alternative specifications, we experiment with a larger set of variables such as poverty rate, income, population density, size of business payroll, number of uninsured, the number of hospital registered nurses, the size and racial mixes of Medicare enrollees etc. These variables do little to explain the variation in dialysis capacity and therefore we did not include them in our main specification.

5.3 Details in implementing the estimators

We estimate the model using the estimators described in Section 4. Table 4 presents the results. Panel A, B and C present the results from the two-stage estimator $\hat{\theta}^{TS}$, the maximum likelihood (nested fixed-point) estimator $\hat{\theta}^{FL}$, and the GMM estimator $\hat{\theta}^{GM}$ respectively. We now provide further details in the implementation of these estimators.

In the first step of the two-stage estimation, we adopt the Poisson regression approach to estimate each provider's expected capacity in equilibrium. That is, we fit the observed capacity choices to a Poisson distribution, and use it to estimate a provider's expected capacity. A Poisson regression is convenient because the observed capacity choices are non-negative with many observations censored at zero. In a finite sample with moderate size such as ours, a Poisson distribution fit the data better than the nonparametric alternative of polynomial approximation.[24] In the second step, we use a Tobit model to estimate the effect of $\widehat{\mathbb{E}}(K^*_{-i}|X)$ and X on K_i, where $\widehat{\mathbb{E}}(K^*_{-i}|X)$ is the predicted capacity obtained from the first step. We follow a standard bootstrap procedure to calculate the standard errors of the estimates, based on 300 bootstrap samples.

We estimate $\hat{\theta}^{FL}$ by reformulating the nested fixed-point MLE as the MPEC optimization strategy introduced by Judd and Su (2011). The standard maximization routines for calculating the nested fixed-point MLE is computationally demanding as it requires solving for equilibrium outcomes defined by the fixed-point mapping (7) in every market for every iteration of parameter values throughout the maximization routine. Besides, the issue of multiplicity arises in such routines because a given parameter may well admit more than one Bayesian Nash equilibria in general.

[24] The R^2 in Poisson regression are 31%, 30% and 23% for FMC, DaVita and non-Chain while they are 22%, 22% and 18% in polynomial approximation.

In comparison, the MPEC algorithm maximizes the likelihood with respect to both model parameters and providers' strategies (as characterized by each provider's expected capacity) in each market subject to the constraints that the expected capacity choices constitute an equilibrium in the model. As shown by Judd and Su (2011), the solution to the constrained maximum likelihood is equivalent to the solution of the nested fixed point. MPEC differs from nested fixed-point MLE computationally in that the constrained maximization in MPEC doesn't require solving for the non-linear fixed-point equation in every market. For our application, there are 1,320 markets with three choice variables in each market. The likelihood is maximized with respect to 3960 more parameters (in addition to the covariates of our empirical specification) subject to 3,960 constraints defined by (7). Besides, MPEC is also known to have dealt with the issue of multiple equilibria implicitly: That is, evaluating the likelihood at an MPEC solution is equivalent to evaluating the likelihood at a nested fixed-point MLE solution when the equilibrium selection mechanism is degenerate at an equilibrium that yields the highest likelihood. (For more details, see Proposition 1 in Judd and Su (2011) and the subsequent discussions.) The standard errors are obtained through the Hessian of the likelihood function evaluated at our estimates.

To implement our GMM estimator, we use two sets of moment conditions as defined in (8) in Section 4. The first set consists of the first-order condition for maximizing the likelihood defined in (6). The second set of moments match the expected capacity predicted in equilibrium to that directly recovered from data. To reduce computational costs, we use fitted values from a Poisson regression as the first-step estimates $\hat{\varphi}_i$ and use the MPEC algorithm to find the maximizer of the GMM objective function. We follow a standard sequential approach for estimation using GMM: That is, first obtain an initial GMM estimate by setting the weight matrix to be the identity matrix and then use it to compute the optimal weight matrix. We then re-estimate the model by substituting the optimal weight matrix into the GMM objective function. The standard errors for the GMM estimator $\hat{\theta}^{GM}$ are then calculated using the classical approach as in Section 6 of Newey and McFadden (1994).[25]

6 Results

6.1 Estimates

The estimates from each panel of Table 4 are close in magnitude. The standard errors for GMM estimators are often smaller than those for the two-step estimators (e.g. population, nephrologist,

[25] This classical approach essentially amounts to stacking all moments used for estimation together (i.e. including those used for estimating the linear coefficients in the Poisson regressions in the first step), and then estimating the covariance matrix based on such an augmented set of moments.

diabetes rate, register nurse, CON regulation etc.), especially the standard errors on coefficients of strategic variables. This seems to suggest gains in estimation efficiency from exploiting the equilibrium structure of our model. Since GMM is advantageous over two-stage and fixed point maximum likelihood, we will focus our discussion based on GMM estimates (unless otherwise indicated).

The strategic effect of rival's capacity is strongly significant with a negative sign. This result is robust to the estimators used. The magnitudes of the strategic coefficients suggest that FMC competes aggressively with all other providers. For example, according to the GMM estimates, the effect of FMC on DaVita is about 50% larger than the effect of non-Chain (-2.17 vs. -1.45) while it is 30% larger than the effect DaVita on non-Chain (-0.82 vs. -0.61). Nevertheless, there is no significant evidence that competition is more intense between the two chain providers. The difference in the strategic effects may be ascribed to the heterogeneity in providers and market conditions. For example, different providers often have access to different networks of nephrologists that they can expect to get referral from. Discrepancies in business strategies or management styles across providers may also explain part of the heterogeneities.

The strategic effects are quite large. A quick calculation of the marginal effects (similar to those in a Tobit model) suggests that, holding other factors in the profits fixed at their mean value, a one unit increase in DaVita's expected capacity in equilibrium decreases FMC's capacity by 0.24 units and a one unit increase in non-Chain's expected capacity decreases FMC's capacity by 0.27 unit. For both DaVita and non-Chain, FMC poses a stronger competitive pressure. A one unit increase in FMC's expected capacity reduces DaVita's capacity by 0.37 units while it reduces non-Chain's capacity by 0.21 units.

The strategic interactions between dialysis providers also imply a strong effect of capacity choices on competitors' entry probabilities. Our estimates imply that FMC poses the strongest competition to both DaVita and non-Chain. A one unit increase in FMC's capacity decreases the entry probability of DaVita and non-Chain by 0.03 and 0.01 in a market with average characteristics, which translates into 12.5 and 3.3 percentage point decreases.[26] Since each provider generally chooses different levels of capacity, a rival's presence should have a non-uniform effect across markets and the competition should be more intense when the rival chooses a higher capacity level. A model that focuses on discrete market entry decisions would have overlooked these heterogeneous competitive interactions.

The negative impact of competitors' capacities on a provider's profits may come from several distinct channels. First, additional competitors affect a provider's profits by splitting the existing customers from that provider. By diverting patients away from incumbents, the presence of an additional

[26] The percentage points are computed based on the mean entry probability of 0.24 and 0.30 for DaVita and non-Chain. The 0.03 points decrease in probability is equivalent to 0.03/0.24=12.5% in percentage points.

competitor may lower the utilization of the facilities, increase the variable cost per unit in capacity and lead to a lower margin per unit in capacity. Second, competition can also lead to a lower price for privately insured patients (e.g. Cutler and Dafny and Ody (2012)), and therefore lowers the average per-patient margin. Third, providers also compete for a limited supply of trained personnel (e.g. nurses and technicians) who operate dialysis stations to generate revenues. Fourth, for each provider, competitors with a higher capacity are likely to offer more flexible schedules, holding other things fixed (e.g. utilization rates) and thus have greater negative impact in terms of splitting customers. With more detailed patient- and facility-level data, it is possible to conduct a full structural analysis of patients' choices on the demand side, and thus distinguish the impacts of competitors' capacity through these distinct channels.

Most of the coefficients in Table 4 are significant with expected signs. The market size, the extent of diabetic population, the supply of local nephrologists and registered nurses are positively associated with the capacity of all providers while entry barriers such as CON regulation is negatively associated with capacity choices. Some market conditions may be important for one firm but not for others. This implies that dialysis firms target different demographics and it is important to account for firm heterogeneity. Distance to headquarters doesn't seem to be very important to the capacity choice of the two leading chain providers.[27] But non-chain providers are more likely to offer positive capacity when the market is farther away from either chain's headquarters.

To better understand the magnitude of these estimates, Table 5 reports the equilibrium response in capacity and the number of markets with high entry probabilities (i.e. greater than 50%) based on the GMM estimates when some market-level variables (i.e. population, number of nephrologists and diabetes prevalence rate) change.[28] To derive the effect on capacity, we resolve the equilibrium based on equation (7) after adjusting these market-level variables upward by 10%. The equilibrium entry probability of a provider on a market characterized by x is computed as

$$\Pr(K_i^* > 0|x) = \Phi[(x\beta_i + \textstyle\sum_{j\neq i} \gamma_{i,j}\mathbb{E}[K_j^*|x] - b_i)/\sigma_i] \tag{9}$$

and $E(K^*|X)$ is the new equilibrium capacity after the adjustment of market variables. We also calculate a measure of provider-specific "market penetration" under these hypothetical adjustments. Such a measure is defined as the proportion of markets in the sample where a provider would enter with probability greater than 50% under the adjustment considered.

[27] Distance to FMC's headquarter is marginally significant for DaVita. All other distance variables are insignificant for the two chain providers.

[28] The two-stage and maximum likelihood estimates generates very similar outcomes.

The effect of market size is quite substantial. When population increases by 10%, the total capacity unambiguously increases by 7%, 9% and 8% for FMC, DaVita and non-Chain while the market penetration (as measured by the number of markets with high entry probabilities for a provider) increases by 12%, 19% and 15% respectively. There are mild increases in capacity and market penetration measures when the number of nephrologists increases by 10%. The effect on non-Chain provider is the smallest. This is probably not too surprising since many non-chain dialysis facilities are owned and operated by the local nephrologist group. By contrast, chain facilities benefit more from a larger nephrologist stock since such stocks make it easier to locate medical directors with an established referral base. The increase in the prevalence rate of diabetes has heterogeneous effects on different providers. While FMC increases the capacity substantially, non-chain providers reduce the capacity while the capacity of DaVita remains almost constant. This seems to suggest that FMC exerts an intense competitive pressure on its competitors. In general, a larger diabetic patient base in a market increases the profitability of the dialysis business as a whole. However, for DaVita or non-Chain providers, this positive effect on profits is neutralized or reversed by an offsetting competition effect due to the expansion of FMC in the new market equilibrium. Such a competition effect is evident from our estimates for the negative strategic effects of capacity, which imply downward sloping reaction curves for all providers. A similar intuition could explain why both DaVita and non-Chain respond mildly to the repeal of CON regulation by increasing capacity while FMC increases capacity substantially.

As robustness checks, we estimate the model using a larger sample with 3129 markets (HSAs) with no population restrictions and the two-stage estimator. We report the results in Panel A of Table A1 in the appendix. This includes 92% of all HSAs in the continental US. In addition, we experimented with alternative sample selection criteria by focusing on markets with total capacity less than 80 or 40 (instead of 60 as in Panel A). The results in Panel B and Panel C of Table A1 remain qualitatively similar to those in Table 4.

It is worth noting that the results from Panel A in Table A1 also helps to justify indirectly the assumption that providers' private information are independent. To see these, suppose providers' private information is correlated due to some market conditions that are not reported in data but commonly known to all providers (e.g. limited supply of experienced nurses or managers). If such omitted conditions vary across markets and are known to be correlated with other market characteristics reported in data, then we should expect to obtain very different estimates of coefficients in the profit function using samples that differ in these reported market characteristics. In our context, it is plausible that unobserved conditions (such as the limited supply of qualified facility managers and staffs) are correlated with the population density of the markets. Table A1 (Panel A) reports estimates of strategic coefficients using the two-stage estimator in an enlarged sample with 3129 markets, which include those with substantially different population densities. These estimates are very similar to those based on a smaller sample in Table 4 (Panel A). This offers some evidence that the independent private information assumption works reasonably well in our setting.

6.2 Model Fit

We compute the fitted (implied) values of capacity choices and entry probabilities using three sets of estimates $\hat{\theta}^{TS}$, $\hat{\theta}^{FL}$, and $\hat{\theta}^{GM}$ respectively, and compare them with observed outcomes in data. Overall, the three estimators produce very similar results. Such a similarity is not surprising ex-post, because these estimators essentially use the same set of information.[29] These predictions also suggest that our model fits the data quite well.

First, we compute the expected capacity choice $\mathbb{E}(K^*|X)$ implied by model estimates. These expectations are solutions to the fixed-point equation in (7) based on the parameter estimates. We find the predicted expected capacity from all three estimators are close to the average capacity in data. For example, the average capacities in data are 6.40, 4.40 and 5.32 for each provider while our GMM estimates predict 6.06, 4.23 and 5.08 respectively. Results obtained from the two-stage and maximum likelihood estimates are similar. This suggests that our model estimates explain capacity choices quite well on average.

Second, we compute the implied entry probabilities for each provider, and compare them with entry probabilities observed in data. The predicted entry probabilities are calculated using (9) where $\mathbb{E}[K_i^*|x]$ solves the fixed-point equation in (7). The right panel in Table 6 reports the means and the standard deviations of such probabilities for each provider. The predicted entry probabilities are close to the entry proportions reported in data. For example, the empirical entry probability for DaVita is 0.23 in data, while our model predicts an average entry probability of 0.24. We also impute binary entry decisions based on whether the implied entry probability of a market is greater than 50% or not. Based on such imputations and GMM estimates, we find our model correctly predicts the binary entry decisions in 70%, 78% and 73% of the markets for FMC, DaVita and non-Chain respectively. Similarly, the proportion of correct predictions are 70%, 78%, and 65% based on the two-stage estimates; and 65%, 77% and 74% based on the maximum likelihood estimates. Overall, our model does well in

[29] Even in the ML estimator, the MPEC algorithm implicitly uses data to guide through multiple equilibria by always picking the vector of parameters and strategies that maximizes the likelihood. GMM estimator is computationally different from ML since one set of moments consists of the first order conditions (in analytical form) for maximizing the likelihood. Depending on the shape of the likelihood function around the true value of parameters, GMM estimates may be less susceptible to "optimization errors" in the minimization routine.

dealing with the censoring in capacity data.

Finally, we extrapolate from our sample and use our estimates to predict the capacity choices in 1809 medium to small HSAs that are not currently included in the sample used in Table 4.[30] Our model also does a good job in the out-of-sample prediction. Appendix Table A2 presents the comparison between the implied and the observed outcomes in the out-of-sample markets.

6.3 Counterfactual Analyses

Our counterfactual experiment is motivated by policy debates on how to curb the rapid growth of dialysis expenditure. Medicare started to implement a new bundled dialysis payment system in 2011. The new system incorporates the formerly separate billable items into a new bundled flat rate.[31] This effectively lowers the dialysis providers' margin per treatment. To capture this policy effect, let λ be a multiplication factor for variable profits and Δ for the costs.

The counterfactual payoffs under the alternative profit and cost factors is:

$$\Pi_i = \lambda K_i(x\beta_i + \textstyle\sum_{j\neq i}\gamma_{i,j}\mathbb{E}_{\varepsilon_j}[K_j(x,\varepsilon_j) \mid x] - \varepsilon_i) - \Delta(a_i K_i^2 + b_i K_i). \tag{10}$$

As shown in Section 3, under the scale normalization $a_i = 1/2$, the counterfactual equilibrium choices of capacity for provider i (denoted by $\tilde{K}_i$) must satisfy:

$$\tilde{K}_i(x,\varepsilon_i) = \max\left\{0, \frac{\lambda}{\Delta}\left(x\beta_i + \textstyle\sum_{j\neq i}\gamma_{i,j}\mathbb{E}_{\varepsilon_j}[\tilde{K}_j(x,\varepsilon_j) \mid x] - \varepsilon_i\right) - b_i\right\}. \tag{11}$$

For all i, let $\tilde{\varphi}_i = \mathbb{E}_{\varepsilon_i}(\tilde{K}_i(x,\varepsilon_i) \mid x)$ be the expected counterfactual capacity defined by the following equilibrium condition:

$$\tilde{\varphi}_i = \Phi\left(\frac{x\beta_i + \sum_{j\neq i}\gamma_{i,j}\tilde{\varphi}_j - b_i\frac{\Delta}{\lambda}}{\sigma_i}\right) * \frac{\lambda}{\Delta} * \left\{ x\beta_i + \textstyle\sum_{j\neq i}\gamma_{i,j}\tilde{\varphi}_j - b_i\frac{\Delta}{\lambda} + \sigma_i \frac{\phi\left(\frac{x\beta_i + \sum_{j\neq i}\gamma_{i,j}\tilde{\varphi}_j - b_i\frac{\Delta}{\lambda}}{\sigma_i}\right)}{\Phi\left(\frac{x\beta_i + \sum_{j\neq i}\gamma_{i,j}\tilde{\varphi}_j - b_i\frac{\Delta}{\lambda}}{\sigma_i}\right)} \right\}. \tag{12}$$

The predictions reported in Table 6 are for the status quo in data (i.e. when $\lambda = 1, \Delta = 1$). If the costs per unit in capacity increases by 20% and variable profits per unit incapacity decreases

[30] These markets are used to perform robustness analysis in Panel A of Appendix A1. There are 3129-1320=1809 markets, where 1320 is the number of markets included in the sample used in Table 4.

[31] The new system also incorporates some pay-for-performance incentives. Penalties will be imposed on providers whose dialysis quality measures (namely, patient's hemoglobin and urea levels) did not meet standards. The maximum payment reduction is up to 2 percent. We didn't explicitly investigate the pay-for-performance incentive in our analysis for two reasons. First, the incentive is relatively small. Second, several existing papers (Grieco and McDevitt 2012, Cutler, Dafny and Ody 2013) find that dialysis quality is not sensitive to competition.

by 10%, the counterfactual capacity distribution is obtained by adjusting $\frac{\lambda}{\Delta} = \frac{0.9}{1.2} = 0.75$ in (12). A similar counterfactual was applied by Schaumans and Verboven (2011) to investigate the market for healthcare professionals. According to MedPAC, the base composite rate under the old system is about \$142 per patient in 2012 (after excluding the \$20 drug add-on payment). Since the separate billable drugs account for approximately 40% of total Medicare payment for dialysis, this leads to an estimated average of \$257 per treatment payment. Given the new composite payment base rate of \$235 in the same year, there is approximately a 5% reduction in the per-patient payment. Due to the lack of the detailed data on patient-level payments and costs, we cannot precisely measure the reduction on the per-patient margin as a result of the reduction in the payment rate. Instead, we qualitatively investigate the new policy by lowering $\frac{\lambda}{\Delta}$ to different levels.[32] In Table 7, we report the predicted equilibrium outcome when $\frac{\lambda}{\Delta}$ is reduced by 2%, 5% and 8%. Possibilities also remain that the margin goes up for facilities who don't rely too much on the separate billable drugs. We also simulate the outcome when $\frac{\lambda}{\Delta}$ increases by 2%. Finally, we simulate the heterogeneous response to the policy reform by adjusting $\frac{\lambda}{\Delta} = 98\%$ for DaVita while holding the ratio $\frac{\lambda}{\Delta}$ constant for other providers. This is motivated by the established fact that DaVita relies heavily on drug revenues.

Table 7 presents predicted results for different counterfactual scenarios based on our GMM estimates.[33] The first three columns, labeled under "E(Capacity)", give summary statistics (i.e. the mean, the quartiles and the standard deviation) of the empirical distribution of expected equilibrium capacities predicted for each market. Likewise, the two columns, labeled under "E(Entry)" and "E(Capacity | Entry)", present summary statistics from the predicted distribution of counterfactual entry probabilities as well as the expected capacity choice conditional on entry for each provider.

For each provider, the quartiles and the mean under the new policy are almost always decreasing in the ratio experimented with. For example, for FMC, the median of the expected equilibrium capacities predicted for 1320 markets in data is 4.76 for the status quo ($\lambda/\Delta = 100\%$), but is decreased to 3.54 or 0.83 when $\lambda/\Delta = 98\%$ or 92%. The same pattern shows up for the other providers uniformly across all ratios experimented with. This seems to suggest the counterfactual distribution of expected capacities are stochastically decreasing in the size of reduction in the ratio λ/Δ. This conforms with the intuition that providers reduce their capacity choices in response to reductions in the margin.

[32] While it is clear that λ/Δ is closely related to the Medicare payment rate, the exact mapping between the two λ/Δ is not transparent due to our model specifications and in particular, due to the lack of facility-level data. If facility level data is available, one could regress the imputed provider profits implied by our model against the observed facility profits, come up with a factor that relates the model implied margin to the observed margin and use this factor to infer the magnitude of the change in λ/Δ as a result from the new policy. Our counterfactual analysis qualitatively investigates the effect of the new policy by lowering λ/Δ to various levels.

[33] Both the two-stage and maximum likelihood estimates give predictions that are very similar to the GMM estimates. To economize on space, we only report the results obtained from the GMM estimates in the paper.

The magnitudes of changes in response to the adjusted margins, however, are heterogeneous across the providers. The size of capacity changes at DaVita and FMC are less drastic than that for non-Chain providers. For example, for non-Chain providers, the median of the expected capacity increases from 4.19 to 6.30 when the ratio λ/Δ increases from the status quo to 102%; and reduces to 0.33 when the ratio drops to 92%. In comparison, for DaVita, the median of the expected capacity increases from 3.06 to 3.32 when the ratio λ/Δ increases from the status quo to 102%; and reduces to 0.55 when the markup ratio drops to 92%. This seems to suggest the local independent and non-chain providers are affected the most by a policy reform that reduces the margin for all providers uniformly by the same proportion.

Another finding from our estimates is that the capacity adjustment of DaVita tends to be negatively correlated with that of FMC. In fact, DaVita increases its capacity stock in 108 markets when $\frac{\lambda}{\Delta} = 95\%$. This pattern could be ascribed to the downward sloping reaction curve that results from strategic interactions in capacity choices. When a competitor reduces its capacity, the downward sloping reaction curve incentivizes a provider to increase its capacity. It also helps mitigate the negative impact on providers' choices of capacity and market presence when there are negative profit shocks.

The entry probabilities respond in a similar manner when the margin for all providers decreases by the same proportion. Non-Chain providers respond more strongly than FMC and DaVita. Though the average entry probability for DaVita decreases unambiguously with lower profit-to-cost ratio $\frac{\lambda}{\Delta}$, the number of markets with high entry probability increase substantially for DaVita when $\frac{\lambda}{\Delta} = 98\%$. Nevertheless, when the ratio is further reduced to $\frac{\lambda}{\Delta} = 95\%$, the number of such markets with high entry probabilities is remarkably lower than that under the status quo for DaVita.[34]

Since the policy reform can imply a positive profit shock for providers who are less reliant on drug revenues, we also investigate the outcome when $\frac{\lambda}{\Delta} = 102\%$ for all providers. FMC responds with more substantial increase in its capacity than non-Chain and DaVita. All in all, when the providers share the same market-wise profit shocks (such as reduction in the margin induced by the new payment policy), DaVita is expected to be more resistant to negative profit shocks and less responsive to positive profit shocks. This may arise from the asymmetries in providers' profit and cost structures as well as the difference in their strategic responses to their rival's capacity choice.

We then study the predictions under a provider-specific policy reform where there is a negative

[34] The counterfactual analysis in Table 7 also suggests that a small decrease in margin could induce significant reduction in capacity choices and entry probabilities. This is probably because even a small percentage reduction in markup on each dialysis station could sum up to a significant amount given that an average facility owns 18-20 stations. Another possible explanation of the large estimated effect of the policy change is that in most markets in our data, the markups are quite high (i.e. the difference between variable profits and fixed costs are reasonable large) so that a small discrepancy in the change of λ and Δ would affect the profitability of providers non-trivially. Besides, this effect is also compounded through the strategic interactions between providers.

profit shock for DaVita while there are no shocks for FMC and the non-chain providers. Specifically, we set $\frac{\lambda}{\Delta} = 0.98$ for DaVita and $\frac{\lambda}{\Delta} = 1$ for FMC and non-chain providers.[35] Our model predicts that DaVita reduces the capacity stock substantially while both rivals slightly increase their capacities. The negative profit shock for DaVita is magnified by the downward sloping reaction curve. When the margin decreases, a direct response for DaVita's is to reduce capacity. This motivates both FMC and non-Chain to increase their capacity through the reaction curve, which in turn serves as an additional incentive for DaVita to reduce capacity in the new equilibrium. Overall, our model suggests that with the downward sloping reaction curve, even a seemingly small asymmetric profit shocks could induce significant changes in dialysis providers' capacity choices.

We also report outcomes of counterfactual experiments for markets with different population and prevalence rate of diabetes. Table 8 presents the mean and the standard deviation of counterfactual expected capacity choices and entry probabilities in heterogeneous groups of markets with different population or prevalence rates of diabetes. Our goal is to learn about the distribution of counterfactual distributions of expected capacities and entry probabilities in different markets if Medicare were to adopt discriminatory reimbursement policies based on these observed market attributes.

We continue to find heterogeneities across FMC, DaVita and non-chain providers in their responses to margin reductions conditional on market characteristics. In addition, there is strong evidence that responses differ substantially across markets with different population or diabetes prevalence rates. For instance, if the profit margins measured by λ/Δ are reduced by 2% for markets with population above the median, then the average of expected choices of capacity in equilibrium will be reduced to 6.92, 6.76 and 5.32 for FMC, DaVita and non-chain providers respectively. Likewise in this case the average expected capacities will be reduced to 2.32, 1.29 and 1.39 respectively in markets with population below the median.

It is also worth noting that, other things being equal, the counterfactual distributions of expected choices of capacity and entry probabilities in markets with higher population or diabetes prevalence rates stochastically dominate those in markets with lower population or prevalence rates. This pattern could be explained by the fact that profits from markets with larger consumer bases respond more dramatically to changes in profit margins.

[35] As we explained previously, this is motivated by the observation that DaVita relies heavily on drug revenue. In 2007, New York Times reported that 40% of DaVita's revenue comes from dialysis related drugs. In comparison, 25% of FMC's revenue depends on drug.

7 Conclusion

Dialysis providers in the U.S. usually choose their operation scales (as measured by the number of dialysis stations) when they start to serve a market. Such capacity choices rarely change after the initial entry and vary substantially across providers and markets. To capture these empirical regularities, we propose a structural model of Bayesian games with continuous actions and use it to estimate providers' payoff structure and, in particular, the strategic interaction between providers' capacity choices. We estimate the model using several estimators, including a GMM estimator that fully exploits the structural relationship. We use the estimates to investigate counterfactual policy interventions that change providers' profit margin per unit in capacity.

Our estimates suggest the strategic interaction between providers leads to a downward sloping reaction curve in capacity choices. A dialysis provider's choice of capacity decreases with that of competitors. A unit increase in the expected capacity of a competitor reduces a provider's entry probability rather substantially. This suggests that conventional models of binary entry decisions would overlook the heterogeneity of strategic effects on providers' capacity choices and market presence. Our counterfactual analyses suggest that providers' responses to payment policies are heterogeneous; and the strategic interaction between the choices of capacity plays a significant part in determining these responses. Our econometric method is also of interests in its own right and can be applied to a wider class of Bayesian games with continuous choices.

Table 1. Summary Statistics of Capacity Distribution

Variable	Definition	Mean	Std.	min	max
K_{fmc}	FMC's Capacity Decision	6.40	11.4	0	60
K_{dav}	DaVita's Capacity Decision	4.40	9.22	0	54
$K_{nonchain}$	Non-Chain's Capacity Decision	5.32	10.0	0	58
I_{fmc}	$I(K_{fmc} > 0)$	0.31	0.46	0	1
I_{dav}	$I(K_{dav} > 0)$	0.23	0.42	0	1
$I_{nonchain}$	$I(K_{nonchain} > 0)$	0.28	0.45	0	1
$K_{fmc} \mid I_{fmc} = 1$	FMC's Capacity Decision Conditional on Entry	20.4	11.2	2	60
$K_{dav} \mid I_{dav} = 1$	DaVita's Capacity Decision Conditional on Entry	19.3	9.24	7	54
$K_{nonchain} \mid I_{nonchain} = 1$	Non-Chain's Capacity Decision Conditional on Entry	18.9	10.0	1	58

Note: obs=1320

Table 2. Capacity Correlations

	Correlation					
	I_{fmc}	I_{dav}	$I_{nonchain}$	K_{fmc}	K_{dav}	$K_{nonchain}$
I_{fmc}	1					
I_{dav}	-0.12	1				
$I_{nonchain}$	-0.13	-0.07	1			
K_{fmc}	0.83	-0.12	-0.12	1		
K_{dav}	-0.14	0.88	-0.04	-0.13	1	
$K_{nonchain}$	-0.13	-0.09	0.85	-0.13	-0.06	1

Note: obs=1320

Table 3. Summary Statistics of Market Variables

Variable	Definition	Mean	Std Dev
pop*	Total HSA pop from DA	75,531.17	65,734.43
black	Percent black from Census	0.07	0.09
white	Percent white from Census	0.88	0.11
latino	Percent latino from Census	0.09	0.11
asian	Percent asia from Census	0.02	0.03
age1	Percent pop age between 22 and 44 from Census	0.33	0.04
age2	Percent pop age between 44 and 65 from Census	0.34	0.04
age3	Percent pop age 65+ from Census	0.14	0.03
neph	Number of nephrologist per 1000 pop from DA	1.51	1.00
bed*	Number of hospital bed per 1000 pop from DA	2.59	0.89
rn	Number of registered nurse per 1000 pop from DA	1.32	0.27
dbrate	Prevelence rate of diabetes	8.42	1.63
conreg	CON regulation indicator	0.21	0.41
NE	Northeast region indicator	0.23	0.42
MW	Midwest region indicator	0.24	0.42
West	West region indicator	0.17	0.37
dfmc	Distance to FMC's headquarter in 1000 miles	1.03	0.73
dfmc2	dfmc sqaured	1.60	2.04
ddav	Distance to DaVita's headquarter in 1000 miles	1.10	0.38
ddav2	ddave sqaured	1.34	0.83

Note: obs=1320. Variables labeled by * enter the estimation in logs and are reported without logging in this table. Explanatory variables come from the DA (Dartmouth Atlas) or Census when indicated and otherwise are constructed by the authors.

Table 4. Strategic Capacity Model

	Panel A: Two-Stage Estimation ($\hat{\theta}^{TS}$)						Panel B: Fixed Point ML ($\hat{\theta}^{FL}$)						Panel C: GMM ($\hat{\theta}^{GM}$)					
	FMC		Dav		Non-Chain		FMC		Dav		Non-Chain		FMC		Dav		Non-Chain	
	EST	SE	EST	SE	EST	SE	EST	SE	EST	SE	EST	SE	EST	SE	EST	SE	EST	SE
K_{fmc}			-1.06	0.24***	-0.73	0.24***			-1.88	0.19***					-2.17	0.09***	-0.82	0.10***
K_{dav}	-1.07	0.26***			-0.68	0.26***	-2.32	0.25***			-1.86	0.22***	-0.76	0.10***			-0.61	0.08***
$K_{non-chain}$	-1.43	0.26***	-1.04	0.30***			-1.44	0.20***	-1.73	0.26***	-1.58	0.23***	-0.86	0.17***	-1.45	0.16***		
lpop	25.0	2.20***	24.9	2.43***	21.7	2.10***	25.0	1.59***	28.3	2.23***	26.9	2.11***	20.1	1.22***	35.1	1.19***	20.9	0.78***
neph	2.46	0.76***	3.38	0.99***	1.23	0.87	2.11	0.76***	2.34	0.89***	2.11	0.93**	2.00	0.11***	4.36	0.11***	2.00	0.05***
lbed	1.39	4.19	-5.34	4.51	4.04	4.65	-0.37	4.00	-0.55	4.80	-0.04	4.63	3.86	0.97***	4.74	0.80***	1.06	0.89
rn	9.87	4.45**	11.3	4.84**	3.44	5.04	10.8	4.33***	12.1	5.12***	10.7	4.95**	6.39	2.08***	9.59	1.80***	5.35	0.78***
dbrate	2.21	0.76***	1.35	0.93	0.44	0.84	1.47	0.76**	1.47	0.92*	0.91	0.91	2.03	0.68***	2.43	0.55***	0.51	0.67
conreg	-4.84	1.92**	-2.66	1.99	-3.54	2.11*	-3.93	1.90**	-3.91	2.25**	-4.08	2.16**	-4.08	0.42***	-5.10	0.38***	-2.60	0.15***
NE	-8.16	4.04**	-10.0	5.07**	7.68	4.99	-6.17	4.03*	-5.38	4.92	-0.66	4.70	-9.45	3.13***	-16.5	2.88***	5.70	0.98***
MW	-8.80	2.54***	-4.71	3.26	-5.35	2.96*	-7.35	2.61***	-8.09	3.18***	-7.65	3.09***	-6.74	0.98***	-8.54	0.87***	-6.56	0.36***
West	-8.49	4.00**	-10.8	5.18**	10.5	4.10**	4.78	4.35	8.54	5.55*	12.7	4.64***	-7.24	0.88***	-13.4	0.78***	9.10	1.23***
dfmc	10.9	9.18	30.7	10.7***	33.8	11.7***	22.7	10.1**	30.4	12.1***	37.8	11.4***	-1.41	6.10	7.91	5.66*	28.3	2.93***
dfmc2	-3.96	3.03	-8.22	3.69**	-12.3	3.65***	-8.91	3.30***	-11.6	3.98***	-14.4	3.60***	-0.02	1.75	-1.17	1.60	-10.7	0.89***
ddav	12.6	14.2	7.70	16.9	72.9	13.6***	2.51	13.3	10.7	16.0	32.6	15.8**	-4.25	8.39	5.98	6.73	63.2	10.6***
ddav2	-6.27	7.12	2.99	8.38	-33.3	6.85***	-0.73	6.37	-3.74	7.69	-13.6	7.47**	0.00	4.69	-0.62	3.71	-30.3	3.89***
black	60.2	22.6***	22.5	22.5	81.0	44.2*	41.8	19.4**	43.2	20.4**	65.9	32.2**	70.7	14.9***	75.6	9.88***	82.9	88.2
white	22.8	20.7	-14.1	20.3	69.2	43.3	15.6	18.3	15.8	18.4	42.4	30.9*	28.8	18.8*	12.7	12.6	69.1	88.9
latino	38.1	8.56***	7.69	10.3	16.1	10.2	14.7	8.65**	13.5	11.2	12.6	10.1	27.6	16.8*	22.7	13.1**	16.1	10.3*
asian	-86.6	50.1*	21.5	47.5	87.9	56.4	25.3	42.3	40.7	43.8	64.8	49.2*	-30.8	72.1	-11.2	48.9	65.2	110
age1	29.0	45.9	-98.2	52.7*	-12.0	47.8	-7.01	46.3	-18.4	53.3	-9.17	50.4	12.9	175	-78.8	138	20.0	112
age2	81.9	39.7**	-40.7	46.8	7.13	42.9	-3.77	40.3	-16.7	45.7	-18.8	44.0	41.0	131	-29.1	103	35.0	86.6
age3	53.4	37.0	-45.7	43.9	28.2	41.3	90.4	39.7**	90.7	47.9**	86.2	44.9**	44.5	112	10.9	88.6	39.4	74.9
cons	-384	45.6***	-270	55.0***	-382	61.0***	-330	39.6***	-375	51.4***	-395	51.9***	-298	129**	-416	106***	-384	146***
sigma	23.0	0.71***	24.1	0.86***	22.9	0.74***	20.4	0.80***	22.3	1.15***	22.5	1.03***	21.3	0.19***	25.1	0.04***	22.7	0.07***

Note:***p<1%,**p<5%,*p<10%. obs=1320. In panel A, the estimates are obtained using Two-Stage estimator. The expected capacity choice of each provider is estimated in the first step using a Poisson regression with regressors being the polynomials of market characteristics, and the standard errors are calculated using a bootstrap procedure. In panel B, the nested fixed point problem is recast into MPEC and estimated using Knitro. In Panel C, the estimates are obtained through GMM. K_{fmc},K_{dav},$K_{non-chain}$ are the expected capacity choice of FMC, DaVita and Non-Chain respectively. lpop and lbed are logged population and logged number of hospital bed. The definition of other variables are presented in Table 3.

Table 5. Equilibrium Response to Market Variables

	Capacity			No. of HEP markets		
	FMC	Dav	Non-Chain	FMC	Dav	Non-Chain
base case	8003	5586	6700	330	115	214
popuplation increases 10%	8560	6097	7238	368	137	246
nephrologist increases 10%	8066	5784	6766	337	126	216
prevalence rate of diabetes increases 10%	8996	5593	6565	395	107	202
CON regulation =0 for all markets	8336	5593	6795	354	114	216

Note: obs=1320. Capacity is derived from equation (7) after adjusting market variables. The "Capacity" column reports the sum of expected capacity choice for each provider across markets. The number of HEP (high entry probability) markets for a provider is defined as the number of markets in which that provider's entry probability is estimated to be greater than 0.5. It is reported in the "No. of HEP markets" column.

Table 6. Model Fit

	Capacity			Entry Probability		
	FMC	Dav	Non-Chain	FMC	Dav	Non-Chain
			Observed			
Mean	6.40	4.40	5.32	0.31	0.23	0.28
Std dev.	11.4	9.23	10.0	0.46	0.42	0.45
			Two-Stage			
Mean	6.24	4.15	5.13	0.34	0.24	0.30
Std dev.	5.56	4.18	4.62	0.22	0.18	0.19
			Maximum Likelihood			
Mean	6.23	4.16	4.81	0.34	0.24	0.27
Std dev.	7.68	5.82	5.56	0.22	0.18	0.20
			GMM			
Mean	6.06	4.23	5.08	0.35	0.24	0.30
Std dev.	5.33	4.46	4.16	0.21	0.18	0.18

Note: obs=1320. "Mean" reports the sample average. "Std dev" reports the standard deviation. The "Observed" panel reports the statistics from data and the "Two-Stage", "ML" and "GM" panel reports the model prediction from three estimators respectively.

Table 7. Counterfactual Capacity Distribution

	E(Capacity)			Pr(Entry)			E(Capacity | Entry)		
	FMC	Dav	Non-Chain	FMC	Dav	Non-Chain	FMC	Dav	Non-Chain
λ/Δ	100%	100%	100%	100%	100%	100%	100%	100%	100%
25^{th}	2.10	0.16	1.91	0.18	0.08	0.16	11.6	11.4	12.0
50^{th}	4.76	3.06	4.19	0.34	0.21	0.29	14.1	14.3	14.3
75^{th}	8.50	6.11	7.18	0.50	0.36	0.43	17.0	17.1	16.7
Mean	6.06	4.23	5.08	0.35	0.24	0.30	14.6	14.5	14.5
Std. dev	5.33	4.46	4.16	0.21	0.18	0.18	4.45	4.44	3.81
Total	8,237	5,473	6,774	321	131	210	19286	19084	19099
λ/Δ	98%	98%	98%	98%	98%	98%	98%	98%	98%
25^{th}	1.36	0.57	1.03	0.13	0.05	0.10	10.4	10.4	10.5
50^{th}	3.54	2.45	2.62	0.28	0.18	0.21	12.8	13.4	12.6
75^{th}	6.70	5.91	4.81	0.43	0.36	0.33	15.4	16.6	14.6
Mean	4.60	4.00	3.34	0.29	0.23	0.23	13.1	13.8	12.4
Std. dev	4.20	4.59	2.99	0.20	0.19	0.16	3.80	4.67	3.17
Total	6,069	5,280	4,408	218	141	72	17335	18237	16679
λ/Δ	95%	95%	95%	95%	95%	95%	95%	95%	95%
25^{th}	0.60	0.20	0.30	0.06	0.22	0.04	8.81	8.84	8.62
50^{th}	1.90	1.40	1.10	0.18	0.12	0.10	10.9	11.8	10.3
75^{th}	4.30	4.50	2.40	0.32	0.30	0.20	13.2	15.1	12.0
Mean	2.8	3.1	1.6	0.21	0.18	0.13	11.1	12.3	10.3
Std. dev	2.80	4.20	1.70	0.17	0.19	0.11	9.59	4.58	2.47
Total	3,727	4,135	2,116	90	115	8	14666	16288	13642
λ/Δ	92%	92%	92%	92%	92%	92%	92%	92%	92%
25^{th}	0.18	0.04	0.07	0.02	0.01	0.01	7.36	7.38	7.08
50^{th}	0.83	0.55	0.33	0.09	0.06	0.04	9.10	9.84	8.41
75^{th}	2.39	2.57	0.95	0.21	0.20	0.10	11.1	12.9	9.82
Mean	1.56	2.01	0.65	0.13	0.13	0.06	9.31	10.5	8.45
Std. dev	1.84	3.16	0.83	0.13	0.16	0.07	2.57	4.06	1.95
Total	2,060	2,650	859	10	61	0	12299	13885	11156
λ/Δ	102%	102%	102%	102%	102%	102%	102%	102%	102%
25^{th}	2.99	1.25	3.17	0.24	0.10	0.23	12.7	12.2	13.5
50^{th}	6.09	3.32	6.30	0.40	0.22	0.39	15.4	14.8	16.3
75^{th}	10.5	5.76	10.3	0.56	0.34	0.53	18.6	17.0	19.2
Mean	7.69	4.14	7.37	0.41	0.34	0.38	16.2	14.8	16.6
Std. dev	6.55	4.07	5.60	0.22	0.16	0.21	5.21	4.03	4.63
Total	10,148	5,470	9,722	446	86	406	21330	19521	21917
λ/Δ	100%	98%	100%	100%	98%	100%	100%	98%	100%
25^{th}	2.20	0.40	1.97	0.19	0.04	0.16	11.7	9.92	12.0
50^{th}	5.24	1.43	4.38	0.36	0.12	0.30	14.5	12.1	14.5
75^{th}	9.91	2.82	7.61	0.55	0.20	0.45	18.0	13.8	17.1
Mean	6.89	1.84	5.41	0.38	0.13	0.31	15.2	11.8	14.7
Std. dev	6.24	1.77	4.53	0.23	0.10	0.19	5.09	2.76	4.05
Total	9095	2427	7138	403	6	251	20100	15610	19440

Note: obs=1320. Under status quo, λ/Δ = 100% for all providers. 25^{th},25^{th} and 75^{th} report the corresponding quartile of distributions. The Mean capacity row reports the average expected capacity across markets. The total capacity row reports the sum of expected capacity across markets. The mean entry row reports the average entry probability across markets. The total entry probability row reports the total number of markets with high entry probability (i.e., entry probability greater than 0.5).

Table 8. Counterfacutal Capacity Distribution by Market Types

		E(Capacity)			Pr(Entry)			E(Capacity | Entry)		
Market		FMC	Dav	Non-Chain	FMC	Dav	Non-Chain	FMC	Dav	Non-Chain
λ/Δ		100%	100%	100%	100%	100%	100%	100%	100%	100%
pop below 50%	Mean	3.30	1.62	2.36	0.23	0.11	0.17	12.2	11.6	11.9
	Std. dev	3.42	1.81	1.97	0.17	0.11	0.12	3.30	2.90	2.52
pop above 50%	Mean	8.87	6.89	7.84	0.48	0.36	0.43	17.1	17.4	17.1
	Std. dev	5.45	4.78	3.97	0.18	0.16	0.14	4.06	3.76	3.05
db rate below 50%	Mean	4.10	3.69	5.07	0.27	0.21	0.30	13.0	13.7	14.4
	Std. dev	3.52	4.37	4.43	0.18	0.19	0.20	3.35	4.56	4.04
db rate above 50%	Mean	7.99	4.76	5.08	0.43	0.27	0.31	16.2	15.2	14.5
	Std. dev	6.05	4.50	3.89	0.22	0.17	0.17	4.78	4.19	3.56
λ/Δ		98%	98%	98%	98%	98%	98%	98%	98%	98%
pop below 50%	Mean	2.32	1.29	1.39	0.17	0.09	0.12	10.9	10.7	10.5
	Std. dev	2.62	1.69	1.31	0.15	0.10	0.09	2.88	2.90	2.15
pop above 50%	Mean	6.92	6.76	5.32	0.41	0.36	0.34	15.4	17.0	14.8
	Std. dev	4.23	4.95	2.91	0.16	0.17	0.13	3.24	3.94	2.43
db rate below 50%	Mean	3.11	3.30	3.30	0.22	0.19	0.22	11.8	12.9	12.5
	Std. dev	2.86	4.24	3.16	0.16	0.19	0.17	3.05	4.61	3.35
db rate above 50%	Mean	6.06	4.69	3.38	0.36	0.26	0.23	14.5	14.7	12.8
	Std. dev	4.75	4.81	2.81	0.20	0.19	0.15	3.99	4.55	2.99
λ/Δ		95%	95%	95%	95%	95%	95%	95%	95%	95%
pop below 50%	Mean	1.22	0.77	0.54	0.11	0.06	0.05	9.17	9.26	8.60
	Std. dev	1.63	1.33	0.62	0.11	0.09	0.05	2.33	2.69	1.69
pop above 50%	Mean	4.46	5.54	2.69	0.31	0.31	0.21	13.1	15.5	12.1
	Std. dev	2.88	4.66	1.72	0.15	0.18	0.10	2.46	3.93	1.80
db rate below 50%	Mean	1.88	2.39	1.55	0.15	0.15	0.12	10.1	11.3	10.2
	Std. dev	2.00	3.53	1.75	0.13	0.17	0.12	2.64	4.31	2.58
db rate above 50%	Mean	3.75	3.86	1.65	0.26	0.22	0.13	12.1	13.3	10.5
	Std. dev	3.21	4.59	1.60	0.18	0.20	0.11	3.17	4.63	2.34
λ/Δ		92%	92%	92%	92%	92%	92%	92%	92%	92%
pop below 50%	Mean	0.54	0.36	0.16	0.05	0.03	0.02	7.65	7.80	7.07
	Std. dev	0.90	0.85	0.23	0.07	0.06	0.02	1.85	2.28	1.31
pop above 50%	Mean	2.60	3.68	1.15	0.21	0.23	0.11	11.0	13.3	9.86
	Std. dev	1.97	3.73	0.91	0.13	0.17	0.07	2.05	3.56	1.40
db rate below 50%	Mean	0.99	1.43	0.62	0.09	0.10	0.06	8.49	9.59	8.28
	Std. dev	1.27	2.49	0.85	0.10	0.14	0.07	2.24	3.71	2.01
db rate above 50%	Mean	2.12	2.58	0.69	0.17	0.16	0.07	10.1	11.4	8.62
	Std. dev	2.12	3.62	0.80	0.14	0.18	0.07	2.63	4.18	1.87
λ/Δ	102%	102%	102%	102%	102%	102%	102%	102%	102%	102%
pop below 50%	Mean	4.46	1.88	3.72	0.28	0.13	0.24	13.5	12.3	13.5
	Std. dev	4.31	1.84	2.81	0.19	0.10	0.14	3.79	2.79	2.96
pop above 50%	Mean	10.97	6.45	11.08	0.53	0.34	0.53	18.9	17.3	19.7
	Std. dev	6.82	4.41	5.28	0.18	0.14	0.15	5.04	3.47	3.90
db rate below 50%	Mean	5.20	3.79	7.44	0.32	0.22	0.38	14.2	14.2	16.6
	Std. dev	4.30	4.06	5.99	0.19	0.17	0.22	3.75	4.23	4.94
db rate above 50%	Mean	10.13	4.49	7.29	0.49	0.26	0.39	18.1	15.3	16.6
	Std. dev	7.41	4.05	5.18	0.22	0.15	0.19	5.69	3.75	4.31
λ/Δ		100%	98%	100%	100%	98%	100%	100%	98%	100%
pop below 50%	Mean	3.54	0.74	2.44	0.24	0.06	0.18	12.3	9.97	12.0
	Std. dev	3.80	0.84	2.05	0.18	0.06	0.12	3.56	2.20	2.58
pop above 50%	Mean	10.30	2.95	8.43	0.52	0.20	0.45	18.2	13.7	17.5
	Std. dev	6.41	1.77	4.35	0.19	0.09	0.15	4.74	1.84	3.30
db rate below 50%	Mean	4.67	1.65	5.42	0.29	0.12	0.31	13.4	11.4	14.7
	Std. dev	4.30	1.83	4.85	0.20	0.11	0.21	3.87	2.98	4.32
db rate above 50%	Mean	9.07	2.02	5.39	0.46	0.15	0.32	17.0	12.3	14.8
	Std. dev	7.04	1.69	4.19	0.23	0.10	0.18	5.49	2.43	3.76

Note: Rows with "pop below 50%" and "pop above 50%" report estimates using samples with markets whose population is below or above the median respectively. Rows with "db rates below 50%" and "db rate above 50%" report estimates using samples with markets whose diabetes prevalence rates are above or below the median.

A Supplemental Tables

Table A1. Additional Robustness

	Panel A						Panel B						Panel C					
	FMC		Dav		Non-Chain		FMC		Dav		Non-Chain		FMC		Dav		Non-Chain	
	EST	SE	EST	SE	EST	SE	EST	SE	EST	SE	EST	SE	EST	SE	EST	SE	EST	SE
K_{fmc}			-0.82	0.17***					-0.69	0.17***					-0.75	0.23***		
K_{dav}	-1.14	0.20***			-0.88	0.17***	-0.84	0.16***			-0.64	0.16***	-1.46	0.28***			-1.05	0.23***
$K_{non-chain}$	-1.18	0.29***	-0.60	0.28**	-0.55	0.18***	-0.92	0.25***	-0.22	0.25	-0.35	0.15**	-1.45	0.37***	-0.93	0.37**	-0.93	0.28***
lpop	25.1	1.64***	19.7	1.77***	20.7	1.48***	25.1	1.58***	19.6	1.83***	20.5	1.48***	21.6	1.61***	17.0	1.79***	18.6	1.45***
black	51.5	15.1***	9.54	12.4	0.76	11.7	58.7	16.2***	10.0	13.0	-1.53	12.1	42.4	13.0***	8.45	11.9	4.78	10.9
white	10.1	15.2	-17.6	11.8	-23.3	11.4**	15.0	16.2	-20.3	12.6	-25.6	12.0**	4.95	13.1	-13.4	11.2	-20.7	10.6*
latino	26.5	6.98***	3.23	7.85	14.8	6.92**	26.3	7.02***	-1.42	8.20	14.6	7.08**	19.4	6.59***	-1.22	8.04	5.67	7.13
asian	-85.2	33.1***	7.93	29.2	-0.75	27.0	-72.2	32.3**	16.6	29.7	-2.27	27.6	-77.3	31.6**	32.4	29.2	-1.86	26.8
age1	28.1	36.8	-60.9	38.2	-39.5	36.1	33.0	37.5	-65.2	40.1	-39.3	37.2	22.4	34.3	-78.1	38.1**	-47.4	35.9
age2	38.1	33.3	-54.1	34.2	-20.4	31.9	36.1	34.2	-65.5	36.0*	-24.6	33.0	21.6	30.7	-69.7	33.1**	-26.1	30.7
age3	36.0	32.8	-20.4	34.7	24.7	32.1	46.9	33.4	-20.4	36.3	27.7	33.0	32.1	30.6	-26.4	34.4	12.9	31.6
neph	2.23	0.55***	2.54	0.59***	1.32	0.59**	1.98	0.57***	2.50	0.63***	1.14	0.61*	2.26	0.50***	2.16	0.59***	1.41	0.57**
lbed	5.53	3.08*	-2.14	3.32	6.12	3.11**	6.86	3.16**	-2.76	3.50	7.04	3.20**	4.17	2.86	-4.25	3.30	4.41	2.99
rn	10.4	3.47***	6.35	3.69*	3.59	3.47	10.3	3.54***	6.62	3.87*	3.02	3.58	8.68	3.23***	6.70	3.61*	3.26	3.35
dbrate	1.67	0.64***	1.13	0.69	0.59	0.66	1.47	0.65**	0.89	0.72	0.27	0.68	1.52	0.59***	1.15	0.69*	0.75	0.65
conreg	-3.42	1.56**	-2.37	1.70	-3.68	1.59**	-3.76	1.60**	-2.59	1.78	-3.88	1.63**	-2.79	1.46*	-1.60	1.69	-3.70	1.54**
NE	-7.63	3.87**	-12.4	4.07***	7.76	3.64**	-10.2	3.95***	-17.3	4.22***	9.05	3.72**	-9.05	3.67**	-11.3	4.15***	3.77	3.73
MW	-6.10	2.18***	-3.09	2.36	-1.94	2.26	-6.23	2.19***	-3.46	2.43	-1.18	2.29	-6.49	2.03***	-4.47	2.34*	-1.43	2.23
West	-10.0	3.64***	-15.0	4.10***	11.8	3.11***	-10.8	3.65***	-16.6	4.29***	13.2	3.20***	-6.85	3.57*	-11.1	4.14***	11.5	3.03***
dfmc	13.1	8.44	14.9	8.79*	33.1	8.17***	7.29	8.36	10.3	9.02	34.2	8.18***	8.99	7.98	16.8	8.85*	24.6	8.40***
dfmc2	-3.53	2.82	-2.16	2.94	-12.5	2.57***	-1.83	2.80	-0.64	3.04	-13.1	2.59***	-2.80	2.64	-3.83	2.94	-9.58	2.60***
ddav	2.38	11.5	-21.5	11.6*	58.7	11.0***	-1.29	11.4	-29.0	12.0**	61.9	11.2***	-3.53	10.4	-19.5	11.2*	43.8	10.5***
ddav2	0.35	5.69	15.4	5.72***	-26.0	5.45***	1.22	5.64	19.4	5.87***	-27.3	5.52***	2.82	5.28	13.5	5.55**	-19.1	5.29***
cons	-358	35.8***	-192	35.9***	-260	31.0***	-360	36.3***	-177	37.1***	-257	31.4***	-293	32.9***	-151	35.0***	-218	29.3***
sigma	23.0	0.71***	23.5	0.83***	23.0	0.75***	23.9	0.71***	25.0	0.83***	24.1	0.76***	20.2	0.70***	21.9	0.87***	21.1	0.77***
obs	3129						3204						2930					

Note:***p<1%,**p<5%,*p<10%. Results are obtained using a two-stage estimator and standard errors are computed based on 300 bootstraps. This table displays the estimates under alternative sampling criterions. These results are quantitatively similar to those in our main specification. Panel A is based a sample of 3129 markets where only large markets with capacity greater than 60 are dropped. Panel B and Panel C are based on alternative cutoffs when markets with capactiy greater than 80 and greater than 40 are dropped. The market capacity of 80 corresponds to approximately the 95th percentile in capacity distribution and 40 corresponds to the 85th.

Table A2. Model Fit: Out of Sample Prediction						
	Observed			Predicted		
	FMC	Dav	Non-Chain	FMC	Dav	Non-Chain
Panel A: Capacity $E(K\|x)$						
Mean	2.84	2.53	2.55	3.43	2.16	2.36
Std dev	7.57	7.06	7.02	4.96	4.12	3.49
Panel B: Entry $Pr(K>0)$						
Mean	0.16	0.15	0.15	0.21	0.12	0.15
Std dev	0.36	0.35	0.36	0.21	0.17	0.17
No markets:1809						

Note: The out of sample prediction is made based on the GMM estimates reported in Table 4 and the larger sample used for Panel A of Table A1. We report the results after excluding 1320 markets that are currently included in the main specifications. This left 3129-1320=1809 markets.

B Proof of Proposition 1

Proof of Proposition 1.. First, suppose the solution of the maximization problem is in the interior (i.e. $K_i^*(X,\varepsilon_i)>0$). Then the first-order condition of (2) implies that in equilibrium:

$$K_i^*(X,\varepsilon_i)=\frac{1}{2a_i}\left\{X\beta_i+\sum_{j\neq i}\gamma_{i,j}\mathbb{E}_{\varepsilon_j}\left[K_j^*(X,\varepsilon_j)|x,\varepsilon_i\right]-b_i-\varepsilon_i\right\}, \tag{13}$$

where the right-hand side of (13) is necessarily strictly positive. Since $a_i>0$, the second-order condition for such an interior solution would be satisfied automatically. Next, suppose the solution is on the corner, i.e. $K_i^*(X,\varepsilon_i)=0$. Because $a_i>0$ and $\Pi_i(0,K_{-i},x,\varepsilon_i)=0$ regardless of K_{-i}, the first-order condition of (2) evaluated at $K_i^*(X,\varepsilon_i)=0$ and $K_{-i}^*(.)$ is necessarily negative. (Otherwise the solution would be interior.) Therefore, with a corner solution in equilibrium, we have:

$$K_i^*(X,\varepsilon_i)=0 \text{ and } X\beta_i+\sum_{j\neq i}\gamma_{i,j}\mathbb{E}_{\varepsilon_j}\left[K_j^*(X,\varepsilon_j)|x,\varepsilon_i\right]-b_i-\varepsilon_i<0. \tag{14}$$

Combining (13) and (14), we conclude that (3) holds in any PSBNE. ■

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