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COMPETITION AND CROWDING OUT IN THE MARKET FOR OUTPATIENT SUBSTANCE ABUSE TREATMENT*

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U.S. markets for outpatient substance abuse treatment (OSAT) include for-profit, nonprofit, and public clinics. We study OSAT provision using new methods on equilibrium market structure in differentiated product markets. This allows us to describe clinics as heterogeneous in their objectives, their responses to exogenous market characteristics, and their responses to one another. Consistent with crowding out of private treatment, we find that markets with public clinics are less likely to have private clinics. In markets with low insurance coverage, low incomes, or high shares of nonwhite addicts, however, public clinics are relatively likely to be the sole willing providers of OSAT.

1. Introduction

The U.S. government dedicates a significant share of its resources to providing goods and services that private organizations also produce. Examples include education, health care, and housing. Among both academics and policy makers there is extensive debate on whether public provision crowds out private production.[2] Critical questions include how similar the publicly and privately produced goods are, and whether the same consumers might be served by either type of organization. If there is little overlap in the organizations' likely consumers, then public provision might offer a beneficial social safety net for some individuals without affecting the market for the private organizations' products. If instead the public and private organizations are likely to serve the same consumers, then policy makers must consider how consumer preferences for efficiency, equity, and other goals will be served by the two types of organization.

In this article, we study how public and private outpatient substance abuse treatment (OSAT) clinics compete with each other. We specify separate payoff functions for three ownership types of OSAT clinic: public, private nonprofit, and private for-profit. The payoff functions are affected by exogenous market conditions, such as the number of addicts in different demographic groups, as well as the endogenous choices of clinics of various ownership types. Differences in payoff functions across types may reflect differences in political, altruistic, and pecuniary objectives, which in turn affect the extent of competition among different clinic types. By estimating the extent of competition, we are able to characterize the degree to which public OSAT crowds out treatment that would be provided by a private clinic if not for the presence of a

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[2] There exists a rich literature on the relationship between public health programs (e.g., Medicaid) and privately provided health insurance. For examples, see Cutler and Gruber (1996), Brown and Finkelstein (2008), Shore-Sheppard et al. (2000), Rask and Rask (2000), and Lo Sasso and Buchmueller (2004). The relationship between private charitable contributions and public spending is studied by Kingma (1989), Andreoni (1993), and Gruber and Hungerman (2007). Blomquist and Christiansen (1999) review the literature on political economy explanations for the equilibrium presence of public provision.

government-run treatment center. Conversely, we are able to identify the markets in which the observed public OSAT clinic is the only feasible type of addiction treatment, because private clinics are unlikely to serve the market.

Our approach to competition and crowding out among OSAT clinics follows from a model of equilibrium market structure. We assume that potential public, nonprofit, and for-profit clinics strategically consider whether to serve a market, and each observed choice to serve (or not) reflects an optimal decision conditional on the clinic's objective, local market conditions, and the choices of other (potential) clinics. Observed market structures therefore correspond to pure-strategy equilibria in complete-information simultaneous-move discrete games, although there are other games that also share the equilibrium conditions. The discrete nature of the clinics' interaction can lead to multiple market structures satisfying the equilibrium conditions for a single market, as is often the case in entry games. For example, a local government may choose not to open a public clinic if the local populace places no pressure on their elected officials because the residents believe that existing private clinics provide adequate service. Alternatively, if the same market instead has an active public clinic, a potential private clinic may choose not to operate because the residual demand for its treatment services is insufficient to cover operating expenses. Our model allows us to calculate the likelihood that an observed market structure is the only possible configuration for a market satisfying the participation conditions, and therefore identify cases in which public OSAT prevents the operation of a private clinic.

To estimate our model, we build on recently developed empirical techniques for estimating discrete games with heterogeneous strategic agents. In particular, we closely follow Ciliberto and Tamer's (2009) procedure for estimating the parameters of a game in which more than one outcome may be consistent with the underlying economic model, but no equilibrium selection mechanism is imposed to resolve the multiplicity. Our results indicate that payoff functions differ across OSAT providers, and each clinic ownership type is sensitive to the presence of the two remaining clinic types. A central implication of this result is that potential private clinics sometimes forgo offering OSAT in a market because a public clinic is present, i.e., private treatment is crowded out.

Multiple equilibria in the identities of OSAT providers appear often in our sample of 1,583 rural U.S. markets. Averaging across markets, the identified parameter set, and the distribution of unobservables supporting the empirical outcome as an equilibrium, we find a likelihood of about a third that there is another equilibrium that was not realized. The possibility of multiple equilibria is of particular interest when a market's OSAT is provided by a single public clinic. In these cases, there is a sharp distinction between crowding out of private clinics and, alternatively, the chance that public and private clinics serve different types of markets, in which case the removal of the sole public clinic would lead to an absence of OSAT. Among the 224 markets with a single public clinic in our data, the chance of multiple equilibria is relatively high—about two-thirds—implying that public OSAT often exists to the exclusion of private treatment. The full extent of crowding out in these markets is actually greater (between 70% and 78%) due to cases in which a unique equilibrium of public OSAT is replaced by private OSAT if government treatment is made impossible. Due to the heterogeneous characteristics of nonprofit and for-profit private clinics, we find that when crowding out exists, it is more likely to be between public and nonprofit clinics. Despite our finding of substantial crowding out of private OSAT in general, we uncover interesting variation in this impact across markets. Markets with lower median income, a greater share of addicts who are nonwhite, and a greater portion of its population without health insurance are more likely to lose OSAT entirely if a public clinic is removed from the market.

With this article, we contribute to the recently initiated literature on estimating discrete games in which multiple outcomes may be consistent with the underlying economic model. We follow the method of Ciliberto and Tamer (2009), who assume that observed market structures satisfy a minimal set of conditions on firms' payoffs, where the conditions hold in a variety of settings including any pure-strategy Nash equilibrium of a simultaneous-move complete information game among firms making choices about participation in a market. A market's exogenous characteristics and the players' discrete choices are sufficient to estimate the parameters of reduced-form payoff functions for the games' players. The method builds on earlier work on discrete games (Bresnahan and Reiss, 1991a; Berry, 1992; Mazzeo, 2002), which have used assumptions on player homogeneity, equilibrium selection mechanisms, or the timing of choices to avoid the possibility of multiple equilibria. Such restrictions may not be appropriate for OSAT markets, which are complicated by likely differences in agents' objective functions and the policy relevance of whether public clinics crowd out private clinics.

We also contribute to the literature on competition in medical markets, which includes several recent studies of the significant differences that exist across hospitals of different ownership types. Chakravarty et al. (2006) compare the entry and exit choices of for-profit and nonprofit hospitals and find that the former are more sensitive to exogenous changes in demand. Duggan (2000, 2002) offers empirical evidence that public, nonprofit, and for-profit firms respond differently to an exogenous change in financial incentives. Norton and Staiger (1994) show that for-profit hospitals are just as likely to offer charity care as nonprofit hospitals when they operate in similar markets, but for-profit hospitals are more likely to select markets with less demand for charity care. Horwitz and Nichols (2009) find that services offered by hospitals vary systematically with the type of hospital and the share of for-profit hospitals within the market.[3] In this article, we extend this literature by directly accounting for the endogenous relationships among health care providers of different ownership types and do so with minimal restrictions on the equilibrium that may be selected in the observed markets.

The remainder of the article is organized as follows. Section 2 presents background on the provision of OSAT services. In Section 3, we describe the economic model that we assume governs the operating decisions of potential OSAT providers. We describe the data in Section 4, and Section 5 contains our approach to estimating the parameters of the economic model. Section 6 presents the empirical results, which include our crowding-out measures. Section 7 concludes. We collect additional details on the data and estimation approach in the Appendix.

2. OSAT INSTITUTIONAL BACKGROUND

An estimated 16.6 million Americans (7.3% of adults) were classified as having a substance abuse disorder in 2001, and 3.1 million received some kind of treatment.[4] Substance abuse treatment is a large market, with $18 billion spent on treating substance abuse disorders in the U.S. during 2001. The demand for treatment options is increasing as public support for treatment (instead of punishment) broadens and the number of substance abusers continues to grow.[5] Over half of all funding for substance abuse treatment is public. State and local governments provide 38% of all substance abuse treatment funding, whereas Medicaid accounts for another 19%. Treatment services are provided by a variety of types of organizations. In addition to public providers, which represented 15% of U.S. treatment facilities in 2000, nonprofit and for-profit organizations accounted for approximately 59% and 26% of all treatment facilities, respectively.

Although the common interpretation of substance abuse "rehab" often is of treatment in an inpatient (residential) setting, far more treatment programs provide outpatient services. In 2000, 82% of all substance abuse treatment facilities offered outpatient services, and about three-quarters of all nonemergency patient treatment admissions were for outpatient services.[6]

[3] For other examples that contrast the objectives and characteristics of nonprofit and for-profit hospitals, see Gaynor and Vogt (2003), Eid (2006), and Abraham et al. (2007).

[4] See Substance Abuse and Mental Health Services Administration (SAMHSA, 2002). These levels have continued in more recent years. In 2008, SAMHSA estimated 22.2 million (8.9% of the population) had a substance abuse disorder and an estimated 4.0 million received treatment.

[5] Mark et al. (2005) estimate that spending on substance abuse treatment increased an average of 4.6% per year between 1996 and 2001. They also provide an extensive discussion of expenditures on substance abuse treatment.

[6] Emergency treatment occurs when a patient requires immediate detox and is suffering from acute medical complications.

Clinics of all ownership types provide outpatient treatment, although in our sample the distribution of types across markets departs slightly from the statistics described above, which pertain to treatment of all forms in large and small U.S. markets.

There is some evidence that ownership structure is correlated with clinics' choices. For example, Wheeler and Nahra (2000) find that for-profit clinics treat a larger proportion of heroin addicts and fewer alcohol abusers than nonprofit and government clinics. Additionally, clinics vary in the forms of payment they accept, with for-profits accepting Medicare, Medicaid, and various forms of insurance less frequently than public and nonprofit clinics.[7] All types of clinics—including 80% of public clinics—accept cash payment for treatment.

In executing our analysis, we assume that government clinics are uniform in their objectives and responsiveness to competition from private clinics. This includes clinics that are operated by a state government (27% of public clinics); a local, county, or community government (56%); or the federal government (17%). Although there may be differences in decision making at different levels of government, in this article we are more concerned with choices of private organizations as they relate to the presence of public OSAT clinics. In addition, our model may accommodate some differences across public clinics through the model's neutrality regarding equilibrium selection.

3. ECONOMIC MODEL

In this section, we present a model to characterize the behavior of the three OSAT provider types. The model assumes that the decision whether or not to operate a clinic for each potential OSAT provider is governed by a payoff function that differs across the three types. As described in Bresnahan and Reiss (1990, 1991a) and Mazzeo (2002), the operating decisions of potential clinics can be used to infer a long-run reduced-form payoff function. This function represents the return from current and future product market competition for each type of clinic, given the assumption that operating clinics receive positive payoffs and clinics not active in a market would receive negative payoffs from operating. The payoff function for each type depends on a set of economic variables specific to the particular market as well as the decisions made by other agents in the market.

The payoff functions differ across types because each is likely to pursue different objectives. Although for-profit clinics are likely to maximize profits, public and nonprofit clinics may have other goals. For example, nonprofit organizations may be more focused on serving portions of the population with particular demographic backgrounds, and government participation may be responsive to tax revenues or political pressure to provide OSAT for the indigent. These differences in clinics' unobserved objective functions will be reflected—but not explicitly captured—in the reduced-form responses of clinics to market demographics.

We assume that every market (m) is populated by potential OSAT providers of each type (t): government (G), private nonprofit (N), and private for-profit (F). The observed number of clinics of type t in market m is n_{tm}, and the vector of clinics in m is $\mathbf{n}_m = (n_{Gm}, n_{Nm}, n_{Fm})$. We write $\mathbf{n}_{-t,m}$ to indicate the vector of clinic counts for types other than t. The payoff function of a type-t clinic in market m is π_{tm}. This function is a reduced-form representation of a firm's structural objective, and its value depends on the presence of other clinics; a set of observed demand and cost shifters, W_{tm}, which includes some variables that affect all clinics' payoffs and other variables that affect only a single clinic type; a parameter vector θ_t; and unobserved (to the econometrician but not to potential clinics) payoff shifters, ε_{tm}. All potential clinics in m observe all values of ε_{tm} before making their choices whether to offer OSAT in a market.[8]

[7] Available payment methods may be linked to treatment offerings. Olmstead and Sindelar (2005) report that increases in managed care penetration cause for-profit clinics to offer more services and public clinics to offer fewer services.

[8] Pakes et al. (2006) allow the error to contain both a structural component (similar to our assumption on ε) plus additional measurement or expectational error on behalf of the agent. Seim (2006) considers a Bayesian game in which agents know the distribution of the unobservables but do not observe their realizations.

Active clinics' payoffs are additive in the unobservable ε_{tm}, and each potential clinic receives a payoff of zero if it chooses not to offer OSAT in the market. That is,

(1)

$$\pi_{tm}(\mathbf{n}_m, W_{tm}, \varepsilon_{tm}; \theta_t) = \overline{\pi}_{tm}(\mathbf{n}_m, W_{tm}; \theta_t) + \varepsilon_{tm} \quad \text{if the clinic operates in the market,}$$
$$\pi_{tm}(\mathbf{n}_m, W_{tm}, \varepsilon_{tm}; \theta_t) = 0 \quad \text{for a potential clinic that does not operate in the market.}$$

Finally, we assume that the presence of competing clinics acts to reduce the payoffs of an individual clinic: $\frac{\partial \pi_{tm}}{\partial n_{-t,m}} \leq 0$, where $n_{-t,m}$ represents any other individual clinic that may also serve market m.

In our empirical application, we limit the number of potential values n_t may take in order to match the patterns we observe in the data and to maintain tractability.[9] For public and for-profit clinics, we specify that $n_t \in \{0, 1\}$, whereas nonprofit clinics, which are more numerous, may have $n_N \in \{0, 1, 2\}$. We assume that the presence of a second nonprofit clinic reduces the profits of the first nonprofit as well: $\frac{\partial \pi_{Nm}}{\partial n_{N,m}} < 0$. In the remainder of this section we occasionally invoke these limits on n_t in explaining certain features of our model.

3.1. *Equilibrium and the Data Generating Process.* We assume that an organization chooses to operate a clinic if and only if its payoffs are nonnegative, given the choices of the other clinics in a market. That is, our economic model requires that the payoffs of each type of firm, for a given market structure, satisfy the following two conditions: (C1) Each organization with an active clinic must receive a nonnegative payoff, and (C2) each organization without an active clinic would receive a negative payoff from operating in the market. We define an **equilibrium**, therefore, as any configuration (n_G, n_N, n_F) satisfying the following inequalities describing the realized and potential payoffs for each clinic type:

$$\pi_t(n_t, \mathbf{n}_{-t}, W_t, \varepsilon_t; \theta_t) \geq 0 \text{ (Condition C1)}$$
$$\pi_t(n_t + 1, \mathbf{n}_{-t}, W_t, \varepsilon_t; \theta_t) < 0 \text{ (Condition C2)}$$

We suppress the market (m) notation on π for convenience. When we observe a clinic count at its maximum (1 or 2, depending on t) in a market, only condition C1 is necessary to describe the equilibrium for the affected clinic type.

The inequalities in C1–C2 represent an intuitive yet minimal set of conditions that we assume hold for any observed market structure. These conditions are necessary for a pure-strategy Nash equilibrium in a simultaneous-move game over market participation. More generally, Ciliberto and Tamer (2009) describe cross-sectionally observed markets structures as snapshots of the long-run equilibrium in a dynamic game of entry and exit. We do not impose restrictions beyond C1–C2 to guarantee a unique equilibrium market structure, nor do we limit the empirical predictions of the model to features that are invariant across all equilibria, such as the total number of active clinics.[10] Although in this article we often use the language of simultaneous-move games to describe clinic behavior, conditions C1–C2 are also necessary conditions for equilibria in some complete-information sequential-move games. For example, Mazzeo's (2002) sequential game of motel entry and type selection satisfies C1–C2. More generally, it is possible to specify a sequential OSAT clinic entry game in which potential clinic operators continue making participation decisions until no additional players are willing to enter the market, and this game will satisfy C1–C2.[11] Other sequential-move games with a prespecified number of

[9] Such restrictions are common in empirical studies of equilibrium market structure, beginning with Bresnahan and Reiss (1991a) and continuing through Ciliberto and Tamer (2009).

[10] Some prior research on entry games (e.g., Mazzeo, 2002) removes the possibility of multiple equilibria by specifying a sequential-move game with a particular order of moves combined with parameter restrictions.

[11] One possible game would include a finite but large number of players of each type that choose the actions "enter" or "do not enter" in some prespecified order. We might further assume that players who choose the "enter" cannot

moves may not satisfy C2, however, as a potential clinic that has opted out of the market may find that it would have positive profits from entering given the choices of clinics that move later within the game. This violation of C2 could create pressure for revisions of choices or additional rounds of the game that are not natural to rule out a priori. Likewise, conditions C1–C2 may not hold when mixed strategy equilibria are permitted in simultaneous-move games or incomplete information exists about clinics' payoffs, but the apparent ex post "mistakes" that are possible following ex ante optimal behavior could bring pressure to revise actions until they are in line with C1–C2. We do not consider mixed strategies or incomplete information in this article.

When the impacts of W and $\mathbf{n}_{-t}$ on payoffs are finite and ε has sufficiently wide support, then conditions C1–C2 admit multiple equilibria with positive probability in any market.[12] Conditional on knowing the true value of θ along with a market's W, statements regarding crowding out must be probabilistic in that they depend on restrictions on realizations of the vector of error draws, ε. Whenever a particular clinic type is not observed in a market, the realized ε_t may be such that a particular clinic type would either (1) operate and earn positive profits in some equilibria, but not the one that was played, or (2) earn negative payoffs in any configuration in which the other types behave optimally. As discussed below, our model allows us to distinguish between these two possibilities.

The possibility of multiple $\mathbf{n}$ satisfying C1–C2 for a single ε implies that this is an "incomplete" econometric model in which we cannot use standard estimation techniques such as maximum likelihood to estimate θ (see Tamer, 2003). The model is incomplete in that we do not specify an equilibrium selection process to determine which $\mathbf{n}$ is realized in a market when multiple structures satisfy C1–C2. Although the absence of an equilibrium selection mechanism may be viewed as a gap in the model, including a mechanism provides an additional opportunity for introducing misspecification. Such misspecification could alter our results on crowding out and the model's policy interpretation. Because we have little a priori information on how multiple equilibria might be resolved in the OSAT market, we take an econometric approach that permits inference on θ without additional assumptions on the game beyond C1–C2.

3.2. *Crowding Out in the Model.* Crowding out can occur in two ways in our model. First, there may be multiple equilibria in a market, with the distinct equilibria varying in their numbers of clinics of each ownership type. When such equilibria exist and the realized outcome is the one in which there are more public clinics and fewer private clinics, we describe the outcome as crowding out. Second, crowding out can occur when the unique equilibrium outcome has a public clinic active in a market, but a private clinic is willing to operate in the market so long as the public clinic is restricted from entry. We now provide examples of each possibility.

3.2.1. *Example 1: Crowding out due to multiplicity.* Suppose we observe a market with $(n_G, n_N, n_F) = (1, 0, 0)$. Equilibrium condition C1 implies that the public clinic's payoff must be positive in this market. Additionally, conditional on the presence of the public clinic, condition C2 implies that a single nonprofit or for-profit clinic would receive a negative payoff if it participated in the market. There may exist alternative configurations, however, that also satisfy C1–C2 for this market. For example, $(0, 1, 0)$ may satisfy the equilibrium conditions if the public clinic, which was willing to participate in the market as a monopoly, has $\frac{\partial \pi_G}{\partial n_N}$ sufficiently negative to dissuade it from participation as a duopolist. Other potential alternative equilibria include $(0, 0, 1)$ and $(0, 1, 1)$, although these two configurations are not possible simultaneously under

reverse their decision on a later turn, and the game ends when there is a sequence of consecutive turns containing players of each type and no player in this sequence chooses "enter." This game will have a unique equilibrium sequence of actions. C1 will be satisfied because no player will choose the action "enter" when it leads to negative profits. C2 will be satisfied because no player would allow the game to end when it is possible to deviate to the action "enter" and receive a positive payoff.

[12] Bresnahan and Reiss (1991b) show that full support on the εs guarantees the existence of multiple pure strategy Nash equilibria. Also, see Cohen and Manuszak (2005) for graphical representations of the set of pure strategy Nash equilibrium outcomes for entry games with various types of strategic interactions among the players.

C1–C2. More generally, if we observe a market with $(1, n_N, n_F)$ where $(0, n'_N, n'_F)$ is an alternative equilibrium and $(n'_N + n'_F) > (n_N + n_F)$, we say that crowding out has occurred due to the multiplicity of equilibria.

3.2.2. *Example 2: Crowding out despite a unique equilibrium.* Suppose that a potential nonprofit clinic is willing to serve a market as a monopolist, but it would receive a negative payoff if it were to share the market with a public clinic. At the same time, a public clinic is willing to serve the same market both as a monopolist and as a duopolist. This may occur for some values of ε when $\frac{\partial \pi_N}{\partial n_G} < \frac{\partial \pi_G}{\partial n_N} < 0$, all else equal. Then (0, 1, 0) does not satisfy C2 for the G clinic, although (1, 0, 0) can satisfy C1–C2 for both G and N firms. So long as the for-profit clinic is uninterested in serving the market, (1, 0, 0) is a unique equilibrium. If a type G clinic is forbidden from serving the market, however, then the outcome (0, 1, 0) satisfies the equilibrium conditions for the other clinic types. In cases like this example, we say that crowding out has occurred despite the (inferred) uniqueness of the observed equilibrium with $n_G = 1$.

4. DATA

We use data on the location and characteristics of OSAT facilities from the 2000 National Survey of Substance Abuse Treatment Services (N-SSATS), an annual census of substance abuse treatment facilities conducted by the Substance Abuse and Mental Health Services Administration (SAMHSA). The information provided by N-SSATS includes facility ownership structure and the types of services offered. In 2000, there were 13,428 eligible respondent facilities included in the survey.[13] Most clinics (60%) identify substance abuse treatment as the facility's primary focus, and 25% report a mix of substance abuse and mental health treatment services. Unfortunately, the N-SSATS data does not include clinics' prices or quantities, so we are unable to directly estimate treatment demand.

We model the decision to offer OSAT in a distinct geographic area. We assume that treatment markets are defined by U.S. county borders, and we analyze choices within the 1,583 counties with populations between 5,000 and 100,000 that are not within in a Metropolitan or Consolidated Statistical Area (MSA or CSA). Three considerations support this choice of market definition and size. First, as we mention above, it is computationally prohibitive to estimate our model in markets with a very large number of decision makers of each ownership type. Second, potential patients in these small, rural markets are relatively unlikely to cross county lines to receive OSAT. In our sample's counties during 2000, 71% of the employed population worked inside their home county, whereas only 52% of working residents in similarly-sized MSA counties worked in their home county.[14] Patients who receive outpatient treatment attend several hours of individual and group counseling sessions per week that are scheduled around the patient's normal activities. By its very nature, OSAT patients do not travel long distances to receive treatment. Third, the majority of public clinics are operated by a local (city or county) government, and residence is generally required for OSAT treatment at these clinics.

Of the 1,583 counties in our sample, approximately 30% have no OSAT services, whereas about 44% have a single clinic and 18% have two clinics. Nonprofit clinics are the most common, appearing in over 50% of all markets. We top-code at two the number of nonprofit clinics, since fewer than 5% of the observed markets have more than two clinics of this type. The possible outcomes for n_N are therefore in $\{0, 1, 2+\}$, with the final category including all markets with 2 or more nonprofit clinics. See Table A.1 in Appendix Section A.1 for the full distribution of clinic counts. Types G and F clinics are less common than nonprofits, with government clinics

[13] A total of 17,341 facilities were believed to offer substance abuse treatment services. However, 16% were found to be ineligible for the survey because they had closed, were not providing substance abuse treatment on October 1,2000, or treated incarcerated clients only. Of the remaining facilities, about 94% completed the N-SSATS survey. Many of these facilities are in large metropolitan areas, and thus outside of the scope of this article.

[14] These statistics are from the 2000 Census. Across all MSA counties, 63% of the employed population worked in their home county.

TABLE 1
FREQUENCY OF MARKET OUTCOMES

G = Government Clinics F = For-profit Clinics	Zero Nonprofits	One Nonprofit	Two Nonprofits
G = 0, F = 0	0.293	0.263	0.075
G = 1, F = 0	0.142	0.034	0.019
G = 0, F = 1	0.039	0.051	0.035
G = 1, F = 1	0.028	0.014	0.014

NOTE: There are 3 types of clinics and 12 possible outcomes. The sum of all cells equals 1.

appearing in 24% of the sample markets and for-profit clinics appearing in 17% of markets. We top-code the clinic counts at one for G and F facilities; for each type this affects about a fifth of all markets in which at least one clinic of the relevant type is active. Overall, 12% of the sample markets have one or more top-coded variables.[15] Although we do not study clinic entry dynamics in this article, the numbers of clinics of each type are fairly stable between 2000 (our sample year) and 2002 (the next year with available OSAT data). Among the 1,583 markets in our sample, fewer than 10% experience a change in the number of public clinics between 2000 and 2002, and a similar share of markets experience a change in the number of for-profit clinics. The count of nonprofit clinics changes in 22% of markets between 2000 and 2002.

In Table 1 we describe the frequency of different clinic configurations (market structures) in the data. The most common configuration has no OSAT service (464 markets or 29.3% of the sample), followed by a configuration with a single nonprofit and no other clinics (416 markets or 26.3% of the sample). The two least-common structures each appear 22 times in the data (1.4% of markets); each includes one G and one F clinic, and either one or two N clinics.

4.1. *Observed Exogenous Variables.* Let the vector X_m contain demand and cost shifters that may affect all types of clinics in market m, although the extent of these effects may vary across clinic types. To account for the potential demand for substance abuse treatment, we estimate the number of white and nonwhite substance abusers in each county using data from the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC).[16] We distinguish between white and nonwhite addict populations to allow clinics of different types to vary in their response to the race of potential clients. To account for the variance of the addict estimates, we use a parametric bootstrapping procedure to construct the estimates' sampling distribution. In our main estimation procedure, we draw from this distribution to account for potential differences between a market's true number of addicts and our estimate from the NESARC data. See Appendix Section A.2 for a description of the NESARC data and our approach to estimating the number of addicts in a market.

In addition to the two measures of the addict population, we include in X_m a county's median income and the percentage of its over-18 population that lacks health insurance. These variables capture the ability of addicts (and their families) to pay for treatment. The same variables may also describe the overall economic state of a market, including local government tax revenue and employment conditions. Finally, X_m includes the number of doctors per 10,000 county residents. This variable controls for the overall level of medical activity in the market, which

[15] In additional unreported descriptive analysis, we investigate whether the top-coding of clinics masks positive correlation in clinic entry patterns consistent with complementarities across clinic types (and therefore contrary to crowding out). We find no significant evidence of positive effects across clinic types at n values above the top-code thresholds we use in our main analysis.

[16] NESARC is a nationwide face-to-face household survey of 43,093 respondents who were 18 years or older between 2001 and 2002. The survey is conducted by the National Institute on Alcohol Abuse and Alcoholism (NIAAA). Respondents are classified as having either an alcohol/drug dependency or abuse problem according to the NIAAA. For more information on NESARC, see NIAAA (2006).

TABLE 2
MARKET CHARACTERISTICS

	Mean	Standard Deviation
White addict population, 1,000s	1.497	1.237
Nonwhite addict population, 1,000s	0.287	0.480
Median income, 10,000s	3.293	0.615
Pct uninsured among over-18 pop.	16.346	5.063
Doctors per 10,000 pop.	10.109	6.647
Government hospitals	0.453	0.601
Nonprofit hospitals	0.541	0.680
For-profit hospitals	0.104	0.330
State $ to local govts. per capita	1.103	0.395
Nearby nonprofit chain share	0.577	0.221
Nearby for-profit chain share	0.307	0.237
N	1583	

NOTE: The summary statistics on addict populations are calculated using the mean (nonbootstrap) estimates of individual markets' numbers of addicts. Government and for-profit hospitals are top-coded at 2 and nonprofit hospitals are top-coded at 3. This top-coding affects 9 markets.

could be correlated with general medical demand, supply, or both. In the top panel of Table 2 we provide summary statistics for the variables in X_m.[17]

To keep our main empirical analysis tractable, we employ a parsimonious set of variables in X_m. There are several other demographic variables, however, that one might consider adding to the analysis. We have experimented with additional variables (e.g., presidential voting patterns, unemployment rate, divorce rate, income and population growth rates) but found that these variables do not significantly improve the fit of basic descriptive models of clinic participation in markets, which we describe below in Section 4.2. In Appendix Section A.3 we discuss the impact of these additional variables, and we provide summary results in Table A.4 of the Appendix.

Although the variables in X_m enter the payoff function of each clinic type that might participate in market m, we assume that the variables in the vector Z_{tm} affect type t clinics only. This provides exclusion restrictions that aid identification of our model, especially the effect that one type of clinic has on another. For each type of clinic we observe the number of hospitals of the same type (public, nonprofit, or for-profit) that are active in m.[18] We assume that a type t clinic may have lower fixed costs when it operates in the same market as a type t hospital. For the 12% of clinics that operate within a hospital, the effect of a type t hospital on type t clinics is direct because the hospital can reduce the fixed costs of obtaining and maintaining treatment space. For potential clinics outside of hospitals, the presence of a type t hospital in a market may proxy for the presence of local institutions or resources that support clinics of the same type. Further, we assume that the presence of a type t hospital is independent of the local unobserved tastes for any particular type of OSAT clinic. OSAT clinics are generally quite small relative to overall hospital size, so we do not expect OSAT demand to factor into hospital location decisions.

As an additional instrument for G, we calculate the per-capita revenue transfers from each state's government to each market's local governments in 1997 and 2002, and we take the average of the two years' transfers.[19] These transfers include funds for county governments and lower-level (e.g., town) governments. We conjecture that local governments with additional revenue are more likely to operate a public OSAT clinic. In addition, we assume that this

[17] Insurance statistics are available from the U.S. Census Bureau's Small Area Health Insurance Estimates (SAHIE) program. Median income and the number of MDs are available from the Area Resource File (ARF).

[18] We obtained these data from the American Hospital Association survey. We top-code the number of government and for-profit hospitals at 2 and the number of nonprofit hospitals at 3. This top-coding affects 9 markets.

[19] These data are from the 1998 and 2002 editions of the U.S. Census Bureau's Compendium of Government Finances.

aggregate measure of transfers is uncorrelated with state or local public policies that affect the payoff to private clinics.[20]

Finally, we include measures of nearby nonprofit and for-profit clinic chains. For each market, we identify the other counties (within and outside our sample) that have centroids within 20–75 miles of the sample market, and we construct z_{tm} as the share in 1998 of all type t clinics in these counties that are chain affiliated.[21] For example, two distinct markets may each have 20 nonprofit clinics in the surrounding counties, with one market having 15 of 20 clinics as chain affiliated ($z_{Nm} = 0.75$) whereas the other market has 5 of 20 ($z_{Nm} = 0.25$). We conjecture that the market with $z_{Nm} = 0.75$ would be more likely to have one or more type N clinics because these clinics would be able to take advantage of reduced start-up or management costs as part of a local chain. At the same time, the type t chain measure is not affected by the overall level of OSAT service provided in the region by type t clinics; in the example both markets have 20 nearby nonprofit clinics. We use lagged (1998) data to construct z_{tm} in order to alleviate concerns about the simultaneity of clinic decisions across markets, and therefore our assumption of an independently observed cross section of clinic behavior. We also note that the measure of nearby chain concentration is not specific to any particular chain. The lower panel of Table 2 contains summary statistics on variables in Z_m.

4.2. *Descriptive Analysis*. We estimate descriptive models to examine how the presence of each type of clinic is correlated with the number of remaining clinics of other types and the variables in X and Z. We measure the numbers of white and nonwhite addicts with the mean (nonbootstrap) estimates we construct from the NESARC survey, and we use logged values of the addict counts to improve fit. For clinic types G and F we estimate probit models, whereas for nonprofit clinics we estimate an ordered probit. We estimate each model separately and report our results in Table 3. To maintain comparability with the empirical model we introduce below, we include separate indicators for the first and second nonprofit clinics that a type G or F clinic may encounter in a market.

In estimating the probability that $n_G = 1$, we find that the first and second nonprofit clinics in a market are significantly and negatively correlated with a public clinic's presence, whereas the presence of a for-profit clinic has a smaller and marginally significant correlation. Similarly, in the model for nonprofit clinics, we find that n_N is negatively and significantly correlated with the presence of a public clinic, but virtually unaffected by the presence of a for-profit clinic. Finally, the for-profit clinic model shows that both public and nonprofit clinics, while negatively correlated with for-profit clinics, each has relatively small correlations with n_F.

Most of the demographic market characteristics in X have a significant correlation with n_t, and in some cases the differences across models suggest interesting differences in the practices of the three clinic types. All types of clinics respond positively and significantly to the number of white addicts in a market, but only government clinics are significantly correlated with the number of nonwhite addicts. Median income is marginally significant only for nonprofit clinics, whereas to our surprise the percentage of uninsured adults is positively and significantly correlated with n_N and n_F. All types of clinics are positively and significantly correlated with the number of doctors per capita in the market. Turning to the cost-shifting instruments, each type of clinic's respective pair of variables in Z_{tm} is jointly significant in predicting n_t. Although the marginal effects for the numbers of hospitals are generally small across clinic types, the remaining variables in Z have larger effects on average.

Although these descriptive results are suggestive of the relationships among types of clinics, the parameter estimates should be read cautiously. If it is true that OSAT decisions across clinic types are related, as we describe in Section 3's model and as suggested by the descriptive results

[20] This assumption is supported by the data. When we regress n_t on X_t and the full collection of Z variables for all clinic types, government transfers are not significantly correlated with the presence of nonprofit or for-profit clinics.

[21] This variable is created using the question, "On October 1, 1998, was this facility owned by an organization with multiple facilities or sites that provide substance abuse treatment?"

TABLE 3
DESCRIPTIVE MODELS OF CLINIC ACTIVITY

Dependent Variable	$n_G \in \{0, 1+\}$		$n_N \in \{0, 1, 2+\}$		$n_F \in \{0, 1+\}$	
Model	Probit	Marginal Effect	Ordered Probit	Marginal Effect	Probit	Marginal Effect
Market structure indicators						
Government	–	–	−0.764***	−0.203	−0.174*	−0.034
			(0.081)		(0.103)	
First non-profit	−0.922***	−0.221	–	–	−0.182*	−0.037
	(0.097)				(0.101)	
Second non-Profit	−1.015***	−0.191	–	–	−0.085	−0.017
	(0.131)				(0.129)	
For-profit	−0.186*	−0.047	−0.005	0.002	–	–
	(0.107)		(0.084)			
Market level variables						
Log(white addict pop.)	0.198***	0.053	0.733***	0.169	0.805***	0.167
	(0.066)		(0.057)		(0.082)	
Log(nonwhite addict pop.)	0.363***	0.098	−0.048	−0.011	−0.031	−0.006
	(0.042)		(0.030)		(0.044)	
Median income	0.083	0.023	0.122*	0.028	0.128	0.026
	(0.084)		(0.070)		(0.091)	
Percent uninsured	−0.022*	0.004	0.030***	0.007	0.046***	0.010
	(0.013)		(0.011)		(0.014)	
MDs per 10,000 residents	0.039***	0.002	0.027***	0.006	0.031***	0.006
	(0.006)		(0.005)		(0.006)	
Government hospitals	0.080	0.017	–	–	–	–
	(0.063)					
State $ to local govts.	0.609***	0.165	–	–	–	–
	(0.097)					
Nonprofit hospitals	–	–	0.106**	0.024	–	–
			(0.050)			
Nonprofit chain share	–	–	0.498***	0.115	–	–
			(0.147)			
For-profit hospitals	–	–	–	–	0.280**	0.024
					(0.113)	
For-profit chain share	–	–	–	–	0.254	0.053
					(0.180)	

NOTE: $N = 1{,}583$ for all models. Standard errors are in parentheses. The probit models for public and for-profit clinics each contain a constant. The marginal effects reported for the nonprofit clinics are for the outcome where $n_N = 1$. *** indicates $p \leq 0.01$, ** indicates $p \leq 0.05$, and * indicates $p \leq 0.1$.

of Table 3, then the values of $\mathbf{n} = (n_G, n_N, n_F)$ are endogenous and the estimates in Table 3 are inconsistent. Further bias may enter the descriptive models if the individual models' error terms are correlated across clinic type, perhaps because of market-level factors that affect the cost of any type of clinic operating in m. Our main estimation strategy accounts for both potential sources of misspecification.

5. ESTIMATION

We assume that a type t clinic's payoff function takes the following form:

$$\pi_{tm}(n_t, \mathbf{n}_{-t}) = X_m\beta_t + Z_{tm}\phi_t + \sum_{j \neq t} \delta_{tj} 1[n_j \geq 1] + \gamma_{tN} 1[n_N = 2] + \varepsilon_{tm}$$
$$\text{with } \varepsilon_{tm} = u_m + e_{tm}.$$

The parameter vectors β_t and ϕ_t, which capture the effects of X and Z on a clinic's payoff, can vary across clinic types. A clinic of type t that shares the market with one clinic of type j

experiences a change in its payoff equal to δ_{tj}. If the clinic is in the market with a second type N clinic (including when the clinic itself is a nonprofit), its payoff is further reduced by γ_{tN}. Finally, we assume that unobservable payoff shifters are captured by ε_{tm}, which is observed by all potential clinics but unobserved by the econometrician. Given the additive structure of the errors, realizations of ε_{tm} must not affect the way clinics compete with each other, or else values of δ_{tj} would not be constant across markets (e.g., ε_{tm} contains unobserved fixed costs).

The u_m component of ε_{tm} is a market-level unobservable that shifts the return from operating a clinic of any type in market m. Failing to account for such common factors will bias the estimates of the competitive effects toward zero (i.e., against finding any competitive effect). The second term, e_{tm}, is a type-specific unobservable that is i.i.d. across types and markets and is independent of u_m. We assume that both u and e are distributed $N(0, 1)$.[22]

Our estimation procedure is based on finding parameters that are consistent with conditions C1–C2. Even with the functional form and distributional assumptions above, conditions C1–C2 alone do not yield an exact probability for each possible $\mathbf{n}$. When the values of δ and ϕ are negative, for all $\mathbf{n}$ other than $(0, 0, 0)$ and $(1, 2, 1)$ our model predicts that there will exist some realizations of ε such that multiple outcomes satisfy C1–C2, i.e., that there are multiple equilibria. Although exact probabilities are impossible with C1–C2 alone, it is possible to define upper and lower bounds on the probability that an outcome $\mathbf{n}$ satisfies C1–C2. These probabilities are given by integrating over the regions of ε in which each outcome is (1) an equilibrium and (2) the unique equilibrium. The upper bound is the probability that a vector ε is drawn such that $\mathbf{n}$ satisfies the inequalities in C1–C2, regardless of whether any other outcomes satisfy these inequalities. The lower bound is the probability that an ε is drawn such that $\mathbf{n}$ is the *only* outcome that satisfies C1–C2. Put differently, the upper and lower bounds represent opposite treatments of how multiplicity is resolved in favor or against $\mathbf{n}$. These bounds are the basis of our estimation strategy.

We write the upper bound on the probability of observing $\mathbf{n}$ by implicitly assuming that $\mathbf{n}$ always obtains in the region of multiplicity:

$$\overline{P}(\mathbf{n} \mid W; \theta) = \Pr(\text{C1–C2 hold for } \mathbf{n} \mid W; \theta),$$

with $W = [X, Z]$ as in Section 3. We then construct the lower bound on the probability by implicitly assuming that $\mathbf{n}$ never occurs in the region of multiplicity:

$$\underline{P}(\mathbf{n} \mid W; \theta) = \Pr\begin{pmatrix}[\text{C1–C2 hold for } \mathbf{n} \mid W; \theta] \cap \\ [\text{C1–C2 does not hold for any } \mathbf{n}' \neq \mathbf{n}]\end{pmatrix}.$$

These bounds imply a set of inequality restrictions. Given that the model is true, the empirical probability of observing $\mathbf{n}$ must lie between the upper and lower probability bounds predicted by our model:

$$\underline{P}(\mathbf{n} \mid W; \theta) \leq P(\mathbf{n} \mid W) \leq \overline{P}(\mathbf{n} \mid W; \theta).$$

The term $P(\mathbf{n} \mid W)$ is the population probability of observing $\mathbf{n}$ given the set of W variables in a particular market. $P(\mathbf{n} \mid W)$ implicitly depends on the distribution of unobserved market characteristics as well as any equilibrium selection mechanism. Tamer (2003) demonstrates that the relationship between $P(\mathbf{n} \mid W)$ and the model's probability bounds are sufficient to permit inference on θ. We do not know $P(\mathbf{n} \mid W)$, so we replace it with a consistent estimate, $\widehat{P}(\mathbf{n} \mid W)$, obtained from our sample. We use simulation methods to calculate the upper and

[22] In principle, it is possible to estimate the variance of u_m relative to the variance of e_{tm}. This is difficult in practice, however, and for convenience we assume that the variances are equal. Ciliberto and Tamer (2009) estimate some of their model's relative variance terms but not others. In a model with a different approach to equilibrium, Berry (1992) is able to identify the relative variance of the market specific unobservable.

lower probability bounds, and denote these simulated values $\underline{P}^s(\mathbf{n} \mid W;\theta)$ and $\overline{P}^s(\mathbf{n} \mid W;\theta)$. We discuss the construction of $\widehat{P}(\mathbf{n} \mid W)$, $\underline{P}^s(\mathbf{n} \mid W;\theta)$, and $\overline{P}^s(\mathbf{n} \mid W;\theta)$ below. We account for the sampling variance of the addict population estimates when we construct each probability object.

We employ a modified minimum distance (MMD) estimator, as suggested by Ciliberto and Tamer (2009), to find a $\widehat{\theta}$ for which the following restrictions are most nearly satisfied in our sample:

$$\underline{P}^s(\mathbf{n} \mid W;\widehat{\theta}) \leq \widehat{P}(\mathbf{n} \mid W) \leq \overline{P}^s(\mathbf{n} \mid W;\widehat{\theta}). \tag{2}$$

The model implies upper and lower probabilities for all possible market structures $\mathbf{n}$, and not just the observed market structure. Similarly, the empirical probability $\widehat{P}(\mathbf{n} \mid W)$ can be computed for all possible $\mathbf{n}$ in a market. We employ all of this information during estimation, and we evaluate the inequality restrictions in (2) for all possible $\mathbf{n}$ in a market. Let $\mathcal{N}$ be the set of possible market structures $\mathbf{n}$. In our application $\mid \mathcal{N} \mid= 12$.

Our objective function is a distance measure that penalizes values of θ that fail to satisfy the inequality restrictions. Whenever the inequalities are satisfied for a combination of m and $\mathbf{n}$, the contribution to the objective function is zero. When an inequality is violated, the contribution is the distance between $\widehat{P}(\mathbf{n} \mid W)$ and the nearest bound. Thus, $\widehat{\theta}$ is

$$\widehat{\theta} = \arg\min_{\theta} Q(\theta) = \sum_{m=1}^{M} \sum_{\mathbf{n}\in\mathcal{N}} Q_{\mathbf{n}m}(\mathbf{n}, \theta),$$

where

$$\begin{aligned} Q_{\mathbf{n}m}(\mathbf{n}, \theta) = {} & 1[\widehat{P}(\mathbf{n}_m|W_m) < \underline{P}^s(\mathbf{n}_m|W_m;\theta)] \times [\underline{P}^s(\mathbf{n}_m|W_m;\theta) - \widehat{P}(\mathbf{n}_m|W_m)] \\ & + 1[\widehat{P}(\mathbf{n}_m|W_m) > \overline{P}^s(\mathbf{n}_m|W_m;\theta)] \times [\widehat{P}(\mathbf{n}_m|W_m) - \overline{P}^s(\mathbf{n}_m|W_m;\theta)]. \end{aligned}$$

$1[\cdot]$ is the indicator function. The value $\widehat{\theta}$ minimizes the sum of differences between the population probabilities and the probability bounds from the model. We use a simulated annealing algorithm to search over θ values and minimize $Q(\theta)$.

In estimating the model, we normalize the X variables following Mazzeo (2002). For each variable X_k we calculate its mean across markets, $\overline{X}_k$, and generate the transformed variable $X'_k = \log(X_k/\overline{X}_k)$. With this transformation, the explanatory variables have similar means and variances. The variables in Z have more limited ranges and more similar means by their construction, so we do not apply the same transformation to these variables.

Before presenting our results, we provide some additional details about the estimation procedure. First, we discuss the concept of set identification since multiple θs can be consistent with C1–C2 and the data, and likewise more than one $\widehat{\theta}$ could yield the same minimized value of $Q(\widehat{\theta})$. Second, we discuss the "first stage" estimates of $\widehat{P}(\mathbf{n} \mid W)$. Finally, we discuss our algorithm for simulating $\underline{P}^s(\mathbf{n} \mid W;\widehat{\theta})$ and $\overline{P}^s(\mathbf{n} \mid W;\widehat{\theta})$.

5.1. *Set Identification.* Conditions C1–C2 may be satisfied by more than one θ in the population. Suppose, for example, that at the true θ,

$$\underline{P}(\mathbf{n} \mid W;\theta) < P(\mathbf{n} \mid W) < \overline{P}(\mathbf{n} \mid W;\theta) \tag{3}$$

for all "interior" $\mathbf{n}$ in every market. Then, as long as $\underline{P}(\mathbf{n} \mid W;\theta)$ and $\overline{P}(\mathbf{n} \mid W;\theta)$ are continuous in θ, it may be possible to perturb θ by a small amount and keep $P(\mathbf{n} \mid W)$ inside the bounds. If such a perturbation is possible, the true θ cannot be distinguished from the alternative θ. Following the identification argument in Tamer (2003), β and ϕ are point identified by the model's restrictions on the unique equilibrium (0, 0, 0). It is also possible to show that the sums of each type's competitive effects (e.g., $\delta_{GN} + \delta_{GF} + \gamma_{GN}$) are point identified by the model's restrictions on the other unique equilibrium, $(1, 2, 1)$; however, sufficient conditions for identification of the individual competitive effects are quite difficult to verify.

In our setting, we can identify only the set of θs that are consistent with C1–C2. These conditions essentially exclude values of θ that are not consistent with the model and data, which in turn yields a set of θs that could have generated the observed data. Ciliberto and Tamer (2009) refer to the collection of θs that are consistent with the model's restrictions as the "identified set," and they prove that the MMD estimator provides a consistent estimate of this set. Statistical inference requires constructing confidence intervals for the identified set instead of a particular θ.

We follow the method proposed by Chernozhukov et al. (2007) to calculate the confidence intervals.[23] The interval, denoted by Θ_α, is a collection of θs constructed so that they cover the identified set with the desired probability, α. We set $\alpha = 0.95$ to generate our main results. The interval Θ_α is the set of parameters for which the objective function is within a specific neighborhood, c_α, of the minimized objective function. That is,

$$\Theta_\alpha = \theta : Q(\theta) - Q(\widehat{\theta}) \leq c_\alpha.$$

In Appendix Section A.4 we describe the method for finding the appropriate value of c_α as well as other computational details for constructing Θ_α.

5.2. *First Stage Estimator*. The probability $P(\mathbf{n} \mid W)$ is strictly a function of the data, whereas the bounds $\overline{P}(\mathbf{n} \mid W; \theta)$ and $\underline{P}(\mathbf{n} \mid W; \theta)$ depend on the data, the parameters, and our assumptions on how the data are generated (i.e., our model and solution concept). There are several options for obtaining $\widehat{P}(\mathbf{n} \mid W)$. In principle it could be calculated nonparametrically, but we opt for a flexible functional form.[24] In our implementation of the model, we use a multinomial logit model to obtain estimates of $\widehat{P}(\mathbf{n} \mid W)$. To account for the sampling variance of addicts, we draw repeatedly from the distributions of white and nonwhite addicts, estimate a separate multinomial logit model for each draw, and then average the models' predicted probabilities for our final $\widehat{P}(\mathbf{n} \mid W)$. We include all variables in X and Z linearly, quadratic terms for addict populations and income, and an interaction between total addict population and the number of MDs. These calculated probabilities describe the way in which market structures vary with the market characteristics, but they do not provide information about the parameters in agents' payoff functions.

$\widehat{P}(\mathbf{n} \mid W)$ is linked to θ through the economic model and equilibrium concept (i.e., the identifying assumptions, C1–C2). If the equilibrium concept were such that there is always a unique equilibrium outcome, the upper and lower bounds given by the model would be equivalent since whenever $\mathbf{n}$ is observed, it must be the unique equilibrium. In this case, the conditional outcome probabilities in the population should equal the probabilities from the behavioral model at the true θ. We could then form an estimator by minimizing the distance between $\widehat{P}(\mathbf{n} \mid W)$ and $\overline{P}(\mathbf{n} \mid W; \theta) = \underline{P}(\mathbf{n} \mid W; \theta)$.

5.3. *Simulation of Probability Bounds*. Exact computation of $\underline{P}(\mathbf{n} \mid W; \theta)$ and $\overline{P}(\mathbf{n} \mid W; \theta)$ involves finding the regions of u_m and e_{tm} in which $\mathbf{n}$ is *an* equilibrium and the regions in which $\mathbf{n}$ is the *unique* equilibrium. Within estimation, these probabilities must be calculated for each evaluation of the objective function. It is difficult to compute the probability bounds analytically because the limits of integration are defined by restrictions that the model places on u_m and e_{tm}. Therefore, we use simulation methods to obtain estimates of the upper and lower probability bounds.

[23] An alternative method for computing confidence intervals is described in Andrews et al. (2004).

[24] Ciliberto and Tamer (2009) compute probabilities in their airlines application using both nonparametric and parametric methods and find little difference between the two approaches.

We begin by taking random draws of the market- and firm-level unobservables, u_m and e_{tm}, indexing each simulation draw by r. The total number of simulation draws is R. We also draw from the sampling distribution of the white and nonwhite addict estimates, with (X^r_{Wm}, X^r_{Nm}) representing a single draw from the joint distribution. Then, for a given θ, $\varepsilon^r_{tm} = u^r_m + e^r_{tm}$, and (X^r_{Wm}, X^r_{Nm}), we compute simulated payoff function values, π^r_{tm}, in each market for each type of clinic at each possible $\mathbf{n}$. We evaluate whether conditions C1–C2 apply for values of π^r_{tm} at each $\mathbf{n}$, and in doing so we obtain the full set of equilibrium outcomes in a market. We follow Ciliberto and Tamer (2009) in computing $\underline{P}^s(\mathbf{n} \mid W;\theta)$ and $\overline{P}^s(\mathbf{n} \mid W;\theta)$ from these simulated outcomes. Let $E^r_{\mathbf{n}}$ be a dummy variable that is equal to one when $\mathbf{n}$ is an equilibrium for draw r, and zero otherwise. The value of $\overline{P}^s_m$ is then

$$\overline{P}^s_m(\mathbf{n} \mid W_m;\theta) = \sum_{r=1}^{R} \frac{E^r_{\mathbf{n}}}{R}.$$

This procedure is repeated for each $\mathbf{n}$ in each market. The lower bound, $\underline{P}^s_m$, requires evaluation of whether an $\mathbf{n}$ is the unique equilibrium in the market given the simulated profit values for all potential clinics. Let $U^r_{\mathbf{n}}$ be a dummy variable equal to one when $\mathbf{n}$ is a unique equilibrium, and $U^r_{\mathbf{n}} = 0$ otherwise. The simulated lower bound is

$$\underline{P}^s_m(\mathbf{n} \mid W_m;\theta) = \sum_{r=1}^{R} \frac{U^r_{\mathbf{n}}}{R}.$$

We set $R = 100$ to compute the simulated probability bounds.

6. RESULTS

6.1. *Estimates of the Identified Set*. In Table 4 we present our confidence intervals, denoted Θ_{95}, which are constructed so that they cover the identified set with 95% probability. The set itself is a collection of parameter vectors. In our results we present the interval for each of the model parameters; however, the identified set is smaller than the union of the individual intervals. Although we discuss most of our results in terms of Θ_{95}, to aid exposition we also report the vector that minimizes the objective function, $\widehat{\theta}$. This value is not necessarily any more valid or informative than any other parameter vector contained in Θ_{95}. The estimation routine converges to a single $\widehat{\theta}$, despite the model's lack of point identification, when first-stage outcome probabilities cannot be placed between the upper- and lower-bound probability terms of the second-stage behavioral model. Although the bounding of first-stage probabilities should always occur for a sufficiently large sample size and correctly specified model, our limited data sample introduces sampling error and also constrains the parametric flexibility we can build into our first- and second-stage models.

We refer to the estimates of δ and γ as "competitive effects," as they represent the effect of one clinic on another, although the clinics' varying objectives may not suggest competition in the usual sense. The competitive effects across clinics are all negative, which indicates that each type of organization is a substitute for the others. Government clinics are more strongly affected by the presence of nonprofit clinics than for-profit clinics, which is consistent with the coefficient estimates from the descriptive analysis in Table 3. The lower bound of the confidence interval for the second nonprofit on a public clinic is not identified in the data, but this has minimal effect on any results discussed below, including the crowding-out analysis of Section 6.4.[25] Nonprofit

[25] We impose a lower bound of −40 on the competitive effects during estimation. We suspect that the width of this confidence interval is due to the infrequency with which we observe markets with $n_G = 1$ and $n_N = 2$, which implies small first-stage $P(n|W)$ values, on average, for these market structures. This, in turn, means that γ_{GN} values that drive the relevant $P(n|\theta, W)$s toward zero do not yield Q values that are substantially different from $Q(\widehat{\theta})$. Thus, our

TABLE 4
ESTIMATES OF THE IDENTIFIED PARAMETER SET

Type of Clinic	Government	Nonprofit	For-Profit
Competitive effects			
Government	–	[−4.334, −2.347] −2.846	[−2.598, −1.227] −1.795
First nonprofit	[−3.438, −1.458] −1.966	[−2.543, −1.829] −2.201	[−1.630, −0.687] −1.150
Second nonprofit	[−39.996, −0.196] −2.339	–	[−1.444, −0.014] −0.507
For-profit	[−2.043, −0.441] −1.106	[−1.264, −0.157] −0.785	–
Demographic characteristics			
White addict pop	[0.272, 0.859] 0.556	[0.907, 1.430] 1.143	[0.730, 1.585] 1.181
Nonwhite addict pop	[0.121, 0.490] 0.273	[−0.088, 0.115] 0.007	[−0.113, 0.278] 0.084
Median income	[−1.514, 1.124] −0.090	[−0.864, 0.971] 0.135	[−1.214, 1.958] 0.258
Percent uninsured	[−1.133, 0.678] −0.127	[−0.425, 0.716] 0.198	[−0.229, 1.725] 0.696
MDs per 10,000 residents	[0.210, 0.971] 0.608	[0.040, 0.503] 0.301	[0.184, 1.038] 0.604
Government hospitals	[−0.277, 0.270] 0.042	–	–
State $ to local govts.	[0.291, 1.113] 0.709	–	–
Nonprofit hospitals	–	[−0.135, 0.269] 0.043	–
Nonprofit chain share	–	[0.337, 1.540] 0.898	–
For-profit hospitals	–	–	[−0.304, 0.861] 0.323
For-profit chain share	–	–	[−0.178, 1.299] 0.508
Intercept	[−0.674, 0.140] −0.410	[0.062, 0.802] 0.447	[−0.705, 0.176] −0.217

NOTE: The numbers in brackets are the 95% confidence interval, based on the parameter set Θ_{95}. The bottom number in each cell is the value of the parameter at which the objective function for the sample was minimized. The demographic variables common to all clinic types (i.e., X) are normalized using the formula $X'_k = \log(X_k/\bar{X}_k)$ for each variable k.

clinics have strong effects on each other, and government clinics have a stronger effect on nonprofits than do for-profits. Finally, the payoff to type F clinics is reduced significantly by the presence of nonprofit and government clinics, although these effects are smaller in magnitude than the effects that G and N clinics have on each other.

The estimated effects of the demographic variables on payoff functions are largely consistent with the preliminary results in Table 3. All types of clinics have fairly similar (and large) responses to increases in the population of white addicts and in the number of physicians per capita. Only public clinics have a statistically significant and positive response to the size of the nonwhite addict population. Contrary to the results of Table 3, none of the three clinics types are significantly affected by a high population of uninsured adults or median incomes. The cost-shifting instruments each have values of $\widehat{\theta}$ with the intuitive sign, although the hospital counts do

cutpoint procedure for computing confidence intervals cannot reject the possibility of very strong effects through γ_{GN}. We investigated two alternatives to evaluate the impact of this result. First, we computed our measures of model fit while $\gamma_{GN} < -40$. Second, we estimated a version of the model in which nonprofit clinics have a linear effect on public clinics (i.e., we replace γ_{GN} with δ_{GN}). Neither alternative generated significant changes to our main qualitative results.

not significantly affect OSAT provision by the corresponding clinic type. Although we do not ascribe a structural interpretation to the demographic variables' coefficients, these estimates raise interesting questions about demand and the clinics' incentives to provide treatment that might be addressed in future work.

6.2. *Fit of the Model.* One approach to assessing the performance of our model fit is to ask how frequently an empirical market structure is predicted by the model. For a parameter vector in Θ_{95}, we draw a collection of ε values and evaluate the set of equilibria in market m given its observed characteristics (X_m, Z_m) and conditional on the drawn (θ, ε) pair. Whenever the observed $\mathbf{n}_m$ is in the set of equilibria, we count this as a successful prediction. Across all markets in the sample, $\widehat{\theta}$ successfully predicts the observed outcome with probability 0.316. Taking the minimum and maximum probabilities of success implied by the set Θ_{95}, we find that the model predicts the observed equilibrium in the range [0.306, 0.331]. The model is most often successful in predicting the observed (0, 0, 0), (1, 0, 0) and (0, 1, 0) outcomes—the most common ones in the data—which the model does with probability around 0.4. It is encouraging that the model is relatively strong in predicting these outcomes, as they are the most relevant ones for the central calculations of Section 6.4, in which we compute crowding out.

An alternative approach to measuring fit is based on our objective function, $Q(\theta)$, which assigns a penalty to an observation when the empirical conditional probability $\widehat{P}(\mathbf{n} \mid W)$ lies outside of the values of $\overline{P}^s(\mathbf{n} \mid W;\theta)$ and $\underline{P}^s(\mathbf{n} \mid W;\theta)$ implied by the model. In the population, the true θ will produce upper and lower bounds that contain the population probability $P(\mathbf{n} \mid W)$ for most market structures, although sampling error will cause these bounds to be violated in any given sample.[26] For our sample, we assess the performance of the empirical model by asking how frequently we find that $\underline{P}^s(\mathbf{n} \mid W;\theta) < \widehat{P}(\mathbf{n} \mid W) < \overline{P}^s(\mathbf{n} \mid W;\theta)$ at $\widehat{\theta}$. We evaluate these inequalities in all M markets for each of the $|\mathcal{N}| - 2$ market structures where $\overline{P} \neq \underline{P}$ according to our behavioral model, and we find that the empirical probability, $\widehat{P}$, is bounded by the predicted probabilities for 40.7% of the $M \times (|\mathcal{N}| - 2)$ individual configurations. For the remaining observations that do not fall within the bounds, the average difference between $\widehat{P}$ and $\overline{P}$ or $\underline{P}$ (as appropriate) is 1.82 percentage points.

For a final approach to describing the fit and robustness of the model, we re-estimate it on a random subsample of 1,062 markets (67%) and compare the predictions in the subsample to those in the holdout sample of 521 markets. We do this to assess whether the behavioral model performs well in making out-of-sample predictions, which would provide further support for the model's use in the crowding-out counterfactual calculations in Section 6.4.[27] For comparison, we also perform this holdout exercise on the descriptive models reported in Table 3; we estimate the descriptive models jointly and include a market-level $N(0, 1)$ error to facilitate comparison to the main behavioral model.

When we estimate the behavioral model with the subsample of 1,062 markets, we obtain a $\widehat{\theta}_S$ for which the predicted equilibrium set contains the observed equilibrium with probability 0.330. When we use the same $\widehat{\theta}_S$ to calculate equilibria in the 521 holdout markets, we find that these predictions contain the observed outcomes with probability 0.323.[28] The comparable figures for the descriptive models—the average per-market joint likelihood of the data—show a slightly larger drop-off in predictive power. For the 1,062 markets used in estimation, the joint likelihood of the data at the parameter estimates is 0.266, whereas the same parameters

[26] For the outcomes (0, 0, 0) and (1, 2, 1) the equilibrium is unique and the empirical probability always differs from the model-implied probability by some amount.

[27] See Keane and Wolpin (2007) for a discussion of how holdout samples can be beneficial for validating empirical models. Keane and Wolpin focus on the use of nonrandom holdout samples and structural versus descriptive empirical models.

[28] Although these measures of model performance are slightly better for $\widehat{\theta}_S$ than the comparable full-data results using $\widehat{\theta}$, when we use the full data we obtain better per-market values of $Q_{nm}(\widehat{\theta})$ and narrower confidence intervals.

TABLE 5
CONDITIONAL FREQUENCY OF MULTIPLE EQUILIBRIA ACROSS MARKETS

G = Government Clinics F = For-profit Clinics	Zero Nonprofits	One Nonprofit	Two Nonprofits
G = 0, F = 0	0	[0.393, 0.539] 0.452	[0.354, 0.736] 0.516
G = 1, F = 0	[0.571, 0.720] 0.632	[0.449, 0.978] 0.923	[0.000, 0.650] 0.434
G = 0, F = 1	[0.418, 0.741] 0.601	[0.545, 0.807] 0.665	[0.428, 0.785] 0.564
G = 1, F = 1	[0.698, 0.932] 0.785	[0.174, 1.00] 0.820	0

NOTE: Each entry is the average across markets of the probability that an alternative equilibrium exists, conditional on a simulation draw predicting that a market's observed equilibrium is in the set of simulated equilibria. See the note below Table 4 for information on presentation of estimates.

imply a joint likelihood of 0.240 for the 521 holdout markets.[29] The qualitative results from this exercise are not substantially different if we exclude the descriptive model's market-level error or replace the descriptive model with a purer reduced form that predicts each endogenous outcome, n_t, as a function of all X and Z variables but not the n_{-t} values.

6.3. *Analysis of Multiplicity*. To assess the degree of multiplicity in our sample and obtain a preliminary measure of crowding out, we use Θ_{95} to compute the probability that an observed equilibrium is the only equilibrium in a market. For each market and $\theta \in \Theta_{95}$ we draw a collection of ε values such that the observed $\mathbf{n}_m$ is among the predicted equilibrium, thereby rationalizing the outcome of the game conditional on observables and the payoff parameters.[30] We then evaluate the number of cases in which some alternative $\mathbf{n}'_m$ is also an equilibrium. Across θ values in Θ_{95}, we find that the probability of multiple equilibria is in [0.286, 0.405], suggesting that in roughly a third of the joint distribution of observable and unobservable exogenous variables, the model predicts multiple equilibria.

Because the full set of potential market structures in our application is not large, it is easy for us to present the estimated probability of multiple equilibria for each possible clinic configuration. These results are in Table 5. In the cell corresponding to the outcome (1, 0, 0), we find that when a single public clinic serves the market, there is a probability in [0.571, 0.720] that an alternative equilibrium exists. The alternative equilibrium includes one or two nonprofit clinics, a for-profit clinic, or some combination of these outcomes. The possibility of other equilibria suggests that in about two-thirds of cases, a single government clinic prevents the entry of other clinics. This probability is conservative in that some cases with (1, 0, 0) as a unique equilibrium will still permit positive OSAT as an equilibrium if G clinics are forbidden to provide OSAT.

It is more difficult to extract information about crowding out from outcomes with multiple clinic types active in the market. For example, our model predicts that multiple equilibria occur with probability [0.449, 0.978] when the observed outcome is (1, 1, 0). In this case, some of the multiplicity is due to the exogenous variables permitting (0, 1, 1) as an equilibrium, which is relevant for measures of public OSAT crowding out private clinics. The possibility also exists, however, that the multiplicity is due to cases in which (1, 0, 1) is an equilibrium, and the relevant crowd out occurs between types of private clinics.

[29] We compute the "hit rate" for the behavioral model because this model does not have an associated likelihood. It is possible to apply the same approach to the descriptive model, by drawing from the error distribution and comparing the estimated model's predictions to the data, but this would introduce simulation error that we avoid by reporting the joint likelihood.

[30] To insure that we sample sufficiently from the region of the unobservables for the which the observed market structure is an equilibrium, we increase the number of simulation draws to 1,000.

TABLE 6
CROWDING OUT AND SUPPLY BY PUBLIC CLINICS IN (1,0,0) MARKETS

		Model Predictions		Probability that Only Type t Clinics Are Crowded Out	
	N (1,0,0) Markets (1)	Pr(1,0,0) Is Unique (2)	Pr(0,0,0) if G Closes (3)	Nonprofit (4)	For-profit (5)
All markets	224	[0.280, 0.429] 0.368	[0.214, 0.296] 0.254	[0.614, 0.838] 0.710	[0.064, 0.146] 0.104
Markets below median in					
Insurance coverage	132	[0.329, 0.489] 0.423	[0.252, 0.353] 0.303	[0.578, 0.828] 0.692	[0.066, 0.174] 0.118
Median income	125	[0.318, 0.486] 0.415	[0.238, 0.345] 0.295	[0.585, 0.836] 0.697	[0.067, 0.171] 0.117
Share of addicts who are white	164	[0.323, 0.485] 0.419	[0.247, 0.345] 0.296	[0.583, 0.823] 0.694	[0.067, 0.171] 0.119

NOTE: See the note for Table 4. To select the markets with below-median insurance coverage, we take the median county-level value from our overall sample of 1,583 counties. The sets of markets with below-median income and above-median nonwhite addict share are constructed similarly and separately.

6.4. *OSAT Loss and Crowding Out*. As we describe in Section 3, in our model it is possible that the presence of a type G clinic could deter either a type N or type F clinic (or both) from operating. This situation can arise in one of two ways when the observed market configuration includes a G clinic: (1) there exists an alternative equilibrium without the G clinic and with an additional N or F clinic, and (2) the observed structure is a unique equilibrium, but there is an alternative equilibrium with an additional N or F clinic when the G clinic is forbidden from participating in the market. We compute these two effects by making OSAT service by a G clinic impossible[31] and then simulating the new set of equilibria in each market.

We perform the simulation by implementing the following steps. For each $\theta \in \Theta_{95}$ and each market m, we simulate a sequence of ε vectors such that the market's observed $\mathbf{n}_m$ is an equilibrium given θ and the observed market characteristics. We then compute the share of ε vectors that support an outcome of interest (e.g., the absence of any treatment once G clinics are eliminated from the market). This share is our simulated probability, $p_m(\theta)$, of the outcome of interest in market m given θ. We then average $p_m(\theta)$ across a set of markets to obtain $p(\theta)$. In reporting intervals over counterfactual probabilities below, we report the minimum and maximum $p(\theta)$ over all $\theta \in \Theta_{95}$.

We focus on the 224 markets with an empirical (1, 0, 0) configuration. These markets, which constitute over half of all cases in which a public clinic is present, are the clearest case in which public OSAT may be critical to treatment being available. Additionally, at this initial configuration it is possible to add N or F clinics without interference from our assumed upper limits on the numbers of clinics. In some analysis we focus within these (1, 0, 0) markets on cases that satisfy certain demographic conditions, such as a low median income.

We present our results in Table 6. The top row of the table contains results for all 224 markets with the observed configuration (1, 0, 0). We find the share of markets that would lose OSAT entirely if the G clinic is eliminated is between 0.214 and 0.296. This implies that our estimate of crowding out is between 0.704 and 0.786 (i.e., one minus the probabilities of losing OSAT). In most cases, an observed (1, 0, 0) structure allows an alternative equilibrium that includes private clinics. In Columns 4 and 5 we condition on markets that do not lose service when a public clinic exits, and we find that there is a probability between 0.614 and 0.838 that only nonprofit clinics appear in the new equilibrium. The comparable figure with for-profit clinics

[31] We implement this step by drawing values of ε and (X_W, X_N), as described in Section 5.3, and then we replace ε_G with a large negative number, so that a public clinic would never choose to provide service in a market. We then evaluate the set of equilibria for this (adjusted) simulation draw.

is below 15%, reflecting the closer competitive relationship of G and N clinics. In all cases not covered by Columns 4 or 5, the new equilibria include at least one nonprofit clinic (e.g., both $(0, 1, 0)$ and $(0, 0, 1)$ are equilibria).

The crowd-out probabilities above are averages that account for variation in ε draws within markets and also variation in observed market-level characteristics. In the remaining rows of Table 6 we examine markets that may be more likely to rely on public clinics as the sole possible source of substance abuse treatment. We focus (separately) on markets that have a relatively low share of insured adults, a low median income, and a low proportion of addicts who are white. We find that for each demographic condition, the crowd-out rate is lower (i.e., the probability of lost service is greater) than in the full set of observed $(1, 0, 0)$ markets. The result on addicts' race is driven directly by differences in β_t across clinic types for white and nonwhite addicts. The results on income and insurance depend on both the relevant β_t values and how N and F clinics differ in their responses to public clinics. Although for-profit clinics appear attracted to markets with low median incomes and insurance coverage, their choices to participate in these markets are relatively unaffected by the presence of a public clinic. Thus the removal of a public clinic has little effect on the probability of for-profit service. Nonprofit clinics, in contrast, remain out of these markets because the markets' particular demographic characteristics generally have a negative impact on clinic payoffs. Our results on correlation between demographics and OSAT service are similar to those of Norton and Staiger (1994), who find variation in the location choices of hospitals of different ownership types.

7. CONCLUSIONS

This article employs a model of endogenous market structure to study strategic behavior among public, private nonprofit, and private for-profit health care providers. We specifically focus on the decision of outpatient substance abuse treatment clinics to be active within a market. We extend the literature on firms' entry decisions by considering differences across the payoff functions of for-profit, nonprofit, and government organizations. By applying recently developed methods for estimating discrete games with multiple equilibria, we avoid imposing potentially ad hoc restrictions on payoffs, allowing us to analyze the phenomenon of crowding out without imposing any restrictions on what we might find. Our results appear to support this choice, as we find considerable evidence in favor of the existence of multiple equilibria in the identity of clinics that serve a market. Although we focus on small markets due to computational constraints, the qualitative results here are likely to be informative about larger markets as well.

Our results demonstrate that differentiation among the three clinic types is important to understanding how OSAT is provided. We find that public clinics and nonprofit entities (in addition to for-profits) take the actions of other players in the market into consideration in their operating decisions. Our analysis of crowding out indicates that there are many markets in which public OSAT clinics operate to the exclusion of potential private OSAT clinics. The incidence of this crowding out is somewhat less pronounced in poorer markets and markets with a greater share of nonwhite addicts. In many cases, government entities are the only willing providers of OSAT. An important limitation of our results is that we have not done any comparison of the quality of services offered or types of clients treated by different types of clinics. Thus, it is difficult to make normative statements about crowding out since the private provision of OSAT may fail to achieve the same policy objectives as public provision. In addition, for analytic convenience we make an assumption of complete information among OSAT clinics, and we do not know how our results would be affected by an alternative economic model that permitted asymmetric information among clinics.

Finally, although our approach is informative about the nature of OSAT, other data sources and empirical approaches will be required to inform several open questions arising from this article. Topics for future research include (1) the interactions between inpatient and outpatient treatment; (2) the effect of changing health insurance policy on the provision of OSAT by all types; and (3) the degree of patient overlap in public, nonprofit, and for-profit OSAT clinics.

APPENDIX

A.1. *Clinic Distribution by Type*. See Table A.1 for an enumeration of markets by clinic count.

A.2. *Estimation of a Market's Number of Addicts*. We estimate the number of white and nonwhite addicts in each county using data from the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC). The survey asks extensive questions on patterns of alcohol and drug use as well as a variety of questions on sociodemographic information. On the basis of the answers to the questions about drinking and drug use, NESARC classifies respondents as being substance abusers or not; we adopt the term "addict" to describe an abuser of either drugs or alcohol. The interview instrument used to diagnose alcohol and/or drug use disorders is the National Institute on Alcohol Abuse and Alcoholism (NIAAA) Alcohol Use Disorder and Associated Disabilities Interview Schedule DSM-IV Version (AUDASIS-IV). See NIAAA (2006) for additional information on the interview instrument. We present summary statistics in Table A.2. Over 7% of the survey respondents are diagnosed as having an alcohol abuse or dependency problem, and almost 2% have a drug problem.

For each observation in the NESARC survey, we construct an indicator, y_i , for whether an individual i is an addict, with $y_i = 1$ for substance abusers. We also construct a set of dummy variables to capture the demographic characteristics of each individual. The variables include a set of indicator variables for gender, age category (18–24, 25–34, 35–44, 45–64, and 65 or older), race (white, black, Hispanic, American Indian/Native Alaskan, or Asian), whether the

TABLE A.1
NUMBER OF MARKETS BY CLINIC COUNT

Number of Clinics of Type	Government	Nonprofit	For-Profit
0	1,195	785	1,307
1	303	572	218
2	60	159	43
3	17	37	10
4	6	17	3
5	–	9	1
6	2	1	1
7	–	2	–
8	–	–	–
9	–	1	–
Total	1,583	1,583	1,583
Top-coding impact	5.37%	4.23%	3.66%

TABLE A.2
SUMMARY STATISTICS FROM NESARC VARIABLES

Variable	Mean	Standard Deviation
Alcohol abuse/dependence in last 12 months	0.077	0.267
Drug abuse/dependence in last 12 months	0.017	0.128
Hispanic	0.193	0.394
Black	0.191	0.393
American Indian	0.016	0.127
Asian	0.031	0.173
Female	0.570	0.495
Age 18–24	0.121	0.326
Age 35–44	0.211	0.408
Age 45–64	0.298	0.457
Age >65	0.190	0.393
N	43,093	

TABLE A.3
PROBABILITIES OF DRUG/ALCOHOL ADDICTION

	Men			Women		
Demographic Group	Mean	5th Pctile	95th Pctile	Mean	5th Pctile	95th Pctile
White aged 18–24	0.314	0.285	0.340	0.139	0.121	0.159
White aged 25–34	0.205	0.184	0.228	0.093	0.078	0.107
White aged 35–44	0.165	0.149	0.181	0.071	0.059	0.083
White aged 45–64	0.076	0.067	0.084	0.018	0.015	0.021
Black aged 18–24	0.244	0.198	0.286	0.101	0.073	0.128
Black aged 25–34	0.209	0.161	0.255	0.070	0.050	0.091
Black aged 35–44	0.162	0.129	0.202	0.046	0.032	0.059
Black aged 45–64	0.100	0.079	0.121	0.021	0.014	0.029
Hispanic aged 18–24	0.231	0.194	0.266	0.081	0.059	0.105
Hispanic aged 25–34	0.158	0.127	0.183	0.045	0.033	0.060
Hispanic aged 35–44	0.109	0.082	0.136	0.027	0.018	0.037
Hispanic aged 45–64	0.067	0.049	0.083	0.008	0.005	0.012
Native Am. aged 18–24	0.514	0.355	0.690	0.282	0.150	0.421
Native Am. aged 25–34	0.325	0.192	0.472	0.087	0.030	0.171
Native Am. aged 35–44	0.204	0.112	0.298	0.165	0.089	0.241
Native Am. aged 45–64	0.174	0.109	0.233	0.027	0.007	0.053
Asian aged 18–24	0.369	0.211	0.519	0.175	0.076	0.294
Asian aged 25–34	0.224	0.109	0.345	0.104	0.039	0.199
Asian aged 35–44	0.095	0.029	0.171	0.016	0.000	0.046
Asian aged 45–64	0.074	0.017	0.144	0.029	0.000	0.077

NOTE: We obtain the mean probabilities of substance abuse (by age, race, and gender) by using each observation in the NESARC survey exactly once, i.e., without bootstrapping. The reported 5th and 95th percentiles are from the sampling distribution of the estimated addiction probability.

individual's residence is rural, and the individual's home census division. We define the vector d_i to include the census division indicators plus the interaction of dummies for gender $\times$ age $\times$ race, rural location $\times$ gender, and rural location $\times$ race.

We use y and d to construct an estimate of the true numbers of white and nonwhite addicts, X_{Wm} and X_{Nm}, respectively, which we do not observe. Denote the estimates $\widehat{X}$, and let v be their deviations from the true values, so that in market m,

$$\widehat{X}_{Wm} = X_{Wm} + v_{Wm}$$
$$\widehat{X}_{Nm} = X_{Nm} + v_{Nm}.$$

We assume that the error term v is uncorrelated with the clinic- and market-specific unobservables in ε_{tm}. We focus here on the construction of $\widehat{X}$'s distribution, which we use in our main estimation procedure. (To obtain a point estimate of $(\widehat{X}_{Wm}, \widehat{X}_{Nm})$ we use a similar procedure, but employ all of the responses to the NESARC survey exactly once.)

The NESARC survey contains the responses of $N = 43{,}093$ individuals. We draw with replacement 100 bootstrap samples, b, of size N of the variables (y_i^b, d_i^b). Note that the same individual may appear as multiple observations within a given bootstrap sample. For each bootstrap sample we apply the following procedure:

(1) We estimate a probit model that predicts whether an individual is an addict ($y_i = 1$) conditional on his or her characteristics in d_i. Let $\Pr^b(y_i = 1 \mid d_i)$ represent the predicted values from one bootstrap sample. See Table A.3 for summary statistics on the estimated addiction probabilities.
(2) To obtain a market's addict population, we multiply the predicted probability for each distinct gender-age-race-rural-census grouping, g, by the corresponding population from

TABLE A.4
ADDITIONAL AND ALTERNATIVE VARIABLES IN DESCRIPTIVE MODELS

	Government (Probit)		Nonprofit (Ordered Probit)		For-Profit (Probit)	
	Coefficient	Pseudo-R^2	Coefficient	Pseudo-R^2	Coefficient	Pseudo-R^2
Base (n_{-t}, X, and Z_t)	n/a	0.207	n/a	0.152	n/a	0.188
No instruments (n_{-t} and X)	n/a	0.182	n/a	0.147	n/a	0.183
Log(SSI) & Log(Pop.) instead of Log(Addict) counts	n/a	0.196	n/a	0.150	n/a	0.154
Variable added to "Base"						
Log(SSI population)	0.276***	0.214	0.311***	0.166	−0.0766	0.189
	(0.0660)		(0.0517)		(0.0719)	
Median age	−0.00498	0.207	−0.0290***	0.155	0.00127	0.189
	(0.0116)		(0.00970)		(0.0126)	
Poverty rate	−0.0232	0.208	0.0683***	0.158	−0.0114	0.189
	(0.0207)		(0.0163)		(0.0223)	
Unemployment rate	0.0698***	0.211	0.0947***	0.159	0.00789	0.189
	(0.0257)		(0.0207)		(0.0292)	
Divorce rate	2.291	0.208	9.488***	0.163	1.979	0.189
	(2.007)		(1.607)		(2.213)	
Pct. state legislators who are Democrat	−0.512	0.208	0.389	0.153	−1.022***	0.194
	(0.340)		(0.271)		(0.374)	
Percent vote for Gore 2000	0.0467	0.207	1.110***	0.156	−0.529	0.189
	(0.391)		(0.307)		(0.441)	
Mental health parity law	−0.581***	0.236	−0.140**	0.153	0.0918	0.189
	(0.0825)		(0.0633)		(0.0870)	
Mental health parity law with drug and alcohol coverage	−0.112	0.207	−0.131	0.153	0.224*	0.191
	(0.118)		(0.0882)		(0.118)	
Population growth 1999–2001	2.856	0.207	−6.465**	0.154	1.624	0.189
	(3.045)		(2.680)		(3.542)	
Median income growth 1999–2001	−5.162	0.208	0.108	0.152	−2.765	0.189
	(4.749)		(3.867)		(5.433)	

NOTES: The "Base" row reports results from models identical to those described in Table 3. "No instruments" omits the Z_t variables. The third row of results are from a model that replaces log(white addict) and log(nonwhite addict) with the log of the SSI population and the log of the total population. Each remaining pair of rows adds a single variable to the "Base" model and reports the coefficient estimate, standard error, and pseudo-R^2 for the augmented model.

the 2000 decennial Census, and then sum over the white- and nonwhite individuals.[32] This provides one draw from the sampling distribution of $(\widehat{X}_{Wm}, \widehat{X}_{Nm})$. Formally, the b^{th} draw from the distribution is calculated:

$$\widehat{X}^b_{Wm} = \sum_{g|race=white} Pop_{gm} \times \Pr^b(y_i = 1 \mid group = g)$$
$$\widehat{X}^b_{Nm} = \sum_{g|race=nonwhite} Pop_{gm} \times \Pr^b(y_i = 1 \mid group = g).$$

A.3. *Alternative Exogenous Variables.* We use a parsimonious set of explanatory variables in our analysis. This choice is strongly influenced by the computational demands of Ciliberto and Tamer's (2009) empirical approach, which we adopt. The results in Table 3 alone, however, are not informative about whether this parsimony represents a strong sacrifice. In Table A.4, we display results from a large collection of alternative models that explore the benefits of adding to our set of exogenous variables. To capture other factors that affect the demand for addiction treatment, we consider the size of the under-65 population that receives Social

[32] We are assuming that the population within each grouping, as reported by the Census, has been measured without error.

Security Insurance (SSI) payments, the median age, the poverty rate, the unemployment rate, and the divorce rate. For local (or state-wide) variation in public policy, we consider the share of Democrats in the relevant state legislature, the percentage of county residents that voted for Al Gore in the 2000 presidential election, whether there is a state law for mental health parity (MHP) in insurance coverage, and additionally whether there is an MHP law that specifies coverage for drug and alcohol abuse. Finally, to capture the effects of growth in county size or wealth, we consider the changes in county population and median income between 1999 and 2001.

We take each variable mentioned above and add it individually to the descriptive models in Table 3. For comparison, we include the pseudo-R^2 from Table 3 and the pseudo-R^2 from Table 3's results when the instruments (Z_t) are excluded. This provides a sense of the degree to which the pseudo-R^2 changes when potentially significant variables are added or subtracted. In most cases, adding the variables listed above has very little impact on pseudo-R^2. There are a few noteworthy exceptions. First, the SSI population has a relatively large effect in the models of public and nonprofit clinic activity. Although this variable could be worthwhile to add to the model (at some computational cost), we note in Table A.4's third row that if we were to replace our addict estimates with SSI population together with total population to represent the size of the treatment market, the predictive power of the descriptive models decline. Second, there are several market-level demographic variables that appear to have a strong effect on nonprofit clinics. The table's other columns, however, show that these variables have minimal impact on public and for-profit clinics. Similarly, for-profit clinics appear to be significantly affected by the party composition of a state legislature, but the variable is not correlated with the presence of the other types of clinics. Third, general MHP laws have a relatively strong effect on the presence of public clinics, but the changes in pseudo-R^2 for private clinics are small. In all, the results of Table A.4 suggest that adding to our set of X variables would not provide us with a substantially improved ability to predict the market participation choices of all three clinic types.

A.4. *Computing Confidence Intervals for the Identified Set.* Recall that the 95% confidence interval for the identified set, Θ_{95}, requires finding the set of θs for which the value of the objective function is within a specified neighborhood, c_{95}, of the minimum. That is,

$$\Theta_{95} = \theta : Q(\theta) - Q(\widehat{\theta}) \leq c_{95}.$$

Chernozhukov et al. (2007) provide a subsampling algorithm to find the correct c_{95} for a given sample. We implement the algorithm using the nine steps detailed below.

1. As part of the simulated annealing routine to obtain $\widehat{\theta}$, we save a collection of 150,000 randomly selected values of θ and the corresponding values of $Q(\theta)$. This collection of θ and $Q(\theta)$ values serve as an approximation of the full set of possible parameter values and the objective function surface, respectively.
2. Construct $B = 100$ subsamples of the M markets. Each subsample, b , is a random selection of 398 markets drawn without replacement from the full sample—approximately 25% of M. There is not much guidance about how large the subsamples should be (see Politis et al. (1999) for some discussion of this issue). Ciliberto and Tamer (2009) report that their intervals are relatively robust to subsample size.
3. To account for sampling variance in $\widehat{P}(\mathbf{n} \mid W)$, we repeat the following steps B times. We take a draw from the addict distribution and use data from all 1,583 markets to re-estimate $P(\mathbf{n} \mid W)$ using a MNL model. We then take one draw from the sampling distribution of the MNL estimates to obtain $\widehat{P}_b(\mathbf{n} \mid W)$.
4. For each subsample b and corresponding $\widehat{P}_b(\mathbf{n} \mid W)$, we compute $\widehat{\theta}_b = \arg\min Q^b(\theta)$. This is an additional minimization step that is completed once for each subsample. We use $\widehat{\theta}$ as our starting value for each subsample. The minimum is obtained by executing the

simulated annealing algorithm for 150,000 iterations, followed by a Nelder–Mead simplex minimization procedure.

5. We use an iterative process to search for c_{95}, the neighborhood around $Q(\widehat{\theta})$ that contains the identified set with 95% confidence. Let c_{95}^{i} represent the ith iteration of this process. We follow Ciliberto and Tamer (2009) in selecting an initial value of $c_{95}^{1} = 0.25 \times Q(\widehat{\theta})$.[33]
6. For the current value of c_{95}^{i}, we find all values of θ for which the objective function is within c_{95}^{i} of the minimum. That is, we find the set Θ_{95}^{i}, defined as

$$\Theta_{95}^{i} = \theta : Q(\theta) - Q(\widehat{\theta}) \leq c_{95}^{i}.$$

7. For each subsample, b, we compute, a_b^i, which is the size of the neighborhood around the subsample objective function value generated by the parameter vectors in Θ_{95}^{i}:

$$a_b^i = \sup_{\theta \in \Theta_{95}^{i}} [Q^b(\theta) - Q^b(\widehat{\theta}_b)].$$

8. Update c_{95}^{i+1} with the 95th percentile of $\{a_1^i, \ldots, a_B^i\}$.
9. Repeat steps 6–8 until the c_{95}^{i}s converge. This converged value is c_{95}, which we use to obtain Θ_{95}.

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[33] Chernozhukov et al. (2007) show that the procedure we follow for updating c_{95}^{i}, outlined in steps 6–9, converges to c_{95} for arbitrary values of c_{95}^{1}.

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