# Measuring Sunk Costs in the Ready-Mix Concrete Industry

Allan Collard-Wexler *
Economics Department, NYU Stern

July 1 2007

**Abstract**

Sunk Costs are key in to determining the ease of entry into a market and understanding market structure.

I find that dynamic and static models give essentially the same measurement of sunk costs.

If the profitability of markets is mismeasured, this introduces an positive correlation between unobserved components of profitability and the number of firms in a market. Using data on entry and exit patterns in the Ready-Mix Concrete Industry from 1976-1999, I show that using market-level fixed effects in a Bresnahan-Reiss entry model reduces the coefficient on demand by 50% and increases the coefficient on competition by 100% compared to the no fixed-effect benchmark.

*This paper is part of my Ph.D. dissertation at Northwestern University under the supervision of Robert Porter, Michael Whinston, Aviv Nevo and Shane Greeenstein. I thank Lynn Riggs, Mike Mazzeo and Ambarish Chandra for their insights. Financial support from the Fonds Québecois sur la Recherche et la Société et Culture and the Center for the Study of Industrial Organization at Northwestern University is gratefully acknowledged. The research in this paper was conducted while the author was a Special Sworn Status researcher of the U.S. Census Bureau at the Chicago Census Research Data Center. Research results and conclusions expressed are those of the author and do not necessarily reflect the views of the Census Bureau. This paper has been screened to insure that no confidential data are revealed. Support for this research at the Chicago RDC from NSF (awards no. SES-0004335 and ITR-0427889) is also gratefully acknowledged.

# 1 Introduction

A key question in industrial economics is the relationship between market structure and competitive outcomes in the product market such as innovation and consumer welfare. For instance, when the Departement of Justice evaluates the impact of a proposed merger between two firms, they evaluate if the merger will lead to an increase in prices. But market structure is itself the result of firms deciding to enter or exit a market. So a complete evaluation of the merger would also take into account both the fact that reduced competition will raise consumers prices *and* if higher concentration will induce new firms to enter the market.

The goal of this paper is to measure the sunk cost of entry for ready-mix concrete firms. These costs are important since they determine the ease of entry into a market. For instance, in Collard-Wexler (2006b) I find that large sunk costs are principally responsible for the dispersion of productivity in the ready-mix concrete industry. Likewise, in Collard-Wexler (2006a) I show that sunk costs are so large that firms choose not to respond to demand shocks by either entering or exiting a market. Moreover, this paper contributes to a growing literature on the estimation of the sunk costs of entry and discusses methodological issues with the measurement of sunk costs. For instance, Sweeting (2006) estimates the sunk costs of format switching in the radio market to understand the effect of mergers on station repositioning. Ryan (2006) shows that environmental regulations substantially increased sunk costs in the cement industry. Finally Dunne, Klimek, Roberts, and Xu (2006) show that most of the difference in turnover rates between dental offices and chiropractors can be explained by higher sunk costs for dentists than chiropractors.

I estimate sunk costs using static models of entry  la Bresnahan and Reiss (1991) *and* dynamic models of entry in the Ericson and Pakes (1995) tradition using the methods of Aguirregabiria and Mira (2006). Both static and dynamic models estimate sunk costs to be about \$ 2 million, which is quite reasonable for the ready-mix concrete industry. Moreover, both static and dynamic models find that the first competitor has a much greater impact on profits than subsequent competitors. Static models, such as those developed by Bresnahan and Reiss (1994), can be used to investigate the presence of sunk costs in the ready-mix concrete industry. These models does not compute the value function from period profits. Instead, the value function is directly estimated, without reference to what will happen in the future, from the current configuration of firms in a market. This "reduced form" model is used to investigate a number of empirical issues, such as which variables best capture demand or different assumptions on the shocks to firms profits. In constrast dynamic models can estimate firm's period profits and be used to perform a much broader set of counterfactual policy experiments.

I believe that dynamic models in the tradition of Bajari, Benkard, and Levin (2006) and static models in the tradition of Bresnahan and Reiss (1991) are complements for understanding entry and exit decisions. A dynamic model can be used to perform a very broad range of policy counterfactuals. For instance in Collard-Wexler (2006a), I look at the effect of demand fluctuations on industry turnover and plant size. For this type of policy counterfactual it is impossible to use a static model since these models cannot envisage changes in the process for demand. On the other hand, static models can be used to evaluate if there are differences in the sunk costs of entry in two different countries, or if a business licensing regulation has increased the sunk cost of entry over time. Moreover, a static model can be coded up within a single day and estimated in under 5 minutes and incorporate many different demand side variables at once. This allows the researcher to perform an exhaustive specification search to examine the robustness of the model to incorporating either market or time controls.

In any particular dataset, the econometrician will observe many components of profitability, such as market population, total number of construction workers and average income within the market. However, certain components of profitability will be neccesarily unobserved, either unobsersed demand shocks such as a taste for concrete construction or unobservables cost shocks such as higher land prices or wages for specialized workers. In Texas concrete is often used to pave roads instead of asphalt, since asphalt will melt in Texas's scorching summer heat. If I do not include a "Texas" control in my specification it will turn up as an unobserved variable. Firms will react to these unobservable components of profitability by entering in greater numbers in more profitable markets. Thus the estimated effect of competition will combine both the true effect of competition on profitability and the correlation between the number of firms in the market and unobserved components of profitability. I correct for the presence of unobserved market heterogeneity by introducing market level "fixed-effect" style estimators for both static and dynamic models of entry. I find that these unobserved components of profitabilty are large for my data on the ready-mix concrete market. Correcting for persistent market heteregeneity increases the effect of competition on firm's profits by more than 50 %.

In section 2 I present the dynamic model of entry and exit and the estimation of the parameters of this model via either static or dynamic structural models. Section 3 discusses the issue of unobserved components of profitability and how to correct for these with market fixed effects. Section 4 presents the data used to estimates the models of entry shown in section 5.

# 2 Model

In this section, I build a dynamic model of entry and exit in oligopoly markets. Later on, I will discuss the specific assumptions used to estimate this model using either a static, pseudo-static and dyanamic structure.

Each market has $N$ firms competing repeatedly, indexed as $i \in I = \{1, 2, ..., N\}$. Some of these firms currently have active plants in the market, others are potential entrants. Denote the state of the firm as $s_i^t$, which can be decomposed in the components that the econometrician observes (denoted $x_i^t$), such as the fact that a firm runs a ready-mix concrete plant, and components that are unmeasured by the econometrician but known to the firm (denoted $\varepsilon_i^t$) such the competence of the manager running the plant. In the empirical specifications I use the observed state $x_i^t$ is simply the presence of a plant in the market. The state of the market (denoted $s^t$) is the composition of the states of all firms and total demand for ready-mix concrete:

$$s^t = \{s_1^t, s_2^t, ..., s_N^t, \underbrace{D^t}_{\text{Demand}}\} \tag{1}$$

The demand state $D^t$ affects all firms in the market and evolves exogenously following a first-order Markov Process $P^D(D^t|D^{t-1})$.

At the start of each period, firms choose actions $a_i^t \in \{\text{in}, \text{out}\}$, either to operate a ready-mix concrete plant or to stay out of the market. Again, denote the action profile in a market as $a^t = \{a_1^t, a_2^t, ..., a_N^t\}$, the composition of actions chosen by each firm. Firms then receive period rewards $r(s^t)$ which depend on the state of the market and pay transition costs $\tau(a_i^t, a_i^{t-1})$ such as a sunk cost of entry if a previously inactive firm enters the market. Thus the firm's value the net present value of rewards the firm will receive, net of transition costs:

$$V(s^0) = \sum_{t=0}^{\infty} \beta^t [r(s^t) + \tau(a_i^t, a_i^{t-1})] \tag{2}$$

In my empirical work I use a simple Bresnahan and Reiss (1991) style reduced-form for the reward function, endowed with parameters $\theta$. It is easily interpreted and separable in dynamic parameters. Specifically, the entry/exit model, in which $a_i^t = 1$ corresponds to activity and $a_i^t = 0$ to inactivity, has the reward function:

$$r(a_i^t, x^t|\theta) = a_i^t \left( \underbrace{\theta_1}_{\text{Fixed Cost}} + \underbrace{\theta_2 M^{t+1}}_{\text{Demand}} + \underbrace{\theta_3 g\left[\sum_{-i} a_{-i}^t\right]}_{\text{Competition}} \right) \tag{3}$$

where $g(\cdot)$ is a non-parametric function of the number of competitors in a market. Transition costs are:

$$\tau(a_i^t, x_i^t|\theta) = \underbrace{\theta_4 1(x_i^t = 0, a_i^t = 1)}_{\text{Sunk Costs}} \tag{4}$$

where $\theta_4$ is the sunk cost of entry.

To make their entry and exit decisions, I assume that firms use symmetric Markovian strategies $\sigma_i(S)$, i.e. their strategies map the state space $S$ defined in equation (1) into mixtures over actions, i.e. $\sigma_i(S) : S \to \Delta A$. Define the strategy profile $\sigma$ as the composition of a strategies for all firms in the market, i.e. $\sigma = \{\sigma_1, \sigma_2, ..., \sigma_N\}$. A *Markov Perfect Equilibrium* is a set of strategies $\sigma^*$ such that all players are weakly better off playing $\sigma_i^*$ given that all other players are using strategies $\sigma_{-i}^*$, i.e.:

$$V(s|\sigma^*) \geq V(s|\{\sigma_i', \sigma_{-i}^*\}) \tag{5}$$

for any strategy $\sigma_i'$, for all players $i$ and states $s$.

## 2.1 Static Model

In constrast to the dynamic model I develloped above, the models entry developed by Bresnahan and Reiss (1991) and Berry (1992) are two-period models. In the first stage, firms make their entry decision. In the second stage they compete in the product market.

There are two interpretations for the static model. The first interpretation proposed by Pakes (2007) is that a two period model is strictly correct only if the state does not change over time, due to either changes in demand or entry and exit of competitors. Thus if the state $s^t$ does not vary over time then the firm's continuation value is proportional to it's period rewards:

$$V(s^0) = \sum_{t=0}^{\infty} \beta^t r(s^0) = \frac{r(s^0)}{1-\beta}$$

Alternatively, we can think of a two period model as a "reduced-form" for the dynamic model of entry and exit. I will discuss this interpretation when we investigate the sunk-cost model of entry and exit.

The original Bresnahan and Reiss (1991) model requires the following assumption on the unobserved firm state $\varepsilon_i^t$:

**Assumption 1 (CS)** *The unobserved state $\varepsilon_i^t$ is common to all firms, i.e. $\varepsilon_i^t = \varepsilon^t$ for all $i$. Moreover, the market level shock $\varepsilon^t$ is i.i.d. across time.*

Assumption **CS** along with the assumption that the firm level state is just $x_i \in \{\text{in}, \text{out}\}$, considerably simplifies the state: there are two groups of firms, those that are in the market, and those that remain out of the market. Firms are identical within the group. To bring this model to the data, the firm's value is assumed to be additively separable in the observed state $x^t$ and the unobserved state $\varepsilon^t$:

**Assumption 2 (AS)** *The firm's value $V(s^t)$ is additively separable in the observed state $x^t$ and the unobserved state $\varepsilon^t$, i.e. $V(s^t) = V(x^t) + \varepsilon_i^t$.*

The equilibrium number of firms $N$ in a market can be characterized by two inequalities:

1. Firms that Enter make Positive Profits

$$V(N, X_m) + \varepsilon_m \quad > \quad 0 \tag{6}$$

2. If an extra firm entered it would make negative profits:

$$V(N+1, X_m) + \varepsilon_m \quad < \quad 0 \tag{7}$$

where $V(N, X_m)$ is the observable component of the firm's value depending on demand factors $X_m$ and the number of symmetric competitors in a market $N$, while $\varepsilon_m$ are unobserved components of profitability common to all firms in a market.

Assume market level shocks $\varepsilon_m$ have a normal distribution with zero mean and unit variance. The probability of observing a market $X_m$ with $N$ plants is the following:

$$\Pr(N = n | X_m) = \Phi[-V(n+1, X_m)] - \Phi[-V(n, X_m)]1(n > 0)$$

where $\Phi(.)$ is the cumulative distribution function of the standard normal. I parameterize the value function as:

$$V(\theta, N, X_m) = \theta_1 a_i^t + \theta_2 M^{t+1} a_i^t + \theta_3 a_i^t \sum_{-i} a_{-i}^t + \theta_4 1(a_i^t = 1, a_i^{t-1} = 0) \tag{8}$$

Note that while this parameterization looks quite similar to the parameterization in equation 4, I fact the parameters that I estimate are quite different, since say $\theta_3$ is the effect of the number of competitors on the firm's continuation value, not the effect on period profits. Parameters can be estimated via Maximum Likelihood, where the likelihood is the following:

$$\mathcal{L}(\theta) = \prod_{m=1}^{M} \prod_{t=1}^{T} \Pr(N_m^t = n | X_m^t, \theta) \tag{9}$$

where $m$ indexes markets and $t$ indexes time periods.

## 2.2 Pseudo-Dynamic Model

An alternate interpretation for two-period models is that they are a "reduced-form" for the fully dynamic model of entry and exit. In the first period firms make their entry decision and receive their continuation value in the second period. To relate the static model to the structure of the dynamic oligopoly game presented above, I use the foundations provided by Campbell and Abbring (2006), who develop a model of oligopoly dynamics in which firms enter and exit using demand threholds, exactly as in Bresnahan and Reiss (1991).

Campbell and Abbring (2006) impose three assumptions to generate their model of demand thresholds. First, as in the Bresnahan and Reiss (1991) model, unobserved component of profitability $\varepsilon_i^t$ are common to all firms in the market.[1] Assumption **CS** is necessary to generate a pattern of demand thresholds for entry and exit. In particular, this assumption rules out simultaneous entry and exit if one firm obtains a very negative profitability shock causing it to exit, while another firm may have obtained a very large positive shock which caused it to enter.[2]

**Assumption 3 (LIFO)** *Firms follow LIFO (Last-In, First-Out) strategies, i.e. younger firms always exit before older firms do.*

The **LIFO** assumption is neccessary to break the problem of multiple equilibria. For instance, firms may expect other firms to exit first, or they may expect themselves to exit first. To obtain a unique equilibria we need to find some way of ordering which firms will either enter or exit first. Thus the **LIFO** assumption assumes that firms which enter earlier will also be the

[1] In fact Campbell and Abbring (2006) can allow for firms within a single market to differ in their profitability. However, the Campbell and Abbring (2006) cannot allow for the profitability ranking of firms to switch over time. Thus firm level differences in profitability are almost completly persistent.

[2] Dunne, Roberts, and Samuelson (1988) document that simultaneous entry and exit is ubiquitous in the manufacturing sector (and the ready-mix concrete sector in particular).

firms that exit later on. In the ready-mix concrete industry I find that older plants tend to exit less often than younger plants. A 1 year old plant has an exit rate of about 7%, while a 15 year old plant has a exit rate of about 4%.

**Assumption 4 (MKP)** *The Markov process for demand ($P^D[D^{t+1}|D^t$) can be represented as a mixture of uniform auto regressions with bounded growth.*

The **MKP** assumption is less transparent than the previous assumptions in this model. What assumption **MPK** rules out is the case where an increase in demand makes a firm more pessimistic about demand in the future. Suppose that this was not the case, then a firm might decide to enter at demand state 1, exit at demand state 2 and reenter in demand state 3 if there is a high probability of transiting to demand state 10 from states 1 and 3, but a low probability of entering demand state 10 from state 2. To avoid this situation, we need to impose structure on the transition process of demand $P^D(D^{t+1}|D^t)$.

Under assumptions **AS**, **CS**, **LIFO** and **MKP**, Proposition 4 in Campbell and Abbring (2006) states that we can characterize the entry and exit policies of firms in terms of demand thresholds.[3] An exit policy is in demand thresholds if a firm exits if demand fall below a certain level, i.e. $\chi(N, D) = 1(D < D^{\chi}_N)$. Likewise, an entry policy is in demand thresholds if a firm enters if demand is above a certain level, i.e. $e(N, D) = 1(D > D^e_N)$. Figure 1 shows that we can decompose demand into entry and exit thresholds. Note that that if firms make unrecoverable sunk costs upon entry, then the exit threshold for $N$ firms will be below the entry threshold for $N$ firms, since firms require higher profits to enter a market than to stay in operation.

[3]Page 11 of Campbell and Abbring (2006) states:

> Proposition 4: Let $(A_S, A_E)$ be the unique symmetric Markov-perfect equilibrium in a LIFO strategy that defaults to inactivity. Assume that $Q(\cdot|C)$ is a mixture of uniform autoregressions with bounded growth. Then, firms with all ranks follow threshold policies.

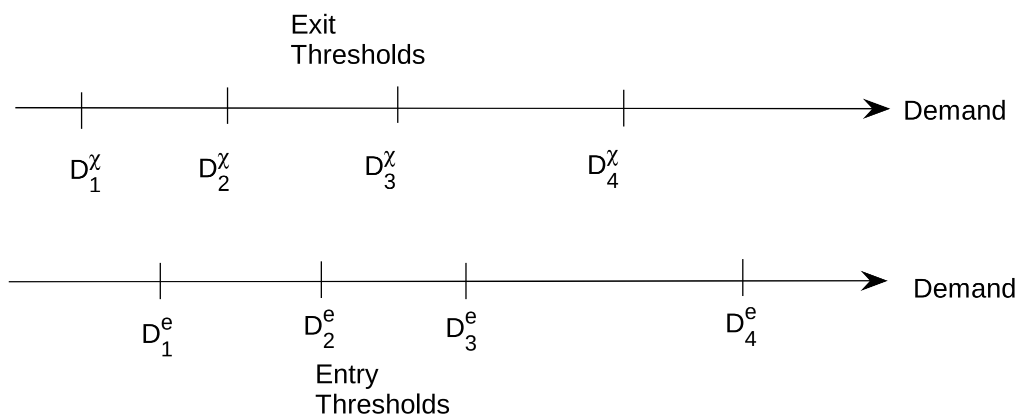


**Figure 1:** Entry and Exit Thresholds for Demand

Firms make sunk, unrecoverable investments when they enter a market. The decision of an incumbent firm to remain in a market differs from the decision of an entrant to build a new plant. The Bresnahan and Reiss (1994) model of exit distinguishes between two types of firms: firms which are already active and firms which are deciding to enter the market. Entrants and incumbents have the same profits, and hence the same continuation values. However, entrants always have lower values than incumbents, since they pay an entry cost that incumbents do not, as is shown by Figure . This implies that there cannot be simultaneous entry and exit: either firms exit, enter, or nothing happens. This is a feature of all models which do not have firm specific shocks and where firms are symmetric: they cannot rationalize the same type of plant in the same market making different choices. I drop market-years in which there is both entry and exit are dropped. With yearly data and markets with on average less than 3 incumbents there is very little simultaneous entry and exit, less than 5% of markets need to be dropped. Moreover, including these markets in the data does not significantly change estimated parameters. So the selection caused by this procedure does not seem to be of great import for this data. Three regimes need to be considered: *entry, exit and stasis.*

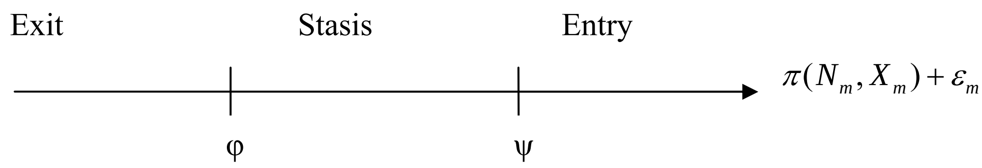


**Figure 2:** Entry Threshold $\psi$ and Exit Threshold $\phi$ based on static profits.

1. Net *Entry*: $N^t > N^{t-1}$

$$\begin{aligned} V(N^t, X_m^t) + \varepsilon_m^t &> \psi \\ V(N^t + 1, X_m^t) + \varepsilon_m^t &< \psi \end{aligned}$$

2. Net *Exit*: $N^t < N^{t-1}$

$$\begin{aligned} V(N^t, X_m^t) + \varepsilon_m^t &> \phi \\ V(N^t + 1, X_m^t) + \varepsilon_m^t &< \phi \end{aligned}$$

3. No Net Change: $N^t = N^{t-1}$

$$\begin{aligned} V(N^t, X_m^t) + \varepsilon_m^t &> \phi \\ V(N^t + 1, X_m^t) + \varepsilon_m^t &< \psi \end{aligned}$$

where $\phi$ is the entry fee that an existing firm pays to enter the market and $\psi$ is the scrappage value of a firm. Entry fees and scrap value are not identified from fixed costs, since it is always possible to increase fixed costs and decrease entry/exit fees by the same amount without changing the likelihood of observing a particular market configuration. Yet, the *difference* between entry and exit fees is identified and can be compared to other quantities such as the effect of an extra competitor.

These equations can be combined into:

$$V(N^t, X_m^t) + \varepsilon_m^t > 1(N^t > N^{t-1})\psi + 1(N^t \leq N^{t-1})\phi \tag{10}$$

$$V(N^t + 1, X_m^t) + \varepsilon_m^t < 1(N^t \geq N^{t-1})\psi + 1(N^t < N^{t-1})\phi \tag{11}$$

The probability of observing a market $X_m$ with $N^t$ plants today and $N^{t-1}$ plants in the last period is:

$$\begin{aligned} \Pr(n^t = N^t, n^{t-1} = N^{t-1} | X_m^t) &= \Phi[-V(n^t + 1, X_m^t) + 1(n^t + 1 \geq n^{t-1})\psi + 1(n^t + 1 < n^{t-1})\phi] \\ -\Phi[-V(n^t, X_m^t) + 1(n^t &> n^{t-1})\psi + 1(n^t \leq n^{t-1})\phi]1(n^t > 0) \end{aligned}$$

which is used to form a maximum likelihood estimator[4]:

$$\mathcal{L}(\theta) = \prod_{m=1}^{M} \prod_{t=2}^{T} \Pr(n^t = N^t, n^{t-1} = N^{t-1} | X_m^t, \theta)$$

## 2.3 Dynamic Model

An alternative strategy is to estimate the model of entry and exit using a fully dynamic model. Applying this framework to data has proven difficult due to the complexity of computing a solution to the dynamic game, which requires at a minimum several minutes of computer time. Hotz and Miller (1993) and Hotz, Miller, Sanders, and Smith (1994) bypass the computation of equilibrium strategies (the approach followed in Rust (1987)'s study of a single agent's dynamic optimization problem) by estimating strategies directly from the choices that firms make. Strategies of rival firms are substituted into the value function of the firm, collapsing the problem into a single-agent problem. This solution only requires that firms play best-responses to their perception of the strategies employed by their rivals, a much weaker assumption than

[4] I drop markets with more than 20 firms at any point in time since the maximum likelihood estimator becomes difficult to estimate with too many firms.

the requirement that firms play equilibrium strategies. The Hotz and Miller approach has been adapted by several recent papers in Industrial Organization such as Bajari, Benkard, and Levin (2006), Pakes, Berry, and Ostrovsky (2006), Pesendorfer and Schmidt-Dengler (2003), Ryan (2006) and Dunne, Klimek, Roberts, and Xu (2006). I employ a refinement of this approach proposed by Aguirregabiria and Mira (2006) (henceforth AM). They start with an initial guess at the strategies employed by firms recovered from the data, and produce an estimate of the parameter value of the firm's payoff functions and the transition probabilities of this system given this guess. Conditioning on the estimated value of the parameters, the initial guess is updated by requiring that all firms play best responses. This procedure is repeated until the strategies used by firms converge, implying that these best responses are in fact equilibrium strategies given estimated parameters. While Aguirregabiria and Mira impose more assumptions than Hotz and Miller, AM delivers more precise parameter estimates in small samples. The first step of the AM technique yields the Hotz and Miller estimates, and thus this algorithm encompasses Hotz and Miller.

Each market has $N$ firms competing repeatedly, indexed as $i \in I = \{1, 2, ..., N\}$, and $N$ is set to 6 in my empirical work. I have chosen a maximum of 6 plants per market, since it allows me to pick up most counties in the U.S. (note that 6 plants is the 95th percentile of the number of plants in a county in Table 6), and keeps the size of the state space manageable. In contrast, for the Bresnahan and Reiss (1994) model, adding many firms to the model does not slow estimation considerably. A county with more than 6 active plants at some point its history is dropped from the sample, since the model does not allow firms to envisage an environment with more than 5 competitors.[5]

Firms also react to market-level demand, $M^t$, which is assumed to be

[5] To allay the potential for selection bias this procedure entails, counties with more than 3000 construction employees at any point between 1976 and 1999 are also dropped.

observable and equals one of a finite number of possible values. I use the number of construction workers in the county as my demand measure. I need to reduce the number of demand side variables in order to limit the number of states in the model, unlike the model of Bresnahan and Reiss (1991) or a purely Hotz and Miller type estimation procedure such as Bajari, Benkard, and Levin (2006). Demand evolves following a Markov Process of the first order with transition probabilities given by $D(M^{t+1}|M^t)$. Demand is placed into 10 discrete bins $B_i = [b_i, b_{i+1})$, where the $b_i$'s are chosen so that each bin contains the same number of demand observations. The level of demand within each bin is set to the mean demand for observations in this bin, i.e. $\text{Mean}b(i) = \frac{\sum_{l=1}^{L} M_l 1(M_l \in B_i)}{\sum_{l=1}^{L} 1(M_l \in B_i)}$, where $L$ indexes observations in the data, and the $D$ matrix is estimated using a bin estimator $\hat{D}[i|j] = \frac{\sum_{(l,t)} 1(M_l^{t+1} \in B_i, M_l^t \in B_j)}{\sum_{(l,t)} 1(M_l^t \in B_j)}$.

The econometrician cannot directly observe strategies, since these depend not only on the vector of observable state characteristics, $x^t$, but also on the vector of unobserved state characteristics, $\varepsilon^t$. However, I can observe *conditional choice probabilities*, the probability that firms in observable state $x^t$ choose action profile $a^t$ denoted as $p : X \times A \to [0, 1]$. These probabilities are related to strategies as:

$$p(a^t|x^t) = \int_{\varepsilon^t} \prod_{i=1}^{N} \sigma_i(\{x^t, \varepsilon^t\}, a_i^t) g^{\varepsilon}(\varepsilon^t) d\varepsilon^t \tag{12}$$

where $g^{\varepsilon}(.)$ is the probability density function of $\varepsilon$. Without adding more structure to the model, it is impossible to relate the observables in this model, the choice probabilities $p(a^t|x^t)$, to the underlying parameters of the reward function. Denote the set of conditional choice probability associated with an equilibrium as $P = \{p(a^t|x^t)\}_{x^t \in X, a^t \in A}$, the collection of conditional choice probabilities for all states and action profiles. To identify the parameters, I place restrictions on unobserved states, similar to those used in the Rust (1987) framework for dynamic single-agent discrete choice, and these assumptions also overlap considerably with the Bresnahan and Reiss (1991) assumptions as well.

First, as in the Bresnahan and Reiss (1991) model, I assume that rewards are additively separable (**AS**) in observed and unobserved states. As well, I assume assume that the unobserved state is serially uncorrelated:

**Assumption 5** *(**SI**) Unobserved states are serially independent, i.e.* $\Pr(\varepsilon^t|\varepsilon^k) = \Pr(\varepsilon^t)$ *for* $k \neq t$*.*

Serial independence allows the conditional choice probabilities to be expressed as a function of the current observed state, $x^t$, and action profile, $a^t$, without loss of information due to omission of past and future states and actions. Formally:

$$\Pr(a^t|x^t) = \Pr(a^t|x^t, \{x^{t-1}, x^{t-2}, ..., x^0\}, \{a^{t-1}, a^{t-2}, ..., a^0\}) \qquad (13)$$

for any $k \neq t$, any state $x^t$, and action profile, $a^t$, since no information is added to equation (12) that would change the value of the integral over $\varepsilon$.

**Assumption 6** *(**SI**) Each firm privately observes* $\varepsilon_i^t$ *before choosing its action,* $a_i^t$*.*

Combined with the assumption of serial independence of the $\varepsilon$'s, private information implies that firms make their decisions based on today's observable state, $x^t$, and their private draw, $\varepsilon_i^t$. In particular, they form an expectation over the private draws of other firms, $\varepsilon_{-i}^t$, exactly as the econometrician: by integrating over its distribution. This leads to the following form for the conditional choice probabilities:

$$p(a^t|x^t) = \prod_{i=1}^{N} p_i(a_i^t|x^t) \qquad (14)$$

The assumption that unobservables for the econometrician are also unobserved by other firms in the market is a strong one. Firms typically have detailed information on the operations of their competitors, which is why in the models Bresnahan and Reiss (1991) or Mazzeo (2002) the unobserved state ($\varepsilon$) is assumed to be common knowledge for all firms in the market.[6] The fact that I obtain similar results from the both the static and dynamic models with these very different assumptions is surprising, and suggests that empirical estimates are robust to tweaking the informational assumptions of the game.

**Assumption 7** *(Logit) $\varepsilon_i$ is generated from independent draws from a type 1 extreme value distribution.*[7]

These assumptions allow the conditional ex-ante value function (before private information is revealed) to be expressed as:

$$V(x|P,\theta) = \sum_{x'} \left\{ r(x'|\theta) + \sum_{a_i} \tau(a_i, x_i|\theta) p_i(a_i|x) + E(\varepsilon|P) + \beta V(x'|P,\theta) \right\} F^P(x'|x) \tag{15}$$

where $E(\varepsilon|P) = \gamma + \sum_{a_i \in A_i} \ln(p_i(a_i|x))$ (where $\gamma$ is Euler's Constant). For the logit distribution, $E(\varepsilon|P)$ is the expected value of $\varepsilon$ given that agents are behaving optimally using conditional choice probabilities $P$. State-to-state transition probabilities conditional on the choice probability set $P$, $F^P(x'|x)$, are computed as:

$$F^P(x'|x) = \left( \prod_{i=1}^{N} p_i(x'_i|x) \right) D[M^{x'}|M^x] \tag{16}$$

It is convenient to develop a formulation for the value function conditional

[6]The model of Seim (2005) uses a combination of common and private unobbservables which can be incorporated into both static and dynamic models. However, adding both types of unobservables complicates estimation.

[7]For the Bresnahan and Reiss (1994) estimates I assumed that $\varepsilon$ was normally distributed. I have estimated the dynamic model using normally distributed shocks (which is very straighforward in the case where there are only two actions) and find similar results to those using the logit distribution.

on taking action $a_j$ today, but using conditional choices probabilities $P$ in the future:

$$V(x|a_j, P, \theta) = \sum_{x'} \{r(\theta, x') + \tau(\theta, x_i, a_j) + \beta V(x'|\theta, P)\} F^P(x'|x, a_j) + \varepsilon_j \tag{17}$$

where $F^P(x'|x, a_j)$ is the state to state transition probability given that firm $i$ took action $a_j$ today:

$$F^P(x'|x, a_j) = \left( \prod_{k \neq i} p_i(x'_k|x) \right) 1(x'_i = a_j) D[M^{x'}|M^x] \tag{18}$$

This allow us to write the conditional choice probability function $\Psi$ as:

$$\Psi(a_j|x, P, \theta) = \frac{\exp\left[\tilde{V}(x|a_j, P, \theta)\right]}{\sum_{a_h \in A_i} \exp\left[\tilde{V}(x|a_h, P, \theta)\right]} \tag{19}$$

where $\tilde{V}(x|a_j, P, \theta)$ is the non-stochastic component of the value function, i.e. $\tilde{V}(x|a_j, P, \theta) = V(x|a_j, P, \theta) - \varepsilon_j$. Note that I normalize the variance of $\varepsilon$ to 1, since this is a standard discrete choice model which does not separately identify the variance of $\varepsilon$ from the coefficients on rewards.

## 2.4 Nested Pseudo Likelihoods Algorithm

An equilibrium to a dynamic game is determined by two objects: value functions and policies. A set of policies $P$ generate value functions $V$, since these policies govern the evolution of the state across time. But policies must also be optimal actions given the values $V$ that they generate.

Suppose I form the likelihood following Rust (1987)'s nested fixed point algorithm, in which the set of conditional choice probabilities $P$ used to evaluate the likelihood at parameter $\theta$ must be an equilibrium to the dynamic game, which I denote as $P^*(\theta)$. To estimate parameters, the following likelihood will be maximized: $\mathcal{L}^{Rust}(\theta) = \prod_{l=1}^{L} \Psi(a_l^t | x_l^t, P^*(\theta), \theta)$. However, each time I evaluate the likelihood for a given parameter $\theta$, I need to compute an equilibrium to the dynamic game $P^*(\theta)$. Even the best practice for solving these problems, the stochastic algorithms of Pakes and McGuire (2001), leads to solution times in the order of several minutes, which is impractical for the thousands of likelihood evaluations typically required for estimation.

To cut through this difficult dynamic programming problem, Aguirregabiria and Mira (2006) propose a clever algorithm:

**Algorithm** Nested Pseudo-Likelihoods Algorithm

1. Compute a guess for the set of conditional choice probabilities that players are using via a consistent estimate of conditional choices $\hat{P}^0(j, x)$, where the index on $\hat{P}$, denoted by $k$, is initially 0. I estimate $\hat{P}^0$ using a simple non-parametric bin estimator, i.e.:

$$\hat{p}^0(a_j|x) = \frac{\sum_{m,t,i} 1(a_{mi}^t = a_j, x_{mi}^t = x)}{\sum_{m,t,i} 1(x_{mi}^t = x)} \tag{20}$$

   which is a consistent estimator of conditional choice probabilities.

2. Given parameter estimate $\hat{\theta}^k$ and an guess at player's conditional choices, $\hat{P}^k$, values $V(x|\hat{P}^k, \hat{\theta}^k)$ are computed according to equation (15). Thus optimal conditional choice probabilities can be generated as:

$$\Psi(a_j|x, \hat{P}^k, \hat{\theta}^k) = \frac{\exp\left[\tilde{V}(x|a_j, \hat{P}^k, \hat{\theta}^k)\right]}{\sum_{a_h \in A_i} \exp\left[\tilde{V}(x|a_h, \hat{P}^k, \hat{\theta}^k)\right]} \tag{21}$$

3. Use the conditional choice probabilities $\Psi(a_j|x, \hat{P}^k, \hat{\theta}^k)$ to estimate the model via maximum likelihood:

$$\hat{\theta}^{k+1} = \arg\max_{\theta} \prod_{l=1}^{L} \Psi(a_l|x_l, \hat{P}^k, \theta) \tag{22}$$

where $a_l$ is the action taken by a firm in state $x_l$ where $l$ indexes observations from 1 to $L$. The Hotz and Miller estimator corresponds is $\theta^1$, the specific case where the likelihood of equation (22) is maximized conditional on choice probabilities $\hat{P}^0$.

4. Update the guess at the equilibrium strategy as:

$$\hat{p}^{k+1}(a_j|x) = \Psi(a_j|x, \hat{P}^k, \hat{\theta}^{k+1}) \tag{23}$$

for all actions $a_j \in A_i$ and observable states $x \in X$.

Note that $\hat{p}^{k+1}$ is not only a best response to what other players were using last iteration($\hat{p}^k$), but also a best-response given that my future incarnations will use strategy $\hat{p}^k$. I have problems with oscillating strategies in this model, i.e. $\hat{P}^k$'s that cycle around several values without converging. To counter this problem, a moving average update procedure is used (with moving average length $MA$), where:

$$\hat{p}^{k+1}(a_j|x) = \frac{1}{MA+1}\left[\Psi(a_j|x, \hat{P}^k, \hat{\theta}^{k+1}) + \sum_{ma=0}^{MA-1} \hat{p}^{k-ma}(a_j|x)\right] \tag{24}$$

is the weighted sum of this step's conditional choice probabilities and those used in previous iterations.

5. Repeat steps 2-4 until $\sum_{a_j \in A_i, x \in X} \left|\hat{p}^{k+1}(a_j|x) - \hat{p}^k(a_j|x)\right| < \delta$, where $\delta$ is a maximum tolerance parameter, at which point $\hat{p}^k(a_j|x) = \Psi(a_j|x, \hat{P}^k, \hat{\theta}^{k+1})$ for all states $x$, and actions $j$. Hence, $\hat{P}^k$ are conditional choice probabilities associated with a Markov Perfect Equilibrium given parameters $\hat{\theta}^{k+1}$.

## 2.5 Auxiliary Assumptions

While the Nested Pseudo-Likelihoods algorithm speeds estimation of dynamic games, two techniques speed up this process even more: symmetry and linearity in parameters.

I impose symmetry (or exchangeability in Pakes and McGuire (2001) and Gowrisankaran (1999)'s terminology) between players, so that only the vector of firm states matter, not the firm identities. Encoding this restriction into the representation of the state space allows for a considerable reduction in the number of states. For instance, an entry-exit model with 12 firms and 10 demand states entails 40960 states, while its symmetric counterpart only uses 240.

As suggested by Bajari, Benkard, and Levin (2006), and also noted by Aguirregabiria and Mira (2006), the *Separability in Dynamic Parameters* assumption (henceforth SSP) is incorporated to speed estimation by maximum likelihood. A model has a separable in dynamic parameters representation if period payoff $r(x'|\theta)+\ \tau(a_i, x_i|\theta)$ can be rewritten as $\theta \cdot \rho(x', a_i, x_i)$ for all states $x', x \in X$ and actions $a_i \in A$, where $\rho(x', a_i, x_i)$ is a vector function with the same dimension as the parameter vector. While this representation may seem unduly restrictive, it is satisfied by many models used in Industrial Organization such as the entry-exit model of equations (3) and (4). Using SSP, period profits can be expressed as $\theta \cdot \rho(x', a_i, x_i)$. Value functions conditional on conditional choice probabilities $P$ are also linear in dynamic parameters, since:

$$\begin{aligned}
V(x|P,\theta) &= \sum_{t=1}^{\infty} \beta^t \left\{ \sum_{x^t \in X} \left[ \sum_{a_i^t \in A} \theta \rho(x^{t+1}, a_i^t, x_i^t) p_i(a_i^t|x^t) \right] F^P(x^{t+1}|x^t) + E(\varepsilon|P) \right\} \\
&= \theta \sum_{t=1}^{\infty} \beta^t \sum_{x^t \in X} \left[ \sum_{a_i^t \in A} \rho(x^{t+1}, a_i^t, x_i^t) p_i(a_i^t|x^t) \right] F^P(x^{t+1}|x^t) \\
&\quad + \sum_{t=1}^{\infty} \beta^t \sum_{x^t \in X} \sum_{a_i^t \in A} \gamma \ln(p_i(a_i^t|x^t))
\end{aligned}$$

Denote by $\tilde{\theta} J(x|P) \equiv V(x|P,\theta)$ the premultiplied value function where

$\tilde{\theta} = \{\theta, 1\}$ is extended to allow for components which do not vary with the parameter vector. The value of taking action $a_j$ is thus:

$$V(x|a_j, P, \theta) = \tilde{\theta} \sum_{x'} \left[\rho(x', a_j, x_i) + \beta J(x'|P)\right] F^P(x'|x, a_j) \tag{25}$$

Let $Q(a_j, x, P) = \sum_{x'} \left[\rho(x', a_j, x_i) + \beta J(x, P)\right] F^P(x'|x, a_j)$. Conditional Choice Probabilities are given by:

$$\Psi(a_j|x, P, \tilde{\theta}) = \frac{\exp\left[\tilde{\theta} Q(a_j, x, P)\right]}{\sum_{h \in A_i} \exp\left[\tilde{\theta} Q(a_h, x, P)\right]} \tag{26}$$

Maximizing the likelihood of this model is equivalent to a simple linear discrete choice model. In particular, the optimization problem is globally concave, which simplifies estimation. This is not generally the case for the likelihood problem where $P$ is not held constant, i.e. $\mathcal{L}^{Rust}(\theta)$ but required to be an equilibrium given the current parameters.

# 3 Unobserved Profitability

The assumption that the epsilon's are serially uncorrelated within markets is heroic. Characteristics of the market that are not observed in the first period, such as a vast road network requiring a large amount of concrete, are the same in each subsequent period. Serial correlation of $\varepsilon$ per se only affects standard errors from maximum likelihood. Presumably, I could correct these standard errors using a clustering procedure for observations in the same market. However, the pattern of correlation of unobservables can also be used to identify, and remove, bias from the Bresnahan-Reiss model. In the next section I discuss the impact of unmeasured

The canonical entry model estimates the profit functions for firms in different markets, where I impose the following functional form:

$$V_{it} = \underbrace{X_m^t \beta}_{\text{Demand}} + \underbrace{g(N_m^t)}_{\text{Competition}} + \underbrace{\varepsilon_m^t}_{\text{Unobservables}} \tag{27}$$

where $\varepsilon_m^t$ is a mean-zero stochastic term which is uncorrelated with both demand ($X_m^t$) and number of firms ($N_m^t$), and $g(.)$ is decreasing. The assumption that $\varepsilon_{it}$ is uncorrelated with regressors is frequently violated in the context of entry models. The econometrician may not observe certain components of profitability, but firms most certainly do. They will react by entering in greater numbers in more profitable markets, leading to a positive correlation between $\varepsilon$ and $N$. Likewise, suppose demand in large markets is qualitatively different than in small markets. For instance, multistory buildings are constructed in greater proportion in large markets relative to small markets, and this type of construction consumes a large amount of concrete. Thus, market size and consumption of concrete are positively correlated.

Unobserved profitability can be statistically decomposed into its correlated components:

$$\varepsilon_m^t = \delta \underbrace{X_m^t}_{\text{observed demand}} + \gamma \underbrace{N_m^t}_{\text{firms}} + \zeta_m^t \tag{28}$$

where $\zeta_m^t$ is an uncorrelated, mean zero shock.

If measured and unmeasured demand are positively correlated, say because areas with large numbers of construction workers and projects also have other features which make demand high, then $\delta > 0$. Similarly, if firms react to unmeasured demand shocks by entering, I expect $\gamma > 0$. Note that both of these statements refer to the correlation between $\varepsilon$ and $X_i^t$ or $N_i^t$, while the values of $\delta$ or $\gamma$ are related to the conditional correlation $E(\varepsilon X|N)$ or $E(\varepsilon N|X)$ for which it is more difficult to make a statement about from intuition. In the case where the conditional correlation has the same sign as the unconditional correlation, I can sign the bias in this model:

The Bresnahan-Reiss model can be expressed as the following inequalities:

$$\begin{aligned} X_m^t\beta + \varepsilon_m^t &> -g(N_m^t) \\ X_m^t\beta + \varepsilon_m^t &< -g(N_m^t + 1) \end{aligned} \tag{29}$$

Substituting expression (28), these inequalities become:

$$\begin{aligned} X_m^t(\beta + \delta) + \zeta_m^t &> -g(N_m^t) - \gamma N_m^t \\ X_m^t(\beta + \delta) + \zeta_m^t &< -g(N_m^t + 1) - \gamma N_m^t \end{aligned}$$

The estimated demand coefficient $(\beta + \delta)$ will be biased upward. Likewise, since the effect of competition is negative, the competitive effects of entry $-[g(N) + \gamma]$ will be biased downwards. If fact, this is what I find in empirical estimates in Table 2. When I correct for unobserved components of profitability (using a market fixed effects strategy described in the next section) I find the ratio of the effect of the first competitor versus 1000 construction employees goes from $-1.3$ without fixed effects (i.e. $-0.910/0.706$) to $-8.2$ (i.e. $-2.31/0.280$) with fixed effects. This indicates that competition plays a much greater role in firm's profitability than demand compared to what the standard Bresnahan-Reiss would suggest.

## 3.1 Panel Data Solution

The panel structure of data can be used to eliminate bias in entry models. Decomposed the unobserved shocks to profitability into:

$$\varepsilon_m^t = \alpha_m(\text{market effect}) + y^t(\text{year effect}) + \upsilon_m^t$$

a component which remains constant over a market's life($\alpha_m$), a component which represents aggregate shocks common to all markets in a year ($y^t$) while remaining unobserved profits are grouped into a mean zero shock $\upsilon_m^t$. Estimates remain biased to the extent that $\upsilon_m^t$ is correlated with demand

and number of firms:

$$\upsilon_m^t = \hat{\delta} X_m^t + \hat{\gamma} N_m^t + \hat{\zeta}_m^t$$

This correlation is likely much smaller than before. Ultimately, the most convincing solution to this problem is to use an instrumental variable strategy. Find a variable $z_m^t$ which is uncorrelated with unobserved profitability $\varepsilon$, but correlated with demand and number of plants, such that $E[\varepsilon z] = 0$. It is then possible to use GMM to estimate an consistent, if not efficient, model of entry.

### 3.2 Computational Details

Fixed effects are commonly introduced into discrete choice models with conditioning techniques such as Chamberlain (1980)'s fixed effect logit. In the case of the ordered probit model with groups of 20 observations (representing the number of periods observed for each market), conditioning is computationally difficult. Instead, a dummy variable for each market is added to the model, and estimated using maximum likelihood as another demand parameter:

$$V_{it}(X_m^t, N_m^t) = X_m^t \beta + \sum_{k=1}^{M} \alpha_k 1(k = m) + \sum_{h=1}^{T} y^h 1(t = h) + \sum_{j=1}^{5} \delta_j 1(N_m^t > j) + \delta_6 \max(N_m^t - 5, 0) \tag{30}$$

where $\alpha_k$ is the market effect fixed.

To estimate parameters, I need to maximize the likelihood over more than 3000 parameters, given the number of markets in the data. Fortunately, the linear objective function of equation (30) along with the structure of an ordered probit yields a globally concave likelihood function. This makes this problem computationally feasible since globally concavebally concave function are straightforward to maximize. I calculate the gradient of the likelihood analytically, bypassing the computation of a rather large number of numerical derivatives. Finally, the market level fixed effect parameters are "incidental" in the sense that their values are not of interest, just the effect they have on economically important parameters such sunk costs and the effects of competitors. The termination criteria reflects this, requiring only that the likelihood to converge $|L(\theta^i) - L(\theta^{i-1})| < \varepsilon$ rather than the full vector of parameters: $\|\theta^i - \theta^{i-1}\| < \delta$, where $i$ denotes the iteration number. The number of iterations required to compute the solution of the model is reduced from 50 to about 5 without changing the value of economically relevant parameters. On a UNIX server, estimating the fixed effect maximum likelihood parameters takes approximately a day, but this operation would be much faster for a sample of markets.

# 4 Data

Data on Ready-Mix Concrete plants is drawn from three different data sets provided by the Center for Economics Studies at the United States Census Bureau. Table 1 illustrates the datasets used. The first is the Census of Manufacturing (henceforth CMF), a complete census of manufacturing plants, every five years from 1963 through 1997. The second is the Annual Survey of Manufacturers (henceforth ASM) sent to a sample of manufacturing plants (about a third for ready-mix) every non-Census year since 1973. Both the ASM and the CMF involve questionnaires that collect detailed information on a plant's inputs and outputs. The third data set is the Longitudinal Business Database (henceforth LBD) compiled from data used by the Internal Revenue Service to maintain business tax records. The LBD covers all private employers on a yearly basis since 1976. The LBD only contains employment and salary data, along with sectoral coding and certain types of business organization data such as firm identification. Construction data is obtained by selecting all establishments from the LBD in the construction sector (SIC 15-16-17) and aggregating them to the county level.

| | CMF | ASM | LBD |
|---|---|---|---|
| Data Set | Census of Manufacturing | Annual Survey of Manufacturing | Longitudinal Business Database |
| Collection | Questionnaire | Questionnaire | IRS Tax Data |
| Years | 1963, 67, 72, 77, 82, 87, 92, 97 | 1972-2000 | 1976-1999 |
| Coverage | All Manufacturing Firms | 30% of Manufacturing Firms | All Private Sector Firms |
| Variables | Input and Output Data including materials and product trailers | Input and Output Data | Employment and Payroll and Birth/Death data |
| Plant Identifiers | PPN, CFN | PPN, CFN | LBDNUM, CFN |

**Table 1:** Description of Census Data Sources

## 4.1 Industry Selection

Production of ready-mix concrete for delivery predominantly takes place at establishments in the ready-mix sector. Hence, establishments in the ready-mix sector are chosen, corresponding to either NAICS (North American Industrial Classification) code 327300 or SIC (Standard Industrial Classification) code 3273, a sector whose definition has not changed since 1963. The criterion for being included in the sample is: *an establishment that has been in the Ready-Mix Sector (NAICS 327300 or SIC 3273) at any point of its life, in any of the 3 data sources (LBD,ASM,CMF).* To create my sample, plants need to be linked across time, since plants can switch sectors at some point in their lives.

## 4.2 Longitudinal Linkages

To construct longitudinal linkages, I use three different identifiers: Permanent Plant Numbers (PPN), Census File Numbers (CFN) and Longitudinal Business Database Numbers (LBDNUM). Census File Numbers (CFN) are the basic identification scheme used by Census for its establishment data. A plant's CFN may change for many reasons, including a change of ownership, and hence they are not well suited as a longitudinal identifier. Permanent Plant Numbers (PPN) is the Census Bureau's first attempt at a longitudinal identifier, as they are assigned to a plant for its entire life-span. These tend to be reliable, but are only available in the CMF and ASM. Moreover, PPNs are missing for a large fraction of observations, leading to the incorrect conclusion that many plants have dropped out of the industry. The third identification scheme is the Longitudinal Business Database Number, as developed by **?**. This identifier is constructed from CFN, employer ID and name and address matches of all plant in the LBD. Since the LBD is the basis for mailing Census questionnaires to establishments, virtually all plants present in the ASM/CMF are also in the LBD (starting in 1976), allowing a uniform basis for longitudinal matching. I use LBDNUM as my basic longitudinal identifier, which I supplement with PPN and CFN linkages when the LBDNUM is missing, in particular for the period before 1976 for which there are no LBDNUMs.

To identify plant entry and exit, I use **?**'s plant birth and death measures. Jarmin and Miranda identify entry and exit based on the presence of a plant in the I.R.S.'s tax records. They take special care to flag cases where plants simply change owners or name by matching the address of plants across time. The measurement of turnover is problematic, since firms do not *themselves* report that they are exiting or that they have just entered. Instead, entry and exit data must be constructed from the presence and absence of plants in the data over time. Specifically entry and exit are defined as: *A plant has entered at time t if it is not in the LBD before time t, but it is present at time t. A plant has exited at time t if it is not in the LBD after time t, but it is present at time t.* [8] Proper longitudinal matches are important for constructing turnover statistics, since measurement error tends to break longitudinal linkages, creating artificial entry and exit, raising the implied turnover rate above its true value. Each year, about 40 plants (or about 1.6% of plants) are temporarily shut down. I do not treat temporary shutdown as exit, since the cost of reactivating a plant is far smaller than building one

[8] If I a plant changes ownership, I do not treat this as an exit event since the cost of changing the management at a plant should be much lower than the cost of building a plant from scratch.

from scratch. [9] [10]

## 4.3 Panel

I select all plants that have belonged to the ready-mix sector at some point in their lives. The entire history of a plant's sectoral coding must be investigated, since a plant can enter and exit the ready-mix sector many times. For instance, many ready-mix concrete plants are located next to gravel pits, to lower their material costs. If a plant's concrete operations are not separated from gravel mining when reporting to Census, then the plant can be classified as a gravel pit (NAICS 212321) or a ready-mix plant. This classification can change from year to year, and differ between data collected by the IRS (LBD) versus data collected by Census (ASM/CMF). Treating these sector switches as exits would confuse shutting down a plant and a change in its product mix. I assume a plant is either in the ready-mix concrete sector for its entire life, or not. I select plants using the following algorithm: 1) Select all CFN's, PPN and LBDNUM's which are in NAICS 327300 or SIC 32730. Call this file the master index file; 2) Add all plants that have the same CFN, PPN or LBDNUM as a plant in the master index file. Add these to the new master index file.

Measurement error in any year that incorrectly labels a plant as part of the ready-mix concrete sector introduces this plant into the sample for its entire life. In particular, sectoral coding data from the LBD is of poorer quality than sector data from the CMF/ASM. These coding errors introduce large

[9] In empirical work with multiple plant states, temporary inactive plants have been found to be more similar to plants with less than 15 employees than to potential entrants. A potential entrant has a very low probability of entering, while the probability of observing a temporarily inactive plant reentering is at least 80%.

[10] If a plant is inactive for more than 2 years, then the IRS will reassign a tax code to this establishment, breaking longitudinal linkages, creating an exit and the potential for a future entry event. I can construct an upper bound on the number of plant births that are in fact old plants being reactivated. If two plants enter in the same 9 digit zip code (an area smaller than a city block) at different dates, assume the latter birth is a reactivation. Under this assumption, less than 1% of births are reactivated plants.

manufacturers, such as cement producers, with different internal organization and markets than concrete producers, into the ready-mix sample. I delete plants from the sample if in either the LBD or the ASM/CMF they are coded in the ready-mix concrete sector for less than half their lives. If a plant is only in the ready-mix sector for one year out of twenty, it is safe to conclude that coding error led to its inclusion into the ready-mix sector. Table **??** offers confirmation, since ready-mix concrete represents 95% of output for plants in my sample. Moreover, when I collect all plants that produce ready-mix concrete, based on their response to the product trailer of the Census of Manufacturing (which collects detailed information on the output of plants), I find that 94% percent of ready-mix concrete is produced by plants in my sample versus only 6% produced by plants outside the sample. Hence, the assumption that ready-mix plants do not switch sectors and produce only ready-mix does little violence to the data.

Table **??** shows that over the sample period there are about 350 plants births and 350 plants deaths each year compared to 5000 continuers. Turnover rates and the total number of plants in the industry are fairly stable over the last 30 years. Indeed, Figure **??** shows annual entry and exit rates hovering around 6% for the period 1976 to 1999, which similar to previous work on the manufacturing sector such as Dunne, Roberts, and Samuelson (1988), with net entry during the booms of the late 1980's and late 1990's, and net exit otherwise. Table **??** and Table **??** in section **??** display characteristics of ready-mix concrete plants: they employ 26 workers on average, and each sold about 3.2 million dollars of concrete in 1997, split evenly between material costs and value added. However, these averages mask substantial differences between plants. Most notably, the distribution of plant size is heavily skewed, with few large plants and many small ones, indicated by the fact that more than 5% of plants have 1 employee, while less than 5% of plants have more than 82 employees. Moreover, Table **??** shows continuing firms are twice as large as either entrants(births) or exitors(deaths), measured by capitalization, salaries or shipments. I aggregate plant data by county to form market level data, for which Table 6 in section **??** presents summary statistics. Notice that the average number of plants per county is fairly small, equal to 1.86, while the 95th percentile of firms per county is only 6. Hence most ready-mix concrete markets are best characterized as local oligopolies.

# 5 Sunk Cost Estimates

Table 2 presents estimates for the Bresnahan-Reiss Entry model and Table 3 for the Sunk-Cost Bresnahan-Reiss Estimator. Note that the coefficient on demand is more than halved and the coefficient on number of competitors becomes twice as negative when fixed effects are added to the model.

| Demand Variables in Thousands | County Fixed Effect | S.E | No Effect | S.E. |
|---|---|---|---|---|
| County Construction Employment | 0.280 | (0.045) | 0.706 | (0.018) |
| County Construction Payroll | -0.003 | (0.001) | -0.008 | (0.001) |
| Concrete Intensity adjusted Construction Employment | -0.672 | (0.316) | -0.230 | (0.209) |
| Concrete Intensity adjusted Construction Payroll | 0.027 | (0.012) | 0.008 | (0.008) |
| Adjacent County Construction Employment | -0.028 | (0.009) | 0.002 | (0.002) |
| Within 10 miles Construction Employment | -0.003 | (0.011) | 0.010 | (0.002) |
| Within 20 miles County Construction Employment | 0.025 | (0.006) | 0.004 | (0.001) |
| Adjacent County Construction Payroll | 0.000 | (0.000) | 0.000 | (0.000) |
| Within 10 miles County Construction Payroll | 0.000 | (0.000) | 0.000 | (0.000) |
| Within 20 miles County Construction Employment | 0.000 | (0.000) | 0.000 | (0.000) |
| Year Effects | Yes | | Yes | |
| | | | | |
| Competitive Variables | | | | |
| 1 competitor | -2.339 | (0.030) | -0.910 | (0.011) |
| 2 competitors | -1.452 | (0.023) | -0.700 | (0.011) |
| 3 competitors | -1.109 | (0.026) | -0.560 | (0.014) |
| 4 competitors | -0.891 | (0.031) | -0.700 | (0.011) |
| 5 competitors | -0.797 | (0.036) | -0.560 | (0.014) |
| 6 competitors | -0.617 | (0.039) | -0.472 | (0.017) |
| More than 6 competitors | -0.696 | (0.029) | -0.560 | (0.014) |
| | | | | |
| Log Likelihood | -13575 | | -25536 | |
| Wald | 13021 | | 6678 | |
| Number of Observations | 18025 | | 18025 | |

**Table 2:** Bresnahan-Reiss Estimates with and without county fixed effects

| Demand Variables in Thousands | County Fixed Effect | S.E | No Effect | S.E. |
|---|---|---|---|---|
| County<br>Construction Employment | 0.142 | (0.057) | 0.520 | (0.022) |
| County<br>Construction Payroll | -0.001 | (0.001) | -0.005 | (0.001) |
| Concrete Intensity adjusted<br>Construction Employment | -0.385 | (0.444) | -0.184 | (0.278) |
| Concrete Intensity adjusted<br>Construction Payroll | 0.021 | (0.017) | 0.012 | (0.011) |
| Adjacent County<br>Construction Employment | -0.012 | (0.013) | 0.005 | (0.002) |
| Within 10 miles<br>Construction Employment | -0.035 | (0.016) | 0.012 | (0.003) |
| Within 20 miles County<br>Construction Employment | 0.031 | (0.009) | -0.002 | (0.001) |
| Adjacent County<br>Construction Payroll | 0.000 | (0.000) | 0.000 | (0.000) |
| Within 10 miles County<br>Construction Payroll | -0.001 | (0.000) | 0.000 | (0.000) |
| Within 20 miles County<br>Construction Payroll | 0.000 | (0.000) | 0.000 | (0.000) |
| Year Effects | Yes | | Yes | |
| | | | | |
| Competitive Variables | | | | |
| 1 competitor | -2.195 | (0.054) | -0.645 | (0.020) |
| 2 competitors | -1.671 | (0.045) | -0.683 | (0.021) |
| 3 competitors | -1.258 | (0.046) | -0.554 | (0.023) |
| 4 competitors | -1.048 | (0.052) | -0.458 | (0.025) |
| 5 competitors | -0.898 | (0.058) | -0.419 | (0.029) |
| 6 competitors | -0.745 | (0.061) | -0.395 | (0.034) |
| More than 6 competitors | -0.897 | (0.040) | -0.471 | (0.022) |
| | | | | |
| Exit Threshold | 1.364 | (0.317) | -1.555 | (0.058) |
| Entry Threshold | 4.743 | (0.319) | 1.665 | (0.058) |
| | | | | |
| Log Likelihood | -5021 | | -9154 | |
| Wald | 5261.9 | | 2598 | |
| Number of Observations | 18025 | | 18025 | |

**Table 3:** Standard and Fixed Effect Sunk Cost Bresnahan-Reiss Estimates for County Markets

| Variable | Definition |
| --- | --- |
| County Employment | Number of construction establishment employees in the county. |
| Construction Payroll | Payroll at construction establishments in the county. |
| Concrete Intensity adjusted | Construction establishments weighted by fraction of their 4-digit SIC code's output coded as concrete work in the Census of Construction. |
| Geography | |
| County | The county. |
| Adjacent County | Set of counties which share a border with the county. |
| Within 10 miles | Set of counties within 10 miles of the county. |
| Within 20 miles County | Set of counties within 20 miles of the county. |

**Table 4:** Variable Definitions for Demand Measures

| | I | | II | | III | | IV(Preferred) | |
|---|---|---|---|---|---|---|---|---|
| Log Construction Workers | 0.018 | (0.00) | 0.019 | (0.00) | 0.040 | (0.01) | 0.054 | (0.01) |
| 1 Competitor* | -0.197 | (0.02) | -0.302 | (0.02) | -0.244 | (0.02) | -0.371 | (0.02) |
| 2 Competitors | 0.113 | (0.02) | 0.153 | (0.02) | -0.006 | (0.02) | -0.043 | (0.02) |
| 3 Competitors | -0.001 | (0.02) | -0.016 | (0.02) | -0.058 | (0.03) | -0.049 | (0.03) |
| 4 and More Competitors | 0.044 | (0.03) | 0.002 | (0.02) | 0.039 | (0.04) | -0.020 | (0.03) |
| Sunk Cost | 6.503 | (0.04) | 6.443 | (0.04) | 6.256 | (0.04) | 6.173 | (0.04) |
| Fixed Cost | -0.265 | (0.01) | -0.202 | (0.01) | | | | |
| Fixed Cost Group 1 | | | | | -0.346 | (0.02) | -0.317 | (0.02) |
| Fixed Cost Group 2 | | | | | -0.216 | (0.02) | -0.124 | (0.02) |
| Fixed Cost Group 3 | | | | | -0.169 | (0.02) | -0.057 | (0.02) |
| Fixed Cost Group 4 | | | | | -0.115 | (0.03) | -0.020 | (0.03) |
| Equilibrium Conditional Choices | | | X | | | | X | |
| Log Likelihood | -13220.4 | | -13124.6 | | -12974.2 | | -12819.3 | |
| Number of Observations | 235000 | | 235000 | | 214000 | | 214000 | |

*The effect of competition displayed is the marginal effect of each additional competitor.

I: Hotz and Miller technique without market heterogeneity.

II: Aguirregabiria and Mira technique without market heterogeneity.

III: Hotz and Miller technique with market fixed effects.

IV: Aguirregabiria and Mira technique with market fixed effects.

**Table 5:** Estimates for the Dynamic Entry Exit Model

# A Tables and Figures sec $sec : tabandfig$

# References


Aguirregabiria, V., and P. Mira (2006): "Sequential Estimation of Dynamic Discrete Games," *Econometrica*, forthcoming.

Bajari, P., L. Benkard, and J. Levin (2006): "Estimating Dynamic Models of Imperfect Competition," *Econometrica*, forthcoming.

Berry, S. (1992): "Estimation of a Model of Entry in the Airline Industry," *Econometrica*, 60(4), 889–917.

Bresnahan, T., and P. C. Reiss (1994): "Measuring the Importance of Sunk Costs," *Annales d'Économie et de Statistique*, 34, 181–217.

Bresnahan, T. F., and P. C. Reiss (1991): "Entry and Competition in Concentrated Markets," *Journal of Political Economy*, 99(5), 33.

Campbell, J. R., and J. H. Abbring (2006): "Last-in first-out oligopoly dynamics,," *Federal Reserve Bank of Chicago Working Paper*.

Chamberlain, G. (1980): "Analysis of Covariance with Qualitative Data," *The Review of Economic Studies*, 47(1), 225–238.

Collard-Wexler, A. (2006a): "Demand Fluctuations and Plant Turnover in the Ready-Mix Concrete Industry," Working Paper, New York University.

——— (2006b): "Productivity Dispersion and Plant Selection in the Ready-Mix Concrete Industry," Working Paper, New York University.

Dunne, T., S. D. Klimek, M. J. Roberts, and D. Xu (2006): "Entry and Exit in Geographic Markets," Working Paper, Penn State University.

| | Observations | Mean | Standard Deviation | 5th Percentile | 95th Percentile |
|---|---|---|---|---|---|
| County Total Value of Shipment (in 000's) | 24677 | 3181 | 12010 | 0 | 14000 |
| County Value Added (in 000's) | 24677 | 1408 | 5289 | 0 | 6500 |
| County Total Assets Ending (in 000's) | 24677 | 1090 | 14134 | 0 | 4700 |
| County Total Employement | 24677 | 22 | 69 | 0 | 100 |
| County Total Salaries and Wages (in 000's) | 24677 | 559 | 2018 | 0 | 2600 |
| County Concrete Plants | 74435 | 1.86 | 3.24 | 0 | 6 |
| County Employment | 74435 | 27.24 | 79.03 | 0 | 110 |
| County Payroll (in 000's) | 74435 | 4238 | 74396 | 0 | 3600 |
| County Plant Births | 74435 | 0.11 | 0.42 | 0 | 1 |
| County Plant Deaths | 74435 | 0.10 | 0.37 | 0 | 1 |
| County 0-5 Employee Plants | 74435 | 0.52 | 1.07 | 0 | 2 |
| County 5-20 Employee Plants | 74435 | 0.78 | 1.34 | 0 | 3 |
| County more than 20 Employee Plants | 74435 | 0.86 | 1.49 | 0 | 3 |
| County Plants Less than 5 years old | 74435 | 0.17 | 0.76 | 0 | 1 |
| County Plants 5-10 Years Old | 74435 | 0.54 | 1.47 | 0 | 2 |
| County Plants over 10 Years Old | 74435 | 1.35 | 2.07 | 0 | 4 |
| County Area | 72269 | 1147 | 3891 | 210 | 3200 |
| Employment in Construction | 69911 | 1495 | 5390 | 11 | 6800 |
| Payroll in Construction (in 000's) | 69911 | 37135 | 163546 | 110 | 160000 |

**Table 6:** Summary Stats for County Aggregate Data

Dunne, T., M. J. Roberts, and L. Samuelson (1988): "Patterns of Firm Entry and Exit in U.S. Manufacturing Industries," *RAND Journal of Economics*, 19(4), 495–515.

Ericson, R., and A. Pakes (1995): "Markov-Perfect Industry Dynamics: A Framework for Empirical Work," *The Review of Economic Studies*, 62(1), 53–82.

Gowrisankaran, G. (1999): "Efficient Representation of State Spaces for Some Dynamic Models," *Journal of Economic Dynamics and Control*, 23(8), 1077–1098.

Hotz, V. J., and R. A. Miller (1993): "Conditional Choice Probabilities and the Estimation of Dynamic Models," *The Review of Economic Studies*, 60(3), 497–529.

Hotz, V. J., R. A. Miller, S. Sanders, and J. Smith (1994): "A Simulation Estimator for Dynamic Models of Discrete Choice," *The Review of Economic Studies*, 61(2), 265–289.

Jarmin, R. S., and J. Miranda (2002): "The Longitudinal Business Database," Working Paper, Center for Economic Studies, US Census Bureau.

Mazzeo, M. J. (2002): "Product Choice and Oligopoly Market Structure," *RAND Journal of Economics*, 33(2), 221–242.

Pakes, A. (2007): "Theory and Empirical Work on Imperfectly Competitive Markets," *Working Paper, Harvard University.*

Pakes, A., S. Berry, and M. Ostrovsky (2006): "Simple estimators for the parameters of discrete dynamic games, with entry/exit examples,," *RAND Journal of Economics*, forthcoming.

Pakes, A., and P. McGuire (2001): "Stochastic Algorithms, Symmetric Markov Perfect Equilibrium, and the 'Curse' of Dimensionality," *Econometrica*, 69(5), 1261–1281.

Pesendorfer, M., and P. Schmidt-Dengler (2003): "Identification and Estimation of Dynamic Games," NBER Working Paper 9726,.

Rust, J. (1987): "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher," *Econometrica*, 55(5), 999–1033.

Ryan, S. P. (2006): "The Costs of Environmental Regulation in a Concentrated Industry," *Working Paper, M.I.T.*

Seim, K. (2005): "An Empirical Model of Firm Entry with Endogenous Product-Type Choices," *forthcoming RAND Journal of Economics.*

Sweeting, S. (2006): "The Costs of Product Repositioning: The Case of Format Switching in the Commercial Radio Industry," Working Paper, Northwestern University.