Demand Fluctuations and Plant Turnover in the Ready-Mix Concrete Industry

Allan Collard-Wexler*
Department of Economics
NYU Stern

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Abstract

Fluctuations in demand cause some plants to exit a market and other to enter. Would eliminating these fluctuations reduce plant turnover? A structural model of entry and exit in concentrated markets is estimated for the ready-mix concrete industry, using plant level data from the U.S. Census. The Nested Pseudo-Likelihood algorithm is used to find parameters which rationalize behavior of firms involved in repeated competition. Due to high sunk costs, turnover rates would only be reduced by 3% by eliminating demand fluctuations at the county level, saving around 20 million dollars a year in scrapped capital. However, demand fluctuations blunt firms' incentive to invest, reducing the number of large plants by more than 50%.

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1 Introduction

Many industries face considerable uncertainty about future demand for their products, perhaps most universally because of aggregate fluctuations in economic activity due to the business cycle. These fluctuations are costly, since firms change their production process to suit the current level of demand, hiring and firing workers, purchasing and scraping machinery, opening and shutting down plants. In this paper, I focus on a single industry, ready-mix concrete, and a specific type of adjustment central to industrial economics, plant entry and exit, to evaluate the cost of demand fluctuations.

As Lucas (2003) points out, is not clear that the business cycle is particularly costly for consumers. Under a set of conventional assumptions, consumers are willing to pay remarkably little to fully insure themselves against aggregate fluctuations. This is a challenge to the relevance of macroeconomic policy. One response is to focus instead on industry. In particular an entire literature entitled "'lumps and bumps"' studies the impact of costly capital adjustment on the response of industry to business cycle fluctuations, most prominently in the work of Caballero and Engel (1999).

The ready-mix concrete industry is unusually well suited to study the impact of fluctuations in demand on entry and exit. The concrete industry witnesses large changes in output from year to year (as illustrated by Figure 1), which are of great concern to ready-mix producers. These fluctuations are caused in part by the effect of changes in interest rates on new construction activity, and variation in government spending on highways and buildings. Moreover, there is substantial regional and local variation in construction activity, that affects ready-mix plants within only a limited area due to high transportation costs. Indeed, wet concrete cannot travel for much more than an hour before it hardens in the barrel of a truck.

There is considerable plant turnover in the ready-mix concrete industry. In a five year period more than 30% of plants will shut down and 30% of plants will be born. Moreover, entry and exit are responsible for 15% of jobs created and destroyed. Would dampening fluctuations in demand for concrete from the construction sector reduce job and plant turnover? What

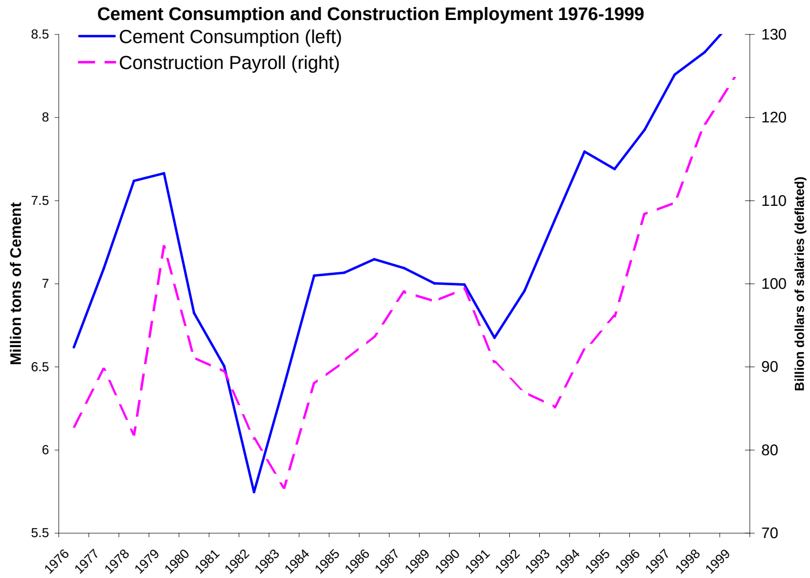

Figure 1: Cement consumption (used in fixed proportion to concrete) and construction sector salaries are very procyclical and volatile.

is the cost to society of this turnover? Moreover, is industry composition substantially altered by these demand fluctuations?

I answer these questions with longitudinal data provided by the Center for Economic Studies at the Census Bureau, on the life histories of over 15 000 ready-mix concrete plants in United States from 1963 to 2000. These data provided detailed information on the inputs and outputs of plants as well as on entry and exit. I estimate a model of dynamic competition in concentrated markets using the Nested Pseudo-Likelihood algorithm (NPL) developed by Aguirregabiria and Mira (2006), that identifies' the parameters of the dynamic game firms play from their equilibrium strategies. Moreover, I incorporate market level fixed effects into this model to control for persistent, but unobserved, differences between markets. I cannot, however, use a static model of entry and exit, such as the models of Bresnahan and Reiss (1994), since these are incapable of performing the counterfactual: a permanent change in the volatility of demand. Instead, a fully dynamic, multi-agent, model is required.

I find that a ready-mix concrete plant entails substantial sunk costs. My estimates indicate that a potential entrant is indifferent between a permanent monopoly market and a permanent duopoly market where she would not have to pay sunk costs.

The econometric model is used to simulate the effect of eliminating yearly changes in demand at the county level. I find that plant turnover would be only 3% lower in a world without demand fluctuations. This number is quite small, implying that 20 million dollars a year is lost due to unnecessary plant shut down and opening. Because of large sunk costs, plants are unlikely to exit during a temporary lull in demand. Sunk costs slow the reaction of firms to short-run fluctuations in demand, since it is costly to build new plants or to shut down old ones. Thus, high entry and exit rates in ready-mix concrete must stem from idiosyncratic shocks to firm profits, caused by a myriad of factors such as mergers and productivity.

However, focusing on industry turnover misses the impact of demand fluctuations on industry composition. Demand uncertainty blunts firms incentives to invest. Eliminating fluctuations increases the number of large plants (above 15 employees) in the industry by more than 50%. Firms are more likely to build larger, potentially more productive plants, if they can be assured that there will be continuing demand for their products.

In section 2, I discuss the source of sunk costs for the Ready-Mix Plants, and the role of spatial differentiation in the industry. Section 2 describes how I construct the data. In section 3, I present a dynamic model of competition, and I describe estimation in section 4. Finally, in section 5 I discuss steady-state industry dynamics predicted by the model for a world with demand fluctuations and one where they have been removed. Some supplementary Tables and Figures are collected in section A, while the nitty-gritty details of computation are relegated to section D.

2 The Ready-Mix Concrete Industry

Concrete is a mixture of three basic ingredients: sand, gravel (crushed stone) and cement, as well as chemical compounds known as admixtures. Combining this mixture with water causes the cement to undergo an exothermic chemical reaction called hydration, turning cement into a hard paste that binds the sand and gravel together. I focus on ready-mix concrete: concret which is mixed with water at a plant and transported directly to a construction site.[1] Ready-Mix is a perishable product that needs to be delivered within an hour and a half before it becomes too stiff to be workable.[2] Concrete is also very cheap for its weight. One producer describes the economics of transportation costs in the ready-mix industry as follows:

> A truckload of concrete contains about 7 cubic yards of concrete. A cubic yard of concrete weights about 4000 pounds and will cost you around $60 delivered to your door. That's 1.5 cents a pound. If you go to your local hardware store, you get a bag of manure weighing 10 pounds for $5. That means that concrete is cheaper than shit.[3]

A ready-mix truck typically drives 20 minutes to deliver a load.[4] Thus, concrete's most salient feature from an economic perspective is that markets are geographically segmented. Figure 2 shows the dispersion of ready-mix producers in the Midwest, with an handful of incumbents in each area. In my empirical work I treat each county as a separate market, one that evolves independently from the rest of the industry.

Table 6 shows that the vast majority of counties in the United States have fewer than 6 ready-mix plants, reflecting a locally oligopolistic market structure. At the same time, because even the most isolated rural areas has

[1]There are of course other types of concrete, such as bag concrete produced in small batches at a construction site, or pre-cast concrete products, such as septic tanks and pipes. These concrete products are neither substitutes for ready-mix concrete, nor are they produced at ready-mix plants.

[2]"ASTM C 94 also requires that concrete be delivered and discharged within 1 1/2 hours or before the drum has revolved 300 times after introduction of water to the cement and aggregates" p.96 in Kosmatka, Kerkhoff, and Panarese (2002).

[3]Telephone interview, January 2005.

[4]The driving time of twenty minutes is based on a dozen interviews conducted with Illinois ready-mix concrete producers. Thanks to Dick Plimpton at the Illinois Ready-Mix Concrete Association for providing IRMCA's membership directory.

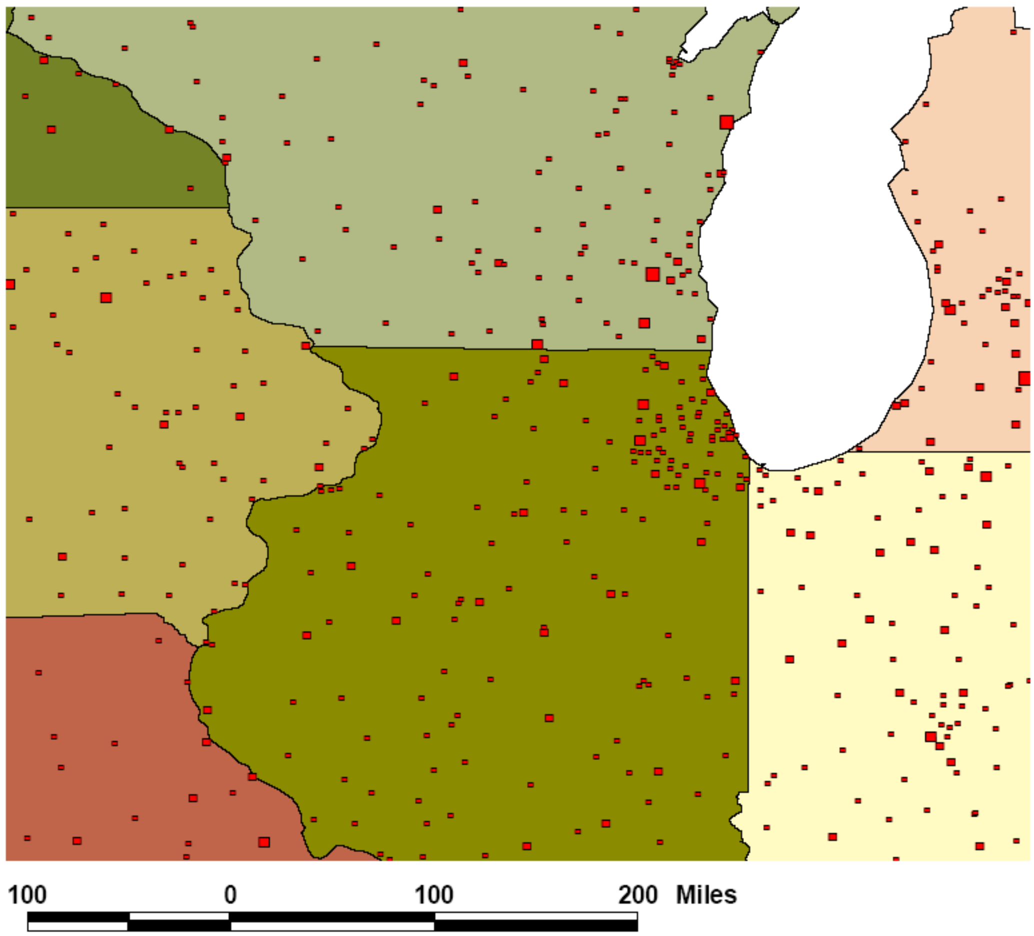

Figure 2: Dispersion of Ready-Mix Plant Locations in the Midwest by zip code.
Source: Zip Business Patterns publicly available dataset at *http://www.census.gov/epcd/www/zbp_base.html*.

demand for ready-mix concrete, most counties are served by at least one ready-mix producer.[5]

Ready-Mix concrete is essentially a homogenous good. While it is possible to produce several hundred types of Ready-Mix concrete, these mixtures basically use the same ingredients and machinery. Because of aggressive antitrust policy on the part of the Department of Justice, the typical ready-mix producer is a single plant operator.[6] Indeed, Syverson (2004) reports that 3749 firms controlled the 5319 ready-mixed plants operating in 1987. Thus I will assume that each firm owns a single ready-mix concrete plant, making plant and firm interchangeable.

Opening a concrete plant is an expensive investment. In interviews, managers of ready-mix plants estimate the cost of a new plant costs at between 3 and 4 million dollars, while Table 11 in section A shows that continuing plants in 1997 had on average 2 million dollars in capital assets. There are few expenses involved in shutting down a ready-mix plant. Trucks can be sold on a competitive used vehicle market, and land can be sold for other uses. The plant itself is a total loss. At best it can be resold for scrap metal, but many ready-mix plants are left on site because the cost of dismantling them outweighs the benefits. An evocative illustration of capital's sunkness is Ramey and Shapiro (2001) study of the resale of capital assets at several aerospace plants. Used capital sells for a fraction of its new value, even after accounting for depreciation. I provide evidence of sunk costs in the ready-mix industry at the plant level, including factors difficult to quantify, such as long term relationships with clients and creditors. Intangible capital assets may account for a large fraction of sunk costs. For instance, ready-mix operators sell about half of their production with a six month grace period for repayment. Accounts receivable have a value equivalent to half of a plant's physical capital assets. It will be more difficult to collect these accounts if the firm cannot punish non-payment by cutting off future

[5] Isolated towns have also been used as a market definition, in the manner of Bresnahan and Reiss (1991). Parameter estimates for a static entry model using isolated markets are similar to those using county markets.

[6] The history of the Department of Justice's policy toward mergers in the ready-mix concrete industry is documented in McBride (1983).

deliveries of concrete.

Concrete is consumed by the construction sector[7]. Table 5 in section A shows that the bulk of concrete purchases are made by the construction sector, to build apartments, houses, roads and sidewalks. I use employment in the construction sector as my demand measure.[8] Demand for ready-mix concrete is inelastic since it is a small part of construction costs. Indeed, Table 5 shows that concrete costs do not exceed 10% of material costs for any construction sector. So it is unlikely that the ready-mix market substantially affects the volume of construction activity. In addition Government purchases about half of U.S. concrete, primarily for road construction.[9] Fluctuations in Government purchases of concrete are mainly due to the discretionary nature of highway spending in state and federal budgets. Government purchases are procyclical, and a major source of uncertainty for ready-mix producers.[10]

Ready-mix concrete has been studied extensively by Syverson (2004), who provides evidence of productivity dispersion across plants. This productivity dispersion is evidence of large differences between plants which are not eliminated by competitive pressures. I provide an explanation for why the competitive adjustment process is not instantaneous.

3Data

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. 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)

[7]For more detail, see the discussion in chapter 1.

[8] I have selected construction employment as my demand measure, out of a panoply of measures of concrete demand such as: interest rates, construction payroll, employment in the concrete contractor sector, area. I have used the static entry models of Bresnahan and Reiss (1994) presented in chapter 3 to select the measure of demand which accounts for most of the differences between markets.

[9] According to the Kosmatka, Kerkhoff, and Panarese (2002) p.9, Government accounts for 48% of cement consumption, with road construction alone responsible for 32% of total consumption.

[10]Conversation with Edward Sullivan, chief economist at the Portland Cement Association, May 2005.

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.

2.1 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.

2.2 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 Jarmin and Miranda (2002). 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 Jarmin and Miranda (2002)'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. Proper longitudinal matches are important for constructing turnover statistics, since measurement error tends to break longitudinal linkages, creating artificial entry and exit. Improper matching raises the implied turnover rate above its true value. Each year, about 40 plants are temporarily shut down. Jarmin and Miranda observe this phenomena as firms moving from the population of employers into the population of the self-employed. I do not treat temporary shutdown as exit, since the cost of reactivating a plant is far smaller than building one from scratch.[11] However, 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.[12]

2.3 Panel

I select all plants that 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 the 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

[11]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%.

[12]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.

than sector data from the CMF/ASM.[13] These coding errors introduce large manufacturers, typically of cement, with different internal organization and markets than concrete producers, into the ready-mix sample. I delete plants from the sample based on how many years they are coded in the ready-mix concrete sector. If a plant is only in the ready-mix sector for one year out of twenty, it is safe to conclude that a coding error led to its inclusion into ready-mix. If a plant is in the ready-mix sector less than half of the time, for either the LBD or the ASM/CMF, then it is eliminated. This rids the sample of plants that are incorrectly coded for one or two years but correctly coded most of the time. Table 7 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 only produce ready-mix does little violence to the data.

Table 8 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 A 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 9 and Table 11 in section A 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

[13] For instance, several cement plants are coded in the ready-mix sector in the LBD, that are much larger than any ready-mix concrete plant.

plants. Most notably 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 11 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 10 in section A 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 local oligopolies.

3 Model

I use the theoretical framework for dynamic oligopoly developed by Ericson and Pakes (1995). 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. One approach, pioneered by Bresnahan and Reiss (1994), is to directly estimate a firm's value function based on the current configuration of plants in the market, without reference to what will happen in the future. This reduced form approach allows for a simple estimation strategy akin to an ordered probit, but limits the counterfactual experiments that can be performed. Alternatively, 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 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 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. I add the assumption of exchangeability to the AM model in order to shrink the size of the state space, and thus incorporate more detailed firm characteristics. I also incorporate techniques that allow for persistent unobserved heterogeneity between markets.

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 10), and keeps the size of the state space manageable. 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. 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. A market with 6 players appears to yield fairly competitive outcomes. The effect of the fifth additional competitor on prices is fairly small, as shown by the relationship between median price and the number of plants in a county presented in Figure A. At any moment, some firms may be active and others not. Since the vast majority of plants are owned by single plant firms, I assume that a firm can operate at most one ready-mix concrete plant. Firm i can be described by a firm specific state $s_i^t \in S_i$ that can be decomposed into states which are observed by the researcher, x_i^t, such as firm activity or age, and states which are unobserved to the researcher, ε_i^t, such as the managerial ability of the plant owner, or the competence of ready-mix truck drivers. In the next section, I will assume that these ε_i^t's are independent shocks to the profitability of different actions and that a firm's observed state x_i^t is either operating a plant or being out of the market. Assume that the set of observed firm states is finite, so that $x_i^t \in X_i = \{1, 2, ..., \#X_i\}$. For now, this is not an assumption, since any information lost when the data is discretized ends up in the unobserved state ε_i^t. The firm's state is the composition of observed and unobserved states: $s_i^t = \{x_{i,}^t \varepsilon_i^t\}$. Firms also react to market-level demand, M^t, which is assumed to be 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. Demand evolves following a Markov Process of the first order (an assumption made for computational convenience, which can easily be relaxed), with transition probabilities given by $D(M^{t+1}|M^t)$.[14] 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. Making the model more realistic by increasing the number of bins above 10 has little effect on estimated coefficients, but lenghens computation time significantly. The level of demand within each bin is set to the mean demand for observations in this bin, i.e. $Mean(i) = \frac{\sum_{l=1}^{L} M_l 1(M_l \in B_i)}{\sum_{l=1}^{L} 1(M_l \in B_i)}$, 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 *state* of a *market* is the composition of firm-specific states, s_i^t, for all firms, and the state of demand; $s^t = \{s_1^t, s_2^t, ..., s_N^t, M^t\}$, which can be decomposed into the observed market state, $x^t = \{x_1^t, x_2^t, ..., x_N^t, M^t\}$ and the unoberserved market state, $\varepsilon^t = \{\varepsilon_1^t, \varepsilon_2^t, ..., \varepsilon_N^t\}$.

In each period, t, firms simultaneously choose actions, $a_i^t \in A_i$ for $i =$

[14] Table 13 in section A shows regressions of current demand on its lagged values, which support a higher order Markov process, most likely because of mean reversion in construction employment to some long term trend.

$1,...,N$. In an entry/exit model, a firm's action is its decision to operate a plant in the next period, so that its action space is $A_i = \{\text{in,out}\}$. In contrast to Ericson and Pakes (1995), where the result of a firm's action is stochastic, I assume that I perfectly observe a firm's action. Specifically, each firm's action in period t, a_i^t, is the firm's observed state in the next period: $a_i^t = x_i^{t+1}$. Hence each's firm's state is either operating a plant, or not. An action profile, a^t, is the composition of actions for all firms in the market $a^t = \{a_1^t, a_2^t, ..., a_N^t\}$. Each firm has a state x_i^t based on being in or out of the market. Each player takes an action a_i^t defined as next periods state x_i^{t+1}.[15] An observation y_{im}^t for player i in market m at time t is a vector composed of the action a_{im}^t taken by the firm and the state of the market from this firm's perspective $y_{im}^t = (a_{im}^t, x_{im}^t, \{x_{km}^t\}_{k \neq i}, M_m^t)$.

Note that each market has 6 firms making a choice every period. Hence, the number of observations is greater than the number of firms in the industry, due to the contribution of potential entrants that choose to remain out of the market.

A firm's per period *reward* function is $r(s^t)$ which depends the state of the market. The firm also pays *transition costs,* $\tau(a_i^t, s_i^t)$ when $a_i^t \neq s_i^t$. For instance, if a firm enters the market it pays an entry fee of $\tau(1,0)$. Note that neither r nor τ are firm-specific, which by itself is not a restriction, since the state, x_i^t, could contain an indicator for the firm's identity. The reward function has parameters, θ, which will be recovered from the data. With slight abuse of notation, denote the parameterized rewards and transition costs as $r(s^t|\theta)$ and $\tau(s_i^t, a_i^t|\theta)$. Without loss of generality, I can rewrite the reward and transition cost functions as additively separable in observed state x^t and unobserved states ε^t: $r(s^t|\theta) + \tau(s_i^t, a_i^t|\theta) \equiv r(x^t|\theta) + \tau(x_i^t, a_i^t|\theta) + \zeta(\varepsilon^t, x^t, a^t, \theta)$.

In my empirical work I use a simple Bresnahan and Reiss (1991) style reduced-form for the reward function, endowed with parameters θ. It is easily

[15] To eliminate incorrect exits, plants that are active today but inactive tomorrow are only counted as exiting if they are also flagged as a Jarmin and Miranda death. Likewise, to obtain the correct entry rate, plants that are inactive yesterday but active today are dropped unless they have been flagged as Jarmin and Miranda births.

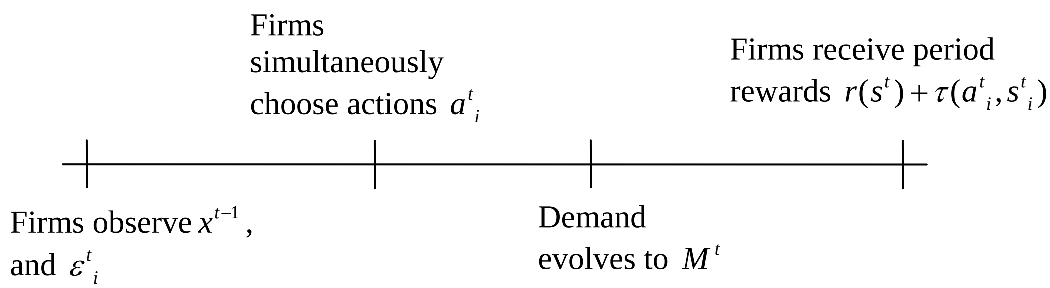

Figure 3: Timing of the game in period t.

interpreted and separable in dynamic parameters, an assumption I discuss in more detail in section 3.3.2. 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:

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

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

$$\tau(a_i^t, x_i^t|\theta) = \underbrace{\theta_4 1(x_i^t = 0, a_i^t = 1)}_{\text{Sunk Costs}} \tag{2}$$

where θ_4 is the sunk cost of entry.

Figure 3 captures the timing of this model: firms first observe the observed states ε^t, then simultaneously choose actions a_i^t. Demand then evolves to its new level M^{t+1}, and firms receive period rewards.

A *Markov strategy* for player i is a complete contingent plan, assigning a probability mixture over actions in each state s. In contrast to the theoretical literature on Markov Perfect Equilibrium (e.g. Maskin and Tirole (1988)), the assumption that firms play Markovian strategies is used not to only to refine the set of equilibria, but also to limit the size of the state space, S. A smaller state space requires less data for estimation and imposes a smaller computational burden. For the purposes of this paper, it is convenient that a strategy be defined as a function $\sigma_i : S \times A_i \rightarrow [0, 1]$, where σ_i is a probability distribution, i.e. $\sum_{a_i^t \in A_i} \sigma_i(s^t, a_i^t) = 1$. A strategy profile $\sigma = \{\sigma_1, \sigma_2, ..., \sigma_N\}$ is the composition of the strategies that each firm is playing. Denote the firm's value, conditional on firms playing strategy profile σ, as $V(s|\sigma)$:

$$V(s|\sigma) = \sum_{a \in A} \left\{ \int_{s'} \left(r(s') + \tau(a_i, s_i) + \beta V(s'|\sigma) \right) f[s^{'}|s, a] ds \right\} \left(\prod_{i=1}^{N} \sigma_i(s, a_i) \right) \tag{3}$$

where $f[s^{'}|s, a]$ is the probability density function of state s' given that firms chose action profile a in initial state s. A *Markov Perfect Equilibrium* is a set of strategies σ^* such that all players are weakly better off playing σ_i^* given that all other players are using strategies σ_{-i}^*, i.e.:

$$V(s|\sigma^*) \geq V(s|\{\sigma_i', \sigma_{-i}^*\}) \tag{4}$$

for any strategy σ_i', for all players i and states s.

3.1 Conditional Choice Probabilities

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, ε^t. However, I can observe *conditional choice probabilities,* the probability that firms in observable state x^t choose action profile a^t denoted as $p : X \times A \rightarrow [0, 1]$. These probabilities are related to strategies as:

$$p(a^t|x^t) = \int_{\varepsilon^t} \prod_{i=1}^{N} \sigma_i(\{x^t, \varepsilon^t\}, a_i^t) g^{\varepsilon}(\varepsilon^t) d\varepsilon^t \tag{5}$$

where $g^{\varepsilon}(.)$ is the probability density function of ε. 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.

Assumption 1 *(Additive Separability) The sum of period rewards and transition costs is additively separable in observed (x^t) and unobserved (ε^t) states.*

This assumption implies that $\zeta(\varepsilon^t, x^t, a^t, \theta) = \zeta(\varepsilon^t, a^t, \theta)$. So that ζ does not vary with the observed state x^t.

Assumption 2 *(Serial Independence) 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:

$$\Pr(a^t|x^t) = \Pr(a^t|x^t, \{x^{t-1}, x^{t-2}, ..., x^0\}, \{a^{t-1}, a^{t-2}, ..., a^0\}) \qquad (6)$$

for any $k \neq t$, any state x^t, and action profile, a^t, since no information is added to equation (5) that would change the value of the integral over ε.

Serial independence of unobserved components of a firm's profitability is violated by any form of persistent productivity difference between firms, or long term reputations of ready-mix concrete operators. Any such persistence would bias my results. In particular, suppose there are two indentical markets in the data, except that one has 4 plants and the other has only 2. Suppose that these configurations are stable. Why don't I see exit from the 4 plant market or entry in the 2-plant market? Intuitively, it seems that there are unobserved profitability differences between two markets. However, the model can only explain these differences in market structure by resorting to high entry and exit costs, which confound true sunk costs with persistent, but unobserved, difference in profitability.

Assumption 3 *(Private Information) Each firm privately observes ε_i^t before choosing its action, a_i^t.*

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

$$p(a^t|x^t) = \prod_{i=1}^{N} p_i(a_i^t|x^t) \tag{7}$$

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. It is of course possible to include shocks which are unobserved by the researcher but common knowledge for all firms, denoted ξ, into the observed state vector x, and integrate over this common shock.[16] The critical assumption is the re-

[16] In particular, I can use simulated maximum likelihood to build an estimator which incorporates common shocks. Draw K realization of the common shocks $\{\xi^k\}_{k=1}^K$ from some distribution $F^\xi(\cdot)$ with a discrete (and finite) support. It is possible to compute the value function conditional on the "extended" observed state $\tilde{x} = \{x, \xi^k\}$ which includes the common shock, as $V(\{x, \xi^k\}|P, \theta)$. The likelihood is then formed by summing all likelihoods conditional on some value of the draw of the common shock ξ^k:

$$\mathcal{L}(\theta) = \sum_{k=1}^{K} \mathcal{L}(\theta|\xi^k) \tag{8}$$

I do not follow this approach because of difficulties associated with computing the likelihood, since the likelihood $\mathcal{L}(\theta|\xi^k)$ is the product of thousands of probabilities, which would become too small to compute very quickly. Notice that ξ^k could also be persistent accross time, and firm specific (but common knowlege).

quirement that private states ε_i^t are serially independent. Suppose that this condition is violated. Then, a firm can learn about the private state of its competitors by looking at their decisions in the past. Serial correlation introduces the entire history of a market $h^T = \{x^t, a^t\}_{t=0}^T$ into the state space, making estimation computationally infeasible.

Assumption 4 *(Logit) ε_i is generated from independent draws from a type 1 extreme value distribution.*

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

$$V(x|P,\theta) = \sum_{x'} \left\{ r(x'|\theta) + \sum_{a_i} \tau(a_i, x_i|\theta) p_i(a_i|x) + E(\varepsilon|P) + \beta V(x'|P,\theta) \right\} F^P(x'|x) \tag{9}$$

where $E(\varepsilon|P) = \sum_{a_i \in A_i} \gamma \ln(p_i(a_i|x))$ (γ is Euler's Constant). For the logit distribution, $E(\varepsilon|P)$ is the expected value of ε 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:

$$F^P(x'|x) = \left(\prod_{i=1}^{N} p_i(x_i'|x) \right) D[M^{x'}|M^x] \tag{10}$$

It is convenient to develop a formulation for the value function conditional on taking action a_j today, but using conditional choices probabilities P in the future:

$$V(x|a_j, P, \theta) = \sum_{x'} \left\{ r(\theta, x') + \tau(\theta, x_i, a_j) + \beta V(x'|\theta, P) \right\} F^P(x'|x, a_j) + \varepsilon_j \tag{11}$$

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

$$F^P(x'|x,a_j) = \left(\prod_{k\neq i} p_i(x'_k|x)\right) 1(x'_i = a_j) D[M^{x'}|M^x] \tag{12}$$

This allow us to write the conditional choice probability function Ψ as:

$$\Psi(a_j|x,P,\theta) = \frac{\exp\left[\tilde{V}(x|a_j,P,\theta)\right]}{\sum_{a_h\in A_i}\exp\left[\tilde{V}(x|a_h,P,\theta)\right]} \tag{13}$$

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 ε to 1, since this is a standard discrete choice model which does not separately identify the variance of ε from the coefficients on rewards.

3.2 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 θ 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 θ, 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.:

$$\hat{p}^0(a_j|x) = \frac{\sum_{m,t,i} 1(a^t_{mi} = a_j, x^t_{mi} = x)}{\sum_{m,t,i} 1(x^t_{mi} = x)} \tag{14}$$

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 (9). Thus optimal conditional choice probabilities can be generated as:

$$\Psi(a_j|x, \hat{P}^k, \hat{\theta}^k) = \frac{\exp\left[\tilde{V}(x|a_j, \hat{P}^k, \hat{\theta}^k)\right]}{\sum_{a_h \in A_i} \exp\left[\tilde{V}(x|a_h, \hat{P}^k, \hat{\theta}^k)\right]} \tag{15}$$

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

$$\hat{\theta}^{k+1} = \arg\max_{\theta} \prod_{l=1}^{L} \Psi(a_l|x_l, \hat{P}^k, \theta) \tag{16}$$

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 θ^1, the specific case where the likelihood of equation (16) is maximized conditional on choice probabilities $\hat{P}^0$.

4. Update the guess at the equilibrium strategy as:

$$\hat{p}^{k+1}(a_j|x) = \Psi(a_j|x, \hat{P}^k, \hat{\theta}^{k+1}) \tag{17}$$

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-reponse 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:

$$\hat{p}^{k+1}(a_j|x) = \frac{1}{MA+1}\left[\Psi(a_j|x, \hat{P}^k, \hat{\theta}^{k+1}) + \sum_{ma=0}^{MA-1} \hat{p}^{k-ma}(a_j|x)\right] \quad (18)$$

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 δ 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 $\hat{\theta}^{k+1}$.

Although this algorithm is analogous to the Hotz and Miller (1993) technique, it is closer to the Expectations Maximizing algorithm (for details on EM see Dempster, Laird, and Rubin (1977)) used to solve Hidden Markov Models, where the equilibrium strategies P are unknowns. Monte-Carlo results show that diffuse priors for initial conditional choice probabilities $\hat{P}^0$, i.e. where first stage conditional choice probabilities for each action $\hat{p}^0(a_j|x) = \frac{1}{\#A_i}$, yield the same results as those where carefully estimated initial conditional choice probabilities were used. This is important since Hotz and Miller (1993) estimates are known to be sensitive to the technique used to estimate initial conditional choice probabilities $\hat{P}^0$. In particular, if there is a large number of states relative to the size of the sample, some semi-parametric technique must be used to estimate conditional choice probabilities. The Aguirregabiria and Mira (2006) estimator bypasses this issue entirely.

3.3 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.

3.3.1 Symmetry

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. For instance, in an entry-exit model where the only observed firm state is activity or inactivity, a market configuration in which firms 2 and 3 are active, represented by the market state vector $[0, 1, 1, 0, M]$ is assumed to lead to the same outcomes as a market where firms 1 and 4 are active $[1, 0, 0, 1, M]$. 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.

3.3.2 Separability in Dynamic Parameters

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 (1) and (2). 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:

$$V(x|a_j,P,\theta)=\tilde{\theta}\sum_{x'}\left[\rho(x',a_j,x_i)+\beta J(x'|P)\right]F^P(x'|x,a_j) \qquad (19)$$

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:

$$\Psi(a_j|x,P,\tilde{\theta})=\frac{\exp\left[\tilde{\theta}Q(a_j,x,P)\right]}{\sum_{h\in A_i}\exp\left[\tilde{\theta}Q(a_h,x,P)\right]} \qquad (20)$$

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. A description of estimation, included "nitty-gritty" computational details, is provided in section D.

3.3.3 Heterogeneity

Different markets can have different profitability levels. These differences are not always well-captured by observables such as demand factors, and can lead to biased estimates. To deal with this problem, I use a fixed effect estimation strategy , in which rewards in market m have a market specific component α_m, i.e. $r_m(x|\theta) = r(x|\theta) + \alpha_m$.

Differences in the profitability of markets also affect the choices that firms make. Each market will have its own equilibrium conditional choice probabilities P^m. The likelihood for this model is:

$$\mathcal{L}^{Het}(\theta, \{\alpha_1, ..., \alpha_M\}) = \prod_{m=1}^{M} \left(\prod_{t=1}^{T} \prod_{i=1}^{N} \Psi(a_i^{t,m} | x_i^{t,m}, P^m, \{\theta, \alpha_m\}) \right) \quad (21)$$

It is then possible to estimate α_m using maximum likelihood techniques as any another demand parameter. However, there are too many markets in the data to estimate individual market specific effects. I therefore group markets into categories based on some common features, and assign each catagory a group effect. In my empirical work, these group are formed based on the average number of firms in the market over the sample, rounded to the nearest integer. The idea for this grouping comes from estimating the static entry and exit models of Bresnahan and Reiss (1994) with county fixed effects (see chapter 3 for more detail). These estimates give similar results to a model with grouped fixed effects.

4 Results

I estimate the model using the Nested of Pseudo-Likelihoods Algorithm. I fix the discount factor to 5% per year. The discount factor is not estimated from the data since dynamic discrete choice models have notoriously flat profile likelihoods in the discount parameters as in Rust (1987). The discount parameter $\hat{\beta}$ that maximizes the profile likelihood is in the range between 20% and 30%. Table 1 presents estimates for two dynamic models, using either the Hotz and Miller (column I and III) or Aguirregabiria and Mira (column II and IV) methods to compute conditional choice probabilities. The two empirical models include one without market heterogeneity (column I and II) and one with market level fixed effects (column III and

IV). These estimates show a number of features. First, competition quickly reduces the level of profits. The first competitor is responsible for 75% of the decrease in profits due to competition. This is consistent with Bertrand Competition with a relatively homogeneous good and constant marginal costs, where price falls to near the competitive level if there is more than one firm in the market. This case is well approximated by the ready-mix concrete industry for competition between firms in the same county. This result is consistent with the relationship between price and the number of competitors displayed in Figure A which indicate that price falls most with the addition of the first competitor, and with estimates of thresholds in the models of Bresnahan and Reiss (1994) presented in chapter which show a similar pattern. Second, estimates of sunk costs are quite large, of the same magnitude as the effect of permanently going from a duopoly to a monopoly (equal to about $0.37/0.05 = 7.4$ in net present value terms, versus 6.2 for sunk costs).[17] Thus, a market's history, as reflected by the number of plants in operation, has a large influence on the evolution of market structure. Third, correcting for unobserved heterogeneity significantly increases the effect of competitors on profits. Note that the effect of the second competitor on profits is positive in the model without market fixed effects (0.11 and 0.15 in columns I and II), but negative when market fixed effects are added (-0.01 and -0.04 in columns III and IV). It is improbable that competitors have positive externalities on their rivals. However, positive coefficients on competition are consistent with more profitable markets attracting more entrants, which induces a positive correlation between the number of competitors in a market and the error term (chapter 3 discusses this point in more detail in the context of a static entry model). Thus, estimates of the effect of entry on profits are biased upwards. The panel structure of data permits a correction for this problem. Furthermore, notice that the fixed costs are significantly higher in markets with fewer firms (reducing profits by -0.30, -0.12, -0.06 and -0.02 respectively in column IV), supporting

[17] This relative magnitude of sunk costs versus the effect of the first competitor is also found in estimates of the models of Bresnahan and Reiss (1994) with market fixed effects that I have also estimated.

the presence of unobserved differences in market profitability.

The estimates of sunk costs may seem high. In fact, they are generally consistent with interview data. Based on my interviews, I reckon the sunk cost of a plant is about 2 million dollars. Alternatively, Figure A shows that prices fall by 3% from monopoly to duopoly (from about \$42 to \$41). According to Table 11 the average continuing plant had sales of \$3 M in 1997, so the average decrease in profits from monopoly to duopoly are on the order of \$90 000 per year (3%×\$3M), which implies that the ratio between a standard deviation of the error and dollars is about \$250 000. Table 14 converts entry-exit parameters from the preferred specification to dollars, where period profit parameters expressed in net present value to be directly comparable to sunk costs. Note that sunk costs are estimated at \$1.24 M, slightly less than what interviewees reported.

Finally, this model does well in fitting the observed industry dynamics. Table 3 compares the steady-state industry dynamics predicted by the model (Baseline) versus those in the data. The model predicts 145 entrants and 145 exits per year, while the average in the data (over all years in the sample) is 142. Likewise, the model predicts 2507 continuing plants versus 2606 in the data. This match is somewhat surprising, since nowhere have I imposed the restriction that the industry is in steady-state.

4.1 Multiple Plant Sizes

In this section, I discuss an extension of the model to allow for large and small plants. I categorize plants as either big or small according to wethever the number of employees at the plants is above or below 15.[18] Employment is used as the measure of size for two reasons. First, Census imputes data on capital assets and shipments for smaller plants. If capital assets were used, the data would include too few small plants relative to large ones. Second, interviewees have indicated that employment is a fair proxy for the number of ready-mix delivery trucks associated with a plant, since each truck is associated with a single driver. Figure A shows that a plant in the lowest

[18]The model was also estimated with different cutoffs for the number of employees, yielding similar qualitative results.

	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 1: Estimates for the Dynamic Entry Exit Model

decile of employment is five times as likely to exit as a plants in the top decile of employment, suggesting that the entry and exit behavior of large and small plants are quite different.

Table 2 displays estimates of the multiple firm size model using the Nested of Pseudo-Likelihoods algorithm, with column I presenting Hotz and Miller estimates and column II presenting Aguirregabiria and Mira estimates. I only show estimates with market level fixed effects since these yield more sensible coefficients. There are a number of salient differences between small and large plants. Note that higher levels of demand increase the profit of large plants five time faster than the profits of small plants, with a coefficient on log construction workers of 0.02 for small plants and 0.14 for large plants in column I. Table 22 shows that larger markets have more plants and more employees per plant (on average). Big plants are x% of plants in a small market, while they represent y% of plants in the largest markets. This is evidence for either returns to scale in the ready-mix concrete industry, or that plants with higher managerial capital have more opportunities to expand in larger markets as in Lucas Jr (1978). However, large plants have entry costs that are 30% higher than those of small plants (6.4 for small plants versus 9.8 for large plants in column II). In the same vein, large plants pay higher fixed costs each period than small plants (0.2 for small plants versus 0.5 for large plants in column II for the first market group). This indicates that while large plants are more profitable if there is sufficient demand, they also have to cover much higher costs of entry and operation. Notice as well that the gap between fixed costs for large and small plants in column I is constant across market groups (equal to 0.26, 0.22, 0.19 and 0.19 for groups 1 to 4 respectively). This indicates that the model can distinguish between two distinct effects: markets with higher profitability have more plants, versus higher operating costs for large plants across all markets. The effect of competitors on large and small plants is similar, with large plants slightly more affected by competition. The first competitor decreases profits for small plants by 0.21, while the first competitor decreases profits for large plants by 0.27. Moreover, the pattern of competition found in the entry-exit model, where each additional competitor had a decreasing marginal effect on profits, is also found in the declining effect of additional competitors on the profits of both small and large plants.

As before, the model's steady-state matches industry turnover well, as indicated by Table 4. Moreover, industry dynamics for the total number of plants in the multitype model are almost exactly the same as those produced by the simple entry-exit model.

5 No-Fluctuation Industry Dynamics

Consider a policy of demand smoothing, under which the smoothed demand transition matrix SD is equal to: $SD(\sigma) = (1-\sigma)\hat{D} + \sigma I$, where $\sigma \in [0,1]$ is the smoothing parameter, $\hat{D}$ is the demand transition process in the data and I is the identity matrix. As σ approaches 1, demand fluctuations are completely eliminated. I consider two polar cases: complete demand smoothing ($\sigma = 1$), where firms know that the current level of demand will stay the same forever, and no demand smoothing($\sigma = 0$), in which case demand will vary from year to year according to the process $\hat{D}$ estimated from the data.

I simulate the effect the of changing the volatility of demand by computing the steady-state (or ergodic) industry dynamics when demand fluctuations are present, and when these have been removed. Remember that the state-to-state transition process $F^P(x'|x)$ of equation (10) depends both on the set of conditional choice probabilities P and on the process for demand D. Thus, if I change the process for demand, this change will alter the underlying equilibrium of the game, and the conditional choice probabilities $P^*(\theta, D)$ associated with it. I recompute the equilibrium both for the world with demand fluctuations($P^*(\theta, \hat{D})$) and without them($P^*(\theta, I)$) using the Pakes and McGuire (1994) algorithm. I can use these new conditional choice probabilities to compute the steady-state industry dynamics for this game, using transition probabilities $F^{P^*(\theta,\hat{D})}(x'|x)$, and generate the ergodic distribution. First, stack state to state transitions $F(x'|x)$ over all values of x and x' to form a matrix, which I denote as F. Second, I choose the initial state of the market, $\hat{Y}$, as the distribution of firms and demand estimated

		I	S.E.	II (Preferred)	S.E.
Log Construction Workers	Small Plant†	0.030	(0.008)	0.024	(0.007)
	Big Plant‡	0.137	(0.017)	0.136	(0.012)
Effect of competition on*					
Small Plant	1 Competitor	-0.156	(0.017)	-0.211	(0.019)
	2 Competitors	-0.004	(0.020)	-0.066	(0.024)
	3 Competitors	0.008	(0.031)	-0.011	(0.027)
	4+ Competitors	0.183	(0.051)	-0.011	(0.031)
Big Plant	1 Competitor	-0.126	(0.037)	-0.274	(0.035)
	2 Competitors	-0.070	(0.047)	-0.104	(0.037)
	3 Competitors	-0.021	(0.079)	-0.008	(0.047)
	4+ Competitors	0.182	(0.090)	-0.021	(0.029)
Transition Costs	Out → Small	-6.471	(0.051)	-6.419	(0.019)
	Out → Big	-9.781	(0.171)	-9.793	(0.118)
	Small → Big	-3.370	(0.110)	-3.478	(0.072)
	Big → Small	-0.932	(0.109)	-0.851	(0.060)
Fixed Cost Group 1	Small Plant	-0.331	(0.017)	-0.277	(0.014)
	Big Plant	-0.576	(0.046)	-0.534	(0.031)
Fixed Cost Group 2	Small Plant	-0.203	(0.023)	-0.136	(0.017)
	Big Plant	-0.470	(0.055)	-0.353	(0.042)
Fixed Cost Group 3	Small Plant	-0.132	(0.031)	-0.063	(0.021)
	Big Plant	-0.381	(0.068)	-0.250	(0.046)
Fixed Cost Group 4	Small Plant	-0.105	(0.054)	-0.015	(0.031)
	Big Plant	-0.339	(0.091)	-0.204	(0.050)
Equilibrium Conditional Choices				X	
Log Likelihood		-10307		-10274	
Observations		214000		214000	

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

† Small: Plant with less than 15 employees.

‡ Big: Plant with more than 15 employees.

I: Hotz and Miller technique with market fixed effects

II: Aguirregabiria and Mira technique with market fixed effects

Table 2: Two Type Entry Model with Non-Parametric Competiton indicators (total number of competitors)

from the data, i.e. $\hat{Y}_x = \sum_{l=1}^{L} 1(x_l = x)$ for all states $x \in X$ and all years in my sample. Note that this initial condition has no effect on the ergodic distribution if it is possible to reach any state x^a from any other state x^b I will show an exceptional case where states do not communicate in the next paragraph. The ergodic (or steady-state) distribution is computed by solving for the distribution of states an arbitrarily large number of periods in the future. Next period's probability distribution over states can be computed as: $Y_{\hat{D}}^{t+1} = Y_{\hat{D}}^{t} F^{P^*(\theta,\hat{D})}$, where Y and F are matrices, and $Y_{\hat{D}}^{0} = \hat{Y}$. The ergodic distribution $W^{\hat{D}}$ produced by the demand transition process $\hat{D}$ can be approximated by $Y_{\hat{D}}^{T}$, where T is a suitably large number of periods in the future.[19]

However, in the case where fluctuations are eliminated demand in the future is solely determined by initial conditions $\hat{Y}$. If the demand transition process is the identity matrix I, then it is impossible to move between two states x^a and x^b if these states have different levels of demand. Thus, the average level of demand could differ substantially between worlds with and without fluctuations. I circumvent this problem by insuring that the ergodic distribution of demand is the same for both the fluctuation and no fluctuation worlds. I first compute the ergodic distribution of demand generated by the process in the data $\hat{D}$, which I denote as $W^{\hat{D}}$. I compute the ergodic distribution of the no fluctuation world using $W^{\hat{D}}$ as my initial condition Y_I^0 and iterating on $Y_I^{t+1} = Y_I^t F^{P^*(\theta,I)}$ for a suitably large number of periods. Thus, $W^I = Y_I^T$ is the ergodic distribution generated by complete demand smoothing, with the demand transition matrix equal to the identity matrix I.

Table 3 shows that smoothing all fluctuations in demand, i.e. setting $\sigma = 1$, decreases plant turnover by 3% from 145 entrants and exitors to 140. Note that both cases yield approximately the same number of plants. The differences in turnover rates are not generated by a change in the mean level of demand , but instead by the change in the volatility of demand. Extrapolating to the industry as a whole (with about 5000 plants as of

[19] I compute the distribution of firms one hundred thousand periods into the future ($T = 100000$), which is a very good approximation to the ergodic distribution.

	Data	Baseline ($\sigma = 0$)	Smoothing ($\sigma = 1$)
Exitors and Entrants*	142	145	140
Number of Plants	2606	2507	2518

*In steady-state, the number of entrants and exitors must be the same.

Table 3: The steady-state number of plants and entrants/exitors under No Demand Fluctuations and Baseline

1999), demand smoothing would lead to 10 fewer plant deaths and 10 fewer plant births each year. If the value of capital lost when a plant is shut down is set at a least 2 million dollars, which accounts for only the physical capital lost when a plant shuts down and not capital embedded into economic relationships, scrapped capital losses would be reduced by 20 million dollars a year.

When the effect of multiple plants sizes is incorporated, as shown by Table 4, a more detailed picture emerges. The number of entrants and exitors is the same for the simple entry/exit model at 145 for the world with fluctuations, and 140 for smoothed demand. However, the number of large plants increases by 50% from 407 to 598 when demand fluctuations are eliminated. Thus demand uncertainty appears to leads firms to lower investment in order to reduce their exposure to negative demand shocks. Eliminating demand fluctuations also reduces the number of plants which switch from small to big and vice-versa by 6 per year, reducing adjustment costs on the intensive margin by a small amount.

To identify the contribution of demand fluctuations to plant turnover, demand shocks need to be separated from plant specific shocks to profitability. These idiosyncratic shocks are potentially large, due to a number of factors. Perhaps the most thoroughly investigated is the reallocation of output towards more efficient units (e.g. Foster, Haltiwanger, and Syverson (2005)), illustrated by Figure A in section A where a plant in the second quintile of productivity is three times more likely to exit as a plant in the top quintile of productivity. Moreover, other plant characteristics, such as plant size, being part of a multi-unit firm, or plant age above 10 years af-

Baseline

To		From		
		Out	Small	Big
To	Out		136	7
	Small*	130	1886	93
	Big**	14	87	407

Smoothed

To		From		
		Out	Small	Big
To	Out		131	8
	Small	125	1806	90
	Big	14	84	598

Data

To		From		
		Out	Small	Big
To	Out		137	7
	Small	151	1972	103
	Big	15	94	491

* Small: Plant with less than 15 employees.
** Big: Plant with more than 15 employees.

Table 4: Steady-State Industry Dynamics with and without demand fluctuations (Basline and Smoothed). Data represents industry dynamics in the data averaged over all sample years.

fects the likelihood of exit of plants, as illustrated by logit regressions on exit reported in Table 15 in section A. Demand shocks do not account for all the observed plant turnover.

6 Conclusion

The Ready-Mix concrete industry is characterized by high sunk costs, due to capital assets with little resale value and long term relationships with customers and suppliers. Competition between plants in the same county is intense, in that a single competitor reduces profits to close to the competitive level. The industry is subject to large demand shocks, on the order of 30% per year. These demand shocks vary across geographically segmented markets, causing plants to exit declining markets and enter growing ones. High sunk costs slow the response of entry to demand shocks, allowing firms to remain in unprofitable markets for some time. High adjustment costs imply that turnover would only be reduced by 3% if demand fluctuations were eliminated. This policy of demand smoothing would save at most 20 million dollars a year for this industry from reduced plant exit. Reducing the volatility of the construction sector is by no means unrealistic, since an important component of demand is driven by government spending decisions and the Federal Reserve's interest rate policy. Yet, demand fluctuations sharply reduce firm's incentives to invest in larger, potentially more efficient units, reducing the number of large plants in the industry by 50%. These larger plants may have an important role in industry productivity.

This study focuses on a single industry, which by itself accounts for less than a tenth of a percent of national output. However, the ready-mix concrete industry provides a window on potential benefits from eliminating demand fluctuations that can inform debates on the management of the business cycle.

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A Tables and Figures

Sector Name	NAICS	Concrete sector as fraction of	
		Total Sales	Materials Used
Owner-occupied dwellings	S00800	21%	NA
New residential 1-unit structures	230110	17%	3%
New residential additions and alterations	230130	10%	7%
Commercial and institutional buildings	230220	9%	2%
Highway, street, bridge, and tunnel construction	230230	8%	7%
New multifamily housing structures	230120	7%	10%
Other new construction	230250	4%	2%
Maintenance and repair of nonresidential buildings	230320	3%	2%
Real Estate	31000	3%	NA
Maintenance and repair of residential structures	230310	2%	3%
Other State and local government enterprises.	S00203	2%	NA
Power generation and supply	221100	2%	NA
Manufacturing and industrial buildings	230210	1%	2%
New farm housing units	230140	1%	7%
Other maintenance and repair construction	230340	1%	2%
Water, sewer, and pipeline construction	230240	1%	1%
Maintenance and repair of highways, streets	230330	0.4%	1%
Total For selected Sectors		92%	

Table 5: Concrete purchases by sector, and relative importance of concrete costs for the sector.
Source: 1997 Benchmark Input-Output Tables.

Number of Concrete Plants	Number of Counties/Years	Percent
0	22,502	30%
1	23,276	31%
2	12,688	17%
3	6,373	9%
4	3,256	4%
5	1,966	3%
6	1,172	2%
More than 6	3,205	4%
Total	74,438	

Table 6: Most counties in the United States are served by less than 6 ready-mix concrete plants.

Product	Fraction of output in value
Ready-Mix Concrete	95%
Unknown	4%
Construction sand and gravel	2%
Precast Concrete Products	1%
Asphalt Paving Mixtures and Blocks	1%

Table 7: Plants in sample tend to produce concrete exclusively

Year	Birth	Continuer	Death
1976	501	4,737	N.A.
1977	557	4,791	410
1978	327	5,043	445
1979	392	5,093	333
1980	271	5,140	387
1981	313	5,069	360
1982	313	4,875	423
1983	273	4,991	315
1984	328	4,972	295
1985	309	4,988	339
1986	300	5,003	305
1987	390	4,898	404
1988	270	5,016	269
1989	248	4,275	448
1990	194	4,103	304
1991	220	3,882	291
1992	214	4,643	348
1993	133	3,668	270
1994	163	3,952	232
1995	196	3,840	243
1996	195	3,734	230
1997	338	4,768	274
1998	239	4,949	267
1999	320	4,961	234

Table 8: The number of Births, Deaths and Continuers is fairly stable over the last 25 years

	Observations	Mean	Standard Deviation	5th Percentile	95th Percentile
Fraction in LBD concrete sic	187825	0.78	0.33	0	1
Fraction in Asm/Cmf concrete ind	187915	0.92	0.22	0.33	1
Tabulated Industry Code	70584				
Total Value of Shipments (in 000's)	70566	3380	25643	41	11000
Total Employment	70566	26	147	1	82
Administrative Record Flag	70622	0.13	0.34	0	1
Building Assets Ending (in 000's)	51246	153	1885	0	420
Building Depreciation (in 000's)	51246	6.23	65	0	21
Building Retirements (in 000's)	51246	4.20	56	0	8
Cost of Advertising (in 000's)	11598	4.06	168	0	6
Cost of Fuels (in 000's)	70566	42	245	0	150
Control File Postal Zip Code	5827				
Total Cost of Materials (in 000's)	70566	1800	15020	16	5700
Cost of Resales (in 000's)	70566	115	1621	0	430
Cost of Contract Work (in 000's)	70566	22	235	0	37
Cost of Purchased Electricity (in 000's)	70566	29	236	0	75
Employer Identification Number	70609				
Value of Export Shipments (in 000's)	37487	144	6627	0	0
Total Value of Inventory (in 000's)	11598	116	3702	0	140
Machinery Assets Ending (in 000's)	51246	754	4463	0	2700
Machinery Depreciation (in 000's)	51246	55	478	0	220
Materials Inventory Ending (in 000's)	70566	151	7204	0	250
Machinery Rents (in 000's)	57073	12	95	0	42
Machinery Retirements (in 000's)	51246	24	238	0	78
Multi-Unit Flag, MU=label	70622	0.51	0.50	0	1
Total New Expenditures (in 000's)	70566	148	1625	0	510
New Machinery Expenditures (in 000's)	70566	128	1351	0	460

Table 9: Summary Statistics for Plant Data

	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 Beginning (in 000's)	24677	921	14431	0	3900
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 Employement	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 above 75 Percentile Productivity Plants	74435	1.83	2.67	0	5
County 25-75 Percentile Productivity Plants	74435	0.22	0.82	0	1
County Below 25 Percentile Productivity Plants	74435	0.11	0.46	0	1
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
Employement in Construction	69911	1495	5390	11	6800
Payroll in Construction (in 000's)	69911	37135	163546	110	160000

Table 10: Summary Stats for County Aggregate Data

Average Shipments (in thousands)	Birth	Continuer	Death
1977	461	1,164	402
1982	1,045	1,503	520
1987	1,241	2,307	601
1992	1,509	2,218	1,417
1997	1,559	3,293	1,358

Average Capital (in thousands)	Birth	Continuer	Death
1977	217	491	185
1982	403	598	187
1987	549	1,050	270
1992	565	1,131	632
1997	728	1,992	770

Average Salaries (in thousands)	Birth	Continuer	Death
1977	83	211	83
1982	185	269	83
1987	205	413	101
1992	257	428	267
1997	243	567	241

Table 11: Characteristics of Plants that are Births, Deaths and Continuers

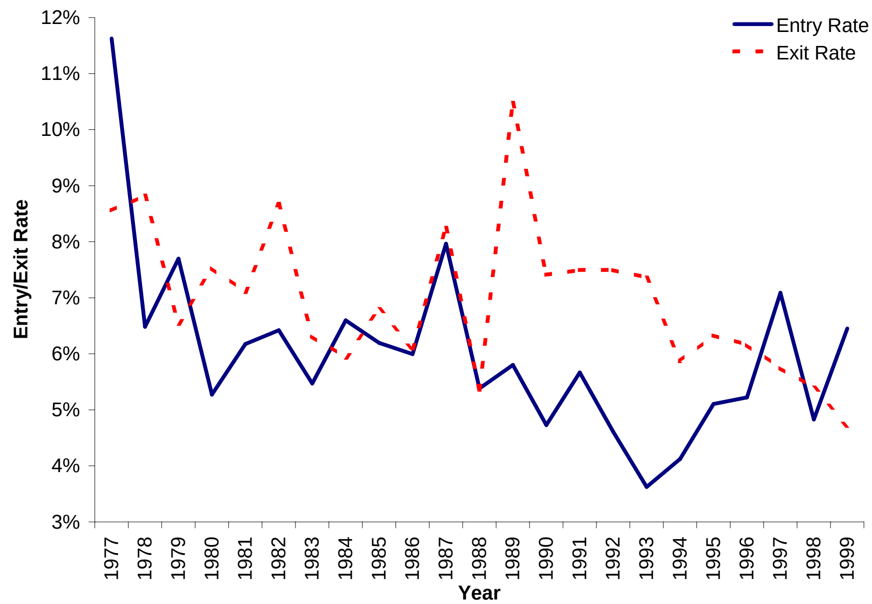

Figure 4: Net Entry is sensitive to the business cycle.

Price per Cubic Yard in 1963 Dollars	Coefficient	S.E.
1 Competitor	-0.95	(0.21)
2 Competitors	-1.19	(0.21)
3 Competitors	-1.38	(0.24)
4 Competitors	-1.33	(0.24)
5 Competitors	-1.57	(0.25)
6 Competitors	-1.69	(0.27)
7 Competitors	-1.72	(0.30)
8 Competitors	-1.78	(0.31)
Area in thousand of acres	0.28	(0.04)
Year Effects(Base Year 1963)	Yes	
Constant	about 42	
Number of Observations	3148	
Sum of Deviations	18225	
Pseudo-R2	17%	

Table 12: Median Regression of Prices pooled over the entire sample on the Number of Plants in a county

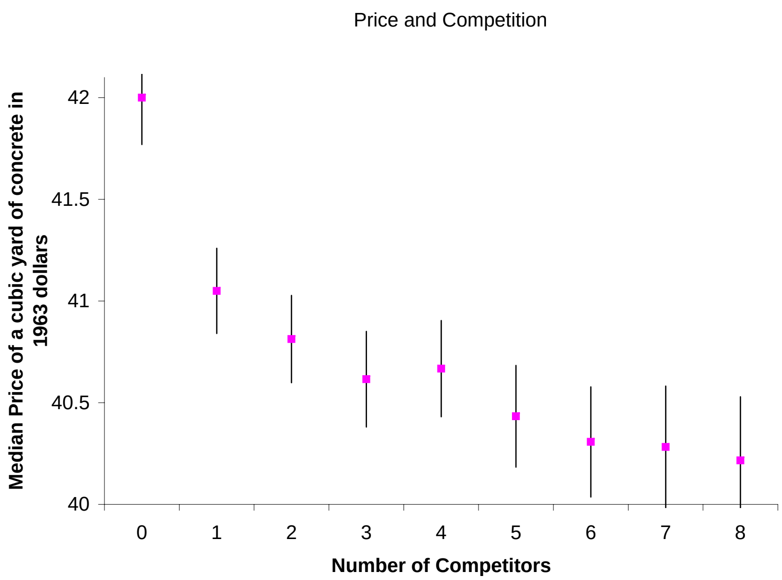

Figure 5: Prices Decline Dramatically with the addition of the first competitors, and little afterwards.
Note: Bars represent 95% confidence interval on median price. I report the complete median regression in Table 12 in section A.[20]

Next Year's Construction Employement	OLS	S.E.	Fixed Effect	S.E.
construction employement t	0.657	(0.008)	0.506	(0.009)
construction employement t-1	0.216	(0.008)	0.129	(0.008)
construction employement t-5	0.114	(0.005)	-0.010	(0.007)
interest rate	-0.012	(0.001)	-0.027	(0.001)
interate rate*payroll	0.000	(0.000)	0.000	(0.000)
constant	0.218	(0.013)	N.A.	
Number of Group	14333		1339	
Number of Time Periods	N.A.		11	
R2	97%		96%	
R2-within	N.A.		49%	
F-statistic	98075		2585	

Table 13: Forecasting the Evolution of Demand for Concrete with OLS and county fixed effect regressions

	Net Present Value in Thousands of Dollars
Log Construction Workers	217
1 Competitor	-1,493
2 Competitor	-171
3 Competitor	-198
4 and More Competitor	-80
Sunk Cost	1,242
Fixed Cost	-499
Normalized By	Decrease in Price in % from monopoly to duopoly times average sales

Table 14: Dollar Value of Sunk Costs from the model match Interview Data

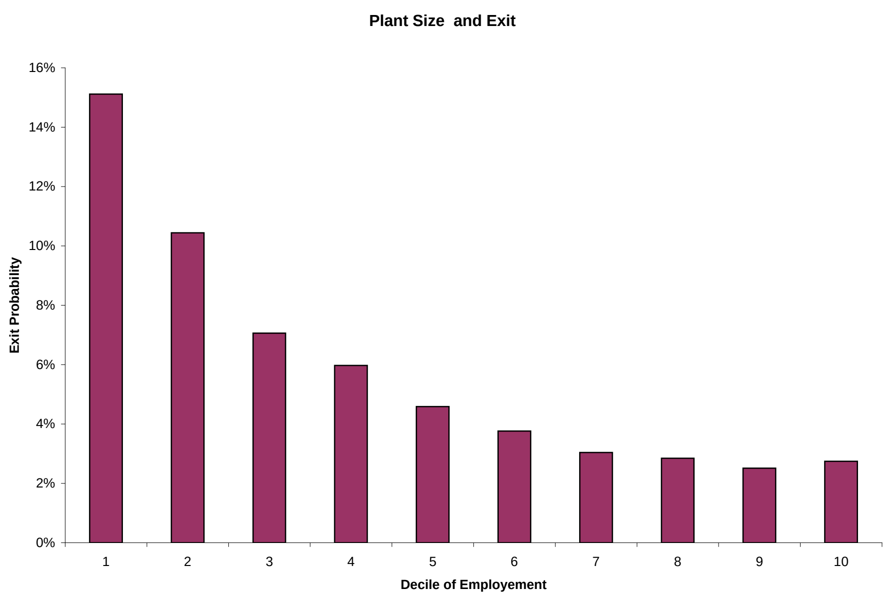

Figure 6: Small firms are much more likely to exit than large firms

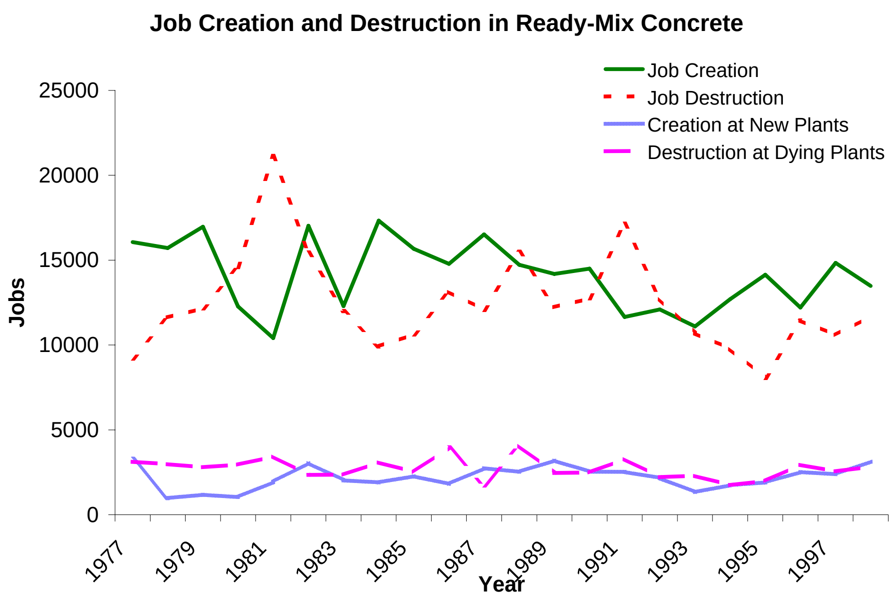

Figure 7: Entry and Exit account for 15% of job creation and destruction. Job Creation and Destruction is constructed in the same manner as Davis, Haltiwanger, and Schuh (1996).

Baseline Exit probability	4.51%	
	Parameter	Standard Error
Employees	-0.11%	(0.02%)
Employees*Employement Construction	0.01%	(0.00%)
5-10 Years Old	0.74%	(0.15%)
0-5 Years Old	0.30%	(0.17%)
Multi-Unit Firm	-1.82%	(0.11%)
Less than 6 employees	4.98%	(0.22%)
Log of county construction employment	-0.24%	(0.19%)
Log of county concrete plants	1.49%	(0.18%)
Square log of construction employement	-0.22%	(0.05%)
Square log of concrete plants	0.00%	(0.01%)
Number of Observations	143204	
Log-Likelihood	-28396	
Pseudo-R2	4.7%	

Table 15: Marginal Effects on the Probability of Exit estimated from a Logit

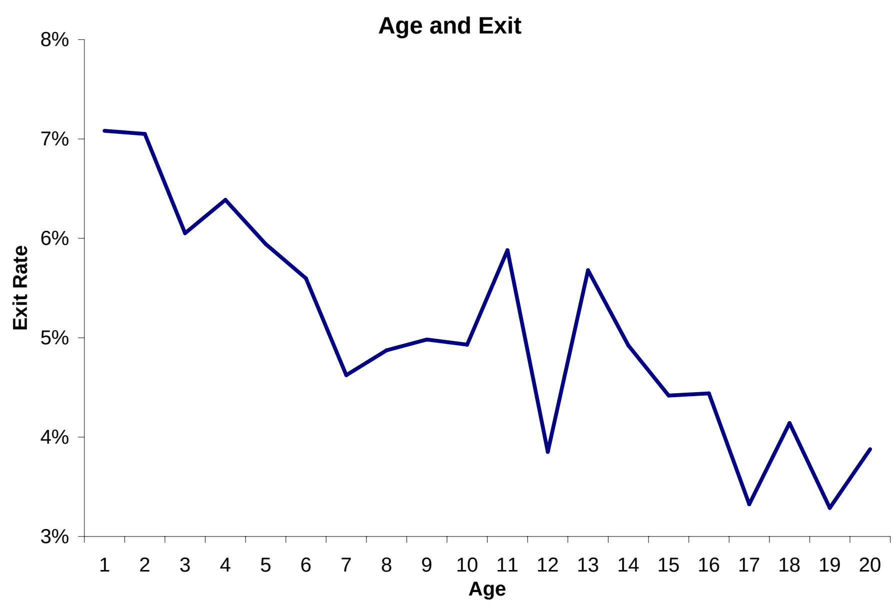

Figure 8: Young firms have slightly higher risks of exiting.

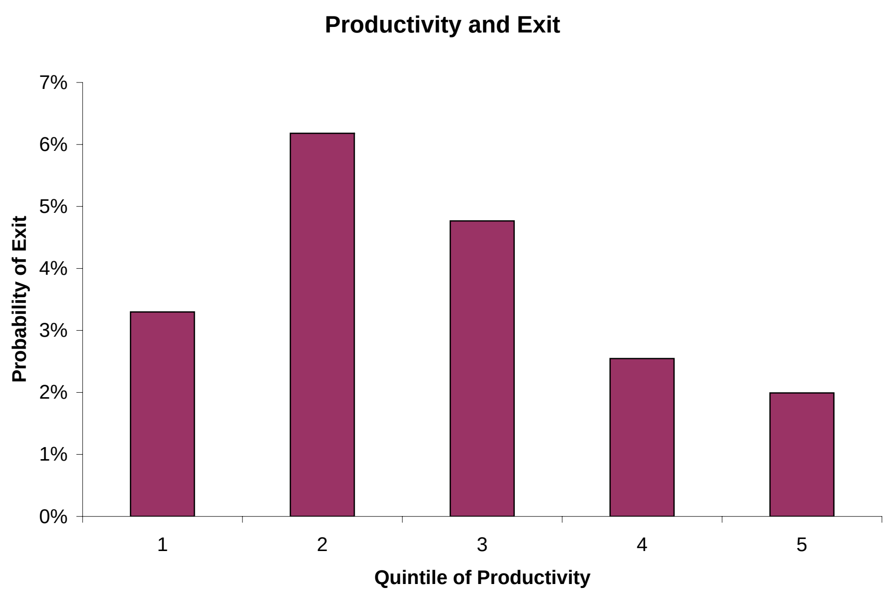

Figure 9: More productive firms are less likely to exit, more or less.

B Robustness Checks

B.1 Alernate Specification for Period Profits

An alternate specification for the per-period profit function follows from the discussion on identification of entry models presented in Berry and Tamer (2006):

1. Demand increases the number of customers in the market. These customers will be shared evenly between firms.
2. Competition decreases the margin per customer arriving to each firm.
3. Fixed Costs are unaffected by either demand or the number of customers.

These exclusion restrictions give rise to the following form for period profits:

$$\pi = \underbrace{f(M)}_{\text{Number of Customers}} \overbrace{g(N)}^{\text{Margin per customer}} + \underbrace{c}_{\text{Fixed Cost}} \tag{22}$$

Thus I assume the following functional form for the period reward function[21]:

$$r(a_i^t, x^t|\theta) = a_i^t \left(\underbrace{\theta_1}_{\text{Fixed Cost}} + \theta_2 \underbrace{M^{t+1}}_{\text{Demand}} * \underbrace{g\left[\sum_{-i} a_{-i}^t\right]}_{\text{Competition}} \right) \tag{23}$$

Table 16 shows estimates for the dynamic model of entry and exit using the functional form for rewards which is multiplicatively separable in demand and competition shown in equation 23. These estimates show a similar relationship between competition and profit and yield similar estimates of sunk costs.

B.2 Second-Order Markov

I also estimate the model where demand is assumed to follow a second-order Markov process, in which demand in the next period depends both demand today and demand a year ago. To estimate this second-order process I use the same non-parametric estimator as before but with a slight twist. Certain demand states are reached very infrequently, such as having very high demand today ($M^t = 9$) and very low demand in last period ($M^t = 1$), and thus there may be no observations

[21] The profit function used in Bresnahan and Reiss (1994) also satisfies this exclusion restriction (i.e. demand affects market size, while competition affects per consumer margin), but has been transformed by taking the logarithm. In the intertemporal expected utility setup that I use, a monotonic transformation of the reward function does not give the same choices. Therefore, I cannot apply the log-transformation to my period reward specification and in particular I should not use the logarithm of demand. I thank Peter Reiss and Bernard Salanié for pointing out this issue.

	I	s.e	II	s.e
Thousand of Construction Workers ×				
Constant	0.30	(0.02)	0.50	(0.04)
Fixed Cost Group 1	-0.42	(0.01)	-0.42	(0.01)
Fixed Cost Group 2	-0.36	(0.01)	-0.38	(0.01)
Fixed Cost Group 3	-0.31	(0.01)	-0.35	(0.01)
Fixed Cost Group 4	-0.31	(0.01)	-0.33	(0.01)
1st Competitor	-0.34	(0.04)	-0.58	(0.05)
2nd Competitor	0.04	(0.02)	0.08	(0.02)
3rd Competitor	0.01	(0.02)	0.00	(0.01)
More than 3 competitors	0.00	(0.01)	-0.01	(0.03)
Sunk Costs of Entry	-6.48	(0.04)	-6.47	(0.04)
Equilibrium Conditional Choices			X	
Likelihood	-12589		-12591	
N	235000		235000	

	Entrants and Exitors	Continuers	Turnover Rate
Baseline	135	2546	5.05 %
Smoothed Demand	125	2287	5.20 %

Table 16: Dynamic Entry-Exit Estimates and Demand Fluctuation counterfactuals with functional form of profits which is multiplicatively separable in demand and competition.

in the ($M^t = 9, M^{t-1} = 1$) bin. To get around this problem I assume that if I have little information on a particular demand state then the probability of observing M^{t+1} conditional on (M^t, M^{t-1}) is the same as the probability of observing M^{t+1} conditional on M^t. This give the following estimator for the second-order Markov demand process:

$$\hat{D}[i|j,k] = \frac{\sum_{(l,t)} 1(M_l^{t+1} \in B_i, M_l^t \in B_j, M_l^{t-1} \in B_k) + N_s \hat{D}[i|j]}{\sum_{(l,t)} 1(M_l^t \in B_j, M_l^{t-1} \in B_k)) + N_s} \tag{24}$$

I use a parameter N_s, set to 9 for estimates in this paper, which can be interpreted at the number of observations coming from the $M^{t+1}|M^t$ process.

Table 17 presents estimates for the model with a second-order Markov process for demand, as well as turnover in the counterfactual world where demand fluctuations have been eliminated compared to the world with demand fluctuations. Notice that the demand coefficient is much smaller in Table 17 than for the first-order markov process for demand presented in Table 1, leading to a much smaller effect of demand fluctuations on steady-state turnover.

B.3 Volatility and Turnover: Reduced Form

The structural model has several unverifiable assumptions. For instance, I assume that there are no persistent unobserved states, i.e. unobserved firm characteristics that are serially correlated. As a check on the validity of the structural model, I look at the relationship between plant turnover and demand fluctuations accross counties in the Continental United States. Different counties have experienced very different levels of demand volatility over the last 20 years. Suppose this heterogeneity in realized demand volatility is due to different processes generating demand shocks. In counties that experienced high demand volatility was there also more plant turnover? I define county i's demand volatility from 1976 to 1999 as:

$$\text{volatility}_i = \frac{\text{sd(construction employees}_i)}{\text{mean(construction employees}_i)} \tag{25}$$

where the measure of demand is the number of construction employees in the county. I construct groups of demand volatility by assigning counties to a demand volatility catagory as well as a market size catagory based on the tercile of volatility and mean construction employement that they belong to. There are large differences in experienced volatility between markets, as counties in lowest tercile of volatility have half the volatility of counties in the highest tercile of volatility, which is shown by Table 18. Table 18 also shows that markets which have experienced more volatility in demand have about 1% more gross plant entry and gross plant exit, where gross plant entry is the number of plant births per continuing plant in a county, while gross plant exit is the number of plant deaths per continuing plant in a county. Table 19 confirms these results by regressing the gross level of plant turnover on a county's demand volatility. These regressions predict that if a county's demand

	I	s.e.	II	s.e.
Fixed Cost Group 1	0.35	(0.01)	0.31	(0.01)
Fixed Cost Group 2	0.19	(0.02)	0.11	(0.02)
Fixed Cost Group 3	0.11	(0.02)	0.02	(0.01)
Fixed Cost Group 4	0.11	(0.02)	-0.02	(0.01)
Log Construction Workers	0.02	(0.00)	0.02	(0.00)
1st Competitor	-0.25	(0.02)	-0.33	(0.04)
2nd Competitor	-0.03	(0.02)	-0.05	(0.03)
3rd Competitor	0.02	(0.04)	0.02	(0.03)
More than 3 Competitors	0.09	(0.04)	-0.04	(0.02)
Sunk Cost of Entry	6.44	(0.04)	6.38	(0.05)
Equilibrium Choice Probabilities			X	
Log-Likelihood	-12033		-11972	
Observations	235000		235000	

	Entrants and Exitors	Continuers	Turnover Rate
Baseline	132	2536	5.18 %
Smoothed Demand	131	2540	5.17 %

Table 17: Estimates and Counterfactual Turnover for the Second-Order Markov Demand Model.

volatility were set to zero, turnover would be reduced by 20%-40%. This result is in striking disagreement with estimates from the structural model, which predict a fall in plant turnover of less 5% if all demand fluctuations were eliminated. One issue with this computation is that it is based on a change in the realized level of demand fluctuations, not in a change in the process generating these fluctuations. Thus it is vulnerable to the Lucas Critique (Lucas (1976)), since I project the effect of a reduction in demand fluctuations by extrapolating from the policies that firms currently use. A change in the volatility in demand will change firm's expectations and the equilibrium of the game that they are playing and thus could have a very different effect on entry and exit decisions.

I can see if the model would replicate this empirical relationship. To do so, I re-estimate the model where the process for demand is estimated separately for each volatility catagory to account for different demand fluctuations, i.e.

$$\hat{D}_k[i|j] = \frac{\sum_{(l,t)} 1(M_l^{t+1} \in B_i, M_l^t \in B_j, l \in K)}{\sum_{(l,t)} 1(M_l^t \in B_j, l \in K)} \tag{26}$$

which allows for markets with a large amount of demand volatility and markets with very little volatility. Table 20 presents estimates from this model. These estimated parameters are quite similar to the results in Table 1. Moreover, these estimates display a lower sensitivity to sensitivity to demand, since the coefficient on demand is only 0.02 in the model with different demand processes for different markets while this coefficient is 0.054 in the model where demand does not vary by market in Table 1. In addition, Table 20 presents estimates with a second Markov Process for demand which yield similar estimates as the model with a first-order Markov process for demand. Tables 21, 23 and 24 show the steady-state level of plant turnover when there are demand fluctuations that happen to vary by market versus when I remove all demand fluctuations by replacing the demand transition process in each market by $D_k = I$ for all k, and the quantity of turnover in each market and volatility catagory in the data. Notice that the pattern in the data of higher turnover for more volatile markets is replicated by the model's steady-state. Moreover, the difference in turnover between the lowest and highest volatility catagory in the data is 0.6% (i.e. 5.76%-5.16%, while in the model's steady state this difference is 0.5% (i.e. 5.75%-5.26%). Thus the model replicates the change in steady-state turnover from low to high volatility markets almost exactly.

Market Size		Volatility Category 1	2	3	Mean Construction Employees	Mean Number of Plants
1	Gross Entry Rate*	5.42%	5.94%	7.24%	189	0.59
	Gross Exit Rate**	6.18%	5.60%	7.34%		
2	Gross Entry Rate	4.89%	5.59%	5.86%	539	1.48
	Gross Exit Rate	4.80%	5.16%	5.20%		
3	Gross Entry Rate	5.37%	5.28%	6.78%	4648	4.75
	Gross Exit Rate	4.98%	4.67%	5.16%		
	Volatility***	0.22	0.33	0.55		

* Gross Entry Rate=Births/Total Plants
** Gross Exit Rate=Deaths/Total Plants
*** Volatility=SD(Construction Employees)/Mean(Construction Employees)

Table 18: Counties with more demand volatility have more plant turnover.

Gross Turnover*	Median Regression	Mean Regression
Volatility**	5.45%	14.05%
	(1.17%)	(1.48%)
Constant	8.49%	8.19%
	(0.48%)	(0.60%)
Number of Observations	2448	2448
R2	0.58%	3.54%

Model Prediction		
Mean Turnover	10.48%	13.32%
Mean Turnover with Volatility=0	8.49%	8.19%

Standard Error in parenthesis
* Gross Turnover=(Births+Deaths)/ Number of Plants
** Volatility=sd(construction employees in county)/mean(construction employees)

Table 19: The regression model predicts a 20% to 40% decrease in plant turnover if all fluctuations in demand were eliminated.

	I	s.e.	II	s.e.
Fixed Cost Group 1	0.25	(0.01)	0.20	(0.01)
Fixed Cost Group 2	0.08	(0.02)	-0.06	(0.02)
Fixed Cost Group 3	0.00	(0.02)	-0.16	(0.02)
Fixed Cost Group 4	-0.02	(0.02)	-0.21	(0.03)
Log Construction Employment	0.00	(0.00)	0.00	(0.00)
1st Competitor	-0.32	(0.02)	-0.48	(0.02)
2nd Competitor	-0.02	(0.02)	-0.04	(0.02)
3rd Competitor	-0.04	(0.03)	-0.05	(0.03)
More than 3 Competitors	0.09	(0.04)	-0.02	(0.03)
Sunk Cost of Entry	6.24	(0.04)	6.15	(0.04)
Equilibrium Choice Probabilities			X	
Log-Likelihood	-12687		-12524	
Number of Observations	235 000		235 000	

Table 20: Dynamic Entry and Exit Model with Different Demand Processes by County Volatility Catagory

NO SMOOTHING

Volatility Catagory	Market Size Catagory	Entrants	Incumbents	Turnover Rate	Volatility Catagory Average Entrants	Incumbents	Turnover Rate
Low Volatility	1	12	189	6.23%	49	932	5.26%
	2	20	336	6.02%			
	3	12	244	4.76%			
	4	6	164	3.50%			
Medium Volatility	1	15	235	6.23%	47	862	5.45%
	2	19	310	6.02%			
	3	10	213	4.79%			
	4	3	105	3.28%			
High Volatility	1	19	298	6.23%	42	731	5.75%
	2	16	258	6.02%			
	3	6	131	4.80%			
	4	2	45	3.56%			

Table 21: Steady-State turnover from the model with demand fluctuations, broken down by volatility and market size catagories

Market Size Category	Size	Share of Plants	Median Number of Plants
1	Small*	35%	1
	Medium**	38%	
	Large***	26%	
2	Small*	31%	3
	Medium**	35%	
	Large***	33%	
3	Small*	30%	5
	Medium**	31%	
	Large***	39%	
4	Small*	27%	16
	Medium**	29%	
	Large***	44%	

* Small: Less than 6 employees
** Medium: 6-20 employees
*** Big: More than 20 employees

Table 22: Larger Markets have bigger plants.

SMOOTHED DEMAND

Volatility Catagory	Market Size Catagory	Entrants	Incumbents	Turnover Rate	Volatility Catagory Average Entrants	Incumbents	Turnover Rate
Low Volatility	1	12	189	6.23%	49	933	5.25%
	2	20	336	6.02%			
	3	12	244	4.76%			
	4	6	164	3.49%			
Medium Volatility	1	15	235	6.23%	47	863	5.45%
	2	19	310	6.02%			
	3	10	213	4.79%			
	4	3	106	3.20%			
High Volatility	1	19	298	6.23%	42	731	5.75%
	2	16	258	6.02%			
	3	6	131	4.80%			
	4	2	45	3.55%			

Table 23: Steady-State Turnover from the model without demand fluctuations, broken down by volatility and market size catagories

DATA

Volatility Catagory	Market Size Catagory	Entrants	Incumbents	Turnover Rate	Volatility Catagory Average Entrants	Incumbents	Turnover Rate
Low Volatility	1	12	199	5.93%	49	949	5.16%
	2	17	344	4.91%			
	3	13	246	5.10%			
	4	7	160	4.63%			
Medium Volatility	1	12	241	4.98%	46	866	5.31%
	2	17	312	5.41%			
	3	12	213	5.73%			
	4	5	100	4.77%			
High Volatility	1	18	300	6.07%	42	729	5.76%
	2	15	257	5.68%			
	3	7	128	5.74%			
	4	2	44	3.76%			

Table 24: Turnover in the Data broken down by volatility and market size catagories

C Computing Bootstrapped Confidence Intervals on Parameters and Policy Counterfactuals

Algorithm 5 *Bootstrapped Nested Pseudo-Likelihood Confidence Intervals:*

1. *Sample the data with replacement as:*

$$y_i^t = \{a_i^t, x_i^t, x_{-i}^t, M_j^t, M_j^{t-1}, empconstruction_j^t\}$$

To do this by drawing a variable q which is uniform on $1, 2, ..., L$. Then pick out $y[q, .]$. Denote this sampled data as Y^k where $k = 1, ..., 10000$.

2. *Compute the Demand Transition Matrix D "non-parametrically" as:*

$$D^k(M|\tilde{M}) = \frac{\sum_{l=1}^{L} 1(M_l^t = M, M_l^{t-1} = \tilde{M})}{\sum_{l=1}^{L} 1(M_l^{t-1} = \tilde{M})}$$

3. *Compute mean demand in each bin.*

$$MD^k(\tilde{M}) = \frac{\sum_{l=1}^{L} empconstruction_j^t 1(M_l^t = \tilde{M})}{\sum_{l=1}^{L} 1(M_l^t = \tilde{M})}$$

4. *Estimate $\hat{\theta^k}$ using the Nested Pseudo-Likelihood Algorithm and the data set Y^k and demand transition process $\hat{D^k}$.*

5. *Compute the ergodic distribution generated by $\hat{\theta^k}$ and estimated demand transition process $\hat{D^k}$. Denote the ergodic distributions as $E^k(D = I)$ and $E^k(D = \hat{D^k})$.*

6. *Sort the parameters $\{\theta^k\}_{k=1}^K$. Take the 500^{th} and $9500th$'s parameter to form confidence intervals. Do likewise for turnover statistics from the ergodic distributions $\{E^k(D = \hat{D^k})\}_{k=1}^K$ and $\{E^k(D = I)\}_{k=1}^K$. The difference in turnover between the world with fluctuations and without is computed as $\Delta Turnover^k = Turnover^{D=\hat{D^k}} - Turnover^{D=I}$.*

Table C shows bootstrapped 95% confidence intervals for the dynamic model of entry and exit using the Aguirregabiria and Mira (2006) while Table C shows bootstrapped confidence intervals for the Hotz and Miller (1993) style model of entry and exit. For both each of these estimated I use the same parameters and data as for the results from Table 1. Note first that these confidence intervals are not noticeably larger than the estimates I obtain from using the inverse of the Hessian of the likelihood. Thus, thus the fact the conditional choice probabilities P as well as the demand transition process D are estimated with error does not lead to much larger uncertainty over the value of the parameters. Morover, the confidence intervals for the models estimated using either the Hotz and Miller (1993) or the Aguirregabiria

Nested Pseudo-Likelihood Estimates

	Distribution of Parameters		
	5%	50%	95%
Fixed Cost			
Group 1	0.309	0.341	0.374
Group 2	0.104	0.148	0.191
Group 3	0.042	0.092	0.140
Group 4	0.032	0.088	0.142
Log Construction Employment	0.053	0.067	0.081
1 Competitor	-0.403	-0.375	-0.348
2 Competitors	-0.101	-0.070	-0.039
3 Competitors	-0.069	-0.028	0.012
More than 3 competitors	-0.058	-0.017	0.017
Sunk Costs	6.137	6.188	6.241
Turnover			
Demand Fluctuations	4.621 %	4.787 %	4.959 %
No Demand Fluctuations	4.473 %	4.727 %	4.907 %
Difference in Turnover	-0.418 %	0.142 %	1.760 %

Table 25: Distribution of parameters for the dynamic model of entry and exit from 10 000 bootstrap replications and associated predicted turnover using the Nested Pseudo-Likelihoods Algorithm.

and Mira (2006) techniques do not overlap. However, in Monte-Carlo's the main difference between the HM and AM techniques was that the variance of the AM estimator is smaller due to the fact that it imposes the additional assumption that conditional choice probabilities are an equilibrium. Thus it seems that some mispecification in the model is causing these two techniques to be different. Given the size of the sample I am using, it cannot be the case that the differences between the conditional choices estimated from the data (i.e. $\hat{P}^0$ and those generated by the Nested Pseudo-Likelihoods Algorithm is due to sampling errors.

Hotz-Miller Estimates

	Distribution of Parameters		
	5%	50%	95%
Fixed Cost			
Group 1	0.336	0.363	0.390
Group 2	0.206	0.240	0.288
Group 3	0.166	0.206	0.262
Group 4	0.159	0.210	0.277
Log Construction Employment	0.038	0.050	0.066
1 Competitor	-0.266	-0.246	-0.220
2 Competitors	-0.045	-0.017	0.020
3 Competitors	-0.100	-0.050	0.090
More than 3 competitors	0.014	0.074	0.155
Sunk Costs	6.227	6.278	6.350

Table 26: Distribution of parameters for the dynamic model of entry and exit from 10 000 bootstrap replications using the Hotz-Miller approach.

D Computional Appendix

I have implemented a version of the Nested Pseudo-Likelihoods algorithm of Aguirregabiria and Mira (2006), with several important modifications. The computational details of my implementation are described in this appendix. First, I discuss the representation of the state space which incorporates exchangeability, the assumption that all players are identical, and the computation of state to state transition probabilities following this assumption. Second, I document how value functions can be computed if period profits are separable in dynamic parameters (SSP). Third, I describe the use of market fixed effects in this dynamic model. Finally, I present my implementation of the Nested Pseudo-Likelihoods algorithm.

D.1 Representing States and Strategies

To manipulate value functions and strategies in the computer, I need to find a way to represent them. Denote the set of states $X = \{1, ..., \#X\}$ where $\#X$ is the number of different states in X. Likewise, denote the set of actions $A_i = \{1, ..., J\}$. Thus the set of conditional choice probabilities P can be represented as an $\#X \times J$ matrix:

$$P = \begin{bmatrix} P[a_i = 1|x = 1] & ... & P[a_i = J|x = 1] \\ ... & ... & ... \\ P[a_i = 1|x = \#X] & ... & P[a_i = J|x = \#X] \end{bmatrix} \tag{27}$$

Likewise, state to state transition probabilities $F^P(x'|x)$ can be represented as an $\#X \times \#X$ matrix:

$$F^P = \begin{bmatrix} F^P[x' = 1|x = 1] & ... & F^P[x' = \#X|x = 1] \\ ... & ... & ... \\ F^P[x' = 1|x = \#X] & ... & F^P[x' = X|x = \#X] \end{bmatrix} \tag{28}$$

I impose symmetry (or exchangeability in Pakes and McGuire (1994)'s terminology) between players, so that only a firm's states matters, not its identity. For instance, a market configuration where firms 2 and 3 are active, represented by the market state vector $[0, 1, 1, 0]$ should lead to the same outcomes as a market where firms 1 and 4 are active $[1, 0, 0, 1]$. Thus, there are two kinds of states: *basic states* for which firm indentities matter, and *high states* where they don't. A basic state from the perspective of player i can be represented by the following vector:

$$x^b = \underbrace{[x_1, ..., x_{i-1}, x_{i+1}, ..., x_N, x_i, M]}_{\text{Basic States}} \tag{29}$$

where x_k is the state of firm k and M is the state of demand, while a high state x^h reduces the characteristics of competitors down to the number of competitors of each type, and thus has the following representation:

$$x^h = \underbrace{[\sum_{k \neq N} 1(x_k = 1), \sum_{k \neq N} 1(x_k = 2), ..., \sum_{k \neq N} 1(x_k = J), x_N, M]}_{\text{High States}} \tag{30}$$

The following Table illustrates the relation between high states and low states from the perspective of firm A for a 3 firm entry/exit model with a single demand state.

Basic State ID	Firm A	Firm B	Firm C	High State ID	Own Firm	Competitors
1	0	0	0	1	0	0
2	0	0	1	2	0	1
3	0	1	0	2	0	1
4	0	1	1	3	0	2
5	1	0	0	4	1	0
6	1	0	1	5	1	1
7	1	1	0	5	1	1
8	1	1	1	6	1	2

(31)

When I will show the algorithm which computes F^P in equation (38) the ordering of basic states will be very important. In particular, basic states must be sorted by the demand states, then the state of firm N, then the state of firm $N-1$ and so on. This sort assures that the Kronecker product yields the transition probabilities in the appropriate order. I build the converter matrix to translate basic states into high states, defined as a matrix of size #basic states×#high states with the following entries:

$$CONVERTER(i,j) = 1(\text{basic state } i \text{ is equivalent to high state } j) \tag{32}$$

To do this, the code goes thought the list of all basic states and computes the high state based on the firm's own state and the number of competitors of each type it faces, as well as demand. In particular, high states can be identified and ranked by computing $x^b ENC'$, where $ENC = [1, N, ..., N^J, N^J J, N^J J\#M]$ and $\#M$ is the number of demand states.

It is also convenient to express the set of conditional choice probabilities P in terms of high states: $P[a_i|x^h]$. An issue with high states is that state x^h from the perspective of firm 1 could be different from state x^h from the perspective of firm 2, since it is important for firm 1 and 2 to know if *they* are active or inactive. Thus, I need to build an table which indicates for each firm in the market, which high state it occupies:

$$PINDEX(k, x^h) = \text{state for firm } k \text{ given that firm } N \text{ is in state } x^h \tag{33}$$

So for the example of a 3 firm entry-exit model the $PINDEX$ table is:

Firm A	Firm B	Firm C
1	1	1
2	2	4
3	5	5
4	2	2
5	3	5
6	6	6

(34)

Again, I build this matrix by going through the list of states x^h for each firm. Likewise for demand, I construct the $DINDEX$ table which maps state each state x^h into the current state of demand $M \in \{1, ..., \#M\}$:

$$DINDEX(x^h) = \text{Demand State } M \text{ in state } x^h \tag{35}$$

by going through the list of high states and picking out the value of demand.

At this point, it is useful to clarify how I take observations in the data y^b that are expressed in basic states, and transform these into high states y^h. I can find a unique id for each state by multiplying the basic states by the encoding matrix, ENC:

$$id = y^b ENC \tag{36}$$

While the id variable has a one to one mapping into the set of high states, and a higher id implies a higher x^h, it is not ordered from 1 to $\#X$. Denote the decoding table, DEC defined as:

$$DEC(id) = \#x^h \tag{37}$$

where the # sign indicates the order of $x^h \in X = \{1, 2, ..., \#X\}$.Thus I convert $y^b \to y^h$ by the following operation: $\#y^h = DEC(y^b ENC)$.

D.2 Computing State to State Transition Probabilities

The main bottleneck in the computation of the equilibrium of a dynamic game is the state to state transition matrix F^P. In particular, the transition matrix F is in general a dense matrix in my empirical work, i.e. $F^P[x'|x] > 0$ for most states $x', x \in X$, since if I observed a transition with zero probability, the model is immediately falsified. This is not the case for Pakes and McGuire (1994) style theoretical models, which typically generate transition matrices F that are quite sparse, and can be much easier to compute and invert. Denote the vector of choice probabilities for state x as $p[x] = \{P[a_i = 1|x], P[a_i = 2|x], ..., P[a_i = J|x]\}$, the vector whose entries list the probability to a firm will take each possible actions, and the vector of demand transition probabilities starting in state x as $D(x) = \{\Pr[M' = 1|M^x], \Pr[M' = 2|M^x], ..., \Pr[M' = \#M|M^x]\}$. The entire set of transition probabilities, in basic state terminology, can be computed as:

$$F^{b,P} = \begin{bmatrix} p[PINDEX(1,1)] \otimes ... \otimes p[PINDEX(N,1)] \otimes D(DINDEX(1)) \\ p[PINDEX(1,2)] \otimes ... \otimes p[PINDEX(N,2)] \otimes D(DINDEX(2)) \\ ... \\ p[PINDEX(1,\#X)] \otimes ... \otimes p[PINDEX(N,\#X)] \otimes D(DINDEX(\#X)) \end{bmatrix} \tag{38}$$

where $\otimes$ is the Kronecker product and $F^{b,P}(a,b)$ is the probability of reaching basic state $x^b = a$ given that the system started in high state $x^h = b$ today. The logic behind this procedure is not immediately apparent, so I will show a little example to give the reader some intuition. Suppose two players, A and B can choose entry probabilities q^a and q^b. The Kronecker product of their strategies gives:

$$[q^a, 1-q^a] \otimes [q^b, 1-q^b] = [q^a q^b, q^a(1-q^b), (1-q^a)q^b, (1-q^a)(1-q^b)] \tag{39}$$

which are the probabilities for all 4 possible outcomes (both enter, only A enters, only B enters, neither enters). To convert this object into high state form, I use the sparse logical converter matrix $CONVERTER$ and sparse matrix multiplication:

$$F^{h,P} = F^{b,P} \times CONVERTER \tag{40}$$

where $F^{b,P}(a,b)$ is the probability of reaching high state $x'^h = a$ given that the system started in high state $x^h = b$ today.

D.3 Expected Period Payoffs

I need to compute expected period payoffs $r^P(x)$, the period payoffs generated by the behavior of a firm and its competitors that use conditional choice probabilities P. If the period reward function is separable in dynamic parameters, then I can express period payoffs as $\theta\rho(x', a_i, x_i)$. This representation is very useful, since it allows me to quickly compute the firm's value (conditional on conditional choice probabilities P) for many different parameter vectors θ. This feature will turn out to be quite important when I estimate parameters θ using maximum likelihood in a later section.

The pre-multiplied expected reward function $r^P(x)$ is:

$$r^P(x) = \sum_{x' \in X} \left(\sum_{a_i \in A} \rho(x', a_i, x_i) P[a_i|x] \right) F^P[x'|x] \tag{41}$$

where $r^P(x)$ is a vector of length $\#\theta + 1$(the size of the parameter vector plus one), so that actual period payoffs can be found as $\{\theta, 1\} \cdot r^P(x)$.[22] The matrix of expected payoffs R^P of dimensions $(\#\theta + 1) \times \#X$ is constructed by stacking $r^P(x)$

[22]Note that this equation can be reexpressed in terms of matrix multiplications instead of sums.

over all states $x \in X$:

$$R^P = \begin{bmatrix} r^P(1) \\ r^P(2) \\ ... \\ r^P(\#X) \end{bmatrix} \tag{42}$$

I also want to find the set of expected period payoffs if a firm choose action j today and reverts to conditional choice probabilities P in the future, denoted $r^{P,j}(x)$:

$$r^{P,j}(x) = \sum_{x' \in X} \left(\sum_{a_i \in A} \rho(x', a_i, x_i) 1(a_i = j) \right) F^{P,j}[x'|x] \tag{43}$$

where $F^{P,j}$ is the state-to-state transition matrix if I choose action j. To compute $F^{P,j}$, I replace $p[PINDEX(N,x)]$ in equation 38 by $p^j[PINDEX(N,x)]$, the conditional choice probability vector if I choose action j, defined as:

$$p^j[a_i|x] = \begin{cases} 1 \text{ if } a_i = j \\ 0 \text{ if } a_i \neq j \end{cases} \tag{44}$$

D.4 Value Function

The pre-multiplied value Q^P can be found as the fixed point of Bellman's equation:

$$Q^P = R^P + \beta Q^P F^{\ddot{P}} \tag{45}$$

where $F^{\ddot{P}}$ is the state-to-state transition matrix that imposes anonymous exit. Firms which exit cannot reenter. This constraint is included in the algorithm, so that the value function in the future given that I have exited in the last period must be 0. In particular, if I exit then I cannot receive any rewards in the future and I cannot reenter. However, from the perspective of my competitors, the slot I occupied is not vacated eternally: another firm could decide to enter in the slot I once occupied. To compute $F^{\ddot{P}}$, as before I replace $p[PINDEX(N,x)]$ in equation 38 by $\ddot{p}[PINDEX(N,x)]$, the conditional choice probability vector that eliminates my payoffs in the future if I decide to exit today:

$$\ddot{p}[a_i|x] = \begin{cases} 0 \text{ if } a_i = 1 \\ \ddot{p}[a_i|x] \text{ else} \end{cases} \tag{46}$$

where the action $a_i = 1$ is normalized to be the action of exiting the market. This is equivalent to eliminating future payoffs for myself if I exit. Note that $\ddot{p}[x]$ is not a probability distribution since $\sum_{j=1}^{J} \ddot{p}[j|x] < 1$ if $p[1|x] > 0$. Probability is being lost in cases where I exit.

The value function can be computed through policy iteration:

$$Q^P = (I - \beta F^{\ddot{P}})^{-1} R^P \tag{47}$$

which is quite effective if the state space is small or the discount rate β is close to 1. I can also compute the firm's value by value iteration:

$$W^{t+1,P} = R^P + \beta W^{t,P} F^{\ddot{P}} \tag{48}$$

where T is the smallest t such that $\left\|W^{t+1,P} - W^{t,P}\right\| < \varepsilon$ giving $Q^P = W^{T,P}$. Value iteration can be useful if the state space is large (over 700 distinct states say), making the inversion of the $(I - \beta F^P)$ matrix quite difficult. I define the$\| \ \|$ norm as the sum the absolute values of all entries in an array. So for a 3 dimensional array A:

$$\|A_{ijk}\| = \sum_i \sum_j \sum_k |A_{ijk}| \tag{49}$$

Notice that Q^P is a $\#\theta \times \#X$ matrix which can be used to find the value $V^P = \theta Q^P$. Suppose I take action j today. My value $Q^{P,j}$ is the following:

$$Q^{P,j} = R^{P,j} + \beta Q^P F^{\ddot{P},j} \tag{50}$$

where $F^{\ddot{P},j}$ is the state-to-state transition matrix that incorporates both the fact that I took action j today and the fact the that I cannot reenter tomorrow if I exited today. Specifically, replace $p[PINDEX(N,x)]$ in equation 38 by $\ddot{p}^j[PINDEX(N,x)]$, the conditional choice probability vector that eliminates my payoffs in the future if I decide to exit today and takes into account the fact that I chose action j today:

$$\ddot{p}^j[a_i|x] = \begin{cases} 1 \text{ if } a_i = j \text{ and } a_i \neq 1 \\ 0 \text{ otherwise} \end{cases} \tag{51}$$

D.5 Market Fixed Effects

I incorporate market level fixed effects by altering the parameter vector θ for each market:

$$\theta_m = \{\alpha_m, \theta\} \tag{52}$$

Note that conditional choice probabilities, P^m, will differ by market, as well as the pre-multiplied payoffs and values they generate for firms, $R^{P,m}$ and $Q^{P,m}$. I can incorporate these changes quite easily. Since there are too many markets in my data to estimate separate fixed effects for each one, I classify markets into groups according to the following criteria:

$$\mu(m) = \sum_{t=1}^{T} \sum_{i=1}^{N} \frac{1(a_i^t \geq 2, x_i^t \in m)}{NT} \tag{53}$$

where groups are formed by rounding $\mu(m)$ to the nearest integer.

D.6 Nested Pseudo-Likelihoods Algorithm

1. For each market group $g = \{1, ..., G\}$, I estimate conditional choice probabilities $\hat{P}^{0,g}$ from the data using a bin estimator:

$$\hat{P}^{0,g}[j|\omega] = \frac{\sum_{l=1}^{L} 1(a_l = j, x_l = \omega, m_l = g)}{\sum_{l=1}^{L} 1(x_l = \omega, m_l = g)} \tag{54}$$

   where m_l indicates which group market m_l belongs to. Denote the matrix of choice probabilities for each group (a $J \times \#X$ matrix) as $\hat{P}^{0,g}$, which stacks $\hat{P}^{0,g}[j|\omega]$ over all actions and states. Build the matrix of choices that firms made $\hat{Z}^g[a_i|x]$ as:

$$\hat{Z}^g[j|\omega] = \sum_{l=1}^{L} 1(a_l = j, x_l = \omega, m_l = g) \tag{55}$$

   where $\hat{Z}^g[j|\omega]$ is the number of times firms in state ω and group g chose action j. Denote the stacked choice matrix $\hat{Z}^g$. Finally, I estimate demand transition probabilities from the data, $\hat{D}$, using a bin estimator:

$$\hat{D}[a|b] = \frac{\sum_{l=1}^{L} 1(M_l^{t+1} = a, M_l^t = b)}{\sum_{l=1}^{L} 1(M_l^t = b)} \tag{56}$$

2. Construct pre-multiplied value functions conditional on choice probabilities $\hat{P}^{k,g}$ and taking action j today according to equation 50 for each market group: $\{Q^{\hat{P}^{k,g},j}\}_{j=\{1,..,J\},g=\{1,...,G\}}$.

3. **M-Step**

   The matrix of choice probabilities C can be computed for each group g as the following:

$$C^{\hat{P}^{k,g},g}(\alpha_g, \theta) = \frac{\left[\exp(\{\alpha_g, \theta\}Q^{\hat{P}^{k,g},1}), ..., \exp(\{\alpha_g, \theta\}Q^{\hat{P}^{k,g},J})\right]}{\sum_{h=1}^{J} \exp(\{\alpha_g, \theta\}Q_h^P)} \tag{57}$$

   Thus the likelihood for this model is:

$$\mathcal{L}(\{\alpha_1, ..., \alpha_G\}, \theta) = \sum_{g=1}^{G} \left\| \log(C^{\hat{P}^{k,g},g}(\alpha_g, \theta)) \cdot \hat{Z}^g \right\| \tag{58}$$

   where $\cdot$ represents element by element matrix multiplication. I use this particular form for the likelihood of the model since there are a great number of observations in the data, but few states. The computational burden from calculating the likelihood depends only on the number of states in the model ($\#X$), and does not increase with the number of observations in the data (L). I maximize the likelihood $\mathcal{L}$ using a simple gradient based algorithm, namely Broyden-Fletcher-Goldfarb-Shannon (BFGS), to find parametes $\{\hat{\alpha}_1^k, ..., \hat{\alpha}_G^k, \hat{\theta}^k\}$.

4. **E-Step**

   I update the matrix of conditional choice probabilities $\hat{P}^{k,g}$ using a moving average of this iteration's conditional choice probabilities and those used in previous iterations:

$$\hat{P}^{k+1,g} = \left[C^{\hat{P}^{k,g},g}(\hat{\alpha}_g^k, \hat{\theta}^k) + \sum_{ma=1}^{MA} \hat{P}^{k+1-ma,g} \right] \frac{1}{(MA+1)} \tag{59}$$

   This moving average update procedure works fairly well with the length of the moving average, MA, set to 5 or 6. The trade-off in choosing MA is that more smoothing considerably slows the execution of the algorithm, but increase the chance that $\hat{P}^{k+1,g}$ will converge.

5. If $\sum_{g=1}^{G} \left\| \hat{P}^{k+1,g} - \hat{P}^{k,g} \right\| < \delta$ stop, else go back to step 2. The Nested Pseudo-Likelihood algorithm usually converges in under 100 iterations. I compute the covariance matrix of estimates by inverting the Hessian of the likelihood in equation 58: $\left(\frac{\partial^2 \mathcal{L}}{\partial \theta^2} \right)^{-1}$.