Mergers and Sunk Costs: An application to the ready-mix concrete industry *

Allan Collard-Wexler †
Economics Department
NYU Stern

October 6, 2009

Abstract

Sunk costs slow the entry of new firms, which makes a horizontal merger have effects on market structure that are long-lasting. A sunk-cost model of entry and exit is developed in the spirit of Bresnahan and Reiss (1994). This model is applied to the ready-mix concrete industry, which is subject to fierce local competition. Sunk costs of entry are estimated to be equivalent to the effects on a firm's continuation value of going from a duopoly market to a monopoly market. Because of large sunk costs, I find that a merger from duopoly to monopoly generates 15 years of monopoly. Thus the entry response of the market to a merger is slow enough to warrant intervention if the damages from monopoly are sufficiently important.

*JEL Code: L13, L41, L74, C51

†This paper is part of my Ph.D. dissertation at Northwestern University under the supervision of Robert Porter, Michael Whinston, Aviv Nevo and Shane Greeenstein. I thank Lynn Riggs, Mike Mazzeo and Ambarish Chandra for their insights and Lanier Benkard for an superb discussion. Financial support from the Fonds Québecois sur la Recherche et la Société et Culture and the Center for the Study of Industrial Organization at Northwestern University is gratefully acknowledged.

1 Introduction

Antitrust is valuable because in some cases it can achieve results more rapidly than can market forces. We need not suffer loses while waiting for the market to erode cartels and monopolistic mergers.

Bork (1978) *The Antitrust Paradox* p.311

I study the role of sunk costs on entry following a merger. In an industry without sunk costs or other entry barriers, merger policy has no role. Since the free-entry condition holds at all points in time, whenever two firms merge, another firm will enter into the market. However, when there are substantial sunk costs or adjustment costs in general, it takes time for the effects of a merger to die out. The industry I look at, the ready-mix concrete industry, has fierce competition between firms and very local markets. Thus, horizontal mergers are a recurrent issue. Moreover, the ready-mix concrete industry has very high sunk entry costs. I estimate the effect of sunk costs and competition using a structural model that extends the work of Bresnahan and Reiss (1994). I find large sunk entry costs. The effect on a firm's value of going from a monopoly to a duopoly is comparable to the sunk cost of entry. These sunk costs will slow the response of an industry to mergers, thus reducing the number of competitors for a substantial amount of time. A merger from duopoly to monopoly will induce 15 years of monopoly in the market.

In an industry without sunk costs, the analysis of merger policy is irrelevant since the number of firms is wholly pinned down by the free-entry condition. The question I address is the speed at which an industry which has had a merger to monopoly reverts to competition.[1] Moreover, when evaluating the effects of a mergers, what is the correct net present value that should be used to evaluate damages to consumers? Antitrust authorities recognize the problem of entry quite overtly, allowing potential entry to influence decisions on proposed mergers. Section 3 of the Horizontal Merger Guidelines (U.S. Department of Justice and Federal Trade Commission, 1997) states:

In markets where entry is that easy (i.e., where entry passes these tests of timeliness, likelihood, and sufficiency), the merger raises no antitrust concern and ordinarily requires no further analysis. ... Firms considering entry that requires significant sunk costs must evaluate the profitability of the entry on the basis of long term participation in the Market...

Ready-mix concrete is one of the most active domestic industries as far as mergers are concerned. Local markets mean that even mergers of two ready-mix concrete firms in a small

[1] In previous work using data on concrete prices (Collard-Wexler, 2008), I find a large decrease in prices from monopoly to duopoly markets, and little subsequent decrease in prices with additional competitors. Since ready-mix concrete is essentially a homogeneous good, competition within a local market can be thought of as approximately Bertrand.

city raise antitrust concerns. Moreover, the two largest domestic price-fixing fines in Europe (Bundeskartellamt, 2001) and in the United States (US Department of Justice, 2005) were for ready-mix concrete firms. Hortacsu and Syverson (2007) and Syverson (2008) document the extent of vertical and horizontal mergers in the ready-mix concrete and cement industries. In contrast, this paper looks at the effect of horizontal mergers within a market, rather than at mergers between firms that own plants in many geographically distinct markets.

To evaluate the long-run effects of mergers on market structure, I estimate a structural model of competition for the ready-mix concrete sector. This model is an extension of the methodology and "Isolated Town" market definition used by Bresnahan and Reiss (1991). Specifically, I extend the Bresnahan and Reiss (1994) prototype sunk costs model of entry and exit (henceforth the Sunk Cost Bresnahan-Reiss model or SBR), by assembling a complete theoretical model of entry and exit via the model of Campbell and Abbring (2009) and fixing a variety of econometric issues with the Bresnahan and Reiss (1994) model. Most notably, I use a market fixed effect estimation strategy, which identifies the effect of competitors and demand from time-series variation within a market, rather than cross-sectional variation between markets. I use data on entry and exit patterns in the ready-mix concrete sector from the U.S. Census Bureau's Zip Business Pattern database for 1994 to 2006, and I define a market as the zip codes surrounding towns that are isolated, i.e. towns that are more than 20 miles from any other town.

A structural model is needed since mergers to monopoly are prohibited in industries where entry is not guaranteed within a two-year period and in industries where market power may impose substantial damage to consumers. Thus, the exact counterfactual that I am thinking about-how long before the effects of a merger die out-is prohibited in the very industries which are of interest to antitrust authorities in the first place.[2]

The recent literature on the estimation of oligopoly dynamics has used variants of conditional choice methods (henceforth CCP), with the most prominent recent example being the work of Benkard, Bajari, and Levin (2007) (henceforth BBL). In this paper, I model the value function as a reduced form, for which I have exact functional forms only in the stationary case. This allows me to bypass the computational difficulties inherent in the forward simulation step in BBL. Moreover, the estimation technique that I use is very fast and allows for fairly flexible identification such as including market-level fixed effect and different demand covariates, something that is difficult to do coherently in the BBL framework.

Perhaps the closest work to this paper is Benkard, Bodoh-Creed, and Lazarev (2008) who look at the long-run effects of airline mergers. Recognizing that the effects of a merger do not

[2] Doing a difference in differences analysis of mergers is complicated by the absence of random assignment to the merger group. In Chandra and Collard-Wexler (2009) page 1065 we discuss the treatment effect identified by comparing merger markets with non-merger markets (for the newspaper industry). The treatment effect is the effect of a merger on a market where firms choose to merge and, the competition authority finds a small enough effect of the merger on competition to permit the merger in the first place. Thus the mergers that occur in the data are selected based on their small anticipated effect on prices.

require the computation of equilibrium policies, since these policies can be recovered directly from the data, Benkard, Bodoh-Creed, and Lazarev (2008) simulate the dynamic effects of several proposed mergers in the airline industry. As well, the importance of sunk costs in mergers is well understood at least since the earlier literature on barriers to entry (Demsetz, 1982; Bain, 1956).

In prior work (Collard-Wexler, 2008), I have estimated a dynamic entry and exit model using a CCP approach, and I found estimates that are consistent with the results in this paper using a SBR approach for the effect of competition, demand or the magnitude of sunk costs. Indeed, if both of these models are well-specified then we should expect this to be the case. I use the SBR model in this paper for two reasons. First, I can use market fixed-effects, in which only time series variation is used to identify the parameters of the model. This is critical for the counterfactual of looking at the effect of changes of market structure, since I do not want to conflate in ϵ unobserved differences between markets and unobserved changes in the profitability within a market. These unobserved changes in the profitability of a market are crucial to evaluating how quickly firms will have opportunities to profitably enter markets. Second, the reduced-form approach used in this paper is simple to estimate and fits with the counterfactual proposed. The main downside is that the SBR model assumes that firms are identical, and permits limited counterfactual experiments. My argument here is that this is a case where a reduced-form approximations to the value function is the only requirement for both estimation and the counterfactual experiments.

Finally, the estimation strategy and data requirements used in this paper make it straightforward for antitrust agencies to evaluate the role of sunk costs and entry in a possible merger. The SBR model can be estimated using readily accessible data from the Census Bureau, and estimated in minutes.

Section 2 discusses the importance of merger policy to ready-mix concrete- section 3 presents the model- section 4 illustrates the construction of the data- section 5 discusses the econometric model, which is estimated in section 6. These results are used to perform counterfactual experiments in section 7. Section 8 concludes. Some details of the construction of the data as well as certain derivations and robustness checks are collected in the appendix.

2 Ready-Mix Concrete

Ready-mix concrete is a mixture of cement, sand, gravel, water and chemical admixtures. After about an hour or so, the mixture hardens into a material with very high strength, who primary use is as a building material. Because concrete is very perishable, average delivery times are about 20 minutes, and markets are local oligopolies. As well, there are few substitutes for ready-mix concrete, so if there are no plants near a construction site, either a mobile plant will be used to produce concrete, or concrete will be mixed by hand. Overall demand for concrete is therefore relatively inelastic, even though concrete itself is close to a commodity generating fierce competition between plants within a market. For both of these reasons the profitability of a ready-mix concrete plant is closely tied to the number of competitors in a local area.

3 Model

I develop a model that will be used to analyze firms' entry and exit decisions. First, I discuss profits in the stage game given demand and the number of competitors in a market. Second, I use the LIFO equilibrium developed by Campbell and Abbring (2009) to characterize the unique equilibrium to the entry game in terms of entry and exit thresholds.

3.1 Period Game

In each period all firms in the market compete in prices. I assume that all firms are identical, so profits are determined by the number of firms in the market, denoted as N, and the size of the market, denoted as D. All that is required for the rest of the model is that variable profits are multiplicatively separable in market size. Denote profits per consumer as $\mu(N)$ which may depend on the number of firms in the market, but not on market size. Period variable profits $\pi^V(N, D)$ then must take the form $\pi^V(N, D) = \mu(N)D$. This condition is satisfied by most models of competition in IO with identical firms.

To fix ideas, I will illustrate the form of period profits using a Salop model which follows Syverson (2004). Concrete plants compete in prices and competitors are spatially differentiated. A Salop model can capture this structure, with N identical firms located equidistantly along a unit circle. A mass D of consumers are distributed uniformly on the circle. They have transportation costs t and have a high enough reservation price r that they will purchase from at least one firm. The marginal cost of production is c for all firms. Firms can charge a different price to each consumer. In equilibrium, variable profits π^V are:

$$\pi^V(N, D) = \begin{cases} tD\left(\frac{1}{N}\right)^2 & \text{If } N > 1 \\ D\left(r - c + \frac{t}{4}\right) & \text{If } N = 1 \end{cases} \tag{1}$$

I can rewrite this equation for variable profits as:

$$\pi^V(N, D) = \underbrace{\eta(N)}_{\text{markup}} \frac{D}{N} \tag{2}$$

Where $\eta(N)$ is the markup over marginal cost, and $\frac{D}{N}$ is the number of consumers purchasing concrete from each firm which can be rewritten as $\pi^V = \mu(N)D$.

3.2 Entry and Exit

Firms can choose to enter, stay or exit a market. Denote the *continuation value* as $V(D, N)$, the net present value of profits for an incumbent of having a plant in a market with N firms and a number of consumers D. A firm will enter, denoted by χ^e, if the continuation value of remaining in the market is greater than the entry costs ϕ- i.e. $\chi^e = 1\left(V(D, N) > \phi\right)$. Likewise, a firm exits if the continuation value $V(D, N)$ is lower that the scrappage value of the firm ψ- thus $\chi^i = 1\left(V(D, N) > \psi\right)$. Note that demand D can change from year to year, so it is only changes in demand that generate entry and exit, and there are no idiosyncratic (or firm-specific) reasons for exit, only market-level ones. There is a strong intuition that the equilibrium entry and exit policies in this game will be in demand thresholds- that is that there is a level of demand above which a single firm enters, and a higher level of demand above which a second firms enters and so on. Likewise, there will be demand thresholds for exit, that it a level of demand below which 2 firms cannot survive, and thus a firm will exit. The level of demand needed to induce a firm to enter are greater than the level needed to sustain this firm once it has entered due to the presence of sunk costs of entry, i.e. costs which are paid by entering firms but cannot be recovered upon exit. In what follows, I assemble a model to justify this intuition of entry and exit thresholds.

I use the foundations provided by Campbell and Abbring (2009), who develop a model of oligopoly dynamics in which firms enter and exit using demand thresholds, exactly as in Bresnahan and Reiss (1994). The Campbell and Abbring (2009) model requires assumptions on strategies and on the demand process. First, firms use last-in first-out (henceforth **LIFO**) strategies which default to inactivity, i.e. firms which enter earlier are the firms that exit later. Given the **LIFO** assumption, Proposition 1 of Campbell and Abbring (2009) shows that the equilibrium of the entry and exit game will be unique. [3] Second, the Markov process for number of consumers in a market $P^D(D'|D)$ must have the properties that 1- higher levels of demand today are always "good news" about demand in the future-i.e. $E[C'|C]$ is weakly increasing in C, 2- the innovation error $\nu = C' - E[C'|C]$ must be independent of C, and 3- the distribution of the innovation error ν must be concave. I denote these assumptions on the demand process as the **MKP** assumptions.

If firms use **LIFO** strategies and the process for demand satisfies **MKP**, Proposition 4 in Campbell and Abbring (2009) states that we can characterize the entry and exit policies of firms in terms of demand thresholds. [4] The LIFO equilibrium will be unique, so I can use estimation techniques such as maximum likelihood, which requires that each parameter vector

[3] In the ready-mix concrete industry I find that older plants tend to exit less often than younger plants. A one-year-old plant has an exit rate of about 7%, while a 15-year-old plant has an exit rate of about 4%. However the age dependence of exit is much weaker than in other industries such as retail trade or restaurants.

[4] An exit policy is in demand thresholds if a firm exits if demand falls below a certain level, i.e. $\chi^i(D, N) = 1(D > D^i_N)$. Likewise, an entry policy is in demand thresholds if a firm enters if demand is above a certain level, i.e. $\chi^e(D, N) = 1(D > D^e_N)$.

is associated with a single prediction of the entry-and-exit model. As well, this equilibrium will be characterized by demand thresholds, so I can talk about the minimal level of demand require to induce entry by an extra firm.

3.3 Entry and Exit Thresholds

Entrants always have lower values than incumbents, since they pay an entry cost that incumbents do not. This implies that there cannot be simultaneous entry and exit: firms exit, enter, or nothing happens. This is a feature of models where firms are symmetric: they cannot rationalize the same type of plant in the same market making different choices. Define the cost of entering the market as $\phi + \gamma$ where γ is the sunk component of entry costs and ϕ is the unsunk component of entry cost, i.e. the scrap value the firms gets when it shuts down the plant. [5]

Three regimes need to be considered: *entry, exit and stasis*.

1. Net *Entry*: $N_t > N_{t-1}$

$$\begin{aligned} V(D_t, N_t) &\geq \phi + \gamma \\ V(D_t, N_t + 1) &< \phi + \gamma \end{aligned} \tag{3}$$

2. Net *Exit*: $N_t < N_{t-1}$

$$\begin{aligned} V(D_t, N_t) &\geq \phi \\ V(D_t, N_t + 1) &< \phi \end{aligned} \tag{4}$$

3. No Net Change: $N_t = N_{t-1}$

$$\begin{aligned} V(D_t, N_t) &\geq \phi \\ V(D_t, N_t + 1) &< \phi + \gamma \end{aligned} \tag{5}$$

These equations can be combined into:

$$\begin{aligned} V(D_t, N_t) &\geq \phi + 1(N_t > N_{t-1})\gamma \\ V(D_t, N_t + 1) &< \phi + 1(N_t \geq N_{t-1})\gamma \end{aligned} \tag{6}$$

Note that if $\gamma = 0$ -i.e. the case without sunk costs- then these equations reduce to the Bresnahan and Reiss (1991) entry thresholds. So the gap between entry and exit thresholds is identified from the difference in the level of demand required to induce a firm to exit a market and the level of demand required to have this firm enter in the first place. Figure 1 shows entry

[5] In a previous version of this paper Collard-Wexler (2005), I estimated the model using confidential data from the RDC program at the Center for Economic Studies at the Census Bureau. Eliminating market-years in which there are firms entering and exiting has virtually no effect on estimated parameters.

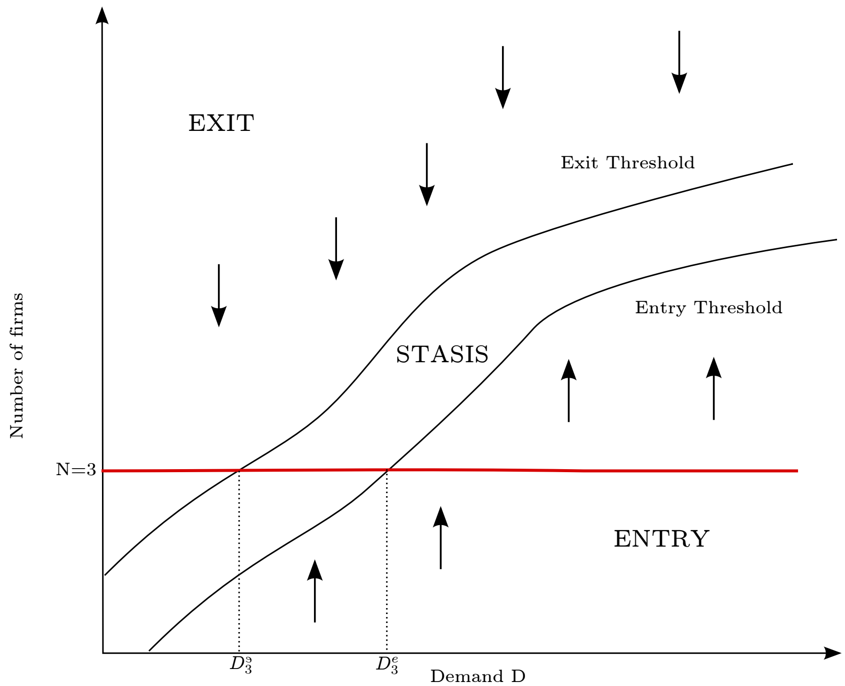


Figure 1: Entry, Exit and Stasis Thresholds

and exit thresholds. [6] There is an SS band in the middle called the stasis zone, where firms neither enter nor exit. The magnitude of sunk costs is identified by the size of this stasis zone.

3.4 Value function

Suppose that demand is constant over time. In this case the value function is just the net present value of period variable profits minus fixed costs f:

$$
\begin{aligned}
V(D,N) &= \sum_{t=0}^{\infty} \beta^t (\pi^V(D,N) - f) \\
&= \frac{Dg(N)}{1-\beta} - \frac{f}{1-\beta}
\end{aligned} \tag{7}
$$

When demand varies over time, I can rewrite the value in terms of deviations from the

[6]The version of this figure with estimated thresholds is in figure 4 on page 17 shows the estimated entry and exit thresholds based on population.

stationary case:

$$(1-\beta)V(D,N) = Dg(N) - f + \underbrace{\left(\sum_{t=0}^{\infty}\frac{\beta^t}{1-\beta}D_t g(N_t) - Dg(N)\right)}_{\text{Deviation of variable profits}} - \underbrace{\left(\sum_{t=0}^{\infty}\frac{\beta^t}{1-\beta}f a_t - f\right)}_{\text{Deviation of fixed costs}} \tag{8}$$

As long as the market does not vary too much over time, the errors from the stationary approximation in equation (7) will be small. In appendix D I present estimates from a CCP style model which computes the exact value function which are roughly comparable with the estimates of the SBR model. Note that while stationarity is important to the interpretation of the value function, for the actual estimation and counterfactual experiment I do not need to know the functional form of the value function. I just need to be able to approximate it in a "reduced-form". [7]

4 Data

I construct data on entry and exit patterns in Isolated Markets for the ready-mix concrete sector. I use Isolated Towns as my market since they allow for clean identification of the role of competition. Then I use the Zip Business Patterns to harvest data on entry and exit patterns in the ready-mix concrete sector, as well as employment data for the construction sector which will be my measure of demand.

4.1 Isolated Towns

I construct markets using the concept of isolated towns in Bresnahan and Reiss (1991). These towns are far enough away from other town so that shipping concrete from outside is difficult. This allows me to abstract from competitors located in neighboring towns. Concrete is a very particular construction material in that it sets within about an hour or two. Moreover, concrete is quite cheap for its weight, as a truck-full of concrete is worth around $500. Thus, shipping times in this industry are 20 minutes on average.

[7] Specifically, one could interpret this exercise as estimating the value function using a sieve maximum likelihood:

$$(1-\beta)V(D,N) \approx c_1 Dg(N) + \sum_k c_k \phi^k(D,N) \tag{9}$$

As long as the number of terms is large enough to approximate the value function well, I will still obtain correct policy counterfactuals, even thought the interpretation of the coefficients is lost.

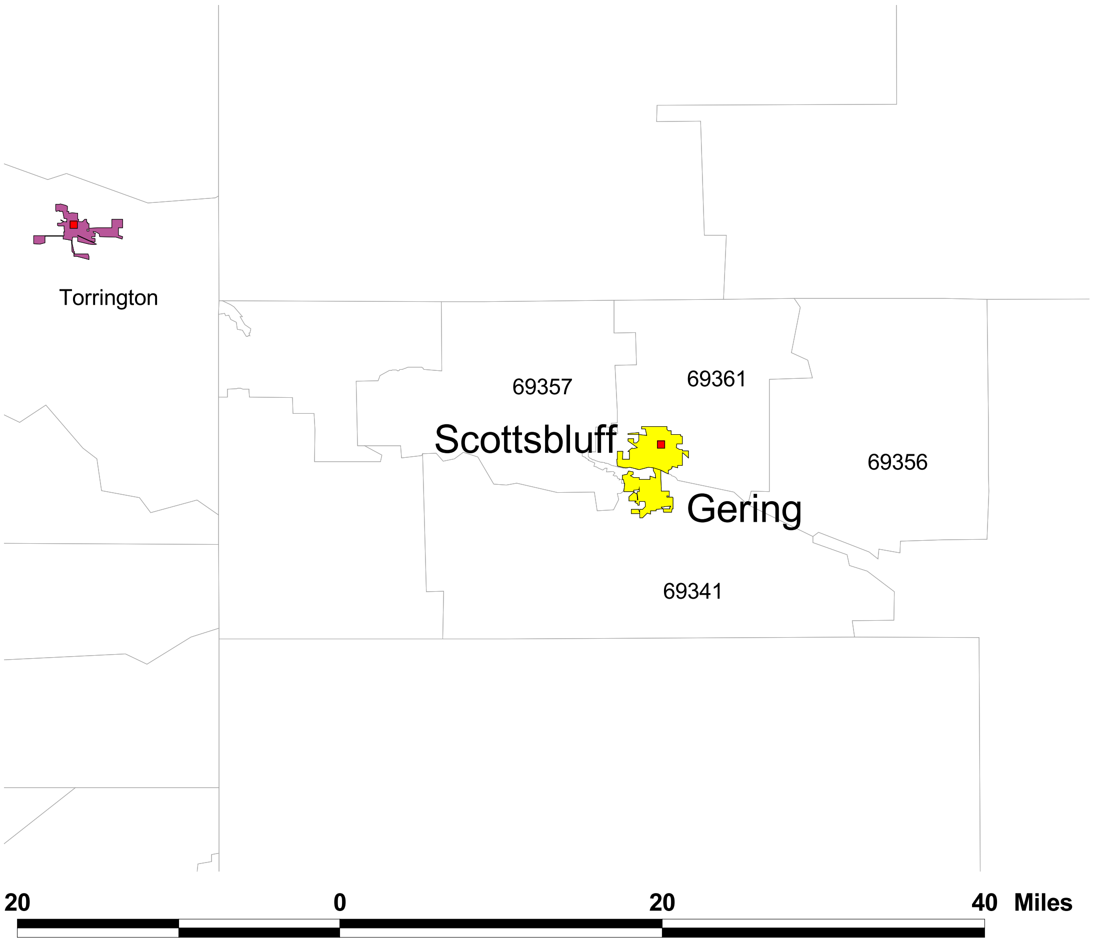


Figure 2: Typical Isolated Town and Zip Codes: Scottsbluff/Gering, Nebraska

I locate towns in the United States in the United States which have more than 2000 inhabitants. Isolated towns are the 449 towns out of more than 10_000 which are at least 20 miles away from any other town, which I identify using GIS software. Figure **??** shows a typical isolated town, Scottsbluff, Nebraska. Scottbluff is "twinned" with Gerring, Nebraska, and thus I treat both of these municipalities as if they composed a single city. The nearest town of at least 2000 inhabitants is Torrington, Wyoming, which is 32 miles or 40 minutes away by car.

Since the data on establishments that I use is based on zip-codes, I find the zip codes that are less than 5 miles from the town. Appendix A discusses the construction of the isolated town dataset in more detail, and both the code and data are available on my webpage.

4.2 Concrete and Construction Data

The data on concrete plants and construction are pulled from the Zip Business Patterns (henceforth ZBP) database produced by the Census Bureau (US Census Bureau, 2009). For confiden-

Number of Plants	Count	Mean Population	Mean Construction Employment	Share of plants with at least 20 employees
0	2,078	11138	382	n.a.
1	2,553	10791	467	44%
2	811	14266	595	42%
3	300	17998	946	37%
4	77	23402	1676	33%
5 and up	18	42252	7306	52%
All	5,837	12031	516	43%

Table 1: Summary Statistics

tiality reasons, the ZBP contains only the total count of plants in a zip code, as well as coarse information on the number of employees at each plant. I can observe the number of plants in a market, but not the number of firms in the market. I use plant and firm interchangeably since most plants in the ready-mix concrete sector are owned by single-plant firms. Moreover, multi-plants firms typically own plants in several adjacent markets, rather than many plants in the same market.[8]

I pull data on establishments in the construction sector (NAICS 23) and the concrete sector (NAICS 327320)- for 1994 to 2006. I use data from the construction sector since almost all demand for concrete comes from the construction sector, and so construction employment will be my primary demand shifter. [9]

Table 1 shows summary statistics of the data decomposed by the number of plants within a market. Notice that about 45% of markets are monopoly markets- and about 35% have no plants at all, while the balance of markets (20%) have more than one plant in the market. Population and employment in the construction sector are higher in markets served by many ready-mix concrete plants. A market served by a single ready-mix plant has employment in the construction sector of under 400 people, while a market served by four plants has employment of about 1600. The average size of establishments does not increase with market size. In monopoly markets, 44% of plants employ more than 20 workers, while a market with 4 plants 33% of plant employee more than 20 workers. Finally, about 20% of markets have a change in the number of plants that serve them each year.

Table 2 shows the transition of the number of firms in a market from year to year. About 20% of markets have a change in the number of firms that serve them each year, and so these markets are fairly dynamic.

[8]In work using confidential data at the Census RDC data I have checked that firms do not own plants in the same county.

[9]See Syverson (2008) for more detail on the role of construction in determining demand for concrete.

One Year Transitions

Plants	Plants last year 0	1	2	3	4	5up
0	728	112	7	1	1	0
1	118	1,068	101	6	0	0
2	6	120	429	48	3	0
3	0	6	47	129	14	1
4	0	3	6	13	34	3
5 and up	0	0	0	4	1	6

Ten Year Transition

Plants	Plants last year 0	1	2	3	4	5up
0	48	93	15	2	2	0
1	95	88	51	8	1	0
2	14	74	31	14	1	0
3	2	12	12	11	5	0
4	0	4	10	2	1	0
5 and up	0	0	0	0	4	1

Table 2: Transition of the number of plants.

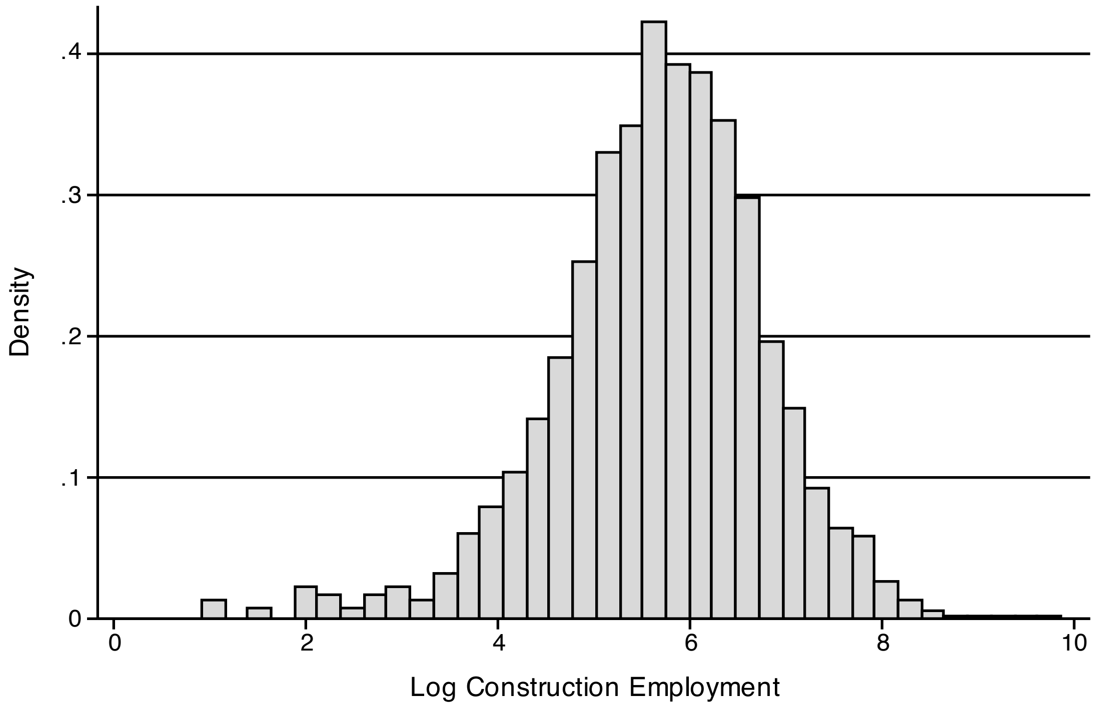


Figure 3: Distribution of Town Size

5 Econometric Model

Certain costs and components of demand will be mismeasured. For instance, demand for concrete is higher in Texas since the high temperatures make asphalt melt, so roads are more frequently paved with concrete. True demand D^* is $D^* = \epsilon D$, where ϵ is the unobserved component of demand and D is the observed components of demand. Alternatively, markups may be higher in certain markets than others. For instance, wages and costs are higher in the North, where ready-mix concrete truck drivers are unionized, versus the South where they are not. Thus, ϵ could also include differences in the marginal costs between markets. Observing a subset of demand or markups leads to a multiplicatively separable effect of ϵ on variable profits.

The entry and exit thresholds in equation (6) can be rewritten using the multiplicative separability of period profits, and the stationary approximation:

$$\begin{aligned} \frac{1}{1-\beta}\epsilon_{mt}D_{mt}g(N_{mt}) &\geq \frac{1}{1-\beta}f + \phi + 1(N_{mt} > N_{mt-1})\gamma \\ \frac{1}{1-\beta}\epsilon_{mt}D_{mt}g(N_{mt}+1) &< \frac{1}{1-\beta}f + \phi + 1(N_{mt} \geq N_{mt-1})\gamma \end{aligned} \tag{10}$$

As long as $g(N)$ is positive, I can express $g(N)$ as $g(N) = e^{h(1)}e^{h(2)}\cdots e^{h(N)}$. Rearranging, taking logs, and combining terms I obtain:

$$\begin{aligned}\varepsilon_{mt} &\geq -\beta_1 \log(D_{mt}) - \sum_{k=1}^{N_{mt}} h(k) + \gamma^E + \gamma^S 1(N_{mt} > N_{mt-1}) \\ \varepsilon_{mt} &< -\beta_1 \log(D_{mt}) - \sum_{k=1}^{N_{mt}+1} h(k) + \gamma^E + \gamma^S 1(N_{mt} > N_{mt-1})\end{aligned} \tag{11}$$

where $\gamma^E = \log(\frac{1}{1-\beta} f + \phi)$ and $\gamma^S = \log(\frac{1}{1-\beta} f + \phi + \gamma) - \log(\frac{1}{1-\beta} f + \phi)$, and $\varepsilon = \log(\epsilon)$.

To accommodate multiple components of demand, such as population and construction employment, I use a single index of demand $d_{mt} = x_{mt}\beta$, where lower-case letters indicate the logarithm of a variable. If $\varepsilon_{mt} \sim \mathcal{N}(0,1)$, then the probability of observing N firms in a market with demand x_{mt} is:[10] [11]

$$\begin{aligned}\Pr[N_{mt}|x_{mt}, N_{mt-1}] =& \Phi\left[-x_{mt}\beta - \sum_{k=1}^{N_{mt}} h(k) + \gamma^E + \gamma^S 1(N_{mt} > N_{mt-1})\right] \\ &- \Phi\left[-x_{mt}\beta - \sum_{k=1}^{N_{mt}+1} h(k) + \gamma^E + \gamma^S 1(N_{mt} \geq N_{mt-1})\right] 1(N_{mt} > 0)\end{aligned} \tag{12}$$

5.1 Fixed Effects

I have a panel of markets, so the assumption that ϵ_{mt} is independent of ϵ_{mt-1} is wrong. I cluster standard errors by market to correct for this serially correlation, but I can also leverage the correlation of ϵ_{mt} to obtain truer estimates of the model. I assume that $\epsilon_{mt} = \mu_m + \eta_{mt}$, i.e. that there are persistent market-level unobservables overlaid with independent shocks. I believe that the bulk of these unobserved differences in demand and costs are persistent, if there is a gravel pit nearby, or if most construction is done using wood-framed buildings without foundations, then these differences will persist over time. One should worry about these persistent unobservables- since more firms enter more profitable markets. This generates attenuation bias between latent continuation value and the number of firms in a market, biasing the effect of competition toward zero. [12] [13]

[10] It may be possible to identify the parameters of this model with a less restrictive functional form, such as a moment equality estimator of Pakes, Porter, Ho, and Ishii (2006). However, there is a real selection problem in this model since I do not have a lower bound on ε_{mt} when I observe no firms in the market.

[11] I normalize the variance to one. Taking the structural model literally, the coefficient on log demand should be one, and thus the coefficient on demand is the inverse of the variance of ϵ.

[12] I have estimated the entry model in a previous version of this paper using data from 1976 to 1999 (Collard-Wexler, 2005). I find that the estimates are similar if I use market fixed effects or market-decade fixed effects, suggesting that the bulk of the unobservables are market-specific.

[13] There are two reasons to go to a fixed effect specification. First, the alternative is to use a serially correlated shock ϵ with an initial conditions distribution of ϵ in the first period. This would leave me with a relatively difficult model to estimate, and the point of going to a semi-static model is to be able to generate inference about market structure

I introduce the fixed effect as "incidental parameters", which I will estimate as any other parameter. The probability of observing N_{mt} plants given N_{mt-1} plants yesterday and D_{mt} level of demand:

$$\begin{aligned}\Pr[N_{mt}|x_{mt}, N_{mt-1}] =&\Phi\left[-\mu_m - x_{mt}\beta - \sum_{k=1}^{N_{mt}} h(k) + \gamma^E + \gamma^S 1(N_{mt} > N_{mt-1})\right] \\ &- \Phi\left[-\mu_m - x_{mt}\beta - \sum_{k=1}^{N_{mt}+1} h(k) + \gamma^E + \gamma^S 1(N_{mt} > N_{mt-1})\right] 1(N_{mt} > 0)\end{aligned} \tag{13}$$

I find parameters $\hat{\theta} = \left[\mu, \beta, h(\cdot), \gamma^E, \gamma^S\right]$ which maximize the log-likelihood:

$$\mathcal{L}(\theta) = \sum_{m=1}^{M} \sum_{t=0}^{T} \log(\Pr[N_{mt}|D_{mt}, N_{mt-1}, \theta]) \tag{14}$$

Note that there will be a large number of parameters to estimate in this model since I am estimating a market fixed effects for 301 markets instead of using a trick such as conditioning (Chamberlain, 1980)or differencing which allows these market effects to drop out.[14] There is a well known issue with using fixed effects in non-linear models, since these fixed effects can contaminate the estimation of other parameters in the model and lead to severely biased coefficients. In Appendix B I look at the finite sample bias of the fixed-effect SBR model using a Monte-Carlo experiment, and I find relatively small bias (on the order of at most 20%, or well within the estimated confidence intervals) which attenuates the coefficients. The relatively small bias of the fixed-effect SBR model leads me to conclude that the length of the panel ($T = 12$) in my data is long enough to make the bias of the fixed-effect model small enough to be a side issue. The likelihood $\mathcal{L}$ is globally concave (since it is a linear ordered probit), which aids maximization of the likelihood enormously. Without the global concavity of the likelihood, maximizing a non-linear function with over 400 parameters is a hopeless task.

6 Results

Table 3 shows estimates of the SBR model. Column VI shows estimates with market fixed-effects while all other columns show estimates without market fixed effects. Since this is an ordered probit, the coefficients cannot be interpreted directly, but the sign and the ratios

and sunk costs in a straightforward way. As well, fixed effects are easier to interpret than a serially correlated random effect model: I am only using cross-sectional variation to identify the parameters.

[14] I drop markets with no variance in the number of firms over time, that are almost exclusively markets with no plants in them over the 12 year period. This reduces the number of markets in the sample from 449 to 301.

between coefficients are meaningful. First, the coefficient on log construction employment is 0.3 for all specifications but V (mean log construction employment is 5.6), so demand has a strong effect on continuation values. Other measures of demand estimated in column II- such as log population and the presence of an interstate highway are not significant and have a fairly small estimated magnitude in any case. To check for how hermetic my isolated markets really are, I look at the effect of construction activity and concrete plants located near my isolated market. Column III shows that estimates of the effect of demand within 10 or 20 miles are much smaller than the effect of demand within a 5 miles. Likewise, column IV shows that concrete plants between 5 and 20 away have an insignificant and small effect (the average for log of plants within 20 miles is 0.68) on entry. Both of these results support the market definition, yielding markets that do not interact with any other markets. In column V, I look at the role of past and future demand to gauge the expectations of firms about the future. In particular do firms anticipate future changes in demand. I find that firms react a significantly to past demand, and have a large negative (but not significant) reaction to the construction activity will occur over the next 3 years. At a minimum this suggests that firms are not informed about future construction projects.

The estimates show large effects of competition, as the effect of going from monopoly to duopoly is -1.09 for the no fixed-effects models and -3.03 for the fixed-effect model. These effects decline for each subsequent competitor, reaching -0.58 for the effect of each competitor above four. Note that a perhaps overly strict interpretation of $h(1)$ would imply that markups time share falls by $1-\exp(-1.09) = 67\%$ in the no fixed-effect model and $1-\exp(-3.03) = 94\%$ when going from monopoly to duopoly, versus a prediction that these should fall by 50% if markups do not change.[15] This indicates that the ready-mix concrete industry is fiercely competitive, and at least in the fixed effect specification, fairly similar to Bertrand competition. When I add market fixed effects in column VI, I get competition coefficients that are 3 times larger. Section 6.1 discusses why introducing market fixed-effects leads to larger estimates of the effect of competition.

The sunk cost parameter γ^S is estimated at 3.2 in columns I-V, and 4.5 for the fixed-effect estimates in column VI, which are larger than any other coefficient. Remember that $\gamma^S = \log(\frac{\frac{1}{1-\beta}f+\phi+\gamma}{\frac{1}{1-\beta}f+\phi})$, and so it measures the ratio of sunk costs to unsunk costs plus the net present value of fixed costs. This indicates that sunk costs are many times larger that fixed costs plus unsunk entry costs. These estimates cohere with interviews I have done with ready-mix concrete producers in Illinois, in which I reckon the sunk costs of entry at 2 million dollars. In comparison, average sales of concrete are about 3 million dollars per year and both markups and fixed costs are quite low.

Figure 4 illustrates the coefficient estimates of the model by plotting the expected entry and

[15] Campbell and Abbring (2009) show that under with certain demand processes, the Bresnahan-Reiss model can produce important effects of competition even if markups do not change as the number of firms increase. In appendix D I show that even when accounting for dynamics I still get strong effects of competition.

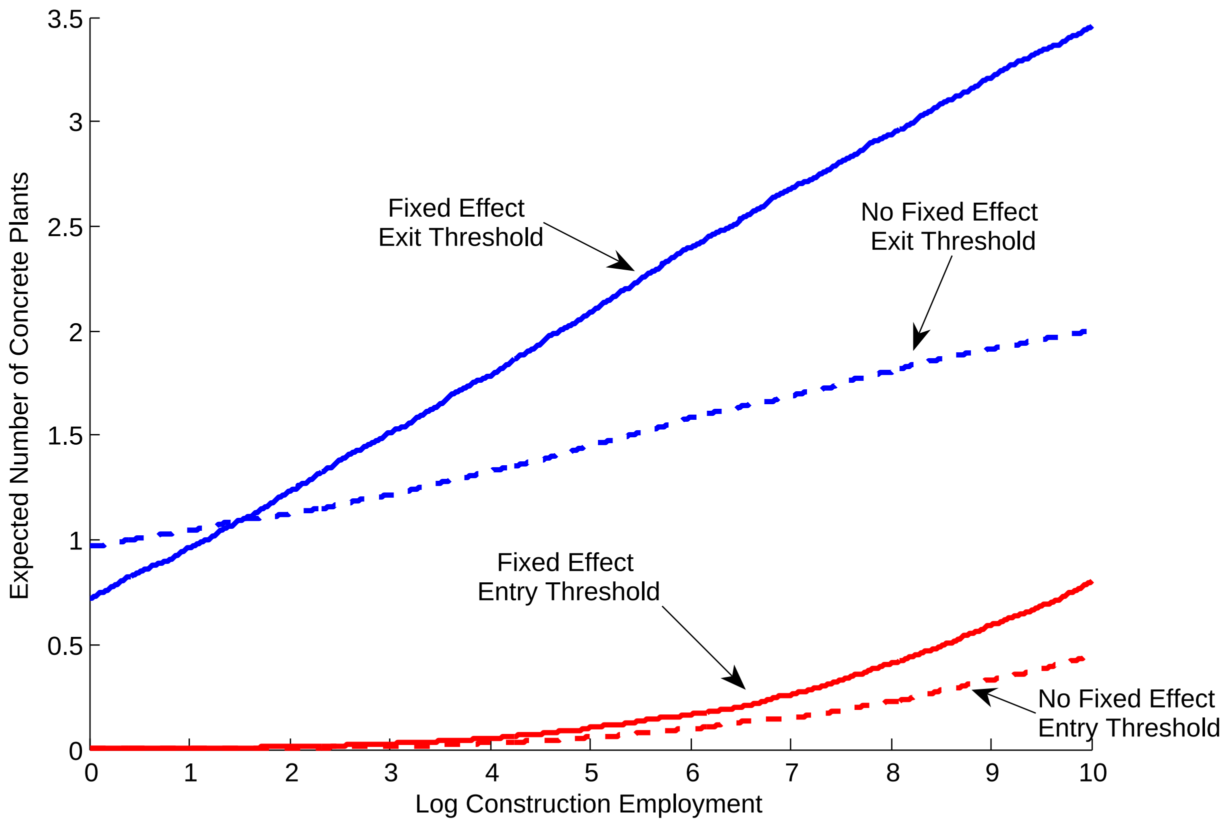


Figure 4: Estimated Entry and Exit Thresholds

exit thresholds for the estimates in columns I and VI (market f.e.) in Table 3. I use the mean entry cost across markets in the fixed-effect model, and 10000 simulation draws of ε to get the expected thresholds. The effect of large sunk costs is to have a huge stasis zone, as evidenced by the gap between the entry threshold and the exit threshold. Demand from a market with 3000 construction employees (equal to 8 in log terms) is sufficient to support between 0.5 and 2.5 firms in the market. The fixed effect model has a much flatter slope than the model without fixed effects. Due to much larger competitive effects, the effect of higher demand is nullified by competition in the fixed effect specification.

6.1 Persistent Unobservables

Note that the effect of competition is far larger in the model with market fixed-effects than the model without them. This is due to the effect of unobserved but persistent differences in demand and markups in various markets. The econometrician may not observe all components of profitability, but firms most certainly do. They enter in greater numbers in markets which are more profitable markets either because of observable or unobservable demand, leading to a positive correlation between ε_{mt} and N_{mt}. I statistically decompose ε_{mt} into the component

	I	II	III	IV	V	VI F.E.
Log Construction Employment	0.31	0.32	0.36	0.31	0.13	0.30
	(0.06)	(0.07)	(0.06)	(0.06)	(0.15)	(0.20)
Log Population		0.00				
		(0.12)				
Log Area		0.02				
		(0.06)				
Interstate Highway dummy		-0.12				
		(0.12)				
Log Construction Employment			-0.01			
10 miles			(0.06)			
Log Construction Employment			-0.13			
20 miles			(0.05)			
Log Concrete Plants within				0.05		
20 miles				(0.08)		
Next 3 years of					-0.24	
Log Construction Employment					(0.19)	
Previous 3 years of					0.46	
Log Construction Employment					(0.18)	
1 competitor	-1.09	-1.09	-1.10	-1.09	-1.05	-3.03
	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)	(0.23)
2 competitor	-0.89	-0.89	-0.90	-0.89	-0.81	-2.70
	(0.07)	(0.07)	(0.07)	(0.07)	(0.09)	(0.25)
3 competitor	-0.76	-0.76	-0.78	-0.76	-0.82	-2.03
	(0.10)	(0.10)	(0.10)	(0.10)	(0.13)	(0.25)
4 competitor	-0.75	-0.75	-0.79	-0.74	-0.68	-2.15
	(0.18)	(0.18)	(0.18)	(0.18)	(0.25)	(0.54)
Competitors above 4	-0.58	-0.58	-0.62	-0.58	-0.64	-1.39
	(0.09)	(0.09)	(0.09)	(0.09)	(0.12)	(0.09)
Entry Cost γ^E	-3.81	-3.85	-3.26	-3.85	-3.98	
	(0.35)	(0.88)	(0.39)	(0.36)	(0.42)	
(Average Entry Cost $\bar{\gamma}^E$)						-3.19
Sunk Entry Cost γ^S	3.26	3.26	3.29	3.26	3.20	4.54
	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)	(0.22)
N	3612	3612	3568	3612	1806	3612
Log Likelihood	-1665	-1663	-1623	-1665	-834	-702

(Standard Errors Clustered by Market.)

Table 3: Sunk-Cost Bresnahan-Reiss Model Estimates

that is correlated with N_{mt} and the component that is not:

$$\varepsilon_{mt} = \delta N_{mt} + \zeta_{mt} \tag{15}$$

Substituting this decomposition into the estimating equation I obtain:

$$V(d_{mt}, N_{mt}) = x_{mt}\beta + \sum_{k=1}^{N} [h(k) + \delta] + \gamma + \gamma^S 1(N_{mt} > N_{mt-1}) + \zeta_{mt} \tag{16}$$

so the estimated effect of competition, $\hat{h}(k) \rightarrow h(k) + \delta$, will be biased upwards, toward finding too small an effect of competition on latent profits. When I use market fixed effects, I remover a large portion of unobserved demand, and this eliminates a chunk of the correlation between ε_{mt} and N_{mt}.

7 Counterfactual

Suppose that a merger from duopoly to monopoly is proposed, and the antitrust authority wants to evaluate the long-run effects of this merger on market structure. I perform the following counterfactual experiment: I simulate the evolution of the market in the world where the merger occurred and the world where the merger did not happen. I choose to focus on a merger from duopoly to monopoly, since in the ready-mix concrete industry, a merger to monopoly is the most important concern. As well I assume that the effect of a merger between two firms is exactly the same as eliminating a plant, which is only true if there is very little spatial differentiation between plants and if there are no capacity constraints from running a single plant. In the case where the merged firm operates two plants, this will lower the value of entering the market for a potential entrant, which will increase the number of years before an additional firm enters the market beyond what I find in my counterfactual.

To perform this counterfactual, I need to use the estimates of the continuation value V and sunk costs estimated in the previous section as well as a model for the evolution of demand. I estimate the demand process $P^d[d^t|d^{t-1}]$ from the data, where $d_t = \log(D_t)$, specifically:

$$d_{mt} = \beta_0 + \beta_1 d_{mt} + \beta_2 d_{mt}^2 + \beta_3 d_{mt}^3 + \eta_{mt} \tag{17}$$

where $\eta_{mt} \sim \mathcal{N}(0, \sigma_0 + \sigma_1 d_{mt})$. P^d is estimated by maximum likelihood and Table **??** presents estimates of the demand process. Columns I and II show that the coefficient on lagged demand is essentially 1, i.e. a unit root process for demand. There is substantial variation in demand from year to year since the estimated variance is 0.21, but this variation is more important in small markets since log construction employment reduces the variance of η. Columns III and IV show similar features of the demand process, but include higher-order terms making

Dependent Variable: Log Construction Employment		I	II	III	IV
Last Year	Log Construction Employment				
	Linear	1.01	0.99	0.61	0.86
		(0.00)	(0.00)	(0.09)	(0.08)
	Squared			0.06	0.01
				(0.02)	(0.01)
	Cube			0.00	0.00
				(0.00)	(0.00)
	Constant	-0.03	0.10	0.89	0.42
		(0.02)	(0.02)	(0.17)	(0.18)
Variance σ_η	Constant	0.21	0.48	0.21	0.49
		(0.00)	(0.00)	(0.00)	(0.01)
	Construction		-0.05		-0.05
	Employment		(0.00)		(0.00)
Observations		3311	3311	3311	3311
Log-Likelihood		371	684	442	732

Table 4: Estimated Demand Transition Process

interpreting the coefficients more difficult. For the counterfactual, I use the demand process estimated in column IV, but the results are quantitatively similar across all demand specifications.

To evaluate the effect of mergers, I run the following counterfactual :

Algorithm 1 *Dynamic Merger Simulation Algorithm*

1. Set the initial number of firms in the market as $N_0^{nmk} = 2$ if the merger does not happen and $N_0^{mk} = 1$ if it does happen.
2. Draw next period's demand $d_t^k \sim P^d(\cdot|d_{t-1}^k)$.
3. Draw next period's unobserved demand shifter $\epsilon_t^k \sim \mathcal{N}(0, 1)$.
4. Both N_t^{nmk} and N_t^{mk} satisfy the entry and exit conditions estimated in equation (11) on page 14.

I use $k = 1, \cdots, 10\ 000$ simulation runs 50 years in the future to look at the expected effects of the merger, and initial demand is set at $d_0^k = 6.39$, the average level of demand conditional being in duopoly market. Figure 5 shows the effect of the merger on the number of firms in the industry, plotting the expected number of firms in the industry over time. The top panel uses estimates from the fixed-effect specification (with the fixed effect taken to be the average fixed effect conditional on having two firms in the market, $\mu = -0.71$), while the bottom panel uses estimates from the no-fixed-effects specification. Notice that it takes about 50 years for the market which had a merger to become indistinguishable from the market where the merger did not occur in the fixed effect specification, while in the no fixed effect version, it

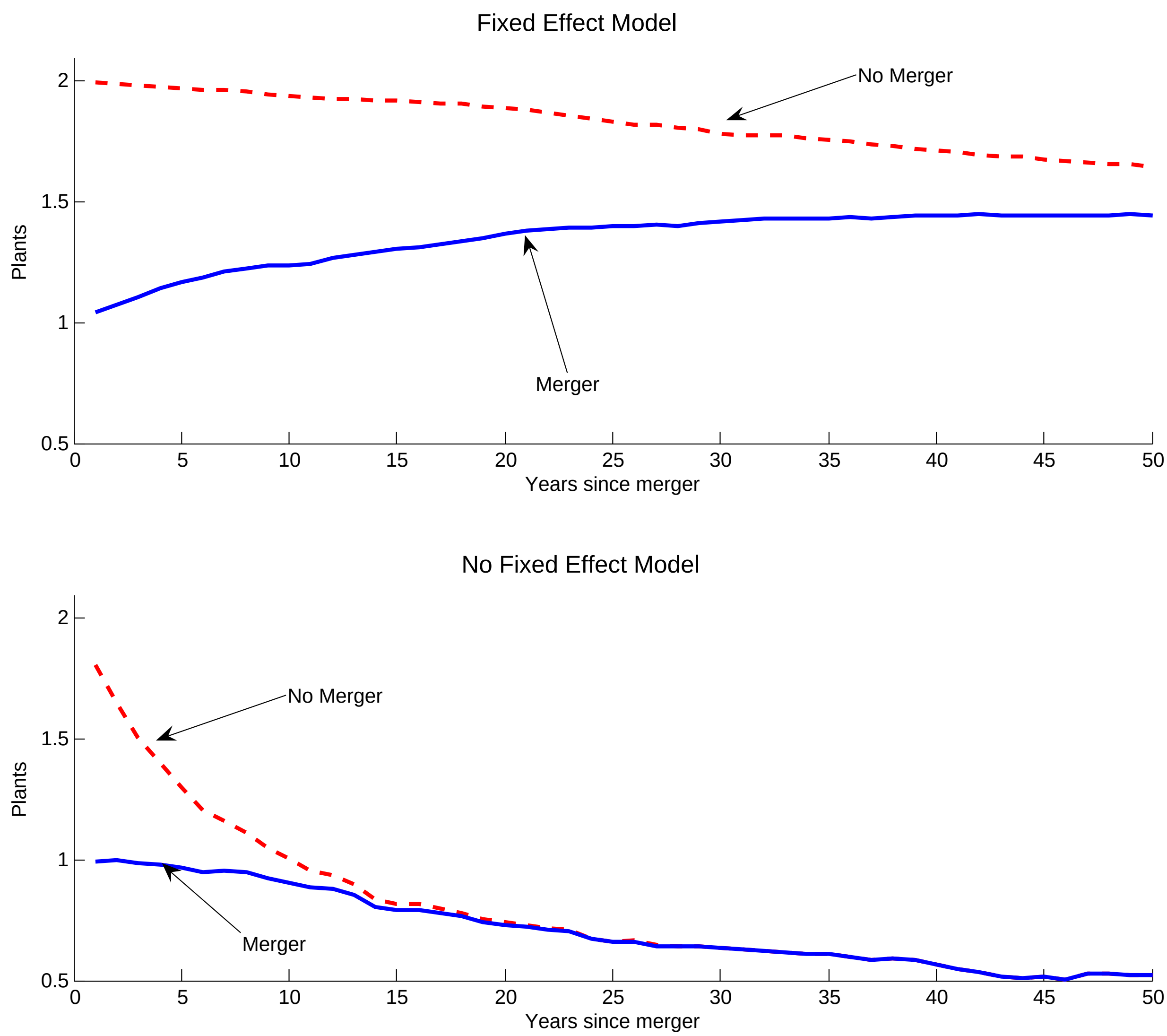


Figure 5: Effect of a Merger on the expected number of firms in the industry.

only takes 15 years for this to happen. However this fast convergence is generated by the fact that the no fixed effect model predicts that the market's steady state is a monopoly regardless of the merger.

Table 5 shows a more detailed slice of the counterfactual. I aggregate across time by computing the expected net present value of market structure using a 5% discount rate, both for the world in which the merger happened and did not. I show results using the fixed-effect specification (column IV of Table 3) or the no-fixed-effect specifications (column I of Table 3). The fixed-effect model predicts that there would be monopoly in 13 years in NPV following the merger while there would be monopoly in 2 years in NPV if the merger does not take place. On net, the merger induces 11 more years of monopoly in NPV, the equivalent o 15 years. The no fixed effect specification predicts monopoly for 12.6 years in NPV after the merger versus

NPV of Plants	Fixed Effects			No-Fixed Effects		
in market	Merger	No Merger	Difference	Merger	No Merger	Difference
0	0.00	0.00	0.00	4.06	4.06	0.00
1	12.74	1.77	10.97	12.58	9.41	3.17
2	4.80	15.77	-10.97	0.88	4.04	-3.17
3+	0.00	0.00	0.00	0.02	0.02	0.00

Table 5: Counterfactual: Merger and No-Merger Comparison

9.4 NPV years without the merger, a net effect of 3.2 years in NPV or equivalent to 3 years of monopoly. I believe that the fixed effect model is far more reasonable since it does not predict that the number of firms will decrease markedly in the future. Moreover, it uses the right counterfactual experiment: How does variation in demand *within* a market generate entry and exit patterns?

Table 5 also highlights the differences between the fixed-effect and no-fixed-effect specifications. In the fixed-effect world, the number of firms rarely strays from 1 or 2, while in the no-fixed-effect world the number of firms in the market sloshes around far more, with a substantial probability of ending up with either no firms or more than two firms in the same market. [16]

8 Conclusion

Entry plays a significant role in blunting the long-run damages from mergers. Indeed, the preferred specification indicates that merger from duopoly to monopoly has the expected effect of inflicting monopoly for 15 years, or generating damages that are 11 times the damages from one year of monopoly. Note that the responsiveness of a market to a merger is slowed by the high estimates of sunk costs. Using market fixed-effects substantially increases the estimated effect of competition, implying that market structure is far more predetermined within a market than the no-fixed-effect estimates imply.

When we evaluate horizontal merger policy, we should be aware that we are not comparing the static costs of market power with the static benefits of efficiency, as in Williamson (1968), but the costs of 15 years of market power with a long-term flow of efficiency gains. However, for the ready-mix concrete industry entry is not nearly quick enough to eliminate scrutiny from the antitrust authority, and the need to quantify the effect of post-merger market power on consumer surplus.

[16]Note that there are no differences in the no-plant and the triopoly NPV between merger and no merger. This is an outcome of the S-S structure of the entry model: as soon as the number of plants in the market changes, then the effect of past number of plants disappears.

References

BAIN, J. (1956): *Barriers to new competition: their character and consequences in manufacturing industries*. Harvard Univ. Press.

BENKARD, C., P. BAJARI, AND J. LEVIN (2007): "Estimating dynamic models of imperfect competition," *Econometrica*, 75, 1331–1370.

BENKARD, C., A. BODOH-CREED, AND J. LAZAREV (2008): "The Long Run Effects of US Airline Mergers," Working Paper, Yale University.

BORK, R. (1978): *The antitrust paradox: A policy at war with itself*. Basic Books New York.

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

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

BUNDESKARTELLAMT (2001): "First cartel proceedings concluded against ready-mixed concrete firms," `http://www.bundeskartellamt.de/wEnglisch/News/Archiv/ArchivNews2001/2001_05_09.php`, Accessed February 4, 2009.

CAMPBELL, J. R., AND J. H. ABBRING (2009): "Last-in first-out oligopoly dynamics," *Econometrica*, forthcoming.

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

CHANDRA, A., AND A. COLLARD-WEXLER (2009): "Mergers in Two-Sided Markets: An Application to the Canadian Newspaper Industry," *Journal of Economics & Management Strategy*, 18(4), 1045–1070.

COLLARD-WEXLER, A. (2005): "Panel Data Reduces Bias in Entry Models," Working Paper, New York University.

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

——— (2008): "Demand Fluctuations in the Ready-Mix Concrete Industry," *Working Paper, New York University*.

DEMSETZ, H. (1982): "Barriers to entry," *The American Economic Review*, 72(1), 47–57.

GREENE, W. (2001): "Estimating econometric models with fixed effects," *Stern School of Business, Department of Economics, Working Paper*, pp. 01–06.

——— (2004): "Fixed effects and bias due to the incidental parameters problem in the Tobit model," *Econometric Reviews*, 23(2), 125–147.

HECKMAN, J. J. (1981): "The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process," in *Structural Analysis of Discrete Data with Econometric Applications*, pp. 179–197. MIT Press.

HORTACSU, A., AND C. SYVERSON (2007): "Cementing Relationships: Vertical Integration, Foreclosure, Productivity, and Prices," *Journal of Political Economy*, 115(2), 250–301.

PAKES, A., J. PORTER, K. HO, AND J. ISHII (2006): "Moment inequalities and their application," *Unpublished Manuscript*.

SYVERSON, C. (2004): "Market Structure and Productivity: A Concrete Example," *Journal of Political Economy*, 112(6), 1181–1222.

SYVERSON, C. (2008): "Markets: Ready-Mixed Concrete," *Journal of Economic Perspectives*, 22(1).

US CENSUS BUREAU (2009): "Zip Business Patterns," `http://www.census.gov/epcd/www/zbp_base.html`, Accessed February 4, 2009.

US DEPARTMENT OF JUSTICE (2005): "Indiana Ready-Mix Concrete Producers and Four Executives Agree to Plead Guilty to Price Fixing Charge," `http://www.usdoj.gov/atr/public/press_releases/2005/209816.htm`, Accessed February 4, 2009.

U.S. DEPARTMENT OF JUSTICE, AND FEDERAL TRADE COMMISSION (1997): "Horizontal Merger Guidelines," `http://www.usdoj.gov/atr/public/guidelines/hmg.htm`.

WILLIAMSON, O. (1968): "Economies as an Antitrust Defense: The Welfare Tradeoffs," *American Economic Review*, 58(1), 18–36.

A Constructing Isolated Markets

I choose my markets to be the area surrounding towns in the Continental United States. The data on places comes from the U.S. Census bureau. However, to limit the issue of competitors in other towns affecting the pricing behavior in the central place, I need to find towns that are isolated- i.e. towns for which there is no other place located nearby.

First, I drop places in my dataset that fall below a certain population threshold. In the Continental U.S., there are many very small towns, such as Western Grove, Arizona which only had 415 inhabitants as of 1990. These small towns are unlikely to support most types of retail activity (such as the operation of a ready-mix concrete plant). Thus, small towns should not be considered as potential sources of competition for establishments in larger towns. When I verify that any particular town is isolated, I do not consider any place in the United States with fewer than either 2000 or 4000 inhabitants in 1990 as potential neighbor for an isolated town. To be consistent with this definition of a neighbor, an isolated town must have more than either 2000 or 4000 inhabitants. Otherwise, for a hypothetical area populated with towns with fewer than 2000 inhabitants, each town in this area would be an isolated town.

Many towns are "twins": there is another municipality which is adjacent. I do not consider these "twinned" cities to be separate towns, I combine them if they are within a mile of each other.

Second, I need to check if a town is isolated. To do this I have coded a routine in Arcviewl' that counts the number of towns located within a specific distance from the central place. Thus, if for instance there are no towns located within a 20 miles from Tuba City, Arizona, then I can conclude that Tuba City is an isolated town. A town is isolated if there are no other towns located within 20, 30 or 40 miles away from it. Table 6 presents the number of isolated towns in the Continental United States:

No neighboring cities of a least 2000 inhabitants within	Number of Towns	Mean Population	Mean Houseunits	Mean Land Area
20 miles	371	21395	8946	32
30 miles	100	8429	3402	17
40 miles	103	6682	2914	10
Other Cities	9,685	19305	7851	10

Table 6: Isolated Towns

Several towns are adjacent to each other. An analogy to this situation is the Minneapolis-Saint Paul MSA, that is composed of two adjacent cities: Minneapolis and Saint-Paul. If I do not consider Minneapolis and Saint-Paul as a single city then I automatically count this agglomeration as having at least one neighboring town. To eliminate the problem of a single town which is split up into two municipalities, a town located within 1 mile of the central place is not counted as a neighbor. There are 374 towns that have no other city within 1 mile, while 75 cities do have a "twin", i.e. another town within 1 mile.

A.1 Zip Codes

To make this dataset more useful to researchers, I also select zip codes within a certain distance of the isolated towns. Zip codes can be used, for instance, to count the number of establishments within 5 miles of the central place, since ready-mix concrete plants frequently locate outside the boundaries of the municipality, and thus will not be part of the municipality proper, but will belong to a zip code located within a small distance from the central town. Again, the data on zip codes come from the U.S. Census Bureau. I include all zip codes within 5, 10 and 20 miles of an isolated town.

B Monte-Carlo Study of the Fixed-Effects Ordered Probit

There are a limited number of econometric models which allow for fixed-effect estimation, most notably: 1- linear model where fixed-effects can be differenced out, 2- the conditional logit model of McFadden and 3- moment inequality models such as Pakes, Porter, Ho, and Ishii (2006). The Pakes, Porter, Ho, and Ishii (2006) model seems to provide a good solution for differencing out the fixed effects. In particular, if we take the difference between profits in a market at times t and τ:

$$\xi = \pi(D_{mt}, N_{mt}) - \pi(D_{m\tau}, N_{m\tau} + 1) \geq 0$$

this difference will be positive and the market level fixed effect will be differenced out. However, this moment inequality is conditional on having at least one firm per market, a condition which is frequently violated in the data. Dropping these markets will generate an error ξ which is no longer mean zero unless we focus our attention on markets where the zero firm count problem is never an issue.

In most non-linear model, however, fixed-effects need to be estimated individually. The variance in the estimates of these fixed effects or incidental parameters in the terminology of Heckman (1981) contaminates the rest of the coefficients, and has been shown to generate bias in these coefficients. Indeed, Greene (2004) p.126 summarizes the existing literature as:

> The now standard "result" is that the fixed-effects estimator is inconsistent and substantially biased away from zero when group sizes are small (e.g., by 100% when $T = 2$)

Thus the fixed-effect estimator in a non-linear model such as the ordered probit type model used in this paper, can be biased for small panel lengths T, even if the number of markets M is quite large. Yet, it is an open question of how quickly the bias of the fixed-effect ordered probit model shrinks as T increases. For instance, Greene (2001) discusses the bias of estimating non-linear models with fixed effects (typically with maximum likelihood), and Greene (2004) finds relatively small bias in a fixed-effect tobit model.

The purpose of this section is to look at the finite sample bias of the ordered-probit estimator used in this paper using a Monte-Carlo study. I find that the bias of the fixed-effect estimator is relatively small, i.e. less than 20% of the coefficients, which is within the standard errors, the bias attenuate the parameter estimates relative to their true values. Furthermore, the estimates of the model than leave out fixed-effects have far greater bias, on the order of more than 100%, and in particular the estimated competition coefficients are biased downwards by a factor of 3.

Algorithm 2 *Monte-Carlo for Fixed-Effect Ordered Probit*

For $k = 1, \cdots, 1\,000$:

1. Draw $\epsilon_t^k \sim \log(\mathcal{N}(0,1))$.

2. Predict number of firms i.e., N_t^k that satisfies:

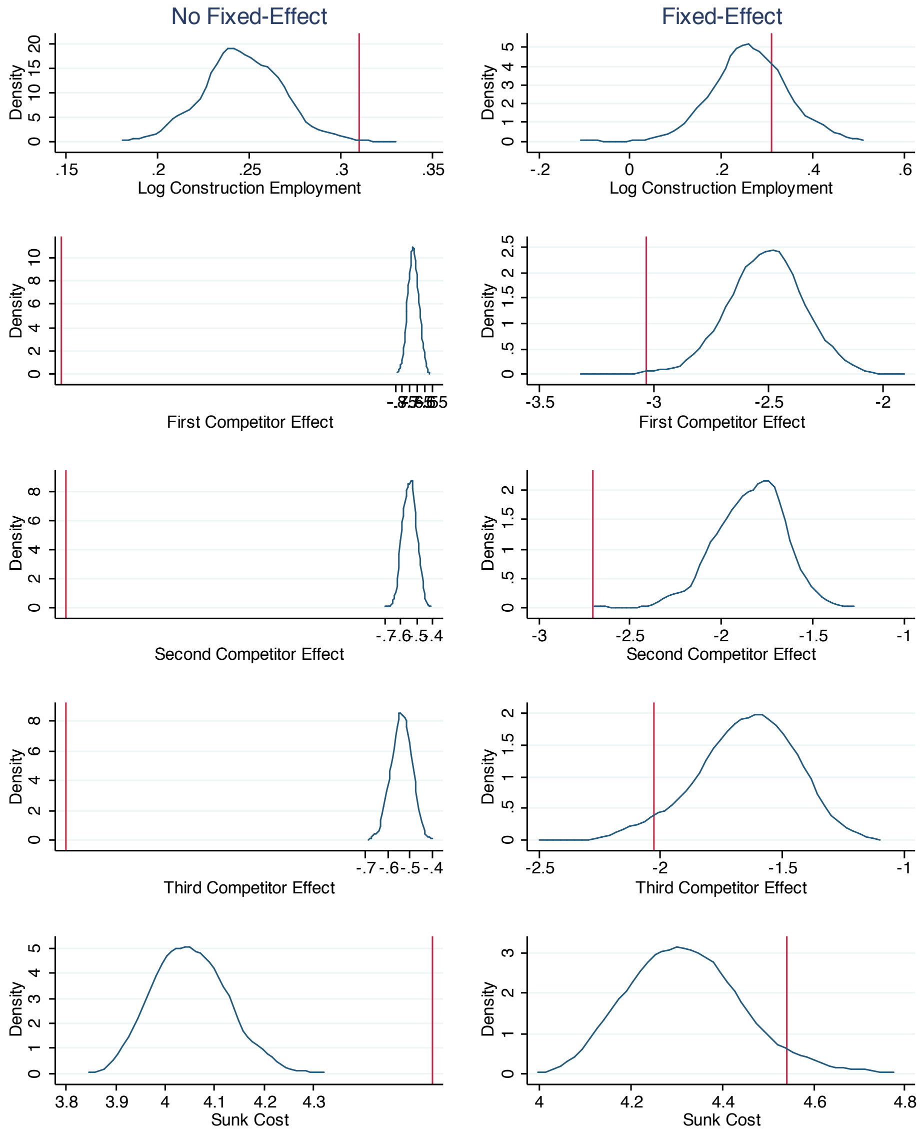
$$V^{\theta^0}(\epsilon_t^k D_t, N_t^k) \geq \phi + 1(N_t^k > N_{t-1}) \underbrace{(\psi - \phi)}_{\gamma}$$

$$V^{\theta^0}(\epsilon_t^k D_t, N_{t-1}^k) < \phi + 1(N_t^k \geq N_{t-1}) \underbrace{(\psi - \phi)}_{\gamma}$$

   where θ^0 are the estimates from column VI of Table 3 on page 18, including all market level fixed effects. Note that D_t and N_{t-1} refer to demand and lagged number of firms in the data.

3. Use data set $X^k = \{N_t^k, N_{t-1}, D_t\}$ to estimate parameters $\hat{\theta}_{FE}^k$ and $\hat{\theta}_{NE}^k$ (no fixed-effects).

Table 6 shows the results of Monte-Carlo exercise. The first column shows results without fixed-effects, while column II shows results with market fixed effects. Notice that the no fixed effect model misses the competition parameters completely, underestimating these coefficients by a factor of three, which is approximately the coefficient estimates in the non-fixed estimates of Table 3. This backs up the assertion that persistent differences in the profitability of markets generate the differences between the competition estimates in the fixed-effect and non fixed effect models. The fixed-effect coefficients are somewhat biased, on the order of up to 20% for certain competition parameters. This bias is in the direction of attenuating the parameters so the large increase in the size of the competition parameters is an underestimate. Moreover, this bias is well within the confidence intervals, so our interpretation of the parameters is not modified very much.



Note: Line is true value of the parameter. Kernel Density from 1000 Monte-Carlo replications using estimates from fixed-effect sunk-cost model, i.e. column VI of Table 3 on page 18.

Figure 6: Monte-Carlo Estimation of Sunk Cost Entry Model with and without market level fixed effects.

C Linear Model

In this section I look at the model where I assume that the error is additive in variable profits rather than multiplicative in demand. It may be more costly to build a concrete plant in an area where land and labor are more expensive. Suppose for instance that the true value function is:

$$V^*(D_{mt}, N_{mt}) = V(D_{mt}, N_{mt}) + \epsilon_{mt} \tag{18}$$

where m indexes the market and t is a time index, while ϵ_{mt} is the difference between the real and measured continuation value. Note that ϵ_{mt} could also include differences in the entry costs in different markets. If I had assumed instead that the the level of demand D_{mt} is mismeasured, I would get an expression for the value as $V^*(D_{mt}, N_{mt}) = V(\epsilon_{mt} D_{mt}, N_{mt})$ where ϵ_{mt} is log-normally distributed. The leads to an econometric model which is multiplicatively separable, rather than additively separable, which is the path taken by Bresnahan and Reiss (1991).

The entry and exit thresholds in equation (6) can be rewritten as:

$$\begin{aligned} \epsilon_{mt} &\geq -V(D_{mt}, N_{mt}) + \phi + 1(N_{mt} > N_{mt-1})\gamma \\ \epsilon_{mt} &< -V(D_{mt}, N_{mt} + 1)\phi + 1(N_{mt} \geq N_{mt-1})\gamma \end{aligned} \tag{19}$$

Using the multiplicative separability of period profits, and the stationary approximation, I can rewrite equation (19) as:

$$\begin{aligned} \epsilon_{mt} &\geq -\frac{1}{1-\beta} D_{mt} g(N_{mt}) + \frac{1}{1-\beta} f + \phi + 1(N_{mt} > N_{mt-1})\gamma \\ \epsilon_{mt} &< -\frac{1}{1-\beta} D_{mt} g(N_{mt}) + \frac{1}{1-\beta} f + \phi + 1(N_{mt} \geq N_{mt-1})\gamma \end{aligned} \tag{20}$$

where f are period fixed costs, and β is the firm's discount rate. The scrap value of the plant cannot be separately identified from the net present value of fixed costs, so equation (20) can be rewritten as:

$$\begin{aligned} (1-\beta)\epsilon_{mt} &\geq -D_{mt} g(N_{mt}) + \underbrace{f + (1-\beta)\phi}_{\hat{\phi}} + 1(N_{mt} > N_{mt-1}) \underbrace{(1-\beta)\gamma}_{\hat{\gamma}} \\ (1-\beta)\epsilon_{mt} &< -D_{mt} g(N_{mt}) + \underbrace{f + (1-\beta)\phi}_{\hat{\phi}} + 1(N_{mt} \geq N_{mt-1}) \underbrace{(1-\beta)\gamma}_{\hat{\gamma}} \end{aligned} \tag{21}$$

To accommodate multiple components of demand, such as population and construction employment, I use a single index of demand $D_{mt} = X_{mt}\beta$. I assume ϵ_{mt} is normally distributed with mean 0 and variance $1 - \beta$. The variance is normalized since it is not possible to identify the variance in this ordered discrete choice model. Using the functional form in equation (7) I get the following expression for the probability of observing N firms in a market with demand D.

$$\begin{aligned} \Pr[N_{mt}|D_{mt}] =& \Phi\left[-(X_{mt}\beta)g(N_{mt}) + \hat{\phi} + 1(N_{mt} > N_{mt-1})\hat{\gamma}\right] \\ & - \Phi\left[-(X_{mt}\beta)g(N_{mt}+1) + \hat{\phi} + 1(N_{mt} \geq N_{mt-1})\hat{\gamma}\right] 1(N_{mt} > 0) \end{aligned} \tag{22}$$

	I	II	III	IV
Construction	1.26	1.26	3.20	3.19
Employment	(0.00)	(0.00)	(0.01)	(0.12)
1 competitor	-0.79	-0.82	-0.96	-0.96
	(0.08)	(0.09)	(0.12)	(0.15)
2 competitor	-0.51	-0.55	-0.94	-0.95
	(0.08)	(0.10)	(0.12)	(0.19)
3 competitor	-0.35	-0.39	-0.38	-0.38
	(0.08)	(0.09)	(0.10)	(0.14)
4 competitor	-0.32	-0.38	-0.27	-0.28
	(0.14)	(0.16)	(0.10)	(0.13)
More than 4 competitors	-0.21	-0.26	-0.20	-0.21
	(0.05)	(0.07)	(0.10)	(0.12)
ϕ	-1.96	-1.94	-2.41	-2.40
	(0.08)	(0.08)	(mean f.e)	(mean f.e)
γ	3.05	2.60	3.57	3.49
	(0.07)	0.11	0.11	0.22
Total Establishments$*\gamma$		0.26		0.04
		(0.06)		(0.13)
Log-Likelihood	-2064	-2046	-1192	-1192
Observations	3014	3014	3014	3014

Table 7: Additive ϵ Sunk Cost Entry Model

Table 7 shows estimates of the linear model with and without market fixed effects, and with and without sunk entry costs which vary by the number of firms in a market.

D Dynamic versus Reduced Form/Static Estimates

Table 8 shows estimates of the dynamic model, which are estimated in Collard-Wexler (2006). To makes these estimates comparable to the static model, the coefficients need to be multiplied by about 20 since I have used a discount factor of 5%, with the exception of sunk entry costs. Note how close the estimates resemble the static estimates presented in the rest of the paper.

	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 8: Estimates for the Dynamic Entry Exit Model