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

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Abstract

Horizontal mergers have a large impact by inducing a long-lasting change in market structure. Only in an industry with substantial entry barriers, such as sunk entry costs, is a merger not immediately counteracted by post-merger entry. To evaluate the duration of the effects of a merger, I develop a sunk-cost model of entry and exit in the spirit of Bresnahan and Reiss (1994) and Abbring and Campbell (2010). This model is estimated using data from the ready-mix concrete industry, which is subject to fierce local competition. Because of high sunk costs, I find that the level of demand required to keep 3 firms in the market is comparable to the level of demand required to induce a single firm to enter the market in the first place. Simulations using estimates from the model predict that a merger from duopoly to monopoly generates between 9 and 10 years of monopoly in the market.

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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 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 due to transportation costs. Horizontal mergers are a recurrent issue. Moreover, ready-mix concrete plants have 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) via the framework of Abbring and Campbell (2010). The importance of sunk entry costs are identified from the difference between the level of demand that is required to induce N firms to enter the market and the level of demand that is sufficient to keep these N incumbents in the market. In the absence of sunk costs there is no reason why incumbency should matter, and these demand levels are identical. I find large sunk entry costs. The estimated level of demand that is required to induce a monopolist to enter the market is similar to the level of demand that is required to keep three incumbents.

These sunk costs will slow the response of an industry to mergers, reducing the number of competitors for a long time. Using estimates of the model, I simulate the evolution of market structure following a merger. I find that a merger from duopoly to monopoly will induce between 9 and 10 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 that 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:

[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.

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 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.

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 "isolated" towns, that is towns that are more than 20 miles from any other town.

To evaluate the long-run effects of mergers on market structure, I estimate a structural model of competition for the ready-mix concrete sector. To incorporate dynamic considerations absent in the static entry literature, I extend the less well known Bresnahan and Reiss (1994) prototype sunk costs model of entry and exit (henceforth the Sunk Cost Bresnahan-Reiss model or SBR). To do this I rely on the theoretical model of oligopoly dynamics of Abbring and Campbell (2010) (henceforth the AC model).

Notably, I use a market random effect estimation strategy, which allows for persistent differences in the profitability of a market. Allowing for serially correlated unobservables is critical, since it allows me to separate the role of sunk costs from unobserved heterogeneity, and substantially reduces the gap between the level of demand required to induce entry versus the level of demand required to keep an incumbent in the market.

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 that are of interest to antitrust authorities in the first place.

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 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 Condition Choice Probability approach. These estimates show large sunk costs and important effects of competition on the profitability of the firm. I use the SBR model in this paper for two reasons: first, I can use market random effects, allowing for serially correlated unobservables. This is critical for the counterfactual of looking at the effect of changes of market structure, since I do not want to conflate unobserved fixed 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, which is akin to an ordered probit, 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.

Finally, the estimation strategy and data requirements that are 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. At a minimum, the approach described in this paper casts light on how long-lived the effects a merger might be. In contrast to the well developed literature on estimating market power, there is virtually no empirical guidance on this issue.

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; its 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.

According to the U.S. Census Bureau (2004) there are 5500 ready-mix concrete plants in the country, which ship on average 3.8 million dollars of concrete, of which 1.9 million is value added. These plants employ an average of 18 workers and have assets worth 1.7 million as well as large amounts of rented machinery. Plants can be built very quickly, but except for trucks most of their capital assets are sunk, and it is common to see abandoned ready-mix concrete plants in the countryside.

I will use information on 449 markets for ready-mix concrete for 1994 to 2006. On average, these markets have a single ready-mix concrete plant.

The importance of local competition and the potential for exercising market power means that horizontal mergers may be blocked for anti-competitive reasons. The organization and control file in the Research Data Program at the Census bureau provides information on the number of mergers in the industry from 1972 to 1997. Out of about 5000 plants in the industry, 654 are acquired by other firms during the period. Most of these acquiring firms are in the ready-mix concrete industry, as the acquiring firms own on average 7.5 ready-mix concrete plants. Furthermore the industry is highly concentrated at the local level, since acquired plants have a 41% share of payroll at the county level pre-acquisition.

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 Last-In First-Out (henceforth LIFO) equilibrium developed by Abbring and Campbell (2010) to characterize the unique equilibrium to the entry game. Third, I show conditions on the process for demand such that entry and exit decisions are characterized by demand thresholds, again following Abbring and Campbell (2010) .

3.1 Period Game

In each period all firms in the market compete in prices. I assume that all firms are identical, so variable profits are determined by the number of firms in the market N, and the size of the market 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 $ppc(N)$ that 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 $\pi^V(N, D^*) = ppc(N)D^*$. 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 that 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 is 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 $\pi^V = ppc(N)D^*$.

3.2 Entry and Exit

I turn now to entry and exit.[2] There are two types of firms: incumbents (denoted C) who already have a plant in the industry, and potential entrants (denoted E). Demand is generated by an exogenous Markov process $P^{D^*}[D^{*\prime}|D^*]$. Firms simultaneously choose to enter, stay, or exit, and then today's demand $D^{\prime *}$ is revealed,. I denote the exit decision of continuers as $\chi = 1$ and the entry choice of potential entrants as $\chi^E = 1$. Firms make entry and entry decisions based on the *continuation value* $V(D^*, N)$: the expected net present value of profits for an incumbent at time $t = 0$ of having a plant in a market with N_0 firms and a number of consumers D^*_0, which is given by:

$$V(D^*_0, N_0) = \mathbf{E} \sum_{t=0}^{\infty} \beta^t \left(\pi^V(N_t, D^*_t) - f\right) 1(\chi_t = 0) + \beta^t \psi 1(\chi_t = 1) \tag{3}$$

where f denote fixed costs and ψ denotes the scrap value of the firm.

To characterize the equilibrium of the entry and exit game, I use the foundations provided by Abbring and Campbell (2010), who develop a model of oligopoly dynamics in which firms enter and exit using demand thresholds, exactly as in Bresnahan and Reiss (1994). The AC model requires assumptions on strategies and on the process for demand. I assume that firms use **LIFO** strategies which default to inactivity; firms that enter earlier are the firms that exit later.[3] Given the **LIFO** assumption, Proposition 1 of Abbring and Campbell (2010) shows that

[2] Through the paper, entry and exit will refer to denovo entry and permanent exit. In the ready-mix concrete industry there is no conversion of plants from other industries and very little mothballing of plants.

[3] In the ready-mix concrete industry I find that older plants tend to exit less often than do 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%.

the equilibrium of the entry and exit game will be unique. This means that the model generates a single prediction, considerably simplifying counterfactual experiments and allowing for estimation techniques such as maximum likelihood, which requires that each parameter vector is associated with a single prediction of the entry-and-exit model.

A firm will enter if the continuation value of remaining in the market is greater than the entry costs, both sunk (denoted ϕ) and unsunk (denoted ψ);i.e., $\chi^E = 1$ if and only if $V(D^*, N) > \phi + \psi$. Likewise, a firm exits if the continuation value $V(D^*, N)$ is lower that the scrappage value; thus $\chi = 1$ if and only if $V(D^*, N) \leq \psi$. 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. Entrants always have lower values than do 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 with pure strategies and symmetric firms: they cannot rationalize the same type of plant in the same market making different choices.[4]

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

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

$$\begin{aligned} V(D_t^*, N_t) &> \phi + \psi \\ V(D_t^*, N_t + 1) &\leq \phi + \psi \end{aligned} \tag{4}$$

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

$$\begin{aligned} V(D_t^*, N_t) &> \psi \\ V(D_t^*, N_t + 1) &\leq \psi \end{aligned} \tag{5}$$

3. No Net Change (*Stasis*): $N_t = N_{t-1}$

$$\begin{aligned} V(D_t^*, N_t) &> \psi \\ V(D_t^*, N_t + 1) &\leq \phi + \psi \end{aligned} \tag{6}$$

3.3 Demand Thresholds

There is a strong intuition that the equilibrium entry and exit decisions in this game will be in demand thresholds; i.e., 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 continuation. More formally, an exit decision is in demand thresholds if a firm exits when demand falls below a certain level: $\chi(D^*, N) = 1$ if and only if $D^* \leq D_N^C$.

[4] I have 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.

Likewise, an entry policy is in demand thresholds if a firm enters when demand is above a certain level: $\chi^E(D^*, N) = 1$ if and only if $D^* > D_N^E$. In what follows, I assemble a model to justify entry and exit thresholds. Suppose that the Markov process for demand $P^{D^*}(D^{*\prime}|D^*)$ has the properties that 1) higher levels of demand today are always "good news" about demand in the future: $E[D^{*\prime}|D^*]$ is weakly increasing in D; 2) the innovation error $\nu = D^{*\prime} - E[D^{*\prime}|D^*]$ must be independent of D^*; and 3) the distribution of the innovation error ν is concave. I denote these three assumptions on the demand process as the **MKP** assumptions.

If firms use **LIFO** strategies and the process for demand satisfies **MKP**, Proposition 4 in Abbring and Campbell (2010) states that we can characterize the entry and exit decisions of firms in terms of demand thresholds.[5] I can compute the entry threshold as $D_N^E = \min D^*$ s.t. $V(D^*, N) > \phi + \psi$ as the minimum level of demand that is required to induce an N^{th} firm into the market, and the continuation threshold as $D_N^C = \min D^*$ s.t. $V(D^*, N) > \phi$, the minimal level of demand required to keep N firms in the market. Note that the case without sunk costs with $\phi = 0$, the entry and continuation thresholds are the same: $D_N^E = D_N^C$. Thus the gap between entry and exit thresholds indicates 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, identifying the importance of sunk costs.

Figure 1 shows entry and continuation thresholds as well as the phase diagram for the industry.[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. In section 5 I will estimate these entry and continuation thresholds.

4 Data

I construct data on entry and exit patterns in isolated markets for the ready-mix concrete sector. I use the area around isolated towns as my markets 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.

[5] In a single-agent model, it would be straightforward to show that entry and exit decisions are characterized by demand thresholds, since under standard conditions on the process for demand, a firm's value function is increasing in demand. This is not true in an oligopoly. Higher demand may induce an additional firm to enter the market, and thus higher demand may reduce an incumbent's value. Thus Proposition 4 in Abbring and Campbell (2010) on demand thresholds is critical for the estimation strategy in this paper.

[6] The version of this figure with estimated thresholds is shown in Figure 3 on page 20.

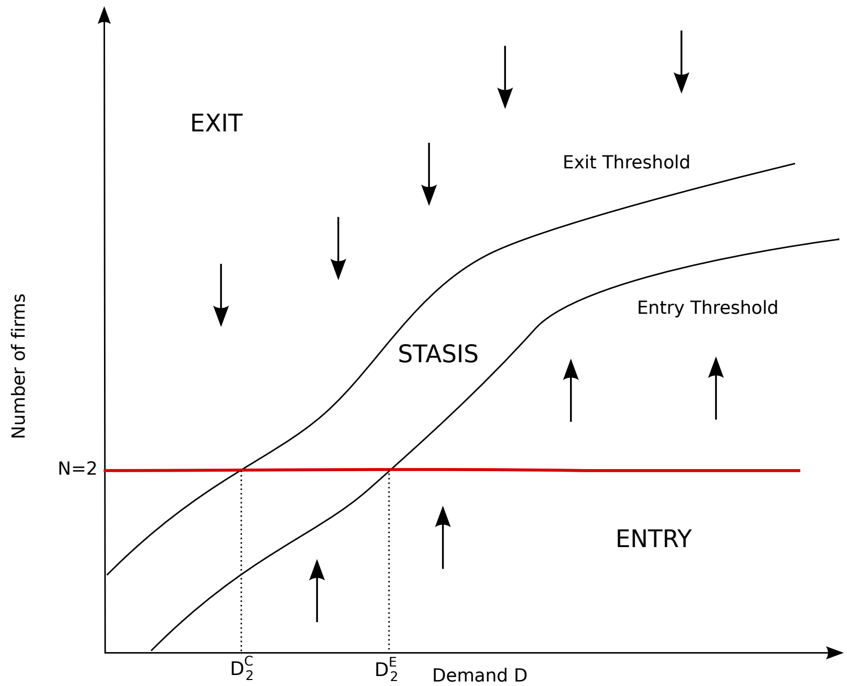


Figure 1: Entry and Continuation Thresholds

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 towns so that shipping concrete from outside is difficult. This allows me to abstract from competitors that are 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 8 cubic yards of concrete is worth around $600. Thus, shipping times in this industry are 20 minutes on average.

I locate "places" (as defined by the Census Bureau) in the United States that have more than 2000 inhabitants.[7] Many of these towns are "twins": they are adjacent to another place. I treat both of these municipalities as if they composed a single city.

Isolated towns are the 449 places out of more than $10,000$ that are at least 20 miles away from any other town, which I identify using GIS software. Figure 2 shows a typical isolated town: Scottsbluff, Nebraska. Scottbluff is "twinned" with Gerring, Nebraska. 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

[7] A place is defined by the Census as "cities, boroughs, towns, and villages" as well as "settled concentrations of population that are identifiable by name but are not legally incorporated". The interested reader can find exact definition in `http://www.census.gov/geo/www/cob/pl_metadata.html`.

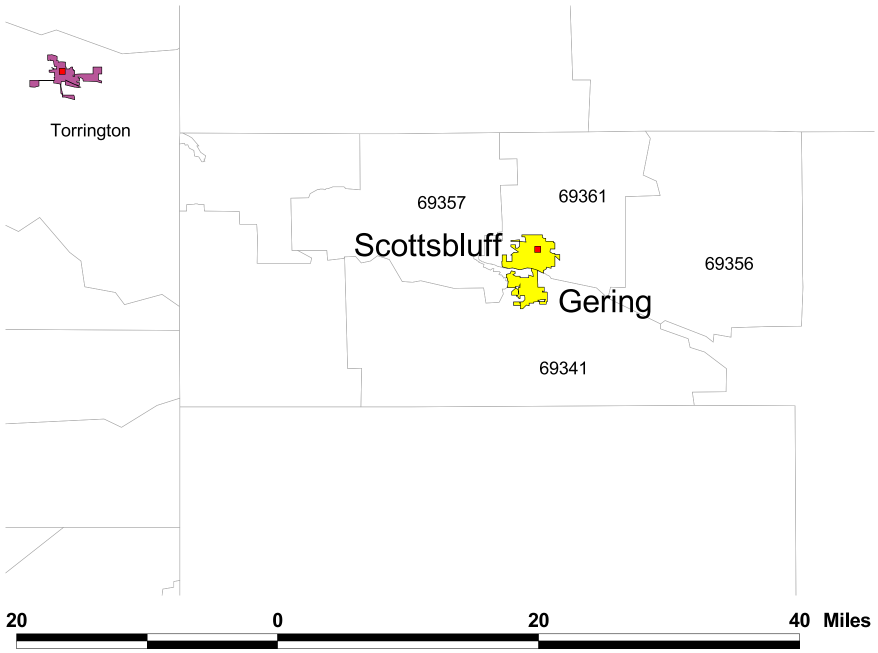


Figure 2: Typical Isolated Town and Zip Codes: Scottsbluff/Gering, Nebraska, and Zip codes 69357, 69341, 69356, 69361.

town dataset in more detail.

4.2 Concrete and Construction Data

The data on concrete plants and construction are pulled from the Zip Business Patterns (henceforth ZBP) database that is produced by the Census Bureau (US Census Bureau, 2009). For confidentiality 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, in small towns multi-plants firms typically own plants in several adjacent markets, rather than multiple plants in the same market.

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 emanates from the construction sector, and so construction employment will be my primary demand shifter.[8]

Table 1 presents summary statistics for the 449 isolated towns in the data over a twelve year period. Towns have an average population of 12,000 inhabitants, with very large skewness in this distribution as it varies from 4,000 to 176,000. There are considerably more inhabitants

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

living in the zip codes within 5 miles of this town, on average 29,000 inhabitants living in 12,000 housing units. One reason for the larger population in surrounding zip codes is the fact that the land area covered by these zip codes differs considerably, from 26 and 6500 square miles.

I use construction employment as a measure of demand, and there are on average 500 employees at construction establishments in zip codes within 5 miles of the town, and this varies from 3 employees to 7500. Moreover, Figure 6 in the Appendix shows more detailed distributional graphs of town size measured by either population, housing units, construction employment and land area.

There are between zero and six concrete plants in a market, with an average of 0.94. There is also considerable time series variation in construction employment and concrete plants. The standard deviation of the difference between the number of plants and the market mean is 0.37. This is a fairly large, as the cross-sectional standard deviation of the number of plants is 0.92. As well log construction employment has considerable variability, with a standard deviation within the market of 0.22, again compared to a cross-sectional standard deviation of 1.11, indicating that demand for concrete is volatile.

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Highway within 5 miles of place	0.28	0.45	0	1
Land area in square miles of zip codes†	861	825	26	6573
Population of place∗	12006	14332	4019	176576
Population in zip codes∗	28526	24625	3538	190759
Housing units in zip codes∗	12279	9784	989	64331
Log of population in place∗	9.10	0.67	8.29	12.08
Log of zip Population in zip codes∗	9.99	0.71	8.17	12.16
Construction employment in zip codes	502	606	3	7529
Log construction employment	5.69	1.11	0.92	8.93
within 10 miles	5.89	1.11	0.92	8.94
within 20 miles	6.05	1.09	0.92	9.84
Concrete establishments in zip codes	0.94	0.92	0	6
Standard deviation of				
log construction employment within market⋄	0.22	0.15	0	1.43
Standard deviation of				
number of concrete plants within market⋄	0.37	0.32	0	1.56

The data is a fully balanced panel of 449 markets over a 12 year period. † Zip codes refers to the zip codes within 5 miles of the isolated town (or place). ∗Denotes a measure in the year 2000. ⋄The standard deviation within a market is the standard deviation of $y_{mt} - \bar{y}_m$.

Table 1: Summary statistics

Table 2 shows summary statistics of the data decomposed by the number of plants within a market. Notice that 45% of markets are monopoly markets, 35% have no plants at all,

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 more	18	42252	7306	52%
All	5,837	12031	516	43%

Table 2: Summary Statistics by Market Structure

while the balance of markets (20%) have more than one plant. Population and employment in the construction sector are higher in markets that are served by multiple 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.

To illustrate changes in market structure, Table 3 shows the transition probabilities of the number of firms in a market on a one and ten-year horizon. About 20% of markets have a change in the number of firms that serve them each year: these markets are fairly dynamic. Furthermore the ten-year transition probabilities show, for instance, that a duopoly market has a 55% probability of being a monopoly market ten years later and a 35% probability of having two or more plants ten years later.

5 Econometric Model

Certain costs and components of demand will be mismeasured. For instance, the demand for concrete is higher in Texas since the high summer temperatures there make asphalt melt. Thus roads in Texas are more frequently paved with concrete. More generally there will be differences in the profitability of different markets that are difficult to capture with observable demand shifters. True demand D^*, which is the demand in the model that I discussed in section 3, is equal to $D^* = \xi D$, where ξ is the unobserved component of demand and D is the observed components of demand.[9]

The number of firms in a market m at time t, denoted N_{mt}, must lie between the entry and

[9] To retain the property that D^* is first-order Markov there are some strong restrictions that need to be imposed on the process for D and ξ.

One Year Transition Probabilities

	Plants this year						
Plants Last year	0	1	2	3	4	5+	Total
0	0.86	0.13	0.01	0.00	0.00	0.00	849
1	0.09	0.83	0.08	0.00	0.00	0.00	1293
2	0.01	0.20	0.71	0.08	0.00	0.00	606
3	0.00	0.03	0.24	0.65	0.07	0.01	197
4	0.00	0.05	0.10	0.22	0.58	0.05	59
5 and more	0.00	0.00	0.00	0.36	0.09	0.55	11

Ten Year Transition Probabilities

	Plants this year						
Plants Ten years ago	0	1	2	3	4	5+	Total
0	0.30	0.58	0.09	0.01	0.01	0.00	160
1	0.39	0.36	0.21	0.03	0.00	0.00	243
2	0.10	0.55	0.23	0.10	0.01	0.00	134
3	0.05	0.29	0.29	0.26	0.12	0.00	42
4	0.00	0.24	0.59	0.12	0.06	0.00	17
5 and more	0.00	0.00	0.00	0.00	0.80	0.20	5

Table 3: Transition of the number of plants on a one and ten year horizon.

exit thresholds. Thus,

$$\xi_{mt} D_{mt} > D^E_{N_{mt}} 1(N_{mt} > N_{mt-1}) + D^C_{N_{mt}} 1(N_t \leq N_{mt-1})$$
$$\xi_{mt} D_{mt} \leq D^E_{N_{mt+1}} 1(N_{mt} \geq N_{mt-1}) + D^C_{N_{mt+1}} 1(N_{mt} < N_{mt-1})$$

I define $\varepsilon = \log(\xi)$, $\log\left(D^E_{N_{mt}}\right) = \sum_{k=2}^{N_{mt}} h^C(k) + \gamma^E + \gamma^S$, and $\log\left(D^C_{N_t}\right) = \sum_{k=2}^{N_{mt}} h^E(k) + \gamma^E$. Taking the logarithm of the previous equation I obtain the following expression:

$$\begin{aligned}\varepsilon_{mt} > & -\log(D_{mt}) + \gamma^E + 1(N_{mt} > N_{mt-1}) \left(\sum_{k=2}^{N_{mt}} h^C(k) + \gamma^S \right) \\ & + 1(N_{mt} \leq N_{mt-1}) \sum_{k=2}^{N_{mt}} h^E(k) \\ \varepsilon_{mt} \leq & -\log(D_{mt}) + \gamma^E + 1(N_{mt} \geq N_{mt-1}) \left(\sum_{k=2}^{N_{mt}+1} h^C(k) + \gamma^S \right) \\ & + 1(N_{mt} < N_{mt-1}) \sum_{k=2}^{N_{mt}+1} h^E(k)\end{aligned} \tag{7}$$

I assume that the difference between the entry and exit thresholds is constant in log demand, i.e. $h^E(k) = h^C(k) = h(k)$ for all k, and in Appendix C I show that if the value function can be well approximated by a stationary version of it, then this assumption will be true. This

assumption is made primarily to reduce the number of parameters that I need to estimate.[10] Thus the thresholds become:

$$\begin{aligned}
\varepsilon_{mt} &\geq -\log(D_{mt}) + \gamma^E + 1(N_{mt} > N_{mt-1})\gamma^S + \sum_{k=2}^{N_{mt}} h(k) \\
\varepsilon_{mt} &< -\log(D_{mt}) + \gamma^E + 1(N_{mt} \geq N_{mt-1})\gamma^S + \sum_{k=2}^{N_{mt}+1} h(k)
\end{aligned} \tag{8}$$

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:

$$\begin{aligned}
\Pr[N_{mt}|x_{mt}, N_{mt-1}] =& \Phi\left[-x_{mt}\beta - \sum_{k=2}^{N_{mt}} h(k) + \gamma^E + \gamma^S 1(N_{mt} > N_{mt-1})\right] \\
& - \Phi\left[-x_{mt}\beta - \sum_{k=2}^{N_{mt}+1} h(k) + \gamma^E + \gamma^S 1(N_{mt} \geq N_{mt-1})\right] 1(N_{mt} > 0)
\end{aligned} \tag{9}$$

Notice that equation 9 differs from an ordered probit only in the inclusion of the γ^S term. I find parameters $\hat{\theta} = \left[\beta, h(\cdot), \gamma^E, \gamma^S\right]$ that maximize the log-likelihood given by:

$$\mathcal{L}(\theta) = \sum_{m=1}^{M} \sum_{t=0}^{T} \log(\Pr[N_{mt}|D_{mt}, N_{mt-1}, \theta]) \tag{10}$$

5.1 Market Effects

I have a panel of markets, so the assumption that ϵ_{mt} is independent of ϵ_{mt-1} is hard to believe given that the unobserved components of demand, such as how intensively concrete is used in construction, are most likely similar from one year to the next. 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 $\epsilon_{mt} = \mu_m + \nu_{mt}$; i.e., that there are persistent market-level unobservables that are overlaid with independent shocks η_{mt} which are normally distributed with mean 0 and variance 1. 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, these differences will endure.

One should worry about persistent unobservables for three reasons. First, to the extent that

[10] I also estimate the model without the assumption that the difference between the log demand entry and continuation thresholds is constant, $h^E(k) = h^C(k)$. Unfortunately the estimates give odder entry and continuation thresholds and are presented in Table 11 in the Appendix on page 37.

more firms enter more profitable markets, there will be positive correlation between the number of firms in a market and unobserved demand. Specifically, the estimated continuation and entry thresholds D_N^C and D_N^E will rise too slowly with N; or, in other words, the effect of competition will be underestimated. Second, the gap between entry and continuation thresholds captures the sunk costs of entry. However another reason for a large stasis zone, the fact that a single level of demand can support a wide range of firms, could be due to unobserved difference in demand between markets. Thus controlling for these unobserved differences should shrink the size of the stasis zone that we attribute to sunk costs of entry. Finally, to perform the merger counterfactual I will need to simulate the evolution of D^* over time which includes the evolution of both observable and unobservable demand. Thus getting the right time-series process for unobserved demand is key.

I use a random effects estimation strategy, where I assume that the market level mean μ_m is normally distributed, with mean zero and variance σ_μ^2: $\mu_m \sim \mathcal{N}(0, \sigma_\mu^2)$. The probability of a single observation conditional on μ is:

$$\begin{aligned}\Pr[N_{mt}|x_{mt}, N_{mt-1}, \mu] =&\Phi\left[-\mu - x_{mt}\beta - \sum_{k=1}^{N_{mt}} h(k) + \gamma^E + \gamma^S 1(N_{mt} > N_{mt-1})\right] \\ &-1(N_{mt} > 0)\Phi\left[-\mu - x_{mt}\beta - \sum_{k=1}^{N_{mt}+1} h(k) + \gamma^E + \gamma^S 1(N_{mt} \geq N_{mt-1})\right]\end{aligned} \tag{11}$$

And the likelihood for the entire model is given by[11] :

$$\mathcal{L}(\theta) = \sum_{m=1}^{M} \log\left[\int_\mu \prod_{t=1}^{T} \Pr[N_{mt}|x_{mt}, N_{mt-1}, \mu]\phi\left(\frac{\mu}{\sigma_\mu}\right) d\mu\right] \tag{12}$$

I also present fixed effect estimates, i.e. where I estimate a market parameter $\hat{\mu}_m$ for every market in the data, to give a sense of how I can identify the model based on variation within a market. 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 technique such as conditioning (Chamberlain, 1980) or differencing which allows these market effects to drop out.[12] There is a well known "incidental parameters problem" when using fixed effects a non-linear model, since these fixed effects can contaminate the estimation of other parameters in the model and lead to biased coefficients. In Appendix D I look at the finite sample bias of the fixed-effect SBR model using a Monte-Carlo experiment. I find relatively small bias (on the order of at most 20%, or well within the estimated confidence intervals) which attenuates

[11] I approximate the integral in equation 12 over μ with a twelve point Gauss-Hermite quadrature.

[12] For the fixed effect specification, 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.

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 yield a small bias of the fixed-effect model.

6 Results

The estimated SBR model that I present is essentially an ordered probit of the number of firms in the market on demand shifters, which also includes dependence on the lagged number of firms. Thus the coefficients cannot be interpreted directly, but the sign and the ratios between coefficients are meaningful.

Table 4 shows the main estimates of the SBR model. Column I shows estimates where I set $\gamma^S = 0$ and therefore are comparable to Bresnahan and Reiss (1991) (henceforth BR). The BR estimates highlight the differences between the BR model, which predict market structure, versus the SBR model, which predicts changes in market structure. Column VI shows estimates with market random effects and Column VII shows estimates with market fixed-effects while the remaining columns show estimates without market effects (henceforth no-effect). In order, I will discuss the estimates of demand, competition, sunk costs, and the market random-effects

First, the coefficient on log construction employment is 0.4 for the column I (the BR model), 0.3 for all SBR specifications except for column V (random effect specification) where I find a much larger coefficient of 0.59. Thus log construction employment is a large part of total demand D^*. Other measures of demand estimated in column III- such as log population and the presence of an interstate highway are not significant and have a fairly small magnitude in any case. Furthermore, Table 10 in the Appendix shows the SBR model estimated with different demand measures such as housing units and population. I find that using measures at the zip code level rather than at the town level yields larger effects of demand. However, the coefficient on either population or housing units is similar to the coefficient on construction employment, and it is difficult to separately identify the individual contribution of each of these components of demand. As such, I use construction employment as my primary measure of demand.

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 IV 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. Table 9 in the appendix shows estimates using different selections of markets, namely, markets whose zip codes within 5 miles are less than 850 squares miles of area (i.e. less than the mean), towns without an interstate highway, markets where more than 70% of the population in zip codes within 5 miles lives in the town per se, and towns without a neighboring town within 40 miles. While the estimates differ, none show substantially larger effects of either demand or competition, so I conclude that cleaning up my market definition

has a second order effect on the merger counterfactual.

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 significantly to past demand, and have a large negative (but not significant) response to the construction activity that will occur over the next 3 years. At a minimum this suggests that firms are not informed about future construction projects.

Second, turning to the effect of competition, the coefficients show the marginal effect of each additional competitor on the demand thresholds; $h(k) = \log(D_k^X) - \log(D_{k-1}^X)$ for $X = \{C, E\}$. 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 -0.70 for the effect of each competitor above four in the no-effect model and -1.21 in the random effects model. When I add market random or fixed effects in column VI and VII, I get competition coefficients that are up to 3 times larger. Section 6.1 discusses why introducing market random or fixed-effects leads to substantially different estimates.

Third, the sunk cost parameter γ^S shows the distance between the entry and continuation thresholds; i.e., $\gamma^S = \log(D_N^E) - \log(D_N^C)$, which is estimated at 3.2 in columns II-V, and 4.5 for the random and fixed-effect estimates in column VI and VII. To put these numbers into context, note that the no-effect columns II-V indicate that the demand threshold that is required to induce a monopoly entrant (D_1^E) is similar to the demand threshold that is required to sustain 4 incumbents (D_4^C). Turning to the random and fixed effect estimates, I find that the level of demand required to induce a monopoly entrant D_1^E is in between the level of demand needed to maintain 2 or 3 competitors (D_2^C and D_3^C). Thus the market effects models have a smaller stasis zone than do the no-effect models. The large estimated stasis zone indicates the presence of substantial sunk costs of entry, which coheres with interviews that 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.

The magnitude of the stasis zone induced by sunk costs has a direct impact on the persistence of the effects of a merger. If the stasis zone is zero, then a merger only has an impact for a single period, and likewise, if the stasis zone is infinite, then a merger permanently alters market structure.

Fourth, I find that the persistent unobserved component of demand μ_m is considerable. In the random effect estimates in column VI, the standard deviation of μ_m is 2.44, and in the fixed effect specification, the standard deviation of the estimated market fixed effects $\hat{\mu}_m$ is 2.17. To put these numbers into perspective, this means that 86% of the variance of unobserved demand can be accounted for by a persistent component, and the balance of unobserved demand is transient.

Dependent Variable	I	II	III	IV	V	VI	VII
Number of Plants in a Market	BR					R.E.	F.E.
Log Construction Employment	0.41	0.29	0.28	0.35	0.15	0.59	0.30
	(0.07)	(0.05)	(0.05)	(0.05)	(0.13)	(0.05)	(0.20)
Log Population			0.04				
			(0.11)				
Log Area			0.03				
			(0.06)				
Interstate Highway dummy			-0.09				
			(0.11)				
Log Construction Employment				-0.03			
zip codes within 10 miles				(0.05)			
Log Construction Employment				-0.11			
zip codes within 20 miles				(0.04)			
Next 3 years of					-0.23		
Log Construction Employment					(0.16)		
Previous 3 years of					0.38		
Log Construction Employment					(0.14)		
1 competitor	-0.51	-1.08	-1.08	-1.10	-1.03	-2.79	-3.03
	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)	(0.01)	(0.23)
2 competitor	-0.28	-0.89	-0.89	-0.90	-0.82	-2.41	-2.70
	(0.05)	(0.06)	(0.08)	(0.08)	(0.09)	(0.02)	(0.25)
3 competitor	-0.26	-0.82	-0.82	-0.82	-0.91	-1.91	-2.03
	(0.05)	(0.10)	(0.10)	(0.11)	(0.14)	(0.02)	(0.25)
4 competitor	-0.25	-0.91	-0.91	-0.91	-0.90	-1.91	-2.15
	(0.07)	(0.22)	(0.21)	(0.22	(0.39)	(0.08)	(0.54)
Competitors above 4	-0.33	-0.70	-0.70	-0.70	-0.69	-1.21	-1.39
	(0.38)	(0.10)	(0.10)	(0.10)	(0.16)	(0.06)	(0.09)
Entry Parameter γ^E	-1.97	-2.95	-2.95	-2.99	-3.03	-4.51	
	(0.36)	(0.26)	(0.26)	(0.82)	(0.30)	(0.19)	
σ_μ						2.44	
						(0.01)	
(Average Entry Parameter $\bar{\gamma}^E$)							-3.20
(S.D. of Entry Parameter $\hat{\gamma}^E_m$)							2.17
Sunk Cost Parameter γ^S	-	3.56	3.56	3.58	3.53	4.63	4.54
		(0.07)	(0.07)	(0.06)	(0.09)	(0.01)	(0.22)
Observations	5321	5321	5321	5245	2658	5388	3612
Markets	445	445	441	441	445	449	300
Log Likelihood	-6495	-1791	-1789	-1749	-880	-1306	-702

(Standard Errors Clustered by Market, except for column VI, random effects.)

Table 4: Sunk-Cost Bresnahan-Reiss Model Estimates

6.1 Market Effects

The inclusion of market random or fixed effects has important effects on the estimates in Table 4. First, remember that the numbers in this table should be interpreted as the coefficient scaled by the variance of ϵ. Since the fixed and random effect models have less variation attributed to ϵ, coefficients for random and fixed effects will be larger.

Second, the stasis zone, as measured by the sunk cost parameter γ^S is far smaller in the no-effects model that in the market random or fixed effect models. To understand this difference, suppose that we observe two markets with the same level of demand D^*, but one market has 1 firm in it while the other market has 3 firms. To accommodate this fact, the no-effect model needs a very large stasis zone, and in particular requires $D_2^E > D^*$ *and* $D_3^C < D^*$. In contrast, the market random effect model can explain this pattern with resorting to a stasis zone, since the 3 firm market might have a much higher unobserved demand μ than the 1 firm market.

Third, the fixed and random effect model differ with respect to the importance they attribute to log construction employment, which is 0.3 in the fixed effect model and 0.6 in the random effect model. While the random effect model imposes independence between the market random effect μ_m and construction employment d_{mt}, the fixed effect model does not. It turns out that markets with higher construction employment also have higher estimated fixed effects $\hat{\mu}_m$, and this correlation is unsurprisingly about 0.3.

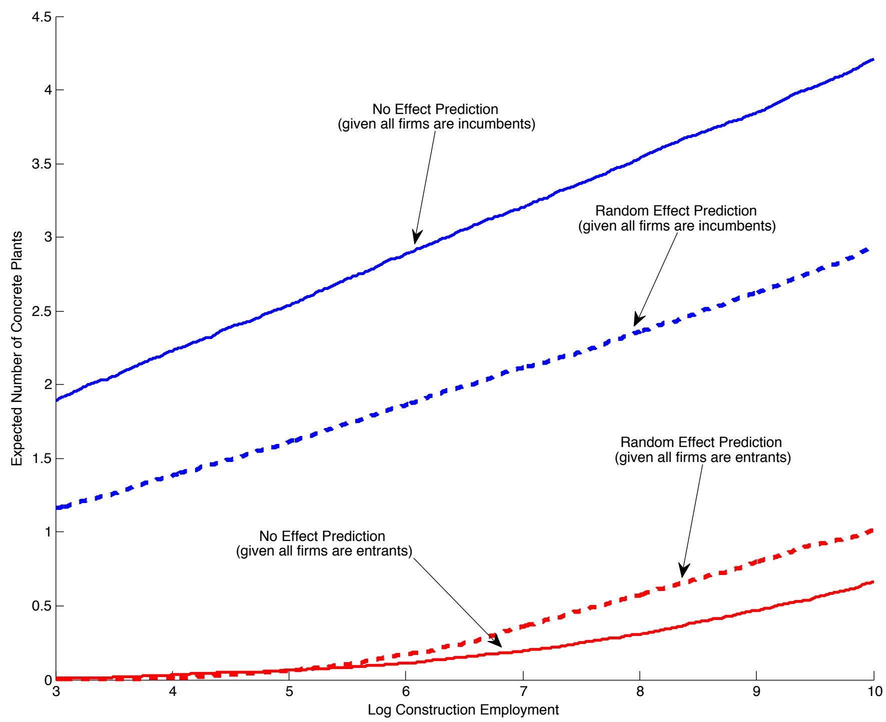
The choice between random and fixed effects is complicated by the fact that utilizing fixed effects eliminates the large cross-sectional variation of construction employment, and there is a worry that focusing on the more limited - and likely less well measured - time-series variation in construction employment will lead to attenuated demand estimates. I choose to keep the identification from cross-sectional variation in construction employment, and thus focus on the predictions using the random effect estimates.

6.2 Model Fit

Figure 3 illustrates the predictions of the SBR model by plotting the expected number of firms in a market given either that all firms are incumbents (akin to the continuation threshold), or given that all firms are entrants (akin to the entry threshold) against demand. I use the estimates in columns II (no-effect) and VI (market random effect with μ_m set to zero) in Table 4. This Figure is an analogue to the S-s diagram in section 3. To compute the expected number of firms given all firms are entrants, for each level of log construction employment d, I draw an $\epsilon^k \sim \mathcal{N}(0,1)$ and compute the number of firms in the market N^{Ek} that satisfies the entry and continuation threshold in equation 8 on page 14 given there were zero firms in period $t-1$. I plot the the mean predicted number of firms in the market; i.e., $\bar{N}^E(d) = \frac{1}{K}\sum_{k=0}^{K} N^{Ek}$, where I use K=10,000 simulation draws. Likewise, for the expected number of firms given all firms are incumbents $\bar{N}^C(d)$ I perform the same computation, but assume that there are a large

number of firms in period $t-1$.[13]

The no-effect estimates show that demand from a market with 3000 construction employees (equal to 8 in log terms) is sufficient to support between 0.3 and 3 plants in the market. The random effects model has a much smaller stasis zone as the same level of log construction employment can support between 0.4 and 1.6 plants. Notice as well that large changes in log construction employment are needed to to change the expected number of firms in a market. The first reason for this is that construction demand does not precisely pin down changes the number of firms in each market. The second reason is that the i.i.d. unobservable component of demand plays a large role in determining the number of firms in a market, i.e. it may take several years before an ϵ high enough to induce an additional entrant into the market arrives and Figure 3 only shows the one year effect of demand on the number of firms in the market.



The expected number of firms given that all firms are entrants, is the mean of the predicted number of firms given there are zero firms in the market is the last period. The expected number of firms given that all firms are incumbents, is the mean of the predicted number of firms given there are 5 firms in the market in the last period. Note that I set the market random effect $\mu = 0$ to plot the predictions from the random effect model.

Figure 3: Estimated Entry and Continuation Thresholds

To further illustrate the model's estimates I present a table of mean "marginal effects", i.e. predictions for the estimates in column II (no-effect) and column VI (market random effects).

[13]In practice, assuming there are 5 firms in the market in period $t-1$ yields the same answer as assuming any larger number of firms.

Specifically, given construction employment d_{mt}, the number of firms last year N_{mt-1} and a draw of ϵ^k_{mt} and of the market random effect μ^k_m, I compute the predicted number of firms N^k_{mt}. Table 5 present the mean of the predicted number of firms, entry and exit rates, as well as the effect of changing d_{mt}, ϵ, μ_m, and N_{mt-1} on the number of plants per market.

Note that to compute the random effect estimates I need to draw μ^k_m, and I use the posterior distribution of μ for a market m given by Bayes's Rule:

$$\Pr[\mu_m|\{N_{mt}\}^T_{t=1}, \{x_{mt}\}^T_{t=1}, \theta] = \frac{l_m(\theta, \mu_m)}{\int_\mu l_m(\theta, \mu) d\mu} \tag{13}$$

where the likelihood of μ, denoted $l_m(\theta, \mu) = \prod^T_{t=1} \Pr[N_{mt}|x_{mt}, N_{mt-1}, \mu, \theta]$.[14]

In the data, there are 0.91 plants per market (on average), while the no effects model predicts 0.94 plants per market and the random effects model predicts 0.92 plants per market. The effect of increasing construction employment by one log point is to raise the number of firms by 4% in the no effect model and 5% in the random effect model. Thus construction employment has a somewhat small effect on the number of firms in the market, even if the computed effect only shows the one-year response of a change in demand.

Raising the i.i.d. component of unobserved demand ϵ to the 90th percentile of the distribution, increases the number of firms by 12% in the no-effect model versus 8% in the random effect model. This shows that unobserved shocks account for a large proportion of demand, and these shocks are far larger for the no-effects model than for the market random effects model. Raising the persistent market unobservable μ_m to its 90th percentile has a far greater effect, as the predicted number of firms increases from 0.92 to 3.21. Indeed, there are large persistent differences in market structure that cannot be accounted for by construction employment.

Removing all firms from the market; i.e., setting $N_{mt-1} = 0$, would yield a predicted number of firms today of 0.13 for the no-effects model and 0.35 for the random effects model. Thus the effect of past market structure on the number of firms today is substantial and we should see a slow response of market structure after a firm exits the market. As well, the random effects model predicts a much faster reversion of market structure than no-effects model. Likewise, the effect of filling up the market with firms, i.e. setting $N_{mt-1} = 5$ (choosing a number larger than 5 has little effect) would raise the number of firms today to 2.84 in the no-effect model and 1.81 in the market random effect model.

Where the SBR model fails is in its prediction of the entry and exit rates. While the entry and exit rates in the data are 7.3% and 6.5% respectively, the no-effect model predicts entry and exit rates of 3.8% and 4.8%, and the random effect model predicts a 2.1% entry rate and a 2.4% exit rate. Thus both models significantly underpredict entry and exit rates, and since the random effect model has a smaller variance of ϵ; i.e. the i.i.d. component of unobserved

[14] As a practical matter, I simulate the distribution of the market random effect μ using a grid of 100 Halton points j and use $\Pr[\mu_m = \sigma_\mu j] = \frac{l_m(\theta, \sigma_\mu j)}{\sum^{100}_{k=1} l_m(\theta, \sigma_\mu k)}$ as probability weights for these .

demand, this will induce less turnover.[15]

Variable	Data	No Effect Model	Random Effect Model
Mean Number of Plants **(Baseline)**	0.91	0.94	0.92
1 Log point demand increase	-	0.97	0.97
1 Log point demand decrease	-	0.86	0.89
10th percentile ϵ	-	0.77	0.86
90th percentile ϵ	-	1.08	1.00
10th percentile μ (random effect)	-	-	0.62
90th percentile μ (random effect)	-	-	3.21
Removing all firms†	-	0.13	0.35
Filling the market††	-	2.84	1.81
Entry Rate	7.3%	3.8%	2.1%
Exit Rate	6.5%	4.8%	2.4%

† Removing all firms refers to the the one year prediction when $N_{t-1} = 0$, and †† Filling the market refers to the prediction where 5 plants are in the market (adding more has no effect), i.e. $N_{t-1} = 5$.

Table 5: Model "Marginal Effects"

Finally, to understand the model's long-run forecast for market structure, I simulate the evolution of markets for 10 years, using as an initial distribution the number of firms and log construction employment in the data in 1994. I find that in the no-effect model predicts that in 10 years 72% of markets will be monopoly markets, versus 42% of market in the data and 47% in the simulation of the random effect model. Essentially the no-effect model has the same ergodic distribution for all markets, and this distribution converges quickly to monopoly. In contrast, the market random effect predicts a distribution of market structure in the future that is reasonably close to the distribution in data 10 years hence.

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

[15] It is not surprising that the estimates of the SBR model under-predict turnover. The AC model rules out firm-level or idiosyncratic shocks, which is necessary to obtain a unique equilibrium. Thus the main driver of turnover in most models of industry dynamics is absent.

exactly the same as eliminating a plant.[16] Moreover, this counterfactual abstract from the issue of merger selection, i.e. are markets that have a merger systematically different.[17] Finally, this counterfactual only considers a "one-time" merger as it does not deal with future mergers.[18]

To perform this counterfactual, I need to use the estimates of the entry and continuation thresholds from the previous section as well as a model for the evolution of demand, both observed and unobserved. I estimate the demand process for observable demand $P^d[d_{mt}|d_{mt-1}]$ from the data:

$$d_{mt} = \beta_0 + \beta_1 d_{mt} + \eta_{mt} \tag{14}$$

where $\eta_{mt} \sim \mathcal{N}(0, \sigma_0 + \sigma_1 d_{mt})$. P^d is estimated by maximum likelihood and Table 7 presents estimates of the demand process where Column III includes market fixed effects and Columns I and II do not. Columns I and II show that the coefficient on lagged demand is essentially 1, i.e. a unit root process for demand, but this feature disappears when market fixed effects are added. 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. For the counterfactual, I use the demand process estimated in Column II.

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

Dynamic Merger Simulation Algorithm

1. Set the initial number of firms in the market as $N_{0m}^{NMk} = 2$ if the merger does not happen and $N_{0m}^{Mk} = 1$ if it does happen.

2. Draw a market random effect $\mu_m^k \sim \Pr[\mu|\{d_{mt}, N_{mt}\}_{t=0}^T]$ from the posterior distribution computed in equation (13).

3. For $t = 1$ to 50:

   (a) Draw next period's demand $d_{mt}^k \sim P^d(\cdot|d_{mt-1}^k)$.

   (b) Draw next period's unobserved demand shifter $\epsilon_{mt}^k \sim \mathcal{N}(0, 1)$.

   (c) Both N_{mt}^{NMk} and N_{mt}^{Mk} satisfy the entry and exit conditions estimated in equation (8).

[16] This 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.

[17] Firms may choose mergers based on how long they expect to have a monopoly. Figure 5 shows the effect of a merger based on the initial level of demand in the market. Even in the case where firms only consummate mergers which yield monopoly for the longest time period, this would only raise the expected duration of a merger from 7.8 years in net present value to 9.2 years in net present value.

[18] The issue of the dynamic effect of future mergers, such as is modeled in Gowrisankaran (1999), is difficult to handle in this context as the possibility of future mergers will alter the equilibrium of the dynamic entry and exit game, and it's underlying demand thresholds for continuation and entry.

Dependent Variable: Log Construction Employment		I	II	III
Last Year	Log Construction Employment	0.98	0.99	0.62
		(0.00)	(0.00)	(0.02)
	Constant	0.12	0.04	
		(0.02)	(0.02)	
	Market Fixed Effects			X
Variance σ_η	Constant	0.23	0.49	0.43
		(0.01)	(0.03)	(0.01)
	Log Construction		-0.05	-0.04
	Employment		(0.00)	(0.01)
Observations		5312	5312	5312
Log-Likelihood		162	694	1375

Note: Standard Errors Clustered by Market.

Table 6: Estimated Demand Transition Process

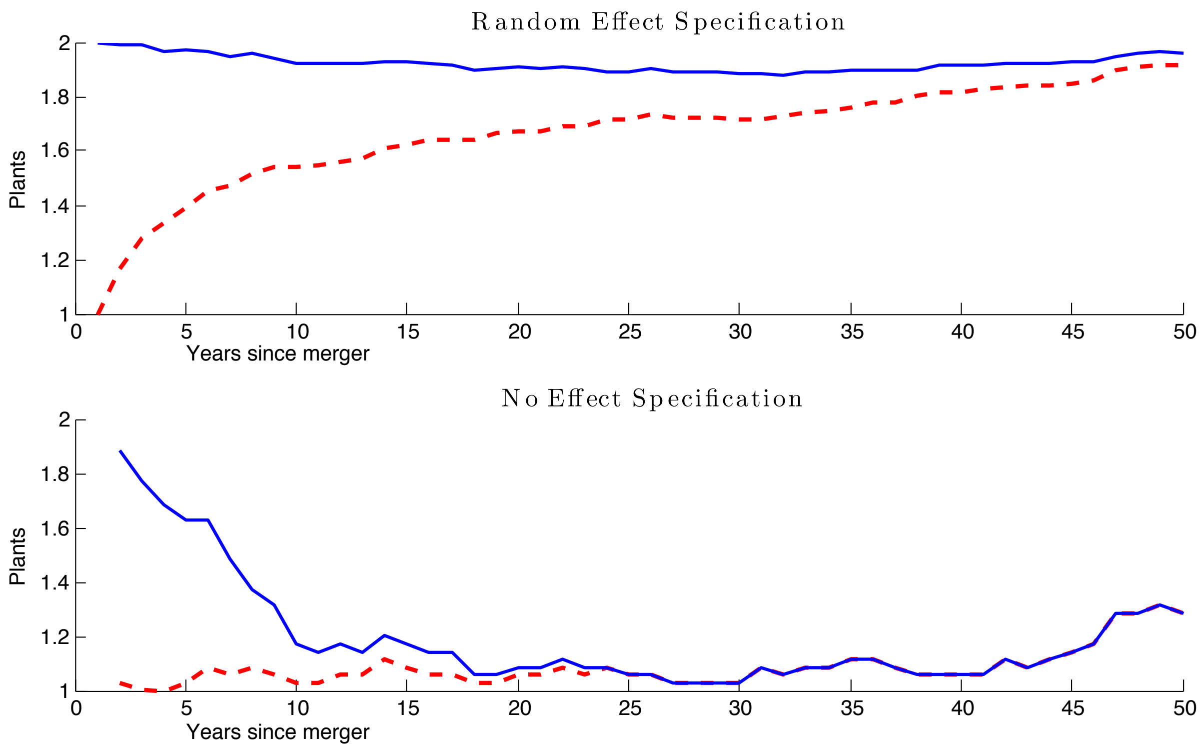
To select initial levels of construction employment and market random effects that are typical of a market that can support two firms in it, I pick markets and time periods with two firms; i.e. (m, t) such that $N_{mt} = 2$.[19]

Figure 4 plots the effect of the merger on the expected number of firms in the industry over time, and the evolution of the number of firms absent the merger. The top panel uses estimates from the random-effect specification, while the bottom panel uses estimates from the no-effects specification. Notice that it takes 50 years for the market that had a merger to become indistinguishable from the market where the merger did not occur in the random effect specification, while in the no-effect version, it only takes 15 years for this to happen. However, the fast convergence in the no-effect simulation is generated by the prediction that the market's steady state is a monopoly regardless of the merger. This echoes the ten year simulation of market structure in the previous section, which showed that the no-effect model predicts a rapid convergence of a market to monopoly.

7.1 Welfare Effects

To evaluate the welfare effects of a merger, denoted W, I compute the loss in consumer surplus due to the merger, given by the difference in the net present value of consumer surplus between

[19]Specifically, I use the set of markets and time periods $C = \{(m, t) s.t. N_{mt} = 2\}$, which is a way of weighting the sample by the frequency with which a market finds itself in a two firm state. For observations in C I pull this market's random effect μ_m and the initial level of demand in this market d_{mt}. If I do not condition on the fact that a market is in a two firm state, then the number of firms in the market quickly falls to the mode in the sample of one firm per market.



The solid line indicates the mean number of plants in the no-merger simulation, i.e. where $N_{0m}^{NM} = 2$, while the dashed line shows the mean number of plants in the merger simulation where $N_{0m}^{M} = 1$.

Figure 4: Effect of a Merger on the expected number of firms in the industry.

the merger and no-merger scenarios:

$$W = \mathbf{E}\sum_{t=0}^{\infty}\beta^t CS[D^*_{mt}, N^{NM}_{mt}] - \mathbf{E}\sum_{t=0}^{\infty}\beta^t CS[D^*_{mt}, N^{M}_{mt}] \tag{15}$$

where $CS[D^*_{mt}, N_{mt}]$ is the per period consumer surplus in a market with demand D^*_{mt} and firms N_{mt}. The AC model has an s-S structure whereby market structure in the merger and no-merger worlds are identical as soon as the number of firms leaves the monopoly or duopoly region in either of them. Additionally, since i) demand is not affected by the number of firms in a market, and ii) if price depends only on the number of firms in the market (as in the Salop model presented in Section 3, then I can rewrite W as:

$$W = \underbrace{(cs[1] - cs[2])}_{\text{Per Consumer Loss in CS from Monopoly}} \times \underbrace{\mathbf{E}\sum_{t=0}^{\infty}\beta^t D^*_{mt}\left[1(N^M_{mt} = 1) - 1(N^{NM}_{mt} = 1)\right]}_{\text{Demand Weighted NPV of Additional Years of Monopoly due to the Merger}} \tag{16}$$

where $cs[N]$ is the per consumer surplus in the market with N firms. Note that this expression is the period per consumer loss due to monopoly, multiplied by the demand weighted net present value of additional years of monopoly due to the merger. In what follows, I focus on the computation of the second term in equation 16: the net present value of market structure in the merger and no-merger worlds, as the empirical IO literature has typically been able to provide ample guidance on how to compute the first term in equation 16: the static loss in consumer surplus due to monopoly.

Table 7 shows the expected net present value of market structure using a 5% discount rate, both for the world in which the merger occurred and did not occur. I show results using the no-effect and random effect specifications, as well as the random effect specification where I weight observations using demand $D^*_{mt} = \exp(d_{mt} + \mu_m + \nu_{mt})$ as in equation (16).

The no-effect specification predicts monopoly for 13.6 years in NPV after the merger versus 9.4 NPV years without the merger, a net effect of 3.2 years in NPV (equivalent to 3 to 4 years). Note that this small effect of a merger is driven by the prediction that even in the absence of a merger, the market would quickly become a monopoly. In contrast, the random effect model predicts 12 NPV years of monopoly following a merger, versus 4.2 years of monopoly without a merger. This is net effect of 7.8 years in NPV or between 8 and 9 actual years.

Table 7 also highlights the differences between the random effect and no-effect specifications. In the random effect world, the number of firms rarely strays from 1 or 2, while in the no-effect world the number of firms in the market sloshes around, with a substantial probability of ending up with either no firms or more than two firms in the same market.

Finally, the demand-weighted computation of the effect of a merger shows a substantially different picture. In both the merger and no-merger worlds, there are at least 3 firms for 10.2

NPV of Plants in market*		No Effects	
	Merger⋄	No Merger⋄	Difference
0	4.06	4.06	0.00
1	13.58	9.41	4.17
2	0.88	5.04	-4.17
3+	0.02	0.02	0.00
		Random Effects	
	Merger	No Merger	Difference
0	0.02	0.02	0.00
1	11.97	4.17	7.80
2	5.58	13.38	-7.80
3+	0.89	0.89	0.00
	Random Effects Demand Weighted†		
	Merger	No Merger	Difference
0	0.00	0.00	0.00
1	2.47	0.26	2.21
2	5.82	8.03	-2.21
3+	10.17	10.17	0.00

*: The net present value is computed using a 50 year simulation with a 5% discount rate. For instance, the net present value of zero firms in the Merger world is given by $\mathbf{E}\sum_{t=1}^{50}\beta^t 1(N_{mt}^M = 0)$. $\diamond$: The merger world refers to the simulate where the initial number of firms is one, i.e. $N_{m0}^M = 1$, and the no-merger world has two firms in it initially. †: Demand Weighted indicates the observations are weighted by demand $D_{mt}^* = \exp(d_{mt} + \mu_m + \nu_{mt})$, i.e. the demand weighted net present value of zero firms in the merger world is given by $\mathbf{E}\sum_{t=1}^{50}\beta^t D_{mt}^* 1(N_{mt}^M = 0)$

Table 7: Counterfactual: Merger and No-Merger Comparison

NPV years. This occurs because markets with more than 2 firms account for a disproportionate share of consumers. Following a merger, there is monopoly for 2.5 years in NPV, versus 0.3 years in NPV without a merger, yielding a net effect of 2.2 years in net present value. While a merger causes monopoly for between 8 and 9 years, the average consumer sees monopoly for only 2 to 3 years. Again, this is due to the large skewness of demand, whereby the largest markets account for the vast majority of consumers, and in these high demand markets the is a fast entry response after the merger. Thus the exact markets where we might worry about mergers the most: large and growing markets, are those where the entry response is fastest.[20]

[20] A caveat to the small effect of a merger on correctly demand-weighted consumer surplus is that much of the skewness of demand is generated not only by the observed number of construction workers, but also by the skewness of the unobserved demand components ϵ and μ which are each log-normal. Thus one should be cautious about interpreting the demand-weighted numbers since they depend strongly on the tails of the log-normal distribution.

7.2 Market Size and Merger Effects

To address the question of which mergers may be particularly damaging, Figure 5 displays merger effects for different levels of initial demand d_{m0} and for different value of the market random effect μ_m. I plot the net present value of additional years of monopoly on the vertical axis and the initial level of log construction demand on the horizontal axis. The three lines correspond to the predictions for three different distributions of μ, corresponding to the posterior distribution $\Pr[\mu_m|\{N_{mt}, d_{mt}\}_{t=0}^{T}]$ for markets with on average 0.7 to 1.3 plants (henceforth the 1 plant average markets), 1.7 to 2.3 plants (henceforth the 2 plant average markets) and 2.7 to 3.3 plants (henceforth the 3 plant average markets).

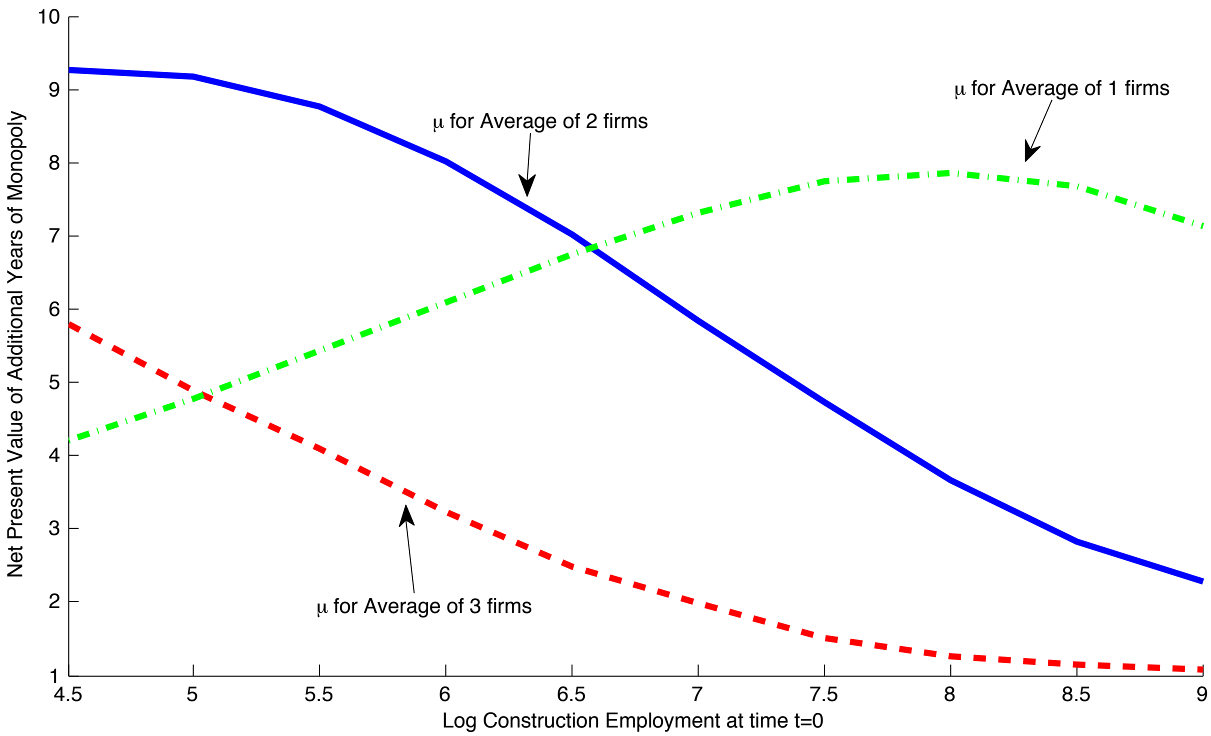
Using the random effects μ typical of a market with on average 3 plants in it, I find the effect of a merger from duopoly to monopoly is fairly short lived, at about 2 years in net present value if log construction employment at the time of the merger is above 6.8. For these types of markets, demand (both measured and coming from the market random effect) is high enough so that eventually 3 firms will enter the market, and thus the entry of a second competitor following a merger will be quite rapid. For a market with an average of 1 plant, the effects of a merger from duopoly to monopoly are short lived when demand is relatively low. For instance, if log construction employment at the time of the merger is 5.0 then the merger will generate 5 years of monopoly. This small effect is due the fact that these relatively low demand markets trend towards monopoly, and thus in the scenario without a merger the second competitor quickly exits.

One can see that a merger has the most long-lasting effects when for a level of demand in the middle of the stasis zone. With either very high or very low demand, the number of firms rapidly increases in the merger world, or decreases in the no-merger world. Thus one should worry about mergers that take place in markets with high enough demand to permit a duopolist incumbent to continue operating, but low enough so that a duopolist does not find it profitable to enter; i.e., $D_2^E \geq D^* > D_2^C$.

8 Conclusion

This paper discusses the role of entry in blunting the long-run damages from mergers. Using data on isolated ready-mix concrete markets, I estimate a simple dynamic model of entry and exit. The estimates of this model exhibit a large stasis zone, i.e. a gap between the demand threshold for entry and the demand threshold for continuation, which are evidence of large sunk entry costs. However the magnitude of this stasis zone is substantially reduced when I include market fixed-effects, indicating the importance of separating sunk costs from unobserved market heterogeneity.

Because of this large stasis zone, the preferred specification indicates that merger from duopoly to monopoly inflicts monopoly for between 9 and 10 years, generating damages that



Note that for markets with one firm on average I choose markets with an average number of firms between 0.7 and 1.3 and pull the posterior distribution on μ denoted $\Pr[\mu_m|\{N_{mt}, d_{mt}\}_{t=0}^{T}]$ for these markets to do the simulation. Likewise for markets with 2 firms on average, I pull the markets with an average number of firms between 1.7 and 2.3 and for 3 firms, an average of between 2.7 and 3.3. The net present value of additional years of monopoly is the difference in the net present value of the number of periods with a monopolist (using a discount rate of 5%) with an initial number of firms equal to 1 versus an initial number of firms equal to 2, over a 50 year period.

Figure 5: Effect of a merger on the additional years of monopoly (in net present value term) depending on initial demand d_0 and market random effect μ_m

are 7.8 times the damages from one year of monopoly. Yet, from an aggregate welfare perspective the effects of mergers are small, since markets with many consumers have a faster entry reaction than the typical market.

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 9 years of market power with a long-term flow of efficiency gains. For the ready-mix concrete industry entry is not nearly quick enough to obviate scrutiny from the antitrust authority, and the need to quantify the effect of post-merger market power on consumer surplus.

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A Constructing Isolated Markets

I choose a market to be the area surrounding a town in the Continental United States. The data on these towns, or more accurately Census "places" comes from the U.S. Census bureau and can be found at `http://www.census.gov/geo/www/cob/pl_metadata.html#gad`. 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: 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 had 415 inhabitants as of 1990. These small towns are unlikely to support most types of construction 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.

Second, I need to check if a town is isolated. To do this I have coded a routine in ARCVIEW that counts the number of towns that are 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 8 presents the number of isolated towns in the Continental United States. As a robustness check, I have re-run the estimates of the SBR model using these different criteria for the degree of isolation of a town.

Third, 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 that is 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": another town within 1 mile.

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

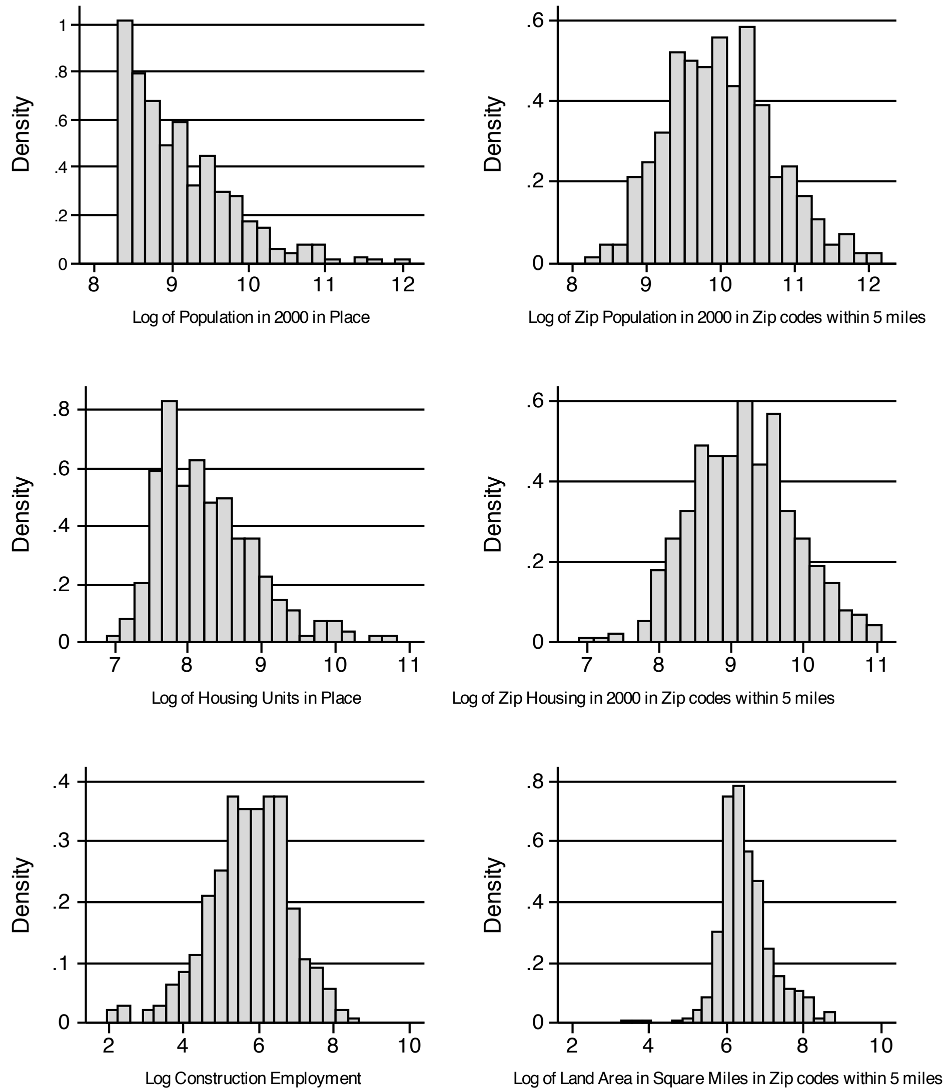
Table 8: Isolated Towns

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 that are 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 that is 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 Additional Tables and Figures



Note: Place refers to the isolated town itself, while Zip refers to the zip codes within a 5 mile distance of the town.

Figure 6: Distribution of Town Size

Dependent Variable: Number of Plants in a Market	I	II	III	IV	V	VI
Market Selection						
All	X					
Zip area below 850 square miles		X				X
No Highway			X			
More than 70% population of zip codes (within 5 miles) in place				X		X
No cities of 2000 people within 40 miles					X	
Log Construction Employment	0.293	0.368	0.240	0.211	0.061	0.448
	(0.05)	(0.06)	(0.05)	(0.12)	(0.06)	(0.13)
Competitor 1	-1.080	-1.073	-1.090	-1.079	-1.222	-1.210
	(0.06)	(0.07)	(0.07)	(0.17)	(0.21)	(0.14)
Competitor 2	-0.890	-0.970	-0.904	-1.259	-0.953	-1.459
	(0.08)	(0.09)	(0.09)	(0.27)	(0.21)	(0.20)
Competitor 3	-0.821	-0.953	-0.851	-0.776		-0.843
	(0.10)	(0.14)	(0.13)	(0.43)		(0.35)
Competitor 4	-0.914	-1.046		-0.128		-0.271
	(0.22)	(0.34)		(0.03)		(0.15)
Competitors above 4	-0.703	-0.560	-1.673	-0.594	-1.108	-0.679
	(0.10)	(0.08)	(0.38)	(0.15)	(0.22)	(0.15)
Entry Parameter γ^E	-2.947	-3.305	-2.629	-2.734	-1.989	-3.648
	(0.26)	(0.32)	(0.27)	(0.64)	(0.38)	(0.72)
Sunk Cost Parameter γ^S	3.564	3.550	3.609	3.837	3.990	3.781
	(0.07)	(0.07)	(0.07)	(0.22)	(0.19)	(0.18)
Log-Likelihood	-1791.8	-1319.8	-1256.3	-251.1	-283.7	-294.0
Observations	5321	3814	3821	1008	1220	1056
Markets	445	319	320	84	102	88

Table 9: SBR Model Estimates Market Definition

Dependent Variable Number of Plants in a Market	I	II	III	IV	V	VI	VII
Log Construction Employment	0.293					0.280	0.178
	(0.05)					(0.05)	(0.05)
Log of Housing Units		0.237				-0.059	
		(0.08)				(0.36)	
Log of Zip Housing in 2000			0.421				0.079
			(0.07)				(0.41)
Log of Population in 2000				0.232		0.096	
				(0.08)		(0.36)	
Log of Zip Population in 2000					0.407		0.172
					(0.07)		(0.40)
Competitor 1	-1.080	-1.020	-1.069	-1.019	-1.066	-1.080	-1.095
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Competitor 2	-0.890	-0.842	-0.899	-0.842	-0.898	-0.891	-0.911
	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)
Competitor 3	-0.821	-0.792	-0.830	-0.795	-0.833	-0.824	-0.840
	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)	(0.10)	(0.10)
Competitor 4	-0.914	-0.870	-0.940	-0.872	-0.944	-0.919	-0.952
	(0.22)	(0.20)	(0.22)	(0.20)	(0.22)	(0.21)	(0.21)
Competitors above 4	-0.703	-0.674	-0.735	-0.681	-0.751	-0.711	-0.747
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.11)
Entry Parameter γ^E	-2.947	-3.233	-5.149	-3.391	-5.356	-3.264	-4.737
	(0.26)	(0.66)	(0.68)	(0.74)	(0.73)	(0.79)	(0.78)
Sunk Cost Parameter γ^S	3.564	3.539	3.571	3.544	3.573	3.564	3.575
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Log-Likelihood	-1791.8	-1840.8	-1794.2	-1841.4	-1795.9	-1791.2	-1778.0
Observations	5321	5321	5321	5321	5321	5321	5321
Markets	445	445	445	445	445	445	445

Standard Errors Clustered by market.

Table 10: SBR Model Estimates: Different Measures of Demand

Dependent Variable:	No Effect			Random Effect		
Number of Plants in a Market	I	II	III	IV	V	VI
Log Construction Employment	0.29	0.28	0.27	0.59	0.71	0.70
	(0.05)	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)
1 competitor	-1.08	-1.14	-1.12	-2.79	-3.04	-3.07
	(0.08)	(0.06)	(0.07)	(0.01)	(0.02)	(0.02)
2 competitor	-0.89	-0.74	-0.91	-2.41	-1.26	-1.37
	(0.06)	(0.08)	(0.08)	(0.02)	(0.02)	(0.02)
3 competitor	-0.82	-1.09	-0.82	-1.91	-1.66	-1.13
	(0.10)	(0.16)	(0.11)	(0.02)	(0.02)	(0.05)
4 competitor	-0.91	-1.09	-1.87	-1.91	-1.44	-1.41
	(0.22)	(0.27)	(0.53)	(0.08)	(0.04)	(0.04)
Competitors above 4	-0.70	-0.79	-0.98	-1.21	-0.92	-0.88
	(0.10)	(0.12)	(0.17)	(0.06)	(0.04)	(0.04)
Entry Parameter γ^E	-2.95	-2.83	-2.82	-4.51	-5.38	-5.35
	(0.26)	(0.25)	(0.82)	(0.19)	(0.15)	(0.15)
σ_μ				2.44	2.59	2.60
				(0.01)	(0.01)	(0.01)
Sunk Cost Parameter γ_0^S	3.56	3.45	3.46	4.63	5.20	5.23
	(0.07)	(0.07)	(0.09)	(0.22)	(0.02)	(0.02)
Sunk Cost Parameter γ_1^S	-	0.80	0.37	-	-1.82	-1.66
More than 1 Firm$*$	-	(0.09)	(0.10)	-	(0.03)	(0.04)
Sunk Cost Parameter γ_2^S	-	-	1.53	-	-	-0.73
More than 2 Firm$*$	-	-	(0.25)	-	-	(0.07)
Observations	5321	5321	5321	5245	5245	5245
Markets	445	445	441	445	449	300
Log-Likelihood	-1791	-1746	-1712	-1306	-1267	-1264

Standard Errors Clustered by Market for columns I, II and III. $*$ Note that $\gamma^S = \gamma_0^S + \gamma_1^S 1(N_{mt} > 1) + \gamma_2^S 1(N_{mt} > 2)$.

Table 11: Non-Constant Gap between entry and continuation thresholds estimates

C Stationary and a Closed Form Solution for Entry and Exit Thresholds

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:

$$
\begin{aligned}
V(D,N) &= \sum_{t=0}^{\infty} \beta^t (\pi^V(D,N) - f) \\
&= \frac{Dg(N)}{1-\beta} - \frac{f}{1-\beta}
\end{aligned}
\tag{17}
$$

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

$$
\begin{aligned}
(1-\beta)V(D,N) = Dg(N) - f \\
&+ \underbrace{\left(\sum_{t=0}^{\infty} \frac{\beta^t}{1-\beta} D_t g(N_t) - Dg(N) \right)}_{\text{Deviation of variable profits}} \\
&- \underbrace{\left(\sum_{t=0}^{\infty} \frac{\beta^t}{1-\beta} f a_t - f \right)}_{\text{Deviation of fixed costs}}
\end{aligned}
\tag{18}
$$

As long as the market does not vary too much over time, the errors from the stationary approximation in equation (17) will be small. When I simulate the demand process, I find that the correlation between demand today D_{mt} and the net present value of demand over the next 50 years is 0.82, thus fairly high. As well, the correlation between the number of firms today N_{mt} and the net present value of the number of firms in the market is 0.91, so again a fairly high number. 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". [21]

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

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

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,

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

$$
(1-\beta)V(D,N) \approx c_1 Dg(N) + \sum_k c_k \phi^k(D,N) \tag{19}
$$

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.

taking logs, and combining terms I obtain:

$$\begin{aligned}\varepsilon_{mt} &\geq -\beta_1 \log(D_{mt}) - \sum_{k=1}^{N_{mt}} h(k) + \gamma^E + \gamma^S 1(N_{mt} > N_{mt-1}) \\ \varepsilon_{mt} &< -\beta_1 \log(D_{mt}) - \sum_{k=1}^{N_{mt}+1} h(k) + \gamma^E + \gamma^S 1(N_{mt} > N_{mt-1})\end{aligned} \tag{21}$$

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 $\varepsilon = \log(\epsilon)$.

D 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 Neyman and Scott (1948) and Heckman (1981) contaminates the remaining 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. Moreover, the bias attenuate the parameter estimates relative to their true values.

Algorithm 1 *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:

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

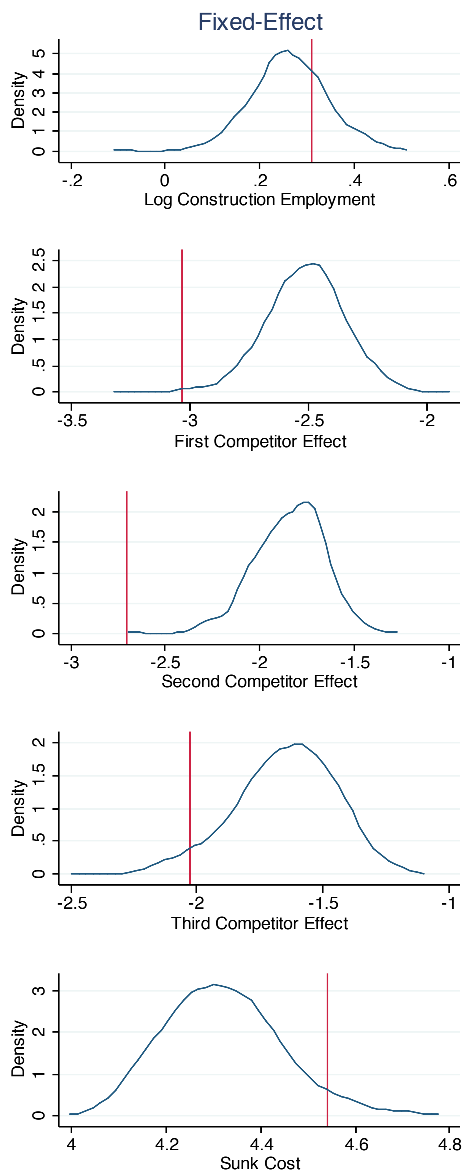
$$V^{\theta^0}(\epsilon_t^k D_t, N_{t-1}^k) < \phi + 1(N_t^k \geq N_{t-1}) \underbrace{(\psi - \phi)}_{\gamma}$$

where θ^0 are the estimates from column VI of Table 4 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).

Figure 7 shows the results of Monte-Carlo exercise. 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.

To further emphasize the small issue of bias with market fixed effects, I estimate the model using a 26 year panel based on data from the Longitudinal Business Database (henceforth LBD) from the Center for Economic Studies from U.S. Census. The data used in the LBD has the same source as data as that in the Zip Business Pattern, the master business register maintained by the IRS and Census, but is available from 1976 onwards. Table 12 finds similar results with a 26 year panel as with a 12 year panel. Moreover, even if the effects of competition are smaller and the sunk cost parameter γ^S is larger with the fixed effect model, hence closer to the no-effects model's estimates, it is hard to know if this is coming from the slow change of the market unobservable over time or an issue of consistency of the fixed effect estimator.



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 4 on page 18.

Figure 7: Monte-Carlo Estimation of Sunk Cost Entry Model with market level fixed effects.

	I	II	III	IV
	Sunk Cost Model		Fixed Effect Model	
	Public Data	RDC Data	Public Data	RDC Data
Log Construction Employment	0.29	0.21	0.30	0.32
	(0.05)	(0.04)	(0.20)	(0.12)
1 competitor	-1.08	-1.14	-3.03	-2.66
	(0.06)	(0.04)	(0.23)	(0.14)
2 competitor	-0.89	-0.84	-2.70	-2.17
	(0.06)	(0.07)	(0.25)	(0.17)
3 competitor	-0.82	-0.59	-2.03	-1.55
	(0.10)	(0.11)	(0.25)	(0.18)
4 competitor	-0.91	-0.50	-2.15	-2.50
	(0.22)	(0.14)	(0.54)	(0.37)
Competitors above 4	-0.70	-0.58	-1.39	-2.16
	(0.10)	(0.08)	(0.09)	(0.25)
Year Fixed Effects		X		X
Entry Parameter γ^E	-2.95	-3.18		
	(0.26)	(0.23)		
(Average Entry Parameter $\bar{\gamma}^E$)			-3.20	-2.00
(S.D. of Entry Parameter γ^E)			2.17	1.73
Sunk Cost Parameter γ^S	3.56	3.54	4.54	4.63
	(0.07)	(0.04)	(0.22)	(0.15)
Observations	5321	10155	3612	10155
Markets	445	445	300	300
Years	12	23	12	23
Log Likelihood	-1791	-3517	-702	-1817

Table 12: SBR Model estimates with and without fixed-effects on the Zip Business Patterns Sample (1994-2006) and on the LBD Sample (1976-1999).