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

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October 13, 2013

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 use the model of Abbring and Campbell (2010) to estimated a simple "reduced-form" specification of demand thresholds for entry and for exit. These thresholds, along with the process for demand, are estimated using data from the ready-mix concrete industry, which is subject to fierce local competition. 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.

*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, John Asker, Ambarish Chandra and Larry White for their insights, Gautam Gowrisankaran and Lanier Benkard for discussions, and many seminar audiences. 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. Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.

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

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.

I look at the effect of mergers in the ready-mix concrete industry, that has fierce competition between firms, and very local markets due to high transportation costs. Ready-mix concrete plants have substantial sunk entry costs. Moreover, horizontal mergers are a recurrent issue.

The question I address in this paper is the speed that a market which has had a merger to monopoly reverts to competition.[1] Using data on 449 isolated ready-mix concrete markets, I estimate the demand thresholds required for a new firm to enter, and the level of demand required for an incumbent to continue operating. Using these demand thresholds, as well as the process for demand, my simulations find that a merger from duopoly to monopoly will induce between 9 and 10 years of monopoly in the market.

Merger Policy

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. Indeed, the possibility of post-merger entry is well understood since at least the earlier literature on barriers to entry (Demsetz, 1982; Bain, 1956).

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

[1] In previous work using data on concrete prices (Collard-Wexler, 2013), 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.

> *that requires significant sunk costs must evaluate the profitability of the entry on the basis of long term participation in the market...*

However, the literature that evaluates the effects of a merger has focused primarily on the static exercise of market power, such as the effect a merger on prices (see, for instance the summary of this literature in Davis and Garcés (2009)). Thus, there is virtually no guidance as to empirical evidence on the persistence of the effect of a merger on market structure.

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, indicating the importance of competition for this industry. 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.

Overview of the approach

To justify the empirical approach in this paper, I use Abbring and Campbell (2010)'s model of oligopoly industry dynamics. They show conditions under which entry and exit decisions can be expressed in terms of demand thresholds for entry and continuation. Similarly to Bresnahan and Reiss (1994), I estimate these demand thresholds, which are a "reduced-form" characteristic of the entry and exit model. Sunk entry costs create a wedge 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.

These demand thresholds are simple to estimate: they reduce to the problem of estimating an ordered response model. Moreover, I allow for serial correlation of the unobserved components of demand, so that there can be persistent unobserved differences between markets. Ultimately, I estimate a multivariate ordered probit using the GHK algorithm.

The data on entry and exit patterns in the ready-mix concrete sector comes from the U.S. Census Bureau's Zip Business Pattern database for 1994 to 2006. I define a market as the zip codes surrounding "isolated" towns, that is towns that are more than 20 miles from any other town.

I find a large differences in the entry and continuation thresholds.[2] This gap between these thresholds will slow the response of an industry to mergers, reducing the number of competitors for a long time. Using estimates of these demand thresholds as well as the process for demand, 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.[3]

Related Literature

By far the most related paper is the work of Benkard, Bodoh-Creed and Lazarev (2009), 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 (2009) simulate the dynamic effects of several proposed mergers in the airline industry. Indeed, I will also show results using their Conditional Choice Probability (henceforth CCP)-based approach.

In prior work (Collard-Wexler, 2013), I have structurally estimated a dynamic entry and exit model of the ready-mix concrete industry using a CCP approach. These estimates show large sunk costs and important effects of competition on the profitability of the firm. I use the reduced-form demand thresholds in this paper, since this approach allows for serially correlated unobservables. This is critical for the counterfactual of looking at the effect of changes of market structure, since the demand shock process – both observed and unobserved – is essential to evaluating the speed of post merger entry. I do not want to conflate unobserved fixed differences between markets, with unobserved changes in the profitability within a market.

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] While in the absence of these sunk costs, there is not reason why the these thresholds should differ, for a given level of sunk costs, the gap between entry and exit thresholds can be amplified by other factors such as the option value generated by demand uncertainty.

[3] I use simulations to assess the duration of the effects of a merger on market structure. This effect cannot be directly estimated by following markets after a merger, since mergers to monopoly are prohibited in the very industries where entry is not guaranteed within a two-year period, and where market power may impose substantial damage to consumers.

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.[4]

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 use the Last-In First-Out (henceforth LIFO) equilibrium model developed by Abbring and Campbell (2010). The unique equilibrium to the entry-exit game will be characterized by demand thresholds. These demand thresholds will form the basis for my

[4]For instance, Concrete Plant Park in New York City is an abandoned concrete plant turned into a park.

estimation strategy, so a reader interested in the details of these estimates can skip to Section 5.

3.1 Model Setup

In each period t, the market is characterized by a demand level D_t, and the set of firms in the market. Each firm $j = 1, \cdots, J$ may either be a potential entrant – call these potential entrants $\mathcal{E}_t$ – or incumbents denoted by $\mathcal{C}_t$. I will refer to the number of incumbent firms as simply N_t. Thus, the state of market s_t is $s_t \equiv \{\mathcal{E}_t, \mathcal{C}_t, D_t\}$.

The timing of the game in period t is as follows, starting in state s_{t-1}:

1. Demand D_t evolves following a first-order markov process $Q(\cdot|D_{t-1})$.
2. Firms earn period profits $\Pi(D_t, N_{t-1})$, which are determined by the number of firms in the market, and the size of the market. I require that variable profits are multiplicatively separable in market size: $\Pi(D_t, N_{t-1}) = \frac{D_t}{N_{t-1}}\pi(N_{t-1}) - \kappa$, which depend on profits per consumer $\pi(N)$ – that is a function of the number of firms in the market, but not on market size – and the number of consumers served by each firm $\frac{D}{N}$, and fixed costs κ. This form of the profit function is satisfied by many models of competition in industrial organization with identical firms.
3. Firm $j = 1, \cdots, J$ move sequentially, with firm $j = 1$ moving first, $j = 2$ moving second, and so on. If a firm is an incumbent, then they choose to exit or not, denoted $\chi_j \in \{0, 1\}$, and receive a scrap value of ψ if they exit. If a firm is a potential entrant, then they can choose to enter, denoted $\chi_j^{\mathcal{E}} \in \{0, 1\}$, and pay entry fee ϕ. These entry and exit decisions yield a new set of incumbents $\mathcal{C}_t$ and potential entrants $\mathcal{E}_t$.[5]

Firm j's value function $V_j^{\mathcal{C}}$, if j is an incumbent firm, is given by the usual Bellman equation:

$$V_j^{\mathcal{C}}(s_t) = \int_{D_{t+1}} [\pi(D_{t+1}, N_t) + \beta \max_{\chi_j \in \{0,1\}} \mathbb{E}\chi_j \left(\phi + V_j^{\mathcal{E}}(s_{t+1})\right) + (1 - \chi_j)\left(V_j^{\mathcal{C}}(s_{t+1})\right)] Q(D_{t+1}|D_t) dD_{t+1} \tag{1}$$

where the expectation operator $\mathbb{E}$ is particular, since at time t, firm j knows both

[5]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.

demand D_{t+1} and the entry and exit choices of firms $1, \cdots, j-1$ that have moved before it.

Likewise potential entrants have the value function:

$$V_j^{\mathcal{E}}(s_t) = \beta \int_{D_{t+1}} [\max_{\chi_j^{\mathcal{E}} \in \{0,1\}} \mathbb{E}(1-\chi_j^{\mathcal{E}})V_j^{\mathcal{E}}(s_{t+1}) + \chi_j^{\mathcal{E}} \left(-\psi + V_j^{\mathcal{C}}(s_{t+1})\right)] Q(D_{t+1}|D_t) dD_{t+1} \tag{2}$$

3.2 Demand Thresholds

The AC model requires assumptions both on strategies and on the process for demand to characterize the equilibrium policies in this game:

A1. Firms use **LIFO** strategies which default to inactivity: the firms that enter the earliest are the firms that exit last.

A2. Stochastic monotonicity: to ensure higher demand today implies a higher distribution of demand tomorrow, expected demand $E[D_t|D_{t-1}]$ must be increasing in D_{t-1},

A3. The innovation error in demand, $u_t \equiv D_t - E[D_t|D_{t-1}]$ must be independent of D_{t-1}.

A4. The demand process $Q(\cdot|D_t)$ must be continuous.

A5. The innovation u in the demand process must be drawn from a concave distribution.

LIFO Equilibrium

If assumption A1 holds, firms use **LIFO** strategies which default to inactivity; firms that enter the earliest are the firms that exit last. 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%.[6] Furthermore, the absence of firm-level shocks also rules out simultaneous entry and exit. With yearly data, and markets with on average less than 3 incumbents, in only 5% of market-years is there simultaneous entry and exit. Moreover, dropping market-year with simultaneous entry and exit does not significantly change my estimates.

Given the **LIFO** assumption, Proposition 1 of Abbring and Campbell (2010) shows that the markov-perfect equilibrium of the entry and exit game will be unique. This means that – in contrast to the rest of the literature on dynamic oligopoly (see Besanko et al. (2010) for instance) – the model generates a unique prediction, considerably

[6]See Collard-Wexler (2013) for a discussion of the measurement of entry and exit in this industry.

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. Moreover, since the ordering of moves – by either continuers or entrants – does not change over time, this combined with the LIFO assumption, ensures that the number of plants in the market N_t is a sufficient statistics to describe the set of entrants $\mathcal{E}_t$ and continuers $\mathcal{C}_t$. Thus under these LIFO strategies, the state at the end of the period can be expressed as $s_t = \{D_t, N_t\}$.

Demand Thresholds

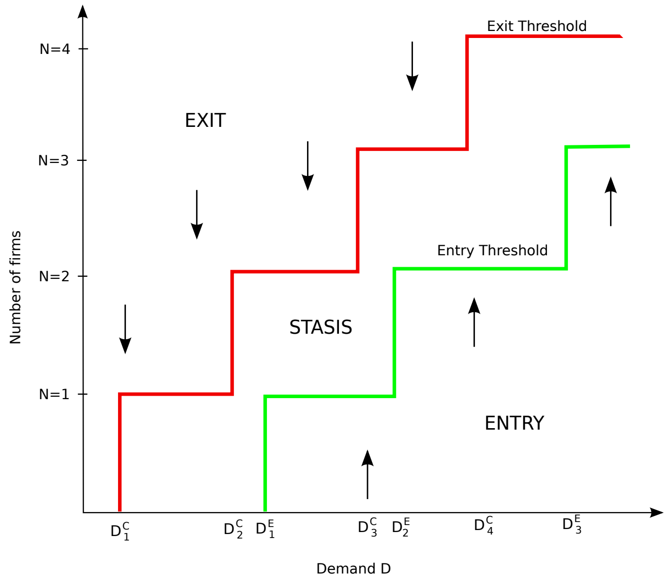
There is a strong intuition that entry and exit decisions will be in demand thresholds; i.e., there is a level of demand above which a single firm enters, and a higher level of demand above which a second firms enters and so on. Likewise for continuation, there will be a level of demand below which an nth firm will exit. Formally, given the LIFO strategies employed by firms, one can label j such that $j = 1$ indicates the oldest incumbent, $j = 2$ the second oldest incumbent, and so on. Exit decisions are in thresholds if $\chi_j(D_{t+1}, N_t) = 1(D_{t+1} \leq D_j^C)$, i.e. a N^{th} incumbent continues if and only if $D > D_N^C$. Likewise entry decisions are in thresholds if $\chi_j^{\mathcal{E}}(D_{t+1}, N_t) = 1(D_{t+1} > D_j^E)$.

Notice that this means that I can characterize the stochastic process for market structure as coming from the process for demand, $D_{t+1} \sim Q(\cdot|D_t)$, and the following conditions on the number of firms N:

$$\begin{aligned} D_{t+1} &> D_{N_t+1}^E \text{ , entry} \\ D_{t+1} &\leq D_{N_t}^C \text{ , exit} \\ D_{N_t+1}^E \geq D_{t+1} &> D_{N_t}^C \text{ , stasis} \end{aligned} \tag{3}$$

Figure 1 encapsulates the predictions of the model by presenting the transition dynamics for the industry, along with the entry and continuation thresholds. The band between the continuation and entry threshold, which indicates level of demand where there will be no change in the number of firms, is the stasis zone. In section 5, I will estimate these entry and continuation thresholds.

Without sunk costs, 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. Notice that the larger the stasis zone, the more likely a merger will have long lasting effects, since when a merger knocks a firm out of the market, it is more probable that the market remains in the stasis zone.



Note: D_1^E represents the level of demand required for 1 firm to enter, and D_2^C represents the level of demand required to keep two existing firms in the market.

Figure 1: Entry and Continuation Thresholds

Conditions for Entry and Exit Decisions in Demand Thresholds

Under assumptions A2, A3, A4, and A5 on the process for demand $Q(\cdot|D_{t-1})$, Proposition 4 in Abbring and Campbell (2010) states that entry and exit decisions will be in demand thresholds. Monotonicity of the demand process, which will be construction employment, is easily satisfied. Indeed, the number of construction employees in the past year predicts higher construction employment this year. However, the conditions on concavity is more difficult to check. As well, larger markets have a larger variance of the innovation error, which is to expected as changes in demand are proportional to current demand. For the task at hand, what these conditions are ruling out is the following case: a first firm enters above 500 construction employees, but would not enter between 750 and 1,000 construction employees because in these markets are more likely to see duopoly in the future. In other words, the entry policy is not monotonic with respect to demand. These policies are ruled out by Proposition 4.

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.

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 concrete cannot be shipped from outside. This allows me to abstract from competitors that are located in neighboring towns.

Concrete is well suited to the isolated market approach as concrete does not travel between adjacent markets. This is because 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 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,

[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`.

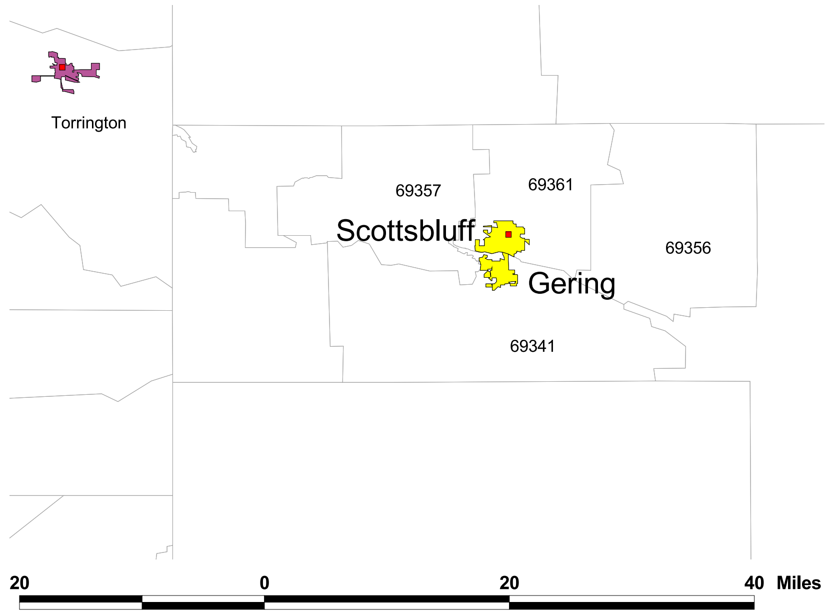


Figure 2: Typical Isolated Town and Zip Codes: Scottsbluff/Gering, Nebraska, and Zip codes 69357, 69341, 69356, 69361.

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. However, using confidential data from the Census RDC, it turns out that very few plants within a market have the same owner. Thus, I use plant and firm interchangeably. Moreover, in small towns multi-plant 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 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.

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

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 A.1 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.

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, 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.

Table 1: Summary statistics

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 $y_{m,t} - \bar{y}_m$.

Table 2: Summary Statistics by Market Structure

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

Panel B: 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

5 Econometric Model

In this section, I will estimate the entry and continuation thresholds, and the process for demand $Q(\cdot|D_t)$, using maximum likelihood.

Certain 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 demand for concrete across markets that are difficult to capture with observable demand shifters. True demand D_t^*, which is the demand in the model that I discussed in section 3, is equal to $D_t^* = D_t + \epsilon_t$, where ϵ_t is the unobserved component of demand and D_t is the observed components of demand. Notice, however, that for every market to have the same underlying demand thresholds D_N^E, and D_N^C, the process for demand $Q(\cdot|D_{t-1})$ must the same in every market.

The number of firms in a market m at time t, denoted $N_{m,t}$, must lie between the entry and continuation thresholds. Thus,

$$D_{m,t} + \epsilon_{m,t} > D^E_{N_{m,t}} 1(N_{m,t} > N_{m,t-1}) + D^C_{N_{m,t}} 1(N_{m,t} \leq N_{m,t-1})$$
$$D_{m,t} + \epsilon_{m,t} \leq D^E_{(1+N_{m,t})} 1(N_{m,t} \geq N_{m,t-1}) + D^C_{(1+N_{m,t})} 1(N_{m,t} < N_{m,t-1}).$$

I define the gap between entry and continuation thresholds as $\gamma^S(N) \equiv D_N^E - D_N^C$. As well, I re-express $D_N^E \equiv \sum_{k=1}^N h(k)$, where $h(k)$ represents the increment in demand thresholds between $k-1$ and k firms.[9]

To reduce the number of parameters that I need to estimate, and will I present estimates where the difference between entry and exit thresholds is either a) constant, i.e. $\gamma^S(N) = \gamma_0^S$, or b) linearly varying with demand $\gamma^S(N) = \gamma_0^S + \gamma_1^S N$. To accommodate multiple components of demand, such as population and construction employment, I use a single index of demand $D_{m,t} = X_{m,t}\beta$.

Thus the thresholds become:

$$\begin{aligned} \epsilon_{m,t} &\geq -X_{m,t}\beta + 1(N_{m,t} > N_{m,t-1})\gamma^S(N_{m,t}) + \sum_{k=1}^{N_{m,t}} h(k) \equiv \bar{\pi}(N_{m,t}, N_{m,t-1}, X_{m,t}, \theta) \\ \epsilon_{m,t} &< -X_{m,t}\beta + 1(N_{m,t} \geq N_{m,t-1})\gamma^S(N_{m,t}) + \sum_{k=1}^{1+N_{m,t}} h(k) \equiv \underline{\pi}(N_{m,t}, N_{m,t-1}, X_{m,t}, \theta) \end{aligned} \tag{4}$$

where the vector of parameters is denoted $\theta \equiv \{\beta, \gamma^S(\cdot), h(\cdot)\}$. This means that my

[9] This change in variables in mainly done because there is larger variance in the demand thresholds, but the increments of these demand thresholds are precisely estimated.

estimating equations will compute the probability that $\epsilon_{m,t}$ is in between $\bar{\pi}$ and $\underline{\pi}$:

$$
\begin{aligned}
&\Pr(N_{m,t}, N_{m,t-1}, X_{m,t}, \theta) \\
&= \begin{cases} \Pr\left(\underline{\pi}(N_{m,t}, N_{m,t-1}, X_{m,t}, \theta) \leq \epsilon_{m,t} < \bar{\pi}(N_{m,t}, N_{m,t-1}, X_{m,t}, \theta)\right) & \text{if } N_{m,t} > 0 \\ \Pr\left(\epsilon_{m,t} < \bar{\pi}(N_{m,t}, N_{m,t-1}, X_{m,t}, \theta)\right) & \text{if } N_{m,t} = 0 \end{cases}
\end{aligned} \tag{5}
$$

In what follows, it will be convenient to assign $\underline{\pi}(N_{m,t}, N_{m,t-1}, X_{m,t}, \theta) \equiv -\infty$ if $N_{m,t} = 0$, so that I not need to keep track two separate cases, and just look at $\Pr(\underline{\pi} \leq \epsilon_{m,t} < \bar{\pi})$.

5.1 Serially Correlated Unobservables

If one assumes $\epsilon_{m,t}$ is and i.i.d. variable which is distributed as a $\mathcal{N}(0,1)$, then this model can be estimated by maximum likelihood almost as if it were an ordered probit. Indeed, equation (5) differs from an ordered probit such as in used in Bresnahan and Reiss (1991) only in the inclusion of the $\gamma^S(\cdot)$ term.

I have a panel of markets, so the assumption that $\epsilon_{m,t}$ is independent of $\epsilon_{m,t-1}$ 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.

Instead, I assume that $\epsilon_{m,t}$ follows an autoregressive process with i.i.d shocks of the form:

$$
\begin{aligned}
\epsilon_{m,t} &= \mu_{m,t} + \eta_{m,t} \\
\mu_{m,t} &= \rho\mu_{m,t-1} + \zeta_{m,t}
\end{aligned} \tag{6}
$$

where $\eta_{m,t} \sim \mathcal{N}(0,1)$, and $\zeta_m \sim \mathcal{N}\ (0, \sigma_\zeta)$.[10]

The likelihood will be based on the probability of a sequence of $\boldsymbol{\epsilon}_m \equiv \{\epsilon_{m,t}\}_{t=0}^T$'s:

$$
\begin{aligned}
&\Pr(\{N_{m,t}\}_{t=0}^T | \{X_{m,t}\}_{t=0}^T, \theta) = \\
&\int_{\mu_{m,0}} \Pr(\{N_{m,t}\}_{t=1}^T | \mu_{m,0}, \{X_{m,t}\}_{t=1}^T, N_{m,0}, \theta) \underbrace{\Pr(\mu_{m,0} | N_{m,0}, X_{m,0}, \theta)}_{\text{Initial Conditions}} d\mu_{m,0}
\end{aligned} \tag{7}
$$

where $\Pr(\{N_{m,t}\}_{t=1}^T | \mu_{m,0}, \{X_{m,t}\}_{t=1}^T, N_{m,0}, \theta)$, which I will refer to as the "ordered

[10]Note that it is possible to estimate the model without $\eta_{m,t}$, but it will computationally attractive later in the paper to do it this way in order to generate a full support probability of observing $N_{m,0}$ firms given a persistent effect $\mu_{m,0}$.

probit" component, is given by:

$$\begin{aligned}&\Pr[\underline{\pi}(N_{m,1},N_{m,0},X_{m,1},\theta)\le\epsilon_{m,1}<\bar{\pi}(N_{m,1},N_{m,0},X_{m,1},\theta),\cdots,\\&\underline{\pi}(N_{m,T},N_{m,T-1},X_{m,T},\theta)\le\epsilon_{m,T}<\bar{\pi}(N_{m,T},N_{m,T-1},X_{m,T},\theta)|\mu_{m,0}]\end{aligned} \tag{8}$$

Notice that equation (7) incorporates both the ordered probit components in equation (8), and the *initial conditions* distribution $\Pr(\mu_{m,0}|N_{m,0},X_{m,0},\theta)$ – the probability of the initial unobservable $\mu_{m,0}$ given the initial demand level and number of firms.

5.2 Initial Conditions

I assume that the number of firms observed at time zero, $N_{m,0}$, is drawn from the stationary distribution generated by the model. Stationarity is a plausible assumption the ready-mix concrete market, since this industry has been in operation for over eighty years, and there is little fluctuation in the aggregate number of concrete plants in the United States from 1963 to 2002.

The stationary distribution of $\mu_{m,0}$ is given by the usual AR(1) formula of $\mathcal{N}(0,\frac{\sigma_\zeta}{\sqrt{1-\rho^2}})$. However, *conditionally* on observing $N_{m,0}$ firms in a market with demand $X_{m,0}$, the distribution $\Pr(\mu_{m,0}|N_{m,0},X_{m,0},\theta)$, is not necessarily a normal.

I compute the stationary distribution by simulation. To do so, I need: i) the process for the unobservables ϵ, ii) the demand process for $X_{m,t}$ – estimated in the next subsection, and iii) the entry and exit model in equation (4). Since there is no closed form for this initial conditions distribution, I approximate it numerically. Appendix C shows the algorithm used to simulate $\Pr(\mu_{m,0}|N_{m,0},X_{m,0},\theta)$.

5.3 Demand Process

I estimate the demand process for observable demand $Q[D_{m,t}|D_{m,t-1}]$ from the data, using $d_{m,t}=\log(D_{m,t})$ (log construction employment):

$$d_{m,t}=\beta_0+\beta_1 d_{m,t-1}+\eta^d_{m,t}, \tag{9}$$

where $\eta^d_{m,t}\sim\mathcal{N}(0,\sigma_0+\sigma_1 d_{m,t})$. Q is estimated by maximum likelihood and Table 4 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. For the counterfactual, and to simulate the initial conditions distribution,

Table 4: Estimated Demand Transition Process

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

Note: Standard Errors Clustered by Market.

I use the demand process estimated in Column I.

5.4 Likelihood and GHK

The likelihood for this model is given by $\mathcal{L}(\theta) = \prod_{m=1}^{M} \Pr(\{N_{m,t}\}_{t=1}^{T} | \{X_{m,t}\}_{t=1}^{T}, \theta)$. Given the AR(1) process with i.i.d shocks in equation (6), the sequence of $\boldsymbol{\epsilon}_m = \{\epsilon_{m,t}\}_{t=1}^{T}$ has a $\mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma})$ distribution.[11] Thus I can approximate the probability in equation (7) using the GHK algorithm, as this is a truncated multivariate normal.[12] Moreover, I modify the GHK algorithm so that it incorporates the initial conditions problem. I provide additional details on the implementation of this procedure in Appendix C.

6 Results

Table 5 present the primary results of the entry-exit model. To make these results more informative about demand thresholds, I normalize the coefficient on construction employment to 1, which allows me to show entry and exit thresholds in terms of construction employment, and Panel B presents the implied entry and continuation thresholds

[11] Where $\boldsymbol{\Sigma}^2 = \boldsymbol{\Sigma}^2_{AR} + \boldsymbol{I}$ and $\boldsymbol{\Sigma}^2_{AR} = \begin{bmatrix} 1 & \rho & \rho^2 & \cdots & \rho^T \\ \rho & 1 & \rho & \cdots & \rho^{T-1} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \rho^T & \rho^{T-1} & \rho^{T-2} & \cdots & 1 \end{bmatrix}$.

[12] While GHK is most commonly used for correlated binary probit models, the logic behind the procedure is applicable to any multivariate normal that is truncated, such as an ordered probit.

Table 5: Sunk-Cost Bresnahan-Reiss Model Main Estimates

Panel A: Estimates

Dependent Variable	I	II	III	IV
Number of Plants in a Market	BR	Base	AR(1)	
Entry Parameter ($h(1)$)	0.62	-4.41	-0.66	-1.00
	(0.00)	(0.00)	(0.00)	(0.00)
First Competitor ($h(2)$)	-3.59	-3.14	-5.67	-6.91
	(0.00)	(0.01)	(0.00)	(0.00)
Second Competitor ($h(3)$)	-2.09	-2.63	-4.98	-4.60
	(0.00)	(0.01)	(0.00)	(0.00)
Third Competitor ($h(4)$)	-2.14	-2.46	-3.88	-2.62
	(0.01)	(0.02)	(0.07)	(0.10)
Fourth Competitor ($h(5)$)	-2.54	-2.85	-4.00	-1.73
	(0.04)	(0.08)	(0.32)	(0.23)
Competitors above 4 ($h(6)$)	-2.59	-3.76	-2.24	-0.47
	(0.09)	(0.18)	(0.19)	(0.08)
Gap Entry-Continuation γ_1^S		10.82	7.38	11.31
		(0.01)	(0.00)	(0.00)
Gap Entry-Continuation γ_2^S				-1.93
$\times$ Number of Firms				(0.01)
Unobservables				
σ_η	2.96	3.04	0.77	0.92
(i.i.d. shock)	0.00	(0.00)	(0.00)	(0.00)
σ_ζ			1.24	1.23
(AR(1) shock)			(0.00)	(0.00)
ρ			0.96	0.96
			(0.00)	(0.00)
Observations	5321	5321	5321	5321
Markets	445	445	445	445
Log Likelihood	6486	1832	1065	1006

Panel B: Implied Entry and Continuation Thresholds

Entry Threshold				
One Firm	-620	4410	660	1000
Two Firm	2970	7550	6330	7910
Three Firm	5060	10180	11310	12510
Four Firms	7200	12640	15190	15130
Five Firms	9740	15490	19190	16860
Continuation Threshold				
One Firm		-6410	-6720	-10310
Two Firm		-3270	-1050	-3400
Three Firm		-640	3930	-1470
Four Firms		1820	7810	2390
Five Firms		4670	11810	8180

Note: Column I and II show estimates with an i.i.d. process for ϵ, while Columns III and IV show an AR(1) – with i.i.d. shocks – process for ϵ. The coefficient on construction employment in thousands normalized to 1. Thus, using Column III's estimates, an entry parameter $h(1)$ of 0.66 implies that the entry threshold is 660 construction employees. In addition, $\sigma_\eta = 0.77$ would imply that the i.i.d. shock has variance of 770 construction employees.

for construction employment.[13]

Column I shows estimates where I set $\gamma^S(N) = 0$ 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 (in Column II), which predicts changes in market structure. Column III and IV shows estimates with an AR(1) process for the unobservable. In order, I will discuss the estimates of entry thresholds, the gap between entry and exit thresholds and the magnitude of unobservable shocks.

The entry threshold for a monopolist, $h(1)$, in Column III is 0.66. In other words, it takes 660 construction employees in order for a first firm to enter the market. However, to induce the next firm to enter, 5660 more construction employees are required. Thus the level of demand necessary to induce two firms to enter the market is much more than twice the level of demand needed to support a single entrant. In a static model of competition, this finding would be rationalized by profits per consumer falling quickly from monopoly to duopoly, and are consistent the Bertrand-like nature of competition in the ready-mix concrete industry. To induce a third and fourth firm, construction employment must rise by an additional 4980 and 3880 employees respectively.

Comparing the entry threshold estimates between Column II and III, I find that the increments to the demand thresholds $h(k)$ are about 80% higher in Column III's AR(1) estimates with serially correlated unobservable than in Column II's estimates with an i.i.d. unobservable. To the extent that 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 measured by $h(k)$ will be underestimated.

The magnitude of the stasis zone 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. In Column III, I estimate the magnitude of the stasis zone at 7,400 construction employees. This means that the level of demand required to induce a monopoly entrant $D_1^E = 660$ is in between the level of demand needed to maintain 2 or 3 competitors (since $D_2^C = -1050$ and $D_3^C = 3930$). These large estimated stasis zone are not too surprising since there is evidence for large sunk entry costs in the ready-mix concrete industry. Indeed, in interviews that I have done with ready-mix concrete producers

[13]The estimated model is akin to an ordered probit, and thus is identified up to a scaling factor. Instead of normalizing the variance of the unobservable to one, as is commonly done, I normalize the coefficient on construction employment.

in Illinois, I reckon 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. Moreover, work by Foster, Haltiwanger and Syverson (2008) finds that the prices that ready-mix concrete producers receive increase over the plant's lifetime, indicating building up a reputation in the market. This type of reputational capital is also entirely sunk.

This gap between entry and exit thresholds falls from 10,800 employees in Column II to 7,400 in Column III. The stasis zone, as measured by γ^S, is 30 percent larger in the i.i.d. model than in the AR(1) model. 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 i.i.d. model needs a very large stasis zone, and in particular requires $D_2^E > D \textit{ and } D_3^C < D$. In contrast, the AR(1) model can explain this pattern with resorting to a stasis zone, since the 3 firm market might have a much higher persistent unobserved demand μ than the 1 firm market.

Notice that the estimates in Column IV, which allow for the gap between entry and continuation thresholds to vary with the number of firms, show that this gap is larger for one firm (i.e. $D_1^E - D_1^C$), and falls for an additional number of firms. Thus there is a larger stasis zone for a single plant market, than a multiple plant market.

The i.i.d. unobservable η is quite large in Column II, at 3,000 thousand construction employees. However, once serial correlation is incorporated in Column III and IV, this number falls to 770. Indeed, the majority of the unobservable is serially correlated, not i.i.d., as the stationary standard deviation of μ, given by the AR(1) formula $\frac{\sigma_\zeta}{\sqrt{1-\rho^2}}$, is 4,400. This serially correlated unobservable is quite persistent as well, with an estimated autocorrelation coefficient of 0.96. Two examples of these highly persistent differences are the size of the road network, which uses a large amount of concrete, and the prevalence of basements in houses in a market.

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 ϵ is key.

6.1 Robustness

In Appendix B, I also present diagnostic regressions on demand covariates and market definition similar to Table 5, but which assume that the unobservable ϵ is an i.i.d. normal.

In Table B.1 I find that using construction employment as a demand measure yields better results than other measures of demand for ready-mix concrete, such as population, housing, or land area. There does not appear to be a strong aggregate component to demand, as including year dummies as a demand covariate do not change the results.

I also investigate alternative market definitions in Table B.2. I find that construction activity in zip codes that are within 10 and 20 miles of an isolated town – versus the 5 miles I use for the main results – have no additional impact on entry and exit of ready-mix concrete plants. As well, excluding markets which have unusually large zip codes (over of 850 square miles in surface area), or markets near cities or major highways, do not substantially change the estimates.

6.2 Marginal Effects

To illustrate the model's estimates I present a table of mean "marginal effects", i.e. predictions for the estimates in Column II (henceforth, the i.i.d. model) and Column III (henceforth, the AR(1) model). Specifically, given construction employment $D_{m,t}$, the number of firms last year $N_{m,t-1}$, and a draw of $\epsilon^r_{m,t}$, I compute the predicted number of firms $N^r_{m,t}$. Table 6 present the mean of the predicted number of firms, entry and exit rates, as well as the effect of changing $D_{m,t}$, ϵ, μ, and $N_{m,t-1}$ on the number of plants per market. Note that to compute the model's prediction I need to draw η from $\mathcal{N}(0,1)$, and draw μ, which I do using the initial conditions distribution $\Pr(\mu_{m,0}|N_{m,0}, X_{m,0}, \theta)$.

Table 6: Model "Marginal Effects"

Variable	i.i.d. Model	AR(1) Model
Mean Number of Plants **(Baseline)**	0.94	0.91
1 Log point demand increase	0.97	1.03
10th percentile η (i.i.d. component)	0.77	0.88
90th percentile η (i.i.d. component)	1.08	1.03
10th percentile μ (persistent component)	-	0.66
90th percentile μ (persistent component)	-	1.31
Removing all firms†	0.13	0.40
Filling the market††	2.84	1.66

† 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. $N_{t-1} = 5$. The process for the unobservable is $\epsilon_{m,t} = \mu_{m,t} + \eta_{m,t}$ where $\eta_{m,t} \sim \mathcal{N}(0,1)$ and $\mu_{m,t} = \rho\mu_{m,t} + \zeta_{m,t}$ where $\zeta_{m,t} \sim \mathcal{N}(0,\zeta)$.

In the data, there are 0.91 plants per market (on average), while the i.i.d. model predicts 0.94 plants per market and the AR(1) 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 i.i.d. model and 5% in the AR(1) 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.[14]

Raising the i.i.d. component of unobserved demand η to the 90th percentile of the distribution, increases the number of firms by 12% in the i.i.d. model versus 8% in the AR(1) model. This shows that unobserved shocks account for a large proportion of demand, and these shocks are far larger for the i.i.d. model than for the AR(1) model.[15]

Raising the persistent market unobservable μ to its 90th percentile has a far greater effect, as the predicted number of firms increases from 0.92 to 1.31. 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 $N_{m,t-1} = 0$, would yield a predicted number of firms today of 0.13 for the i.i.d. model and 0.40 for the AR(1) model. Likewise, the effect of filling up the market with firms, i.e. setting $N_{m,t-1} = 5$ (choosing a number larger than 5 has little effect) would raise the number of firms today to 2.84 in the i.i.d. model and 1.66 in the AR(1) model. Thus the effect of past market structure on the current number of firms is substantial, and we should see a slow response of market structure after a firm exits the market. As well, the AR(1) model predicts a much faster reversion of market structure than i.i.d. model.

6.3 Goodness of Fit

I examine the fit of the SBR model on several different metrics to explore the appropriateness of the approach used in the paper. Moreover, I also include an alternatative approach based on conditional choice probabilities (CCP). These CCPs are compatible with the model of industry dynamics of Ericson and Pakes (1995), which most impor-

[14]There is a small response of the number of firms in a market to changes in log construction employment. Indeed, the correlation between log construction employment and concrete plants is an order of magnitude smaller in the time-series than the cross-section, as a regression of the number of firms on log construction employment yields a coefficient of 0.29, but falls to 0.03 when market fixed effects are included.

[15]The importance of the i.i.d. component of unobserved demand η's echoes a main findings of the industry dynamics literature, that idiosyncratic shocks are responsible much of turnover. Evidence for the importance of idiosyncratic shocks can be deduced from entry and exit coexisting in narrowly defined markets which experience either large increases or decreases in demand (Dunne, Roberts and Samuelson, 1988; Bresnahan and Raff, 1991). Moreover, these idiosyncratic factors are present in both large productivity dispersion, and the volatility of productivity from year to year (Foster, Haltiwanger and Syverson, 2008; Collard-Wexler, 2009).

tantly allows for firm levels shocks generating entry and exit decisions. In Section 7.3 I will discuss this approach in model detail.

Table 7 compares the predictions of the SBR and CCP models with the data. The entry and exit rates in the data are 7.3% and 6.5% respectively, the i.i.d. model predicts entry and exit rates of 3.8% and 4.8%, and the AR(1) model predicts a 5.0% entry rate and a 3.8% exit rate. Thus, both specifications of the SBR models under-predict entry and exit rates. This is not surprising as 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. In contrast, the CCP model predicts much higher entry and exit rates, with an entry rate in the first year of 18.6%.

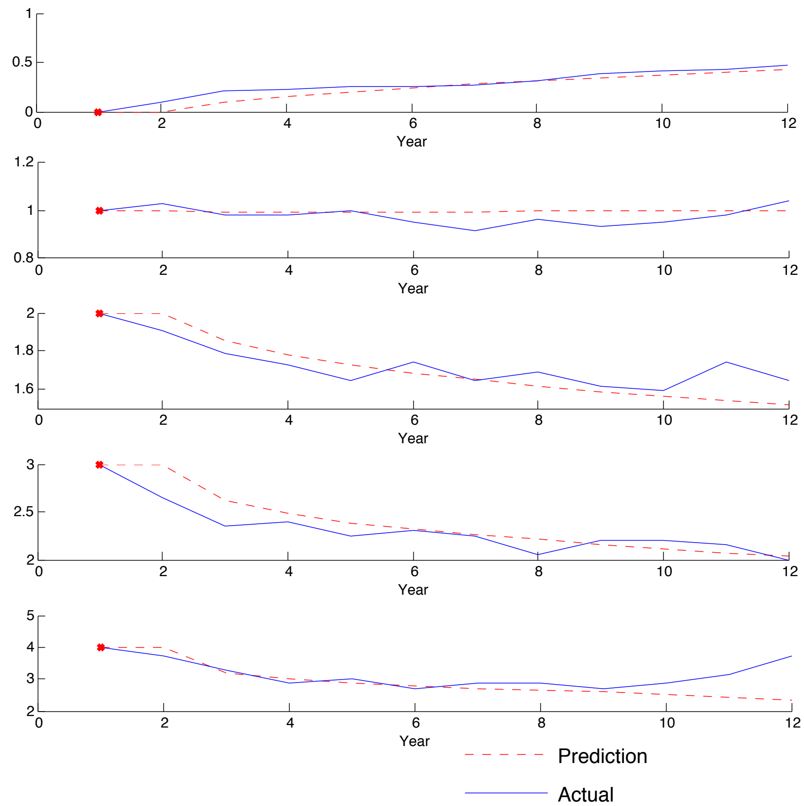
Table 7: Goodness of Fit

Variable	Data	i.i.d. Model	AR(1) Model	CCP
Mean Number of	0.91	0.94	0.91	0.96
Entry Rate	7.3%	3.8%	5.0%	18.6%
Exit Rate	6.5%	4.8%	3.8%	6.4%

To understand the model's long-run forecast for market structure, starting with the number of firms in 1996, I simulate the evolution of markets for the next twelve years. This is an important check for the merger counterfactual, since it is important to check that the model accurately predicts the path of a market *absent* a merger. Figure 3 plots the evolution of the number of firms in the market in the data (shown in solid blue), and compares this to the forecast from the AR(1) model (shown in dotted red). This evolution is broken out by the number of firms in the initial period, the year 1996.

Notice that over a twelve year period, there is a large amount of variation in the number of firms in a market. For instance, a market with no plants in 1996, has 0.5 plants in it, on average, in 2006. Moreover, the AR(1) model does a good job a replicating the time series pattern of the number of firms in the market, as evidenced by the proximity of the model's prediction to the path in the data.

However, the SBR model does a middling job of matching the transition matrix of market structure. Table 8 shows the ten-year transitions of market structure, for the data, the i.i.d. specification, and the AR(1) specification respectively. Both the AR(1) and i.i.d. specifications predict less volatility of market structure that what is observed in the data. As well, both of these specification predict mean reversion in market structure,



The graph shows the average number of plants in a market starting with 0, 1, 2, 3, and 4 plant markets in 1996 respectively from the top panel to the bottom one, both for the actual number of plants in a market (solid blue), and the predicted number of plants by the model (dotted red) using the average of 10,000 simulation draws.

Figure 3: Matching the path of market structure

to the mean in the data of one firm per market, but at a faster rate for the i.i.d. model than the AR(1) model.

Table 8: Ten Year Predicted Transitions of Market Structure

Data

	Plants this year				
Plants Ten years ago	0	1	2	3	4
0	0.30	0.58	0.09	0.01	0.01
1	0.39	0.36	0.21	0.03	0.00
2	0.10	0.55	0.23	0.10	0.01
3	0.05	0.29	0.29	0.26	0.12
4	0.00	0.24	0.59	0.12	0.06

IID Model

	Predicted Plants this year				
Plants Ten years ago	0	1	2	3	4
0	0.45	0.49	0.06	0	0
1	0.08	0.86	0.06	0	0
2	0.07	0.53	0.40	0	0
3	0.06	0.51	0.36	0.06	0
4	0.05	0.38	0.34	0.11	0.12

AR(1) Model

	Predicted Plants this year				
Plants Ten years ago	0	1	2	3	4
0	0.55	0.44	0.01	0	0
1	0.06	0.84	0.10	0	0
2	0	0.36	0.63	0.01	0
3	0	0.06	0.68	0.26	0
4	0	0.01	0.25	0.58	0.16

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, but later I will also consider the effects of three-to-two mergers.

This counterfactual assumes that the effect of a merger between two firms is 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 from those that do not. In section 7.3, I discuss the effect of firms choosing to merge only if the merger keeps them inside the stasis band. Finally, this counterfactual only considers a "one-time" merger as it does not deal with future mergers.[17] As such, one can think of this counterfactual as mimicking the "marginal effect" of permitting one additional merger.

7.1 Dynamic Merger Simulation Algorithm

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 run the following simulation of market structure both following a merger, and absent a merger:

Dynamic Merger Simulation Algorithm

1. Set the initial number of firms in the market as $N_{m,0}^{NM,r} = 2$ if the merger does not happen and $N_{m,0}^{M,r} = 1$ if it does happen, where $r = 1, \cdots, R$ indicates the simulation draw. Start at demand $D_{0,m}$, the level of demand in the data at the initial period.

2. Draw a persistent unobservable $\mu_m^r \sim \Pr(\mu_{m,0}|N_{m,0}, X_{m,0}, \hat{\theta})$ from the initial conditions distribution given the estimated parameters $\hat{\theta}$.

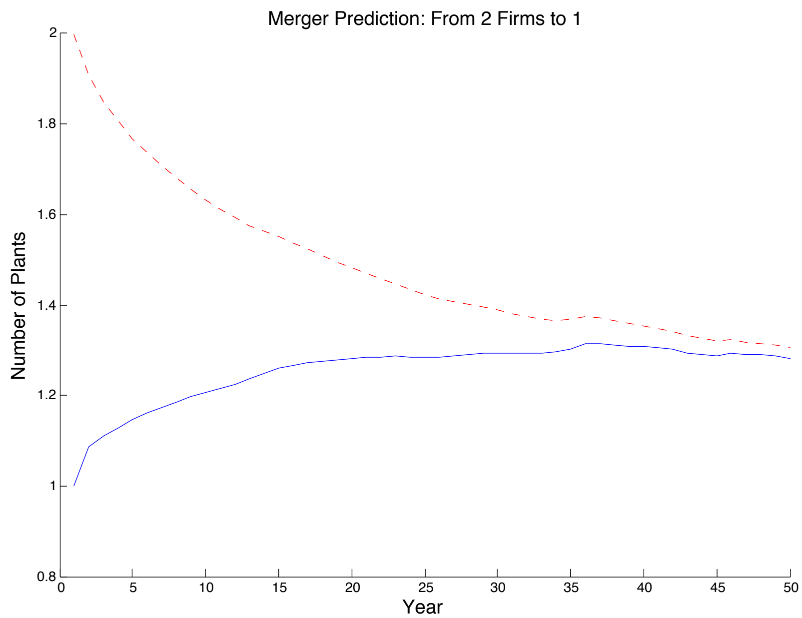
3. For $t = 1$ to 50:

   (a) Draw next period's demand $D_{m,t}^r \sim Q(\cdot|D_{m,t-1}^r)$.

   (b) Draw next period's unobserved demand shifter $\epsilon_{m,t}^r$, by drawing an i.i.d. shock $\eta_{m,t}^r \sim \mathcal{N}(0,1)$ and drawing a new persistent shock $\mu_{m,t}^r = \rho\mu_{m,t-1}^r + \zeta_{m,t}^r$ where $\zeta_{m,t}^r \sim \mathcal{N}(0, \sigma^\zeta)$.

[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]The issue of the dynamic effect of future mergers, such as is modeled in Gowrisankaran (1999) and Nocke and Whinston (2010); Nocke, Whinston and Satterthwaite (2012), 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.



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.

(c) Both $N_{m,t}^{NM,r}$ and $N_{m,t}^{M,r}$ satisfy the entry and continuation conditions estimated in equation (4).

To select initial levels of construction employment $D_{m,t}$ and $\mu_{m,t}$ 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 $N_{m,t} = 2$.[18]

7.2 Counterfactual Results

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, using the dynamic merger simulation algorithm with the AR(1) estimates of the model. Notice that it takes 35 years for the market that had a merger to become indistinguishable from the market where the merger did not occur.

[18] Specifically, I use the set of markets and time periods $\mathcal{C} = \{(m, t) s.t. N_{m,t} = 2\}$, 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 $\mathcal{C}$ I draw this market's persistent unobservable $\mu_{m,t}$ from the initial conditions distribution $\Pr(\mu_{m,t}|N_{m,t}, X_{m,t}, \hat{\theta})$. 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.

To summarize the effect of a merger on market structure, I compute the discounted years of each particular market structure, where I use a 5% discount rate. The preferred AR(1) model finds that after a merger, over for 0.33 discounted years, there are no firms, 14.42 discounted years have one firm, 3.53 discounted years have two firms, and 0.26 discounted years have three or more firms. Without a merger, discounted years of market structure would be 0.33 for no firms, 6.51 for one firm, 11.43 for two firms, and 0.26 for three or more firms. Interestingly, only the difference between the merger and no-merger cases is that a merger will cause 7.91 additional discounted years of monopoly: there is no effect on the probability of either zero or more than two firms. 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.

Table 9 shows the effect of a merger on discounted additional years of monopoly for a variety of different specifications, many of which I will discuss in subsequent sections.

Table 9: Counterfactual: Merger and No-Merger Comparison

Model	Discounted Additional Years of Monopoly
Baseline	
AR(1) model	7.9
I.I.D. model	4.2
Demand-weighted AR(1) model	7.2
Three-to-two Merger	4.4♠
SBR: Alternative Specifications	
AR(1) with No Constant Thresholds*	11.5
AR(1) with a multiplicative ϵ **	7.8
SBR: Merger Process	
AR(1) Omitting mergers outside the stasis zone †	9.2
Conditional Choice Probability Model	
CCP's	3.2

♠ Number of additional years of duopoly. $*$ Uses estimates in Column IV in Table 5, $**$ uses a model with a multiplicative unobservable: $D^*_{m,t} = \epsilon D_{m,t}$ but is identical to the AR(1) model used in the paper. † Only considers states in which a second entrant does not enter immediately after the merger.

The i.i.d. specification predicts monopoly for 13.6 years in discounted year after the merger versus 9.4 discounted years without the merger, a net effect of 4.2 discounted years (equivalent to 4 to 5 years). 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 AR(1) model predicts 7.9 additional discounted years of monopoly –between 9 and 10 actual years. However, the fast reversion of market structure in the i.i.d. simulation is generated by the prediction that the market's steady state is a monopoly regardless of the merger. This is incredible given that the AR(1) model accurately predicts the number of firms in the market absent a merger in Figure 3.

I also compute the additional discounted year of monopoly due to a merger, but weighting these effects by market size – construction employment in this case. This process essentially weights the effect of a merger by the size of the market. The demand-weighted computation of the effect of a merger show a faster response of market structure to a merger. While the merger causes monopoly for an additional 7.9 years, the average consumer only sees monopoly for only 7.2 more years. The largest markets account for the vast majority of consumers, and in these high demand markets there is a faster 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.

Table 9 also shows the effect of a merger between two firms in a three firm market: a three to two merger. In this case, the merger will lead to 4.4 additional years of *duopoly*. To understand why the response to a merger of a market with three firms in it is faster than for a two firm market, there is a faster reversion from three to two firms, than from two to one firm. Thus, in the absence of a merger, exit is more likely in a three firm market than a two firm market, and this blunts the long-run effects of a merger. Thus, mergers in markets with many firms are less damaging not only because the loss in consumer surplus from duopoly is presumably lower than from monopoly, but also because these markets are more likely to see exit in the absence of a merger.

7.3 Robustness

In this section I explore the robustness of my results. First, I consider different specifications for the SBR model. Second, I discuss how moving away from my assumptions on the merger process affects my results. Third, I consider an alternative estimation strategy based on an Ericson and Pakes (1995) model of industry dynamics.

7.3.1 Alternative SBR Specifications

The second panel of Table 9 considers two alternative specifications of the SBR model. First, I consider estimates that allow the gap between the continuation and entry threshold, $\gamma^S(N) \equiv D_N^E - D_N^C$, to vary with the number of firms in the market. This specification was estimated in Column IV in Table 5. Note that these estimates showed that the gap shrinks with the number of firms in the market. This specification predicts that a merger would induce monopoly for an additional 11.5 discounted years, versus 7.9 in the main specification used in this paper that does not allow γ^S to vary with N. The reason for this difference is that Column IV's estimates showed a largest stasis zone, as measured by $\gamma^S(N)$, for one firm than Column III's estimates, at 9,400 versus 7,400 construction employees.

Second, I look at a multiplicative specification for unobserved demand, given by $D^*_{m,t} = \epsilon_{m,t} D_{m,t}$, which yields a log additive structure $\log(D^*_{m,t}) = \log(D_{m,t}) + \log(\epsilon_{m,t})$. I then make the same assumptions on $\tilde{\epsilon} \equiv \log(\epsilon_{m,t})$, an AR(1) process with i.i.d. shocks, that was made in the rest of the paper. This alternative specification predicts 7.8 additional discounted years of monopoly, which is almost the same prediction as the additive model considered in the paper of 7.9.

7.3.2 Alternative Merger Model

The third panel of Table 9 considers an alternative processes for mergers. If firms only choose mergers where they do not expect immediate post-merger entry, then the effect of mergers is raised from 7.9 to 9.2 additional discounted years of monopoly. This is to be expected, as a significant fraction of markets experience entry in the first year following a merger.

7.3.3 Ericson-Pakes Models

A natural question is the robustness of the estimated persistence of monopoly post-merger to how one models dynamic oligopoly games. This paper uses an AC model which rules out idiosyncratic firm shocks, and does not allow any heterogeneity among firms. I investigate an alternative based on the Ericson and Pakes (1995) model, specifically the one suggested by Benkard, Bodoh-Creed and Lazarev (2009), who use a CCP model to recover the transition dynamics of an oligopoly game. To use this CCP based approach, I use confidential data from Longitudinal Business Database in the Census RDC program which allows me to use individual firm identifiers for the same markets and time period studied in the rest of the paper.[19] These conditional choice probabilities are estimated using a multinomial logit on firm's state in the next period given log

[19]The Zip Business Patterns (ZBP) is based on the same Business Register that is used to construct the Longitudinal Business Database (LBD). Thus the ZBP is an aggregated version of the LBD.

construction employment, competition, and the firm's past size (binned into three categories, big, medium, and small based on employment), and shown in Table D.1 in the appendix. I use these estimated policies to simulate the evolution of the market with and without a merger, and more details of the CPP model are in appendix D.[20]

The CCP model predicts a faster convergence of the merger and no-merger worlds, with an estimated additional periods of either monopoly or zero firms of 3.6 discounted years, or about 4 years. Thus these predictions are closer the predictions of the SBR model with i.i.d. unobservables of 4.1 additional discounted years, than the predictions of the AR(1) SBR model, which predicted 7.9 additional discounted years.

To make sense of these difference, notice that the CCP model has idiosyncratic shocks, and thus predicts a higher turnover rate that the SBR model. On the hand, the SBR AR(1) model accurately forecasts the mean number of firms in the future and does not rule serially correlated unobservables. Since each model does better at matching a particular moment in the data, this accounts for the difference in the predictions of these models.

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. However the magnitude of this stasis zone is substantially reduced when I allow for serial correlation of the unobservable, indicating the importance of controlling for 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 are 7.9 times the damages from one year of monopoly. These results are robust, as an range of different specifications yield between 7 and 11 times the damages from one year of monopoly.

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

[20] It is important to notice is that, unlike an AC model, the CCP model's effect cannot be reduced the discounted years of additional periods of monopoly. A merger will lead to fewer periods with either two, three, or four firms in the market. Table D.2 in the appendix discusses this in more detail.

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 A.1 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.

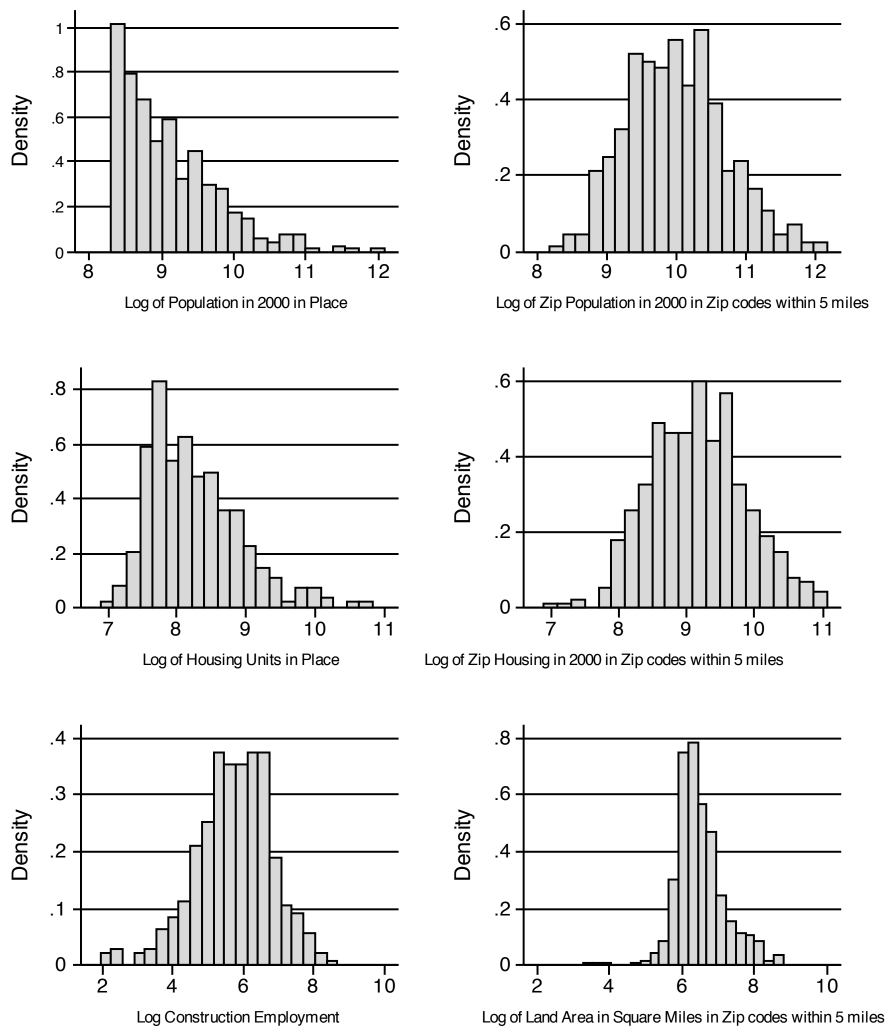
Third, several towns are adjacent to each other. An analogy to this situation is the Minneapolis-Saint Paul MSA, that is composed of two adjacent cities: Minneapolis and Saint-Paul. If I do not consider Minneapolis and Saint-Paul as a single city, then I automatically count this agglomeration as having 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.

Table A.1: Isolated Towns

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

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.



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

Figure A.1: Distribution of Town Size

B Robustness

Table B.1 shows estimates of the SBR model, with and i.i.d. unobservable, which investigate demand covariates. For the estimates in this section, I normalize the coefficient on the variance of the i.i.d. term, $\sigma_\epsilon = 1$. I do this instead of normalizing the coefficient on construction employment as in the body of the paper, since it is difficult to compare estimates that use different measures of demand than just construction employment. Thus, these estimates are 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.

First, the coefficient on construction employment in thousands is 0.38 for the column I (henceforth the Base model), and this coefficient is reasonably similar in columns II, III, VI, and V. Thus construction employment is a large part of total demand D. Other measures of demand estimated in column III- such as population, land area, and the presence of an interstate highway – are not significant and have a fairly small magnitude in any case. Including year dummies also does not change the estimates substantially, indicating that aggregate fluctuations in demand are a secondary issue. Furthermore, Table B.3 shows the SBR model estimated with different demand measures such as housing units and population. Thus, 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 B.2 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, only Column VI shows a substantially larger effect of demand, at the cost of reducing the sample of markets from 449 to 88. Thus, I conclude that cleaning up my market definition has a secondary effect for 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. All I infer from this effect is that it suggests that firms are not informed about future construction projects.

To illustrate how I will detect serial correlation in the unobservable, Column VI includes the number of plants in a market ten years ago as a demand covariate, and finds a strong effect. This is a surprise, as the AC model predicts that the number of plants in a market $N_{m,t}$ is only a function of demand $D_{m,t}$ and the number of plants last year $N_{m,t-1}$. The predictive ability of the lagged number of plants indicates that there must be a serially correlated unobserved components of demand to induce a correlation between $N_{m,t}$ and $N_{m,t-10}$ conditional on $N_{m,t-1}$.

Second, turning to the effect of competition, the coefficients show both the entry threshold for the first firm, $h(1) = D_1^E$, and the marginal effect of each additional competitor on the demand thresholds; $h(k) = D_k^X - D_{k-1}^X$ for $X = \{C, E\}$. The threshold for the first firm to enter is -1.46, while the increase in this threshold to go from monopoly to duopoly is -1.04. These effects decline for each subsequent competitor, reaching -0.72 for the effect of each competitor above four.

Third, the coefficient γ_1^S shows the gap between entry and continuation thresholds; i.e., $\gamma^S \equiv D_k^E - D_k^C$. It is estimated at 3.6 in columns I-V. To put these numbers into context, note that the estimates in column I indicate that the demand threshold that is required to induce a monopoly entrant (D_1^E=-1.46) is similar to the demand threshold that is required to sustain 4 incumbents (D_4^C=-1.46-1.04-0.87-0.82+3.6=-0.56).

Table B.2: SBR Model Estimates Market Definition

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	
Construction Employment in Thousands	0.38***	0.48***	0.39***	0.30	-0.09	1.51***
	(0.09)	(0.12)	(0.11)	(0.21)	(0.15)	(0.27)
Entry Term $h(1)$	-1.46***	-1.43***	-1.45***	-1.62***	-1.63***	-1.74***
	(0.06)	(0.08)	(0.08)	(0.13)	(0.14)	(0.17)
First Competitor $h(2)$	-1.04***	-1.03***	-1.06***	-1.15***	-1.22***	-1.24***
	(0.06)	(0.07)	(0.07)	(0.13)	(0.21)	(0.15)
Second Competitor $h(3)$	-0.87***	-0.94***	-0.89***	-1.20***	-0.96***	-1.63***
	(0.07)	(0.09)	(0.09)	(0.18)	(0.21)	(0.20)
Third Competitor $h(4)$	-0.82***	-0.95***	-0.84***	-0.73**		-1.08*
	(0.10)	(0.14)	(0.13)	(0.27)		(0.45)
Fourth Competitor $h(5)$	-0.93***	-1.05**		-0.36		-0.42*
	(0.21)	(0.33)		(0.21)		(0.19)
More than four Competitors $h(6)$	-0.72***	-0.59***	-1.65***	-0.59***	-1.12***	-1.21***
	(0.10)	(0.09)	(0.38)	(0.16)	(0.22)	(0.23)
Gap Entry-Continuation γ^S	3.56***	3.52***	3.60***	3.85***	4.02***	3.84***
	(0.07)	(0.07)	(0.07)	(0.14)	(0.19)	(0.16)
Log-Likelihood	-1814.1	-1339.1	-1269.8	-439.2	-284.1	-272.6
Observations	5321	3814	3821	1668	1220	1056
Markets	445	319	320	139	102	88

Table B.1: Sunk-Cost Bresnahan-Reiss Model Estimates: Demand Diagnostics

Dependent Variable Number of Plants in a Market	I	II	III	IV	V	VI
Construction Employment (in ’000s)	0.38***	0.38***	0.34**	0.42***	0.36	0.11
	(0.09)	(0.09)	(0.10)	(0.11)	(0.28)	(0.12)
Year FE		X				
Population (in ’000s)			0.00			
			(0.01)			
Land Area (in ’000s)			-0.19			
			(0.17)			
Interstate Highway dummy			-0.12			
			(0.11)			
Construction Employment (in ’000s)				-0.02		
in Zip codes within 10 miles				(0.09)		
Construction Employment (in ’000s)				-0.09*		
in Zip codes within 20 miles				(0.04)		
Next 3 years of					-0.65*	
Construction Employment (in ’000s)					(0.29)	
Previous 3 years of					0.73*	
Construction Employment (in ’000s)					(0.35)	
Number of Plants Ten years ago						0.70***
						(0.11)
Entry Parameter ($h(1)$)	-1.46***	-1.46***	-1.46***	-1.41***	-1.49***	-2.01***
	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.16)
1 competitor ($h(2)$)	-1.04***	-1.05***	-1.05***	-1.05***	-1.00***	-1.34***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)	(0.17)
2 competitor ($h(3)$)	-0.87***	-0.87***	-0.87***	-0.89***	-0.81***	-1.32***
	(0.07)	(0.07)	(0.08)	(0.07)	(0.09)	(0.22)
3 competitor ($h(4)$)	-0.82***	-0.82**	-0.83***	-0.83***	-0.91***	-0.55**
	(0.10)	(0.10)	(0.10)	(0.11)	(0.15)	(0.17)
4 competitor ($h(5)$)	-0.93***	-0.93***	-0.93***	-0.94***	-0.91*	-1.60***
	(0.21)	(0.21)	(0.19)	(0.21)	(0.39)	(0.39)
Competitors above 4	-0.72***	-0.72***	-0.75***	-0.74***	-0.71***	-0.99***
	(0.10)	(0.10)	(0.12)	(0.10)	(0.16)	(0.17)
Gap Entry-Continuation γ_1^S	3.56***	3.57***	3.56***	3.57***	3.53***	3.97***
	(0.07)	(0.07)	(0.07)	(0.06)	(0.08)	(0.19)
Log-Likelihood	-1814.1	-1809.2	-1809.2	-1806.6	-890.0	-225.0
Observations	5321	5321	5321	5321	661	884
Markets	445	445	445	445	445	444

Note: Standard Errors Clustered by Market. The entry threshold for 3 firms D_3^E is given by $D_3^E = h(1) + h(2) + h(3)$, while the continuation threshold for 3 firms would be $D_2^C = h(1) + h(2) + h(3) + \gamma_1^S$. Year FE indicates year dummies are included.

Table B.3: SBR Model Estimates: Different Measures of Demand

Dependent Variable Number of Plants in a Market	I	II	III	IV	V	VI	VII
Construction Employment	0.379***					0.329**	0.143
(in 000's)	(0.09)					(0.11)	(0.11)
Housing units in Place		0.026*					
(in 000's)		(0.01)					
Housing units in zip codes			0.027***				-0.002
within 5 miles (in 000's)			(0.01)				(0.03)
Population in Place				0.010**		0.004	
(in 000's)				(0.00)		(0.01)	
Population in zip codes					0.011***		0.009
within 5 miles (in 000's)					(0.00)		(0.01)
Land Area of Place						-0.191	
(in 000's)						(0.16)	
Entry Term $h(1)$	-1.464***	-1.415***	-1.617***	-1.408***	-1.592***	-1.481***	-1.587***
	(0.06)	(0.07)	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)
First Competitor $h(2)$	-1.045***	-1.012***	-1.049***	-1.013***	-1.046***	-1.045***	-1.054***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Second Competitor $h(3)$	-0.872***	-0.841***	-0.898***	-0.844***	-0.898***	-0.872***	-0.899***
	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Third Competitor $h(4)$	-0.820***	-0.800***	-0.841***	-0.807***	-0.850***	-0.828***	-0.852***
	(0.10)	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)	(0.11)
Fourth Competitor $h(5)$	-0.929***	-0.884***	-1.003***	-0.898***	-1.028***	-0.942***	-1.026***
	(0.21)	(0.20)	(0.21)	(0.20)	(0.21)	(0.20)	(0.19)
More than 4 Competitors $h(6)$	-0.723***	-0.710***	-0.831***	-0.745***	-0.892***	-0.753***	-0.874***
	(0.10)	(0.12)	(0.12)	(0.14)	(0.12)	(0.12)	(0.14)
Gap Entry-Continuation γ^S	3.555***	3.545***	3.569***	3.549***	3.572***	3.558***	3.571***
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
χ^2	17.79	5.44	21.83	7.58	24.04	19.83	23.67
Log-Likelihood	-1814.1	-1841.3	-1798.2	-1837.8	-1796.9	-1811.2	-1793.5
Observations	5321	5321	5321	5321	5321	5321	5321
Markets	445	445	445	445	445	445	445

Standard Errors Clustered by market.

C GHK-Initial Conditions Algorithm

C.1 Initial Conditions Simulator

I compute the initial conditions distribution $\Pr(\mu_{m,0}|N_{m,0}, X_{m,0}, \theta)$ generated by the stationary distribution of the model. This is done numerically by simulating the model for demand and entry/exit starting from a large number of periods in the past.

Algorithm 1 *Stationary Initial Conditions Distribution Simulation (SICDS)*

This algorithm computes the initial conditions distribution $\Pr(\mu_{m,0}|N_{m,0}, X_{m,0}, \theta)$ *by backward simulation. The algorithm starts in a period* $t = -\hat{T}$*, which is far enough the past so that by period* $t = 0$*, the system has reached a stationary distribution. I choose* $\hat{T} = 100$*, but choosing a larger number of periods in the past, such as 500, has little effect on the estimates and simulations.*

1. *Backward Simulate Demand*

   Given the following demand process:

$$d_{m,t} = \beta_0 + \beta_1 d_{m,t-1} + \epsilon^d_{m,t} \tag{C.1}$$

   where $\epsilon^d_{m,t} \sim \mathcal{N}(0, \sigma^d)$*, one can derive the reverse demand process:*

$$d_{m,t-1} = -\frac{\beta_0}{\beta_1} + \frac{d_{m,t}}{\beta_1} + \frac{\epsilon^d_{m,t}}{\beta_1} \tag{C.2}$$

   Using this reverse demand process, I back-simulate the distribution of demand starting with initial demand $d_{m,0}$*. Denote draws* $r = 1, \cdots, R$*, I draw* $\epsilon^{d,r}_{m,t} \sim \mathcal{N}(0, \sigma^d)$ *for* $t = (-\hat{T}, \cdots, 0)$*. Using the initial demand* $d_{m,0}$*, draws on* $\epsilon^{d,r}_{m,t}$*, and the reverse demand process in equation (C.2), I generate the simulated demand series* $\boldsymbol{D}^r \equiv (D^r_{m-\hat{T}}, \cdots, D^r_{m-1}, D_{m,0})$

2. *Forward Simulate* ϵ

   I forward simulate both the persistent component of the unobservable μ*, and the i.i.d. component of the unobservable* η*. For* $r = 1, \cdots, R$*, I draw* $\zeta^r_{m,t} \sim \mathcal{N}(0, \sigma^\zeta)$*, and* $\eta^r_{m,t} \sim \mathcal{N}(0, 1)$*. Using these draws, I simulate the series* $\boldsymbol{\epsilon}^r = (\epsilon^r_{m,-T}, \cdots, \epsilon^r_{m,-2}, \epsilon^r_{m,-1})$*, and* $\boldsymbol{\mu}^r = (\mu^r_{m,-T}, \cdots, \mu^r_{m,-1}, \mu^r_{m,0})$ *via equation (6).*

3. *Predict Number of Firms*

   I initialize the number of firms at the initial period $t = -\hat{T}$ *as zero, i.e.* $N_{m,-\hat{T}} = 0$.[21] *Given the demand series* $\boldsymbol{d}^r$*, and the series on the unobservable* $\boldsymbol{\epsilon}^r$*, I generate the series* $\boldsymbol{N}^r = (N^r_{m,-T+1}, N^r_{m,-T+2}, \cdots, N^r_{m,-1})$ *which satisfy the entry, exit and stasis thresholds in equation (4).*

4. *Compute Probability Weights* w^r_m

[21] The choice of $N_{m,-\hat{T}}$ should be immaterial as long as $\hat{T}$ is far enough in the past.

Given the distribution $\mu^r_{m,0}$, the last year's number of plants $N^r_{m,-1}$, and current demand $d_{m,0}$, I compute the probability of observing the actual number of plants $N_{m,0}$, which is generated by the i.i.d. component $\eta_{m,0}$. This probability is given by:

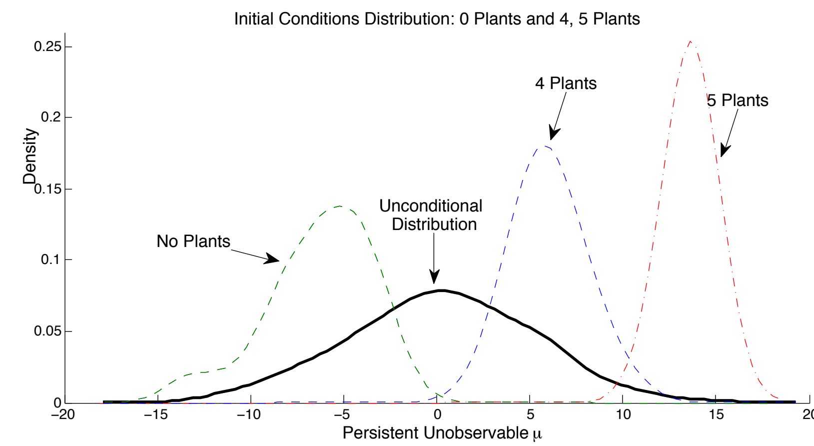
$$\Pr(\mu^r_{m,0}|N^r_{m,-1}, N_{m,0}, d_{m,0}) =$$
$$\Phi\left(-\mu^r_{m,0} - D_{m,0}\beta + 1(N_{m,0} \geq N^r_{m-1})\gamma^S(N_{m,0}) + \sum_{k=1}^{N_{m,0}+1} h(k)\right)$$
$$-\Phi\left(-\mu^r_{m,0} - D_{m,0}\beta + 1(N_{m,0} > N^r_{m-1})\gamma^S(N_{m,0}) + \sum_{k=1}^{N_{m,0}} h(k)\right) 1(N_{m,0} > 0) \tag{C.3}$$

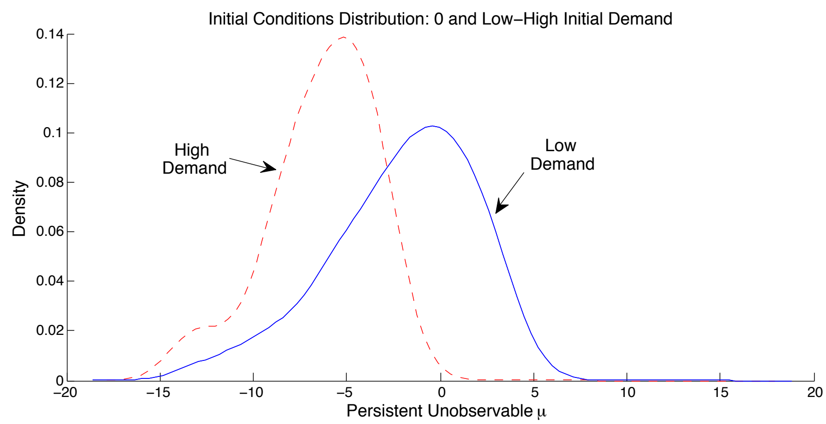
where $\Phi(\cdot)$ is the cdf of the normal distribution.
The weights for $\mu^r_{m,0}$ are thus:

$$w^r_{m,0} \equiv \frac{\Pr(\mu^r_{m,0}|N^r_{m,-1}, N_{m,0}, d_{m,0})}{\sum_{\hat{r}=1}^{R} \Pr(\mu^{\hat{r}}_{m,0}|N^{\hat{r}}_{m,-1}, N_{m,0}, d_{m,0})} \tag{C.4}$$

Notice that a useful aspect of these weights is that they are non-zero, and a smooth function of the parameters θ.

To illustrate the outcome of this procedure, Figure C.1 shows the initial conditions distribution computed using the SICDS algorithm with the estimated parameters. Notice that the distribution of $\mu_{m,0}$ depends quite dramatically on the initial number of plants in the market $N_{m,0}$, and on the initial level of demand $D_{m,0}$.





Top panel shows the distribution $\Pr[\mu_{m,0}|N_{m,0}, D_{m,0}]$ for different choices of $N_{m,0}$ and also presents the unconditional distribution of $\Pr[\mu_{m,0}]$, while the bottom panel shows $\Pr[\mu_{m,0}|N_{m,0}, dDm, 0]$ for different choices of $d_{m,0}$ and $N_{m,0} = 0$, specifically for demand in the 10th and 90th percentile of the distribution.

Figure C.1: Initial Conditions Distribution $\Pr[\mu_{m,0}|N_{m,0}, D_{m,0}]$

C.2 GHK Procedure

The likelihood for the model computes the probability $\Pr(\{N_{m,t}\}_{t=1}^{T}|\mu_{m,0}, \{X_{m,t}\}_{t=1}^{T}, N_{m,0}, \theta)$ of observing a sequence of $\boldsymbol{\epsilon} \equiv \{\epsilon_{m,1}, \cdots, \epsilon_{m,T}\}$ which is $\epsilon \sim \mathcal{N}(0, \boldsymbol{\Sigma})$. Since this is a multivariate normal of dimension $T = 12$, there is no closed form for this expression. The most natural approach to compute this probability would be to simulate a large number of $\boldsymbol{\epsilon}^r$ sequences, where $r = 1, \cdots, R$ indexes draws, and count the number of such sequences that replicate the number of firms observed in the data $\{N_{m,t}\}_{t=1}^{T}$.

This will not work. The log-likelihood for the model with serially correlated unobservable is difficult to compute using this approach, which is an accept-reject simulator. Even when using ten million draws, for some markets, I cannot find a single draw of $\boldsymbol{\epsilon^r}$

that rationalize the data. Instead I will use the GHK simulator discussed in Train (2003) (and the references to the literature therein) on page 126.

Moreover, this GHK algorithm needs to account for the initial conditions distribution, the fact that the initial value of $\mu_{m,0}$ is not necessarily a normally distributed variable with mean zero.

The likelihood for this model is given by $\mathcal{L}(\theta) = \prod_{m=1}^{M} \Pr(\{N_{m,t}\}_{t=1}^{T} | \{X_{m,t}\}_{t=1}^{T}, \theta)$. As well $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma})$. I adapt the GHK procedure for the case where there are initial conditions, i.e. the initial distribution of $\epsilon_{m,0}$ cannot be expressed as a Normal random variable. As well, this version of the GHK algorithm is for normal distribution that is truncated from above and below, essentially a serially correlated ordered probit.

Algorithm 2 *Initial Conditions-GHK Procedure*

1. *Choleski Factorization of* Σ*, denoted* Γ *(i.e.* $\Gamma\Gamma' = \Sigma$ *and* Γ *is lower triangular).*
2. *Draw* $\{\mu_{0m}^{r}\}_{r=1}^{R}$ *and compute the weights* $\{w_{m,0}^{r}\}_{r=1}^{R}$ *for these draws, using the algorithm described in the previous section. Call* $\eta_1^r = \mu^r$*.*
3. *For* $t = 1, \cdots, T$*:*
   (a) $\tilde{p}_t^r = \Phi(a) - \Phi(b)$ *where*

$$a = -\frac{\sum_{\tau=1}^{t-1} \Gamma_{t,\tau}\eta_\tau^r + \underline{\pi}(N_{m,t}, N_{m,t-1}, X_{m,t}, \theta)}{\Gamma_{t,t}}$$

$$b = -\frac{\sum_{\tau=1}^{t-1} \Gamma_{t,\tau}\eta_\tau^r + \bar{\pi}(N_{m,t}, N_{m,t-1}, X_{m,t}, \theta)}{\Gamma_{t,t}}$$

   (b) *Draw* $\eta_t^r \sim T_{N_{a,b}}(0,1)$ *(truncated normal from* a *to* b*).*
4. *Compute the log-likelihood:*

$$L(\theta) = \sum_{m=1}^{M} \log\left(\sum_{r=1}^{R} w_{m,0}^{r} \prod_{t=1}^{T} \tilde{p}_t^r\right) \tag{C.5}$$

D Conditional Choice Probability Simulation

An alternative approach suggested by Benkard, Bodoh-Creed and Lazarev (2009) is to bypass the estimation of a structural model of oligopoly dynamics, and instead use the policy functions employed by firms in equilibrium. This approach has several advantages, most notably, it is simple and avoids the issue of equilibrium selection, and is consistent with an Ericson-Pakes style model of industry dynamics with idiosyncratic shocks.

Following Collard-Wexler (2013), I will consider of model of competition and size choices. At the start of each period t in market m, each firm $i = 1, \cdots, N$ can choose an action $a_{i,m,t}$; the choice of a plant to exit, have less than 7 employees (henceforth *small*), between 7 and 17 employees (henceforth *medium*), and more than 17 employees (henceforth *large*). A firm's state $s_{i,m,t}$ is it's size in the past period, thus $s_{i,m,t} = a_{i,m,t-1}$. The state of the market $s_{m,t} = \{s_{1,m,t}, \cdots, s_{N,m,t}, D_{m,t}\}$, is the collection of the state of each firm in the market, as well as the market's demand level $D_{m,t}$, which is construction employment. A firm's conditional choice probability or CCP, denoted $\Psi[a_{i,m,t}|s_{i,m,t}]$, as the probability that firm i chooses an action $a_{i,m,t}$ in state $s_{i,m,t}$.

To estimate these CCP's, I use a multinomial logit on the choice of a plant to exit, have less than 7 employees (henceforth *small*), between 7 and 17 employees (henceforth *medium*), and more than 17 employees (henceforth *large*), based on the plant's previous size, log construction employment and the number of competitors in the market. I pick the number of firms in the market, both potential entrants, and incumbents, at $N = 10$. This multinomial logit is presented in Table D.1.

To simulate the effect of a merger via these CCPs, use the following algorithm:

CCP Merger Simulation Algorithm

1. Take the initial markets and time period $\mathcal{C} = \{m, t\}$ as those with two firms in the market, i.e. m and t such that $N_{m,t} = 2$
2. Set the number of firms in the merger world to $N^M_{m,t} = 1$, and the number of firms in the no merger world to $N^{NM}_{m,t} = 2$. Thus the initial state absent the merger is $s^{NM}_{m,t} = \{s_{1,m,t}, s_{2,m,t}, D_{m,t}\}$ where $s_{i,m,t}$, and the initial state after the merger is $s^M_{m,t} = \{s_{1,m,t}, D_{m,t}\}$ where $s_{1,m,t}$ is the largest firm in the market.
3. For $t = 1$ to 50 starting in either state $s^{NM}_{m,0}$ or $s^M_{m,0}$.
   (a) For each firm in the market draw their action (entry, exit and size) $a_{i,m,t+1} \sim \hat{\Psi}[a_i|s_{m,t}]$ from the estimated policy function $\hat{\Psi}$.
   (b) Draw demand $D_{m,t+1} \sim Q[\cdot|D_{m,t}]$.
   (c) Update the state $s_{m,t+1} = \{a_{1,m,t+1}, \cdots, a_{N,m,t+1}, D_{m,t+1}\}$.

I perform this merger simulation 10,000 times, and in Figure D.1 I present the average number of firms predicted in both the merger and no-merger worlds. Notice that the model yields a faster convergence of the merger and no-merger cases.

Table D.2 presents the predicted effect of a merger on market structure for the CCP based merger simulation, along with the predictions from the SBR model. First, notice that the CCP model's effect cannot be reduced the discounted years of additional periods of monopoly, unlike an AC model. A merger will lead to fewer periods with

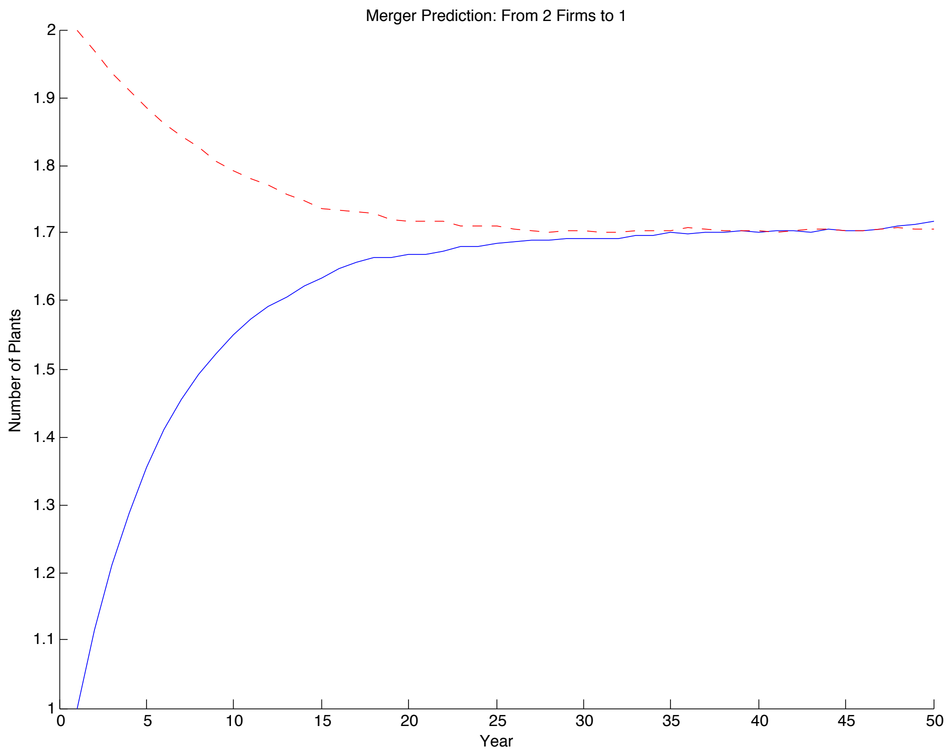


Figure D.1: Effects of a Merger using a CCP Model.

either two, three, or four firms in the market. Second, the CCP model predicts a faster convergence of the merger and no-merger worlds, with an estimated additional periods of either monopoly or zero firms of 3.6 discounted years, or about 4 years. Thus these predictions are closer the predictions of the SBR model with i.i.d. unobservables of 4.1 additional discounted years, than the predictions of the AR(1) SBR model, which predicted 7.8 additional discounted years.

To make sense of these difference, notice that the CCP model has idiosyncratic shocks, and thus predicts a higher turnover rate that the SBR model. On the hand, the SBR AR(1) model accurately forecasts the mean number of firms in the future and does not rule serially correlated unobservables. Since each model does better at matching a particular moment in the data, this accounts for the difference in the predictions of these models.

Table D.1: Multinomial Logit.

Dependent Variable:	Independent Variable	
Small in $t+1$	Small in t	6.14
		(0.09)
	Medium in t	5.60
		(0.11)
	Large in t	4.43
		(0.23)
	Log Construction Employment	-0.06
		(0.03)
	One Competitor	-0.14
		(0.12)
	Log Competitors Above One	-0.10
		(0.19)
	Constant	-3.02
		(0.23)
Medium in $t+1$	Small in t	6.59
		(0.15)
	Medium in t	9.18
		(0.17)
	Large in t	7.90
		(0.21)
	Log Construction Employment	-0.13
		(0.05)
	One Competitor	-0.41
		(0.15)
	Log Competitors Above One	-0.62
		(0.31)
	Constant	-5.94
		(0.31)
Large in $t+1$	Small in t	5.24
		(0.32)
	Medium in t	8.45
		(0.32)
	Large in t	10.96
		(0.38)
	Log Construction Employment	0.43
		(0.06)
	One Competitor	-0.55
		(0.16)
	Log Competitors Above One	-0.38
		(0.26)
	Constant	-8.97
		(0.53)
Log-Likelihood	-11081	
Markets	449	
Observations	34718	

Table D.2: CCP and SBR Merger Predictions

Discounted Years of Plants	CCP Model		
in market	Merger	No Merger	Difference
0	1.30	1.70	0.40
1	5.68	8.89	3.22
2	7.89	5.27	-2.01
3	2.78	2.01	-0.77
4	0.69	0.49	-0.20
	AR(1)		
	Merger	No Merger	Difference
0	0.33	0.33	0.00
1	14.42	6.51	7.91
2	3.53	11.43	-7.91
3+	0.26	0.26	0.00