DEMAND FLUCTUATIONS IN THE READY-MIX CONCRETE INDUSTRY

BY ALLAN COLLARD-WEXLER[1]

I investigate the role of demand shocks in the ready-mix concrete industry. Using Census data on more than 15,000 plants, I estimate a model of investment and entry in oligopolistic markets. These estimates are used to simulate the effect of eliminating short-term local demand changes. A policy of smoothing the volatility of demand has a market expansion effect: The model predicts a 39% increase in the number of plants in the industry. Since bigger markets have both more plants and larger plants, a demand-smoothing fiscal policy would increase the share of large plants by 20%. Finally, the policy of smoothing demand reduces entry and exit by 25%, but has no effect on the rate at which firms change their size.

KEYWORDS: Demand fluctuations, entry and exit, dynamic games, ready-mix concrete.

1. INTRODUCTION

Many industries face considerable uncertainty about future demand for their products. How do these shocks affect the organization of production?

I study the effect of demand shocks in the ready-mix concrete industry. This industry is composed of local oligopolies, as wet concrete cannot travel much more than an hour before hardening. The ready-mix concrete industry experiences large changes in demand from the construction sector from year to year, as the size of the local construction industry fluctuates by an average of 30% per year. Moreover, about half of all concrete is purchased by state and local governments, and these outlays are particularly volatile, due to year-to-year variation in tax revenues.

To investigate the role of demand volatility, I estimate a model of entry and discrete investment in concentrated markets using an Indirect Inference Conditional Choice Probability Algorithm, which allows for considerable plant het-

erogeneity.[2] This model is estimated with Census data on the histories of more than 15,000 ready-mix concrete plants in the United States from 1976 to 1999.

Plant size is directly related to market size in the ready-mix concrete sector: Bigger markets have both more plants and larger plants. Thus, the model's estimates show that construction employment has strong positive effects on profits but disproportionately affects large plants. Competition—in particular, the presence of a first competitor—substantially reduces profits. Firms pay large sunk costs both for entering the market and for increasing or shrinking the size of a plant.

I look at government intervention in the ready-mix concrete market that smooths out short-term fluctuations in demand at the county level. Specifically, the counterfactual mimics the effect of government sequencing its contracts so as to spread demand evenly over each five-year period. However, secular changes in demand, those that move average demand from one five-year period to the next, are preserved. Thus, this policy eliminates short-run—that is, five-year—changes in demand, but preserves longer-run movement in demand.

I find that this demand-smoothing policy reduces entry and exit rates, by 25%, but has no effect on the rate at which plants change their size. The modest effect of the demand-smoothing policy on the dynamics of the industry is due to high estimates of sunk costs of both entry and adjustment. These make it costly for firms to react to short-lived changes in demand. In addition, when demand becomes less volatile, firms get a more precise forecast of future demand. Thus, the direct effect of a smoother demand process is offset by firms becoming more responsive to the remaining changes in demand. This lessens any effect of demand smoothing on turnover.

However, smoothing demand also has a large "market expansion" effect—it raises the number of plants in the industry by 39%. The intertemporal volatility of demand can have large effects on the profitability of a market. To illustrate, consider that in the market for electricity, demand volatility is thought to raise the profits of generators. In periods of peak demand, capacity constraints bind and spot prices can increase quite dramatically. Alternatively, in the ready-mix concrete market, periods of peak demand might raise costs due to the congestion associated with multiple concrete deliveries. In the data, a 1% increase in market size (as measured by construction employment) is associated with a 0.69% increase in the number of ready-mix concrete plants. This indicates a concave response to higher demand, and these nonlinearities of period profits, with respect to demand, indicate that demand volatility affects market

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[2]Previous versions of the paper used an algorithm analogous to that in Aguiregabiria and Mira (2007), where the choice probabilities were updated to match those given by a computed equilibrium of the game, given the estimated parameter vector. This technique leads to similar estimates and counterfactual results as those presented in the paper and are available by request.

size. Thus, some of the more interesting effects of the demand-smoothing policy are expressed in the industry's cross-section rather than in its year-to-year changes.

The counterfactual of smoothing demand raises investment by 44%, from $439 million to $634 million per year, but decreases producer surplus for incumbents by 20%. Moreover, since the market expansion effect is similar to an increase in market size, the size distribution of the industry shifts toward large plants, and the share of large plants (with more than 17 employees) climbs by 20%. Turning toward the effect on consumers, the 39% increase in the number of plants due to the demand-smoothing policy would reduce the share of monopoly markets from 43% to 25%. The resulting increase in competition would make prices fall, and consumers would pay $43 million less per year for ready-mix concrete.

The effect of countercyclical fiscal policy—in particular, with regard to the response, timing, and composition of investments—has been extensively discussed in the public finance literature (see Auerbach, Gale, and Harris (2010) and the references therein). This paper casts light on the effect of active fiscal policy not only on the dynamics of the industry in terms of entry and exit, but also on market structure and industry composition.

This paper proceeds as follows. In Section 2, I discuss the ready-mix concrete industry. Section 3 describes the data. In Section 4, I present a dynamic model of competition. I describe estimation in Section 5 and results in Section 6. Finally, in Section 7, I analyze the effect of policies that would eliminate some of the volatility of demand.

2. THE READY-MIX CONCRETE INDUSTRY

2.1. *The Industry*

2.1.1. *Concrete*

I focus on ready-mix concrete: concrete mixed with water at a plant and transported directly to a construction site.[3] While it is possible to produce several hundred types of concrete, these mixtures basically use the same ingredients and machinery. Thus, one can think of ready-mix concrete as a homogeneous product.

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[3]Concrete is a mixture of three basic ingredients: sand, gravel (crushed stone), and cement, as well as chemical compounds known as admixtures. Combining this mixture with water turns cement into a hard paste that binds the sand and gravel together.

Ready-mix is a perishable product that must be delivered within an hour and a half before it becomes too stiff to be workable.[4,5] Concrete is also very cheap for its weight, and so ready-mix trucks typically drive 20 minutes to deliver their loads.[6]

2.1.2. *Local Oligopoly*

Due to these high transportation costs, concrete markets are geographically segmented: Figure 1 shows the dispersion of ready-mix producers in the Midwest, with a handful of incumbents in each area. For my empirical work, I treat each county as a separate market that evolves independently from the rest of the industry. Furthermore, Table I shows that the vast majority of counties in the United States have fewer than six ready-mix plants, reflecting a locally oligopolistic market structure. However, because even the most isolated rural areas have some demand for ready-mix concrete, most counties are served by at least one producer.

A market with more than three firms appears to yield fairly competitive outcomes. To illustrate, Figure 2 shows the median price of ready-mix concrete in markets with one to seven firms.[7] The first three competitors have a noticeable effect on prices, but additional competitors have little additional impact.[8]

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[4]One producer describes the economics of transportation costs in the ready-mix industry as follows:

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

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

[6]The average price of concrete is around 1.5 cents per pound. The driving time of twenty minutes is based on a dozen interviews conducted with Illinois ready-mix concrete producers. Thanks to Dick Plimpton at the Illinois Ready-Mix Concrete Association for providing IRMCA's membership directory.

[7]Price is given by sales of concrete divided by tons of concrete sold, where I use data from the material trailer to the Census of Manufacturers. I follow Syverson's (2004) procedure, which removes hot and cold deck imputes by dropping all price pairs that are exactly the same. Appendix G of the Supplemental Material (Collard-Wexler (2013)) discusses the construction of price statistics in more detail.

[8]Caution should be exercised when interpreting these price regressions, as the number of firms could be positively correlated with a market that has unusually high prices, as discussed in Manuszak and Moul (2008), so the results in Figure 2 most likely underestimate the price-competition relationship.

Number of Concrete Plants in a Zip Code
- 1
- 2
- 3
- 4 - 6
- 7 - 9
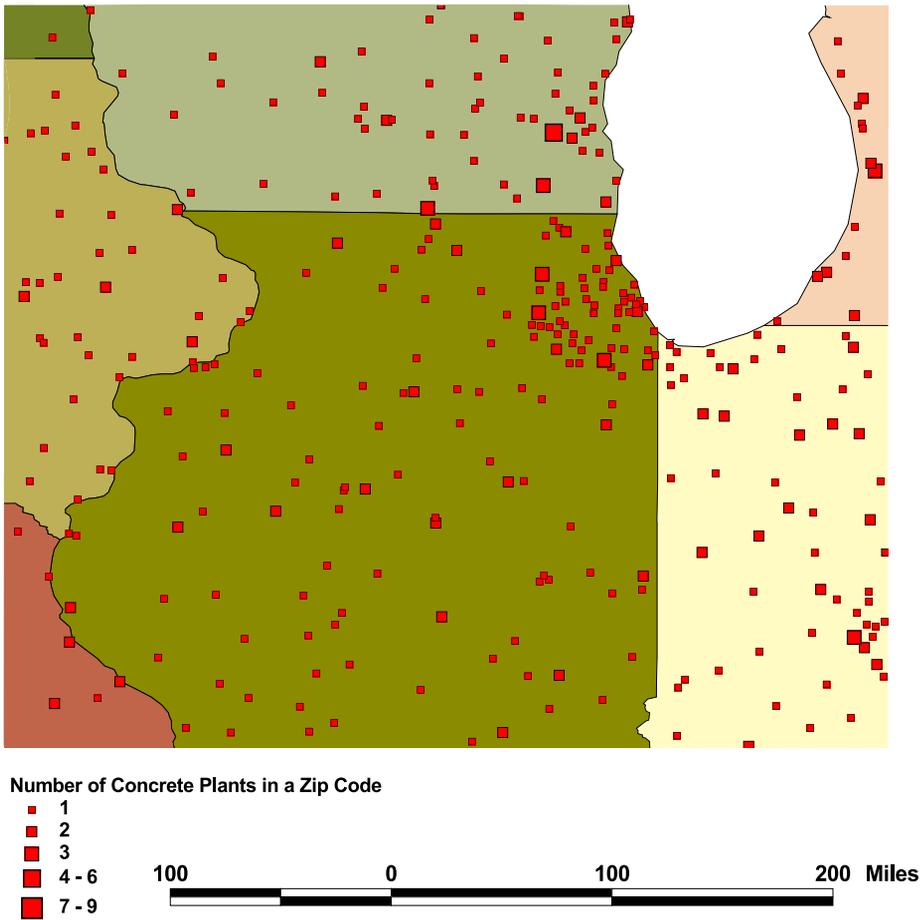
FIGURE 1.—Dispersion of ready-mix concrete plant locations in the Midwest. Source: Zip Business Patterns publicly available data set at http://www.census.gov/epcd/www/zbp_base.html for NAICS Code 327300.

2.2. *Concrete Demand*

Most concrete is purchased for building, so I measure demand with employment in the construction sector. Demand is inelastic because it is a small part of construction costs, as these do not exceed 10% of material costs for any subsector in construction. So it is implausible that the ready-mix market substantially affects the volume of construction activity. As such, changes in construction activity that affect the ready-mix concrete industry's market structure are the main source of exogenous variation.

There are large fluctuations in concrete purchases. The autocorrelation of log county construction employment is 85% for one year, 65% for five years,

TABLE I

MOST COUNTIES IN THE UNITED STATES ARE SERVED BY FEWER THAN SIX READY-MIX
CONCRETE PLANTS

Number of Concrete Plants	Number of Counties/Years	Percent
0	22,502	30%
1	23,276	31%
2	12,688	17%
3	6373	9%
4	3256	4%
5	1966	3%
6	1172	2%
More than 6	3205	4%
Total	74,438	

and 21% for 20 years. This low autocorrelation of construction activity indicates significant year-to-year variation in demand.[9]

The spatial autocorrelation of demand is also negligible. Only 2.1% of the variation in log construction employment in a county is accounted for by
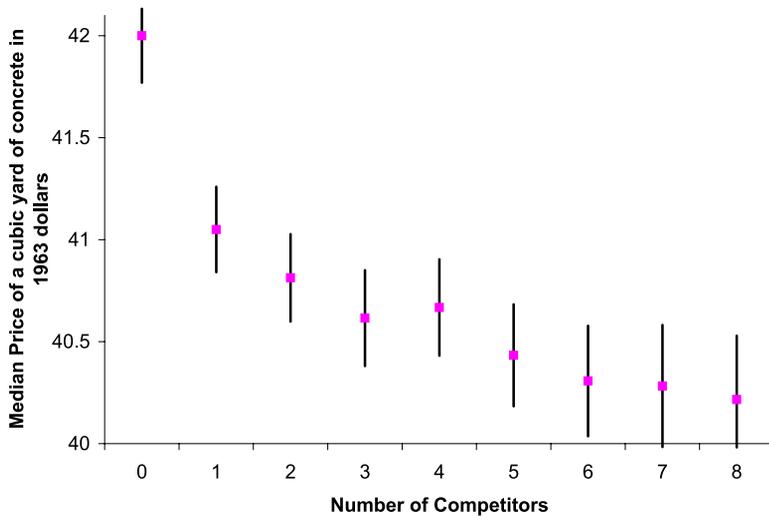
FIGURE 2.—Price declines with the addition of the first competitors, but drops by very little thereafter. Bars represent 95% confidence interval on median price.

[9]However, the demand process has more long-term correlation than an AR process would predict, as an AR(1) process would predict a 4% 20-year autocorrelation, given an 85% 1-year autocorrelation. To capture long-run differences in market size, I estimate the process for demand separately for different markets, as discussed in Section 5.3.

changes in log construction employment in counties that border it.[10] At the county level, we can think of demand evolving autonomously and, thus, focus on policies that interfere with county-level demand patterns, rather than state or national patterns.

2.2.1. *Government*

Governments purchase half of all U.S. concrete, primarily for road construction.[11] These purchases fluctuate, due to the discretionary nature of highway spending in state and federal budgets. Government demand is a major source of uncertainty for ready-mix producers.

2.3. *Sunk Costs*

Opening a concrete plant is an expensive investment. In interviews, managers of ready-mix plants estimate the cost of a new plant at between three and four million dollars, and continuing plants in 1997 had, on average, two million dollars in capital assets. Yet, there are few expenses involved in shutting down a ready-mix plant. Trucks can be sold on a competitive, used-vehicle market, and land can be sold for other uses. The plant itself is a total loss. At best, it can be resold for scrap metal, but many ready-mix plants are left on-site because the cost of dismantling them outweighs their resale value.[12]

3. DATA

I use data on ready-mix concrete plants provided by the Center for Economics Studies at the United States Census Bureau. My primary source is the Longitudinal Business Database (henceforth, LBD) compiled from data used by the Internal Revenue Service to maintain business tax records. The LBD covers all private employers on a yearly basis from 1976 to 1999 and has information about employment and salary, along with sectoral coding and firm identification, but does not record sales, materials, or capital.

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[10]Moreover, any aggregate component of construction employment would show up as spatial autocorrelation of changes in construction activity.

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

[12]I provide evidence of sunk costs in the ready-mix industry, including factors difficult to quantify, such as long-term relationships with clients and creditors. These intangible assets may account for a large fraction of sunk costs. For instance, ready-mix operators sell about half of their production with a six-month grace period for repayment. These accounts receivable have a value equivalent to half of a plant's physical capital assets. They also function as a sunk cost, as it is more difficult to collect these accounts if the firm cannot punish non-payment by cutting off future deliveries of concrete.

Production of ready-mix concrete for delivery predominantly takes place at establishments in the ready-mix sector (NAICS 327300 and SIC 3273), so I choose the establishments in this sector.[13]

To construct longitudinal linkages across plants over time, I adapt the Longitudinal Business Database Number (henceforth, LBDNUM), developed by Jarmin and Miranda (2002). This identifier is constructed from Census ID, employer ID, and name and address matches of all plants in the LBD. I use Jarmin and Miranda's (2002) plant birth and death flags to measure entry and exit.[14] Each year, about 40 plants (or about 1.6 percent of plants) are temporarily shut down. I do not treat temporary shutdown as exit, since the cost of reactivating a plant is smaller than building one from scratch.

I complement the LBD with data from the Census of Manufacturers (henceforth, CMF) and Annual Survey of Manufacturers (henceforth, ASM), which contain more detailed information on plants, such as inputs, outputs, and assets.[15] To obtain data on construction, I select all establishments from the LBD in the construction sector (SIC 15-16-17) and aggregate them to the county level.

The plants in my sample produce 94 percent of the ready-mix concrete shipped in the manufacturing sector. Moreover, for these plants, ready-mix concrete is 95 percent of their output.

3.1. *Panel*

Over the sample period of 1976 to 1999, there were about 350 plant births and 350 plant deaths each year, compared to 5000 continuers. Both turnover rates and the total number of plants were stable over the period.

The average ready-mix concrete plant employed 26 workers and sold about $3.4 million of concrete in 1997. About half of all sales are accounted for by material costs, while the rest is value added. However, these averages mask substantial differences between plants. Most notably, the distribution of plant

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[13]Plants occasionally switch in and out of the ready-mix concrete sector. I select all plants that have belonged to the ready-mix sector at some point in their lives, but disregard plants that switch into the concrete sector for only a small fraction of their lives, since these transient concrete plants are typically miscoded and manufacture products such as cement or concrete pipe. Specifically, I exclude from my sample plants that produce concrete less than 50% of the time.

[14]Jarmin and Miranda (2002) identified entry and exit based on the presence of a plant in the IRS's tax records. They took special care to flag cases where plants simply change owners or names by matching the addresses of plants across time. If a plant changes ownership, I do not treat this as an exit event, since the cost of changing the management at a plant should be much lower than the cost of building a plant from scratch.

[15]Unfortunately, the ASM is only sent to about one-third of plants in the ready-mix concrete sector, while the CMF is available only every five years and excludes all plants with fewer than five employees (i.e., about one-quarter of concrete plants). Since the CMF and ASM have serious issues with missing data, it is difficult to use them alone for longitudinal market-level studies. This is not true of the LBD, which includes the entire population of U.S. plants.

size is heavily skewed, with few large plants and many small ones. For instance, 5% of plants have one employee, and less than 5% of plants have more than 82 employees. Continuing plants are twice as large as either entrants (i.e., births) or exitors (i.e., deaths), measured by capitalization, salaries, or shipments.

Plant size is a crucial difference between plants, as bigger plants ship more concrete and are far less likely to exit. I use employment to measure size at a plant. Employment is a better measure of size than capital stock, since it is available for all plants in the sample, while capital stock is available for less than 20% of plant-years. Moreover, the number of employees is more auto-correlated than capital assets (91% versus 74% for capital), and is a better predictor of both future production (with a correlation of 92% with total shipments versus 43% for capital), and the likelihood of exit.[16,17]

I call a plant *small* if it has fewer than eight employees, *medium* if it has between eight and 17 employees, and *large* if there are more than 17 employees.[18] I also keep track of the largest size a plant attains, since a plant that was previously large may have assets that make it easier for it to ramp up in the future. Table II shows the probability that plants will change size, enter, or exit. In the sample of counties that excludes large markets, 47% of plants are small, 28% are medium, and 25% are big. The history of a plant's size matters. Large plants exit at a rate of 2.6%—one-third the rate of small plants (8.0%)—and plants that were large in the past are more likely to expand in the future. For instance, a medium-sized plant that was large in the past has a 21% probability of becoming large next year, versus only an 8% probability for a plant that has never been large.[19]

I aggregate plant data by county to form market-level data. Since counties in the United States vary greatly in size, I have taken care to exclude counties

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[16]I use employment instead of capital stock, since employment is measured for all plants in the data (it is derived from IRS tax returns in the LBD), while capital is available for all plants in a market for only a small number of markets (as is discussed in Collard-Wexler (2009), which used multiple imputation to fill in missing capital stock). In practice, given the coarseness of my employment bins, classifying a firm based on capital or employment does not matter very much.

[17]Ready-mix concrete has been studied extensively by Syverson (2004), who provided evidence of productivity dispersion across plants. In another paper, Collard-Wexler (2009), I discussed the dynamics of productivity dispersion. Incorporating productivity differences into the model leads to a great number of data challenges, as the data needed to construct productivity are frequently missing or imputed. Moreover, incorporating productivity into a dynamic model leads to a focus on variability in plant-level productivity, since these variations in productivity dwarf variations in demand.

[18]I choose cutoffs of eight and 18 employees because these correspond to the 33rd and 66th quantiles of the empirical distribution of employment.

[19]I do not keep track of past size if a plant is larger today than it was in the past, since it is the largest size of previous employment that determines if a firm has the equipment and land necessary to ramp up in the future. As well, if I kept track of past size, regardless of current size, this would increase the number of plant-level states from seven to 10, raising the size of the state space for the entire industry by a factor of about 14.

TABLE II

AVERAGE YEARLY PLANT TRANSITION PROBABILITIES

| | Size Next Year | | | | |
Current Size	Out	Small[a]	Medium[b]	Large[c]	Total
Out	98.5%	1.2%	0.2%	0.1%	15,134
Small	8.0%	82.4%	8.1%	1.5%	1135
Small, Medium in Past	7.9%	73.6%	17.6%	1.0%	417
Small, Large in Past	11.7%	65.8%	16.4%	6.1%	140
Medium	3.2%	20.1%	68.6%	8.1%	686
Medium, Large in Past	3.2%	11.0%	64.4%	21.3%	307
Large	2.7%	4.1%	11.1%	82.1%	913

[a]Small: Less than 8 Employees.

[b]Medium: 8 to 17 Employees.

[c]Large: More than 17 Employees.

in states, such as Arizona, that have unusually spacious counties and a small number of heavily populated urban counties.[20]

Table III presents summary statistics of the market-level data. On average, there are 1.86 plants per market. Moreover, there is a wide range of construction employment, from 11 employees (5th percentile) to 6800 employees (95th percentile).[21]

TABLE III

SUMMARY STATISTICS FOR COUNTY-AGGREGATED DATA

	Observations	Mean	Standard Deviation	5th Percentile	95th Percentile
Concrete Plant Data					
Concrete Plants	74,435	1.86	3.24	0	6
Employment	74,435	27.24	79.03	0	110
Payroll (in 000's)	74,435	4238	74,396	0	3600
Total Value of Shipment (in 000's)	24,677	3181	12,010	0	14,000
Value Added (in 000's)	24,677	1408	5289	0	6500
Total Assets Ending (in 000's)	24,677	1090	14,134	0	4700
Construction Establishment Data					
Employment	69,911	1495	5390	11	6800
Payroll (in 000's)	69,911	37,135	163,546	110	160,000
County Area (in square miles)	72,269	1147	3891	210	3200

[20]Specifically, I exclude counties with more than 20 ready-mix concrete plants, which are all urban areas. The County Business Patterns reports that there were 20 of these counties in 2007.

[21]Yet, the range of the surface area of counties, in square miles, falls between 210 and 3200—a 10-to-one difference—versus a 500-to-one difference for construction employment.

4. MODEL

I adapt the theoretical framework for dynamic oligopoly developed by Ericson and Pakes (1995) to analyze entry, exit, and investment decisions in the ready-mix concrete industry. In each market, there are $i = 1, \ldots, N$ firms, which are either potential entrants or incumbents. A firm i can be described by a firm-specific state $s_i^t \in S_i$. The typical ready-mix firm owns a single plant, and I assume that each firm owns a single ready-mix concrete plant, making plant and firm interchangeable.[22,23] Firms also react to market-level demand M^t, and thus, the market-level state s^t is the composition of the states for each firm and the aggregate state M^t:

$$s^t = \left\{ s_1^t, s_2^t, \ldots, s_N^t, M^t \right\}.$$

I distinguish between two components of the state s_i^t: x_i^t, which is common knowledge to all firms in the market, and ε_i^t, which is an independent and identically distributed (i.i.d.) private information component.[24] Denote by $x^t = \{x_1^t, x_2^t, \ldots, x_N^t, M^t\}$ and $\varepsilon^t = \{\varepsilon_1^t, \varepsilon_2^t, \ldots, \varepsilon_N^t\}$ the market-level common knowledge and private information state, respectively.

The difficulty in dynamic games is in computing an equilibrium for counterfactuals. More precisely, for this application the main burden is keeping the entire state space in memory. I choose a maximum of 10 plants per market, since this allows me to pick up most counties in the United States (where the 95th percentile of the number of plants in a county in Table III is six), and keeps the size of the state space manageable. A county with more than 10 active plants at some point in its history is dropped from the sample, since the model does not allow firms to envisage an environment with more than nine competitors.[25]

Firm i can be described by a firm-specific state $s_i^t \in S_i$:

$$(1) \qquad s_i^t = \{ \quad \underbrace{x_i^t}_{\text{(Plant Size, Past Plant Size)}} \quad, \quad \underbrace{\varepsilon_i^t}_{\text{i.i.d. shock}} \quad \}$$

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[22]Indeed, Syverson (2004) reported that 3749 firms controlled the 5319 ready-mix plants operating in 1987.

[23]Due to antitrust policy in the United States, ready-mix concrete firms historically were prevented from merging with upstream cement producers. In most other countries, ready-mix concrete plants are vertically integrated with cement producers.

[24]If, instead, ε_i^t was serially correlated, then a firm might find it optimal to condition its strategy on past actions taken by other firms in the market. This would substantially increase the size of the state space. For instance, if a firm conditioned its strategy on the history of the market for even a single year, the state space would be more than 1.9 quintillion.

[25]To allay the potential for selection bias that this procedure entails, counties with more than 10,000 construction employees at any point between 1976 and 1999 are also dropped. This excludes 15% of markets and 35% of plants from the analysis.

a vector of i.i.d. unobserved shocks ε_i^t. The firm's observed state x_i^t is whether a firm is *big*, *medium*, or *small*, as well as the firm's largest previous size, as described in Table II.

In each period t, potential entrants choose whether or not to enter a market, and incumbents can choose to exit the market. Conditional on being in the market, firms pick their common knowledge state x_i^t in the next period. Thus, the firm's action a_i^t is the choice of being out of the market, that is, $x_i^{t+1} = \emptyset$, or their state tomorrow x_i^{t+1} (small, medium, large). Demand evolves following a first-order Markov process with transition probabilities given by $D(M^{t+1}|M^t)$.

I assume the private information vector ε_i^t enters into the profit function as an additive logit shock to the value of each action a_i^t. Payoffs are given by

$$(2) \qquad r(x^{t+1}) + \tau(x_i^{t+1} = a_i^t, x_i^t) + \varepsilon_{ia}^t,$$

where $r(\cdot)$ denote the rewards from operating in the market, and $\tau(\cdot)$ are transition costs, that is, the costs of moving from one state to another. The Results section of this paper is primarily concerned with estimating these reward and transition functions.

The game's timing is:
1. Firms privately observe ε_i^t and publicly observe x^t.
2. Firms simultaneously choose actions a_i^t.
3. Demand M^t evolves to its new level M^{t+1}. Firm-level states evolve to x_i^{t+1}.
4. Payoffs $r(x^{t+1}) + \tau(a_i^t, x_i^t) + \varepsilon_{ia}^t$ are realized.

I define the firm's ex ante (i.e., before observing ε_i^t) value as

$$(3) \qquad V(x^t) = \mathbb{E}_{\varepsilon_i^t}\Big(\max_{a_i^t} \mathbb{E}_{x_{-i}^{t+1}}\big[r(x_{-i}^{t+1}, x_i^{t+1}) + \tau(x_i^{t+1} = a_i^t, x_i^t)$$

$$+ \varepsilon_{ia}^t + \beta V(x^{t+1})\big]\Big),$$

and firms pick the action that maximizes the net present value of rewards:

$$(4) \qquad a_i^{*t} = \operatorname*{argmax}_{a_i^t} \mathbb{E}_{x_{-i}^{t+1}}\big[r(x_{-i}^{t+1}, x_i^{t+1}) + \tau(x_i^{t+1} = a_i^t, x_i^t) + \varepsilon_{ia}^t + \beta V(x^{t+1})\big].$$

Doraszelski and Satterthwaite (2010) showed that if ε_{ia}^t is an additive, action-specific shock that has full support, then there will exist pure strategy Nash equilibria for this game, that is, policies $a^*(x^t, \varepsilon_i^t)$ such that a unilateral, one-shot deviation to strategy $\tilde{a}_i(x^t, \varepsilon_i^t)$ does not lead to a higher net present value of rewards, conditional on all other players using strategies $a_{-i}^*(\cdot)$.[26] Last, I introduce some additional notation. To work out the firm's strategies, I compute

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[26]Proposition 2 in Doraszelski and Satterthwaite (2010) describes conditions under which the Ericson and Pakes (1995) model has a pure strategy equilibrium, essentially pointing out that exit and entry costs need to have full support shocks to ensure the existence of a pure strategy equilibrium. The game I describe has full support shocks to the value of entering and exiting, as well as to the value of taking any action.

the *ex ante choice-specific value function* $W(a_i^t, x^t)$, that is, the net present value of payoffs conditional on taking action a_i^t before ε_i^t is observed, defined as[27]

$$(5) \qquad W\big(a_i^t, x^t\big) = \mathbb{E}_{x^{t+1}|a_i^t}\big[r\big(x^{t+1}\big) + \tau\big(a_i^t, x_i^t\big) + \beta V\big(x^{t+1}\big)\big]$$

$$= \mathbb{E}_{x^{t+1}|a_i^t}\Big[r\big(x^{t+1}\big) + \tau\big(a_i^t, x_i^t\big)$$

$$+ \beta \mathbb{E}_{\varepsilon^{t+1}} \max_{a_i^{t+1}} \big(W\big(a_i^{t+1}, x^{t+1}\big) + \varepsilon_{a_i}^{t+1}\big)\Big].$$

Given the choice-specific value function, it is easy to reckon the firm's conditional choice probability (henceforth, CCP) $\Psi[a_i^t|x^t]$, that is, the probability that a firm will play action a_i^t in an observable state x^t—before observing ε_i^t—using the logit formula:

$$(6) \qquad \Psi\big[a_i^t|x^t\big] = \frac{\exp(W(a_i^t, x^t))}{\displaystyle\sum_{j \in A_i} \exp(W(j, x^t))}.$$

5. PARAMETERIZATION AND CONDITIONAL CHOICE PROBABILITY ESTIMATION

In this section, I first present the parameterized profit function that I estimate. Second, I show the Indirect Inference Conditional Choice Probability estimator (henceforth, IICCP) used to recover these parameters. Third, I discuss details of the estimation of conditional choice probabilities.

5.1. *Profit Function*

I use a simple Bresnahan and Reiss (1991) style reduced form for the reward function, endowed with parameters θ that I estimate:

$$(7) \qquad r\big(a_i^t, x^t|\theta\big) = \sum_{\alpha \in \{\text{Big, Medium, Small}\}} 1\big(a_i^t = \alpha\big)$$

$$\times \bigg(\underbrace{\theta_1^\alpha}_{\text{Fixed Cost}} + \underbrace{\theta_2^\alpha M^{t+1}}_{\text{Demand Shifter}} + \underbrace{\theta_3^\alpha g\Big(\sum_{-i} x_{-i}^{t+1} \neq \text{out}\Big)}_{\text{Competition Parameters}} \bigg),$$

[27]Remember that V and W are linked together by

$$V\big(x^t\big) = \mathbb{E}_{\varepsilon_{a_i^t}} \Big(\max_{a_i^t} W\big(a_i^t, x^t\big) + \varepsilon_{a_i^t} \Big).$$

where $g(\cdot)$ is a nonparametric function of the number of competitors. This reward function is linear in parameters that I exploit during estimation.[28]

Transition costs are

$$(8) \qquad \tau\big(a_i^t, x_i^t | \theta\big) = \theta_4^{l,m} \sum_{l>0, m \neq l} 1\big(a_i^t = l, x_i^t = m\big),$$

so a firm pays a transition cost to change its state. However, I assume that a firm does not pay any exit costs.[29]

Sections 5.2 and 5.3 discuss the estimation of the parameters θ of the profit and transition cost function. The reader can skip to Section 6 for estimates of these parameters.

5.2. *Indirect Inference CCP Algorithm*

Applying the Ericson and Pakes (1995) framework to data has proven difficult, due to the complexity of computing a solution to the dynamic game and multiple equilibria.[30] For single-agent problems, Hotz and Miller (1993) and Hotz, Miller, Sanders, and Smith (1994) bypassed the computation of optimal policies by estimating policies directly from agents' choices. This idea has been adapted to strategic settings by several recent papers in Industrial Organization—most prominently, Bajari, Benkard, and Levin (2007), Pakes, Berry, and Ostrovsky (2007), Pesendorfer and Schmidt-Dengler (2008), Ryan (2012), and Dunne, Klimek, Roberts, and Xu (2006).

I estimate the model by matching the optimal choice probabilities $\Psi(a_i | x, \theta)$ to the data. The natural way to do this would be to compute an equilibrium to the dynamic game's given parameters θ. However, doing this for each candidate parameter vector θ is computationally impractical.

Instead, I have adapted a conditional choice probability estimator that can be applied to games. My CCP algorithm can handle the very large state space in this problem (over 350,000 states), and I use a Simulated Indirect Inference Criterion approach for estimation (Keane and Smith (2003), Gourieroux, Monfort, and Renault (1993), and Gourieroux and Monfort (1996)).[31]

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[28]This "reduced-form" profit function is an approximation to the profits earned by competitors. For estimation purposes, I need to assume that the specification error in r is orthogonal to the state variables x.

[29]While entry, fixed costs, and exit costs are not strictly collinear, Monte Carlo experiments indicate that it is quite difficult to jointly identify all three of these costs. Appendix D of the Supplemental Material (Collard-Wexler (2013)) shows the identification of this model, as well as some intuition for why it is difficult to separately identify fixed costs, entry costs, and exit costs.

[30]Even with the high performance Stochastic Algorithm used in this paper, it takes more than an hour to compute a solution.

[31]In a previous version of this paper, I computed present estimates using an approach in the spirit of Aguiregabiria and Mira (2007), which iteratively updates the strategies used by firms. I find that using an iterated technique yields very similar results to those presented in the paper.

ALGORITHM—CCP Indirect Inference Algorithm (CCPII):

1. *Replace optimal choice probabilities Ψ with an estimate from the data $\hat{P}$. Estimate the demand transition process $\hat{D}[M^{t+1}|M^t]$.*

I assume a single symmetric Markov-Perfect equilibrium played in each observed state x. Thus, I can recover the empirical analogue to Ψ by looking at the empirical frequency of actions in different states $\hat{P} = \{\Pr(a_i^t|x^t)\}_{a_i^t, x^t}$. Likewise, I can estimate the demand transition process (denoted $\hat{D}$) using the observed demand transitions in the data. I discuss the details of the estimation of $\hat{P}$ and $\hat{D}$ in Section 5.3.

2. *Compute the W function up to a vector of parameters θ, conditional on policies $\Psi(a_i^t|x^t) = \hat{P}[a_i^t|x^t]$.*

A final rewriting of the W function is now in order to aid with the estimation of the model. The rewards and transition costs in equations (7) and (8) are linear in parameters θ, so the profit function can be rewritten as $r(a_i, x|\theta) - \tau(a_i, x_i|\theta) = \theta \cdot \vec{\rho}(a_i, x)$, where $\vec{\rho}$ is a function that returns a vector. This implies that the W function is separable in dynamic parameters, as in Bajari, Benkard, and Levin (2007), since

$$
(9) \qquad W(a_i, x|\theta) = \mathbb{E} \sum_{t=1}^{\infty} \beta^t \big(r\big(a_i^t, x^t|\theta\big) - \tau\big(a_i^t, x_i^t|\theta\big) \big)
$$

$$
= \theta \cdot \mathbb{E} \sum_{t=1}^{\infty} \beta^t \vec{\rho}\big(a_i^t, x^t\big) \equiv \theta \cdot \Gamma(a_i, x).
$$

Note that the Γ function only depends on the expected evolution of the state and actions in the future, rather than on the parameter vector θ:

$$
(10) \qquad \Gamma(a_i, x) = \mathbb{E} \sum_{t=1}^{\infty} \beta^t \vec{\rho}\big(a_i^t, x^t\big).
$$

I compute the Γ function using forward simulation, in which I simulate the evolution of the state x and action a_i by drawing from the choice probabilities Ψ and the demand transition process D. Since I have replaced these objects by their empirical analogues $\hat{P}$ and $\hat{D}$, I can perform this forward simulation without solving the model. The forward simulation is done with a discrete action stochastic algorithm (henceforth, DASA) that is close to Pakes and McGuire (2001), presented in Appendix B of the Supplemental Material.

The optimal choice probabilities Ψ can be rewritten as a function of $\Gamma^{\hat{P}}$ and θ (where I include the subscript $\hat{P}$ to emphasize that Γ depends on my estimate

of CCPs):

$$(11) \qquad \Psi\big(a_i | x, \Gamma^{\hat{P}}, \theta\big) = \frac{\exp\big(\theta \cdot \Gamma^{\hat{P}}(a_i, x)\big)}{\sum_{j \in A} \exp\big(\theta \cdot \Gamma^{\hat{P}}(j, x)\big)}.$$

3. Simulated Indirect Inference Estimation

I use an indirect inference criterion function to estimate the model.[32] The estimator matches regression coefficients from the data (denoted $\hat{\beta}$) with regression coefficients from simulated data generated by the model, conditional on a parameter θ (denoted $\tilde{\beta}(\theta)$). I use a multinomial linear probability model as an auxiliary model. It is simple to estimate and is a close analogue to the multinomial dynamic logit model.[33]

I define the outcome vector from the data as $\mathbf{y}_n$ and the predicted choice probabilities given by the model $\tilde{\mathbf{y}}_n(\theta)$ for observation n as

$$(12) \qquad \mathbf{y}_n = \begin{bmatrix} 1(a_n = small) \\ 1(a_n = medium) \\ 1(a_n = big) \end{bmatrix}, \quad \tilde{\mathbf{y}}_n(\theta) = \begin{bmatrix} \Psi(small | x_n, \Gamma, \theta) \\ \Psi(medium | x_n, \Gamma, \theta) \\ \Psi(large | x_n, \Gamma, \theta) \end{bmatrix},$$

where the outcome vector $\tilde{\mathbf{y}}_n(\theta)$ is the predicted choice probabilities Ψ.[34] I run an ordinary least squares (OLS) regression on $y_n = \mathbf{Z}_n \hat{\beta}$ and find the OLS coefficients of the multinomial linear probability model. Likewise, I run an OLS regression on the predicted choice probabilities $\tilde{y}_n$ to obtain the coefficients for the model $\tilde{\beta}(\theta)$, given parameter θ.

The criterion function minimizes the distance between the regression coefficient in the data and in the simulated data:

$$(13) \qquad \mathcal{Q}(\theta) = \big(\hat{\beta} - \tilde{\beta}(\theta)\big)' \mathbf{W} \big(\hat{\beta} - \tilde{\beta}(\theta)\big),$$

[32] Indirect Inference is less sensitive to error in the Γ function than maximum likelihood and, like many GMM estimators, can be consistent even if there is simulation error in Γ, and this simulation error does not vanish asymptotically. For some intuition, if the exit rate in the data is 1%, but the model predicts an exit probability of almost 0%, then a maximum likelihood criterion would have an infinite log-likelihood, while an indirect inference criterion would find an error of 1%. I find it easier to minimize this criterion function versus a criterion of the form $\|y_n - \tilde{y}_n(\theta)\|$, which is closer to traditional GMM.

[33] The auxiliary model does not need to be a consistent estimator and need not have an interpretation of any sort. Its sole responsibility is to provide rich description of the patterns of a data set and to be simple to estimate.

[34] Theorem 1 in Appendix D of the Supplemental Material proves that using the choice probabilities Ψ as predicted actions gives the same θ's as drawing action $a_n \sim \Psi(\cdot | x_n, \Gamma, \theta)$ from the predicted choice probabilities when one uses an infinite number of simulation draws.

where **W** is a weighting matrix. I use $\mathbf{W} = \text{Var}[\hat{\beta}]^{-1}$, the inverse of the covariance matrix from the OLS regression. Appendix D of the Supplemental Material shows conditions under which the estimator is consistent, which is an extension of the consistency of Indirect Inference estimators.[35]

5.3. *Conditional Choice Probabilities*

5.3.1. *Detecting Market Unobservables*

I assumed that the unobserved state $\varepsilon_{a_i^t}$ is an i.i.d. logit, which rules out persistent market-level unobservables. This is a problem. Some markets have higher costs than others, due to, for instance, the presence of unionized workers in Illinois but not in Alabama. In addition, some markets have higher demand for concrete that is not captured by employment in the construction sector—for instance, because asphalt, but not concrete, melts on roads in Texas but not in Maine.[36]

To detect market unobservables, Table IV runs binary logit regressions of a plant's decision to be active in the market (i.e., have a plant) on construction employment, the number of competitors, plant size in the prior year, and largest ever plant size. Column I presents the base estimates, Column II includes market-fixed effects via a conditional logit, and Column III has state- and year-fixed effects. Column IV includes indicators for market categories μ, which I henceforth refer to as market-category effects. These categories are constructed by rounding the average number of plants in a county to the nearest integer. Finally, Columns V, VI, VII, and VIII show alternative category controls based on the lagged average number of firms, the average number of firms before 1983 (on data from 1984 to 1999), average log construction employment, and average total shipments of concrete, again grouped into four categories.[37]

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[35]In a prior version of the paper, I estimated the model by iterating on the conditional choice probabilities, that is, updating them using parameter estimates θ. To implement this procedure (which requires the assumption of a single equilibrium for the dynamic game in order to be consistent), I need to add extra steps where:

4. Replace $\hat{P}[a_i|x]$ with $\Psi[a_i|x, \hat{\theta}]$, where $\hat{\theta}$ is the current estimate of the parameters in the profit function and $\Psi[a_i|x, \hat{\theta}]$ are computed equilibrium policy functions given $\hat{\theta}$.

5. Repeat steps 2–4 until θ converges.

When I iterate on the conditional choice policies, I get results that are very similar to the results obtained when I do not.

[36]There are numerous differences between markets, such as their road network, intensity of use of concrete in construction, density, area served, and input costs for cement and gravel. Thus, construction employment alone cannot possibly capture all components of a market's profitability.

[37]A more thorough discussion of market-category controls can be found in Appendix C.1 of the Supplemental Material.

TABLE IV

BINARY LOGIT REGRESSIONS OF THE DECISION TO HAVE AN ACTIVE PLANT WITH
MARKET-FIXED EFFECTS AND MARKET-CATEGORY EFFECTS[a]

Dependent Variable: Activity	I	II (FE[†])	III	IV (μ)	V	VI	VII	VIII
Log County Construction	0.17***	0.03	0.19***	0.02*	0.03***	0.20***	0.09***	0.07***
Employment	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
First Competitor	−1.40***	−1.26***	−0.85***	−1.07***	−1.01***	−0.69***	−0.73***	−0.85***
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.01)	(0.04)	(0.04)
Second Competitor	0.00	−0.54***	−0.03	−0.48***	−0.47***	−0.03	0.04	−0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Third Competitor	0.03	−0.33***	0.04	−0.32***	−0.32***	0.00	0.07	0.03
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
Log Competitors Above 4	0.02	−0.13***	0.09**	−0.06*	−0.10*	0.10**	0.10**	0.09**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)
Small	6.89***	6.50***	6.92***	6.73***	6.75***	7.06***	6.89***	6.91***
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)
Small, Medium in Past	6.85***	6.36***	6.82***	6.60***	6.61***	6.92***	6.85***	6.83***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
Small, Large in Past	6.41***	5.90***	6.34***	6.19***	6.19***	6.42***	6.40***	6.36***
	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)
Medium	7.72***	7.34***	7.66***	7.54***	7.56***	7.95***	7.72***	7.66***
	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)	(0.08)	(0.06)	(0.06)
Medium, Large in Past	7.72***	7.26***	7.60***	7.47***	7.47***	7.82***	7.71***	7.63***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.10)	(0.08)	(0.05)
Large	7.85***	7.48***	7.71***	7.63***	7.64***	7.91***	7.83***	7.73***
	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
Market-Fixed Effects		X						
State-Fixed Effects			X					
Year-Fixed Effects			X					
Market Classification								
Variable◇								
Average Number of Plants				X				
Lagged Average Plants					X			
Before 1983 Average Plants						X		
Construction Employment							X	
Total Shipments of Concrete								X
Observations	409,850	409,850	409,850	260,170	409,850	409,850	409,850	409,850
Markets	2029	2029	2029	2029	2029	2029	2029	2029
Log-Likelihood	−37,541	−32,759	−37,429	−36,713	−36,695	−22,230	−37,524	−37,384
χ^2	49,545	301,019	51,517	52,775	51,795	34,019	50,302	51,538

[a]Standard errors are clustered by market. [†] Market-fixed effects are implemented via a conditional logit. ◇ Average number of plants (μ) is the mean number of plants in a market, rounded to the nearest integer. Lagged Average Plants is the mean number of plants in the market for years preceding t, rounded to the nearest integer. Before 1983 Average Plants is the mean number of plants in a market before 1983, rounded to the nearest integer. Only years from 1983 to 1999 are used in the regression for this market classification variable in Column V. Construction Employment Classification and Total Shipments of Concrete use the mean of these variables in a market to classify markets into four categories. *, **, *** indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

The effects of the second, third, and additional competitors are close to zero in Column I; they turn negative when I include market-fixed or market-category effects in Columns II and IV. If the market-level shock is ignored, then the number of competitors will be positively correlated with market unobservables. This leads to upward bias in the competition coefficient.

The effect of past plant size has a substantial effect on the probability of activity today, which is to be expected, given the sunk costs of opening a ready-mix concrete plant. However, this effect of past size is smaller in Columns II and IV than in Column I. Past plant size is also related to market size—both observed and unobserved. Thus, past plant size also proxies for serial correlation in unobserved market demand and is biased upwards.

The effect of log country construction employment falls when market-category or market-fixed effects are added. Market effects wash out a large part of the correlation between demand and the number of firms in a market, since much of this comes from cross-sectional variation. As discussed in the context of production function estimation by Griliches and Hausmann (1986), the remaining time-series variation in demand is more likely to suffer from measurement error, which attenuates the demand coefficient. Much of the treatment of market-category effect to follow is a "hack" to navigate the twin issues of upwardly biased competition coefficients and attenuated demand coefficients.[38]

Adding year- and state-fixed effects (Column III) does not substantially change the coefficients from Column I (no effects). Heterogeneity across markets is the issue, rather than year-to-year shocks. Moreover, while there are large differences between states in their use of ready-mix concrete, these do not capture much of the differences between markets.

5.3.2. *Market Categories*

While estimating market-level policy functions is straightforward, it runs into serious data constraints, since I cannot identify parameters from the cross-section. To render the market-fixed effects tractable, I collapse market effects into market-category effects μ. This classification scheme is based on an endogenous variable, but the estimates in Column V that use the lagged number of firms, a variable that is not endogenous, are indistinguishable from the market-category estimates in Column IV.[39] Likewise, Appendix C.2 of the Sup-

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[38]This problem is similar to the use of fixed effects in a production function regression discussed in Griliches and Hausmann (1986), where fixed effects eliminate the most important source of variation in capital stock, thereby leading to a downward bias on the capital coefficient. These two biases are a serious problem: having no market-level controls leads to a market where the number of firms sloshes around, since competition effects are too small to pin down the number of firms, while a model with market-fixed effects predicts a response to demand that is too small and too few changes in the number of plants.

[39]However, this classification scheme, which is based on the lagged number of firms, is harder to fit into the model, since a market can switch categories, which makes the market category a state variable.

plemental Material shows estimates based on categories constructed from estimated market-fixed effects. These types of categories yield similar estimates as those in Column III using market categories μ.

However, other plausible market-category controls do not work. These include the number of firms in a pre-period (Column VI), average log construction employment (Column VII), total shipments of concrete (Column VIII), and the square mileage of a county and its density. They are similar to the estimates without market controls in Column I.

5.3.3. *Estimating CCPs*

Since the $\varepsilon_{a_i}^t$'s are logit draws, I estimate the conditional choice probabilities with a multinomial logit of a firm's choice of its size next year (a_i^t), presented in Table V. Column II has market-category effects μ (henceforth, $\hat{P}^\mu$), but Column I does not (henceforth, $\hat{P}$).[40]

These multinomial logits illustrate the identification in the model. Firms are more likely to exit, or less likely to enter, if there are more competitors or higher demand. Second, past plant size explains a firm's current choice of size and activity, indicating the role of sunk costs. Finally, for this model, the ε shocks are not inconsequential, as these generate entry and exit not connected to observable shifters of profits: demand and competition.

As seen in the findings from Table IV, introducing market-category effects leads to significantly more negative effects of competitors. In particular, the effect of more than one competitor is positive without market-category effects. Positive effects of competition have a toxic effect on both estimation and counterfactuals, since simulating the model forward with positive spillovers between firms makes the market tip from no firms to being completely filled up with firms.

Finally, both the no-effect and category effects estimates show that the effect of demand is much higher for large plants than small ones, as the effect of log construction employment is 0.13 for small plants, versus 0.29 and 0.51 for medium and large plants, respectively. This happens because larger markets have bigger plants, and I return to this issue in Section 6.[41]

5.3.4. *Estimating Demand Transitions*

The demand transition matrix D is estimated by market category μ using a bin estimator $\hat{D}^\mu[i|j] = \frac{\sum_{(l,t)} 1(M_l^{t+1} \in B_i, M_l^t \in B_j)}{\sum_{(l,t)} 1(M_l^t \in B_j)}$ with 10 bins (that differ by cate-

---

[40]Due to limited data, rather than estimating coefficients on the logit $\beta_{a_i}^{\mu,0} + \beta_{a_i}^{\mu,X} X$ that all vary by market category, I assume that the market effects are just additive constants, that is, $\beta_{a_i}^{\mu,0} + \beta_{a_i}^X X$. The main issue is that it is difficult to estimate the effect of, say, the third competitor in a market that has, on average, one firm in it—hence in market category $\mu = 1$, as we rarely see three firms in this type of market.

[41]It is important for the CCPs to be able to replicate firms' expectations over the evolution of the ready-mix concrete market. Section 6.1 discusses this issue.

TABLE V

MULTINOMIAL LOGIT ON THE CHOICE TO BE LARGE, MEDIUM, OR SMALL

Dependent Variable	Independent Variable	I		II (Market Category)	
		Coeff.	S.E.	Coeff.	S.E.
Small in $t+1$	Small	6.59	(0.03)	6.42	(0.03)
	Small, Medium in Past	6.45	(0.04)	6.18	(0.04)
	Small, Large in Past	5.94	(0.06)	5.72	(0.06)
	Medium	6.02	(0.05)	5.81	(0.05)
	Medium, Large in Past	5.41	(0.08)	5.16	(0.08)
	Large	4.58	(0.06)	4.37	(0.06)
	Log County Employment	0.13	(0.01)	−0.06	(0.01)
	First Competitor	−1.42	(0.04)	−1.71	(0.04)
	Second Competitor	0.10	(0.03)	−0.46	(0.03)
	Third Competitor	0.16	(0.04)	−0.26	(0.04)
	Log of Competitors Above 3	0.11	(0.03)	−0.04	(0.03)
	Market Category μ			X	
	Constant	−3.94	(0.06)	−3.17	(0.06)
Medium in $t+1$	Small	6.25	(0.05)	6.08	(0.05)
	Small, Medium in Past	6.96	(0.06)	6.70	(0.06)
	Small, Large in Past	6.43	(0.08)	6.22	(0.08)
	Medium	9.16	(0.06)	8.96	(0.06)
	Medium, Large in Past	9.08	(0.08)	8.83	(0.08)
	Large	7.44	(0.07)	7.23	(0.07)
	Log County Employment	0.29	(0.01)	0.12	(0.01)
	First Competitor	−1.54	(0.05)	−1.87	(0.05)
	Second Competitor	0.00	(0.04)	−0.53	(0.04)
	Third Competitor	0.06	(0.05)	−0.32	(0.05)
	Log of Competitors Above 3	0.02	(0.03)	−0.11	(0.03)
	Market Category μ			X	
	Constant	−6.72	(0.08)	−5.99	(0.09)
Large in $t+1$	Small	5.04	(0.08)	4.88	(0.08)
	Small, Medium in Past	4.53	(0.13)	4.28	(0.13)
	Small, Large in Past	5.78	(0.11)	5.58	(0.11)
	Medium	7.46	(0.08)	7.27	(0.08)
	Medium, Large in Past	8.37	(0.09)	8.13	(0.09)
	Large	9.76	(0.07)	9.56	(0.07)
	Log County Employment	0.52	(0.01)	0.34	(0.02)
	First Competitor	−1.61	(0.05)	−1.94	(0.06)
	Second Competitor	−0.03	(0.05)	−0.58	(0.05)
	Third Competitor	−0.02	(0.06)	−0.42	(0.06)
	Log of Competitors Above 3	−0.04	(0.04)	−0.17	(0.04)
	Market Category μ			X	
	Constant	−8.58	(0.11)	−7.83	(0.11)
	Observations	409,850		409,850	
	Log-Likelihood	84,855		83,814	
	Likelihood Ratio	400,760		402,841	

gory); the demand level within a bin is set to the mean demand level. Note that construction employment varies considerably across market categories, for example, from 285 to 4200 employees from market category 1 to 4.

Finally, the Γ^μ function is computed by market category μ using CCP's $\hat{P}^\mu$ and demand transition process $\hat{D}^\mu$.[42]

6. RESULTS

I fix the discount factor to 5% per year. The covariates of the multinomial linear probability model (denoted z_n) used to estimate the $\hat{\beta}$ coefficients, and used in an auxiliary model in the CCPII, are indicators for the firm's current state, the number of competitors in a market, and the log of construction employment in the county. These coefficients vary by market category μ and by action chosen a_i. Thus, the model matches moments conditioned on market category μ.

Table VI presents estimates of the dynamic model. In line with interviews with producers in Illinois, I calibrate the entry costs for a medium-sized plant to $2 million. This allows me to convert parameters in variance units into dollars. To make sense of the magnitudes of these estimates, note that average sales are $3.4 million per year. The variance of ε is estimated to $133,000 per year, or about 4% of sales, which is below year-to-year changes in profits due to changes in productivity.[43,44] The magnitude of ε is important, since these i.i.d. shocks generate both turnover and changes in plant size that are unrelated to changes in demand.

The fixed costs of operating a plant are about $244,000 for a medium-sized plant, slightly less for a small plant, and slightly more for a large plant. Doubling the number of construction workers in a county increases profits by $6000 for a small plant versus $11,000 and $14,000 for a medium- and a large-sized plant, respectively. This reflects the fact that bigger markets have both more plants and larger plants.

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[42]I can go one step further and include market categories in a firm's profit function, which allows me to estimate a profit function $r^\mu(a_i^t, x^t|\theta)$ where rewards are additively separable in the market-category level component:

$$r^\mu(a_i^t, x^t|\theta) = r(a_i^t, x^t|\theta) + \xi_a^\mu + \varepsilon_{a_i^t}$$

and have a market/action effect $\xi_{a_i}^\mu$. I have also estimated this model with market-category fixed effect. I find that estimating market-category profit shifters yields inferior fit as compared to the procedure used in the paper.

[43]Collard-Wexler (2009) estimated a similar model that allows for productivity differences between producers and found large differences in per-period profits due to differences in productivity.

[44]I could have used revenues of ready-mix plants to convert my estimates into dollars. When I compute plant-level variable profits as the difference between plant-level revenues and plant-level costs, I obtain implausibly high rates of return on capital (on the order of 30%). Thus, I choose not to use revenue data in the estimation of the model.

TABLE VI

ESTIMATES FOR THE DYNAMIC MODEL OF ENTRY, EXIT, AND INVESTMENT[a]

		Coeff.	S.E.[*]
Fixed Cost	Small	−139	(6)
	Medium	−244	(10)
	Large	−285	(6)
Log Construction	Small	20	(1)
Employment	Medium	35	(2)
	Large	45	(1)
1st Competitor	Small	−48	(4)
	Medium	−58	(5)
	Large	−63	(6)
Log Competitors	Small	−17	(3)
(Above 1)	Medium	−44	(4)
	Large	−48	(3)
Transition Costs			
Out → Small		−1002	(11)
Out → Medium[†]		*−2000*	(107)
Out → Large		−1771	(53)
Small → Medium		−332	(7)
Small, Past Medium → Medium		−772	(32)
Small, Past Large → Medium		−325	(8)
Small → Large		−1809	(73)
Small, Past Medium → Large		−608	(19)
Small, Past Large → Large		−343	(16)
Medium → Small		−107	(6)
Medium, Past Large → Small		−314	(6)
Medium → Large		101	(14)
Medium, Past Large → Large		−43	(7)
Large → Small		−254	(7)
Large → Medium		−403	(6)
Standard Deviation of Shock		133	

[a]All estimates in thousands of dollars. [†] The entry costs of a medium-sized plant are calibrated to $ 2 million. [*] Standard Errors are computed using 100 block bootstrap replications, where I reestimate the demand transition process $\hat{D}^{\mu}$ and the conditional choice probabilities $\hat{P}^{\mu}$, then minimize the criterion function $\mathcal{Q}$ to find $\hat{\theta}$. I block bootstrap by market, resampling a market's history from 1976 to 1999, so the computed standard errors account for serial correlation within a market.

Indeed, Figure 3, which plots local polynomial regressions of the log of construction employment in the county against both the average size of a plant (measured by payroll) and the number of plants in a county, shows that plant size is increasing with market size. For instance, a county with 150 construction sector employees has an average payroll per concrete plant of $400,000, while a county with 1010 construction employees has an average that is closer to $600,000. This effect is not specific to the ready-mix concrete industry, as

County Size and the number and size of ready-mix concrete plants
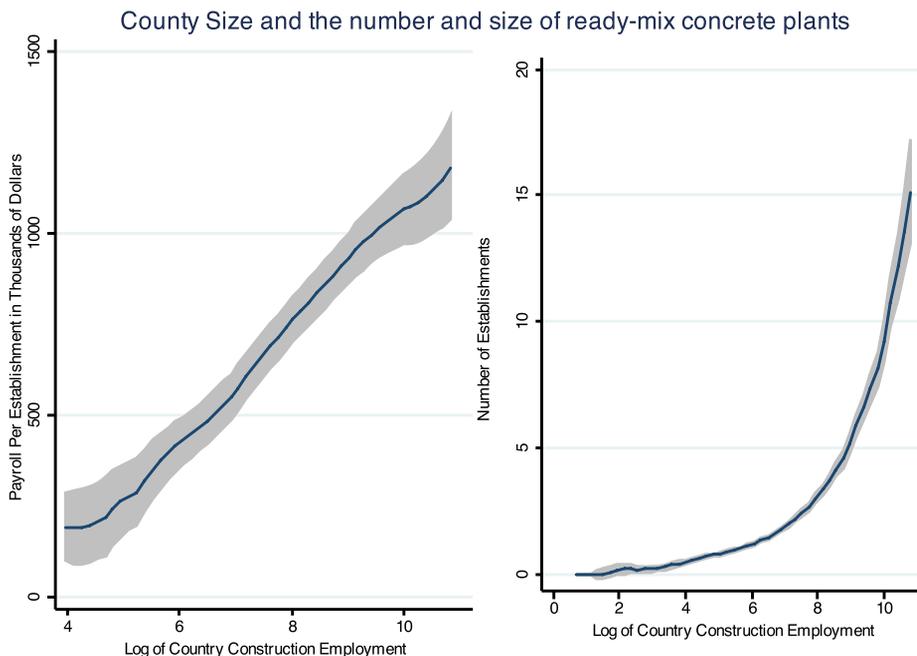
Source: County Business Patterns 2007, Construction: NAICS 23. Ready-Mix Concrete NAICS 327320

FIGURE 3.—Larger markets have both more plants and larger plants. Local polynomial regressions with shaded areas representing the 95% confidence interval.

Campbell and Hopenhayn (2005) have also documented this link for retail trade. Moreover, this implies that any change in the size of a market will alter the industry's size distribution.

Second, there is a linear relationship between the size of establishments and the log of construction employment for the small markets examined in this paper. Regressing the log of the number of concrete plants on log construction employment, I find a coefficient of 0.69, so a 1% increase in construction employment increases the number of firms by less than 1%. This implies that the number of plants in a county is a concave function of construction employment. The concavity of the number of plants per market as a function of construction employment will turn out to have important implications when I run counterfactuals that reduce demand volatility.

The number of competitors in a county has a large effect on profits. The first competitor reduces profits by $58,000 for a medium-sized plant, and doubling the number of competitors (beyond the first competitor) reduces profits by $44,000 per year. The first competitor has a larger impact than subsequent

competitors, which echoes the Bertrand-like nature of competition in the industry. [45]

The patterns in the transition costs reflect the transition patterns for plant size found in Table II. Entry costs are $1.0 million for small plants and $1.7 million for large plants. This is in line with substantial differences in machinery and land for bigger plants. There are also large costs of increasing the size of a plant. It takes about $0.3 million to grow a plant from small to medium, $1.8 million to ramp it up from small to large, and $0.1 million to take a plant from medium to large. Thus, it is cheaper to enter as a small plant and grow to a large plant in the next period, and, indeed, 80% of plants enter as small plants. Finally, the model also estimates substantial costs of ramping back down the size of a plant. These large transition costs imply that plants have a weak response to demand shocks on both the extensive (i.e., entry) and intensive (i.e., size) margin.

A bigger past size reduces the costs of growing a plant at some future point, and small plants that were medium or large in the past find it easier to ramp back up. Likewise, a medium-sized plant that was large in the past has a lower cost of reverting back to being a large plant. This dependence of transition costs on size in previous years lowers implicit adjustment costs, since a plant can shrink today and retain the ability to cheaply increase its size in the future.

6.1. *Model Fit*

To evaluate the fit of the model, I compare the evolution of the concrete industry to the one predicted by the model. I obtain the model's prediction by computing an equilibrium to the dynamic game with a discrete action stochastic algorithm (DASA), presented in Appendix A of the Supplemental Material, given the estimated parameters (henceforth $\hat{\theta}$) in Table VI. The DASA is an adaptation of the stochastic algorithm of Pakes and McGuire (2001).[46] This equilibrium needs to be computed for all four market categories, since they have different demand $\hat{D}^\mu$ processes.

Using computed policies and the demand transition process, I simulate the model from the observed states in 1976 until 1999.[47] Table VII shows moments for the data (Column I), the simulation from the model's prediction given es-

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[45]If I remove market indicators from the covariates z in the auxiliary regression, I find substantially smaller effects of competition. Thus, it is still important to target these market-level moments.

[46]To compute counterfactual industry dynamics, I assume the existence of a single symmetric Markov perfect equilibrium per market category μ. Besanko, Doraszelski, Kryukov, and Satterthwaite (2010) showed that this assumption may be problematic.

[47]Since the estimation of θ used year-to-year moments, rather than predictions on the entire time path of the industry, I am evaluating the model based on moments that were not used in estimation.

TABLE VII
MODEL FIT

Moments	I Real Data (1976–1999)		II Simulated Data Using Model $\hat{\theta}$[a]		III Simulated Data Using CCP $\hat{P}^{\mu}$[a]	
Plant-Level Moments						
Share of Small Plants	48%	(1%)	53%	(1%)	52%	(1%)
Share of Medium Plants	27%	(0%)	23%	(1%)	26%	(1%)
Share of Large Plants	25%	(1%)	24%	(1%)	22%	(1%)
Entry Rate	5.8%	(0.0%)	2.9%	(0.2%)	7.0%	(0.2%)
Exit Rate	5.4%	(0.0%)	2.9%	(0.2%)	7.3%	(0.2%)
Ramping Up Rate	10%	(0.1%)	10%	(0.3%)	11%	(0.2%)
Ramping Down Rate	9%	(0.1%)	10%	(0.5%)	9%	(0.2%)
Market-Level Moments						
Number of Plants per Market	2.0	(0.2)	2.0	(0.4)	2.3	(0.1)
No Plants in Market	2%	(0%)	4%	(1%)	18%	(1%)
Monopoly Market	46%	(1%)	43%	(1%)	32%	(0%)
Duopoly	26%	(1%)	29%	(1%)	18%	(0%)
More Than 2 Plants	26%	(1%)	24%	(1%)	32%	(1%)
Number of Plants in Category 1	1.08	(0.00)	1.18	(0.02)	1.42	(0.06)
Number of Plants in Category 2	1.76	(0.01)	1.80	(0.05)	2.20	(0.06)
Number of Plants in Category 3	2.62	(0.01)	2.32	(0.08)	2.98	(0.08)
Number of Plants in Category 4	4.15	(0.04)	4.25	(0.16)	4.44	(0.10)
Coefficient of Variation						
Number of Plants Within Market	0.7	(0.1)	0.6	(0.2)	1.7	(0.0)
Correlation Demand and Plant Size	0.23	(0.01)	0.26	(0.01)	0.23	(0.01)
Correlation Demand						
and Number of Plants	0.54	(0.01)	0.67	(0.01)	0.28	(0.01)

[a]Data are simulated using either II—computed policies given estimated parameters $\hat{\theta}$ or III—estimated conditional choice probabilities $\hat{P}^{\mu}$, taking as an initial condition the markets in 1976. The market block bootstrapped standard errors shown in parentheses use 50 bootstrap replications.

timates $\hat{\theta}$ (Column II), and simulation using the estimated CCP's $\hat{P}^{\mu}$ (Column III).

The model does well at matching the distribution of plant size, as 47% of plants are small in the data, versus 53% in the simulation, and 25% plants are large in the data, versus 24% in the simulation. However, the model under-predicts the amount of turnover, as entry and exit rates are 5.5% in the data, versus 2.9% in the simulation. Essentially, the model under-predicts the amount of idiosyncratic shocks that yield entry and exit, rather than demand driven turnover. Yet, the model does better at matching the frequency at which firms change their sizes, predicting that 10% of plants increase their size and 9% reduce their size each year, which replicates the rate at which plants grow and shrink in the data.

The model also predicts market structure quite accurately. There are, on average, two plants per market in the data, and the model also forecasts 2.0

plants. Decomposing predicted market structure, in the data 1% of markets have no plants, 45% are monopoly markets, 27% are duopoly markets, and 26% of markets have more than two plants. The model predicts the same number of monopoly markets (43%) and slightly fewer markets with more than two plants (24%). The model also does a good job at matching the number of plants in each market category μ, even though the only way that market categories matter is through differences in the estimated demand transition process $\hat{D}^{\mu}$.

To highlight the model's ability to predict changes in the number of plants, I compute the coefficient of variation (henceforth, CV) of the number of plants within a market. The data and the model predict a CV of 0.7 and 0.6, respectively. The correlation between market size and the number of firms is 0.5 in the data, versus 0.7 in the model's prediction. Likewise, the correlation between market size and plant size (where plant size is just the integers 1, 2, and 3, corresponding to small, medium, and large) is 0.23, which is well matched by the model (0.26). In sum, the model captures many features of the path of the ready-mix concrete industry from the late 1970s to 2000.

The 25-year forecasts using the CCPs in Column III also match the path of the ready-mix concrete industry. This precision is important, as the accuracy of the CCPII's estimates rely on the ability of the estimated CCPs to reproduce firms' expectations about the evolution of the industry. The distribution of plant size, as forecast by the CCPs, is much like in the data, with 52% small plants, 26% medium plants, and 22% large plants. Entry and exit rates are somewhat higher—7.1%, versus 5.6% in the data—while the rate at which plants either grow or shrink is 9%, close to the data. Finally, the CCPs forecast somewhat more plants in the industry than what is indicated by the data—2.3 plants per market, versus 2.0 in the data.

7. COUNTERFACTUAL INDUSTRY DYNAMICS

There are substantial local fluctuations in construction activity. How do these demand shocks affect the ready-mix concrete industry? The counterfactual that I consider would remove much of the short-term fluctuation in construction activity at the county level.

Consider the policy where local governments allocate construction budgets to smooth out changes in demand. Government commits to a five-year sequence of contracts so that demand remains constant over the next five years. Demand stays fixed at its five-year expected level (given current demand), so on average, plants receive the same level of demand over the next five years both with and without this policy. After five years are up, demand reverts to the level it would have had absent demand smoothing, and the smoothing pol-

icy is repeated. The long-run path of demand remains unchanged; this policy simply eliminates short-run "wiggles" in demand.[48,49]

For illustrative purposes, I also show the effect of two other demand-smoothing policies. The first is constant demand. Second, to directly investigate the effect of demand smoothing on the equilibrium strategies used by firms, such as how responsive they are to demand shocks, I consider "myopic" firms. These firms believe that demand is constant over time, but in fact, demand evolves following the process estimated in the data ($\hat{D}^\mu$).

Demand smoothing may alter the rate at which firms both enter and exit, as well as how often firms ramp up and shrink down their size. Moreover, removing fluctuations may change the stationary distribution of the industry, so I also look at the effect of the demand-smoothing policy on the size distribution and market structure of the ready-mix concrete industry.

7.1. *Demand Smoothing, Turnover, and Size Changes*

Table VIII shows statistics on entry, exit, and size changing in the ready-mix concrete industry for the four different demand processes I consider. I present annual statistics 25 years after the policy has been put into place to allow the industry to adjust to the new demand process.[50]

The five-year demand-smoothing policy reduces turnover on the entry/exit margin, and yet has little effect on the frequency at which firms change their size. The turnover rate falls by 25%—from 3.0% in the unsmoothed case to 2.2% with five-year smoothing. The rate at which firms change their size is approximately the same: 17% versus 20% in the unsmoothed case. Moreover,

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[48]This policy would be fairly easy to implement, since it simply relies on local governments being able to borrow and save over relatively short periods of time and assumes that construction projects, such as roads, are efficiently broken up across years.

[49]More formally, I compute the smoothed demand level S as a function of initial demand $M^0 = M$ as

$$S(M) = \frac{1}{5} \sum_{t=0}^{4} E_D[M^t | M^0 = M].$$

And the smoothed process is fixed in periods t in which $t \bmod 5 \neq 0$ and evolved in periods where $t \bmod 5 = 0$ via

$$M \sim D^5(M^t | M^0),$$

where D^5 is the five-year transition process generated by repeating the one-year transition process D for five years.

[50]These annual averages are computed for years 25 to 50 after the policy has been put into place. There is additional exit and entry in the first 25 years as the market adjusts to its new stationary distribution, but these are relatively few in number, compared with overall turnover. I use the effect 25 years after the policy has been put into place to separate the dynamics of transitioning *to* a new stationary distribution from the entry and exit patterns in the stationary distribution *itself*.

TABLE VIII

DEMAND SMOOTHING, TURNOVER, AND SIZE CHANGING

	Unsmoothed Demand ($\hat{D}^\mu$)	5 Years of Smoothing	Constant Demand	Firms Believe Demand is Constant
Turnover				
Entry Rate	2.7%	2.2%	2.2%	4.1%
Exit Rate	2.9%	2.0%	2.1%	4.5%
Change in Size Rate	20%	18%	17%	18%
Investment				
Sunk Entry Costs per Year (in Million $)	132	137	107	155
Size Changing Costs per Year (in Million $)	307	496	407	337
Total Plants	3643	5433	4264	3879

even when *all* demand changes are eliminated, the turnover and the size changing rates are similar to those where demand is smoothed over only five-year periods.

Meddling with the demand process would reduce—but not eliminate—turnover. This is consistent with both the descriptive work of Dunne, Roberts, and Samuelson (1988) and the fact that the entry and exit rates (per incumbent plant) are virtually uncorrelated at the county-year level.[51] These indicate that turnover is not generated solely by market-level shocks, which would lead to either entry or exit—not both, but rather, by idiosyncratic shocks ε_i^t, such as productivity shocks.[52] Remembering that the model under-predicts the amount of turnover due to idiosyncratic shocks, this 25% decrease in turnover most likely overstates the effect of reducing demand volatility on turnover.

Yet, this explanation is incomplete, since it ignores firms' anticipation of changes in demand. Indeed, increased demand volatility makes firms less sensitive to demand shocks. As an example, industry dynamics with either constant or i.i.d. demand are identical, as both demand processes imply that a firm's expected level of demand never changes, even though one demand process has no volatility, and the other one is highly volatile. If I take firms that use the policies corresponding to a constant level of demand, but subject them to the demand process estimated in the data (the myopic counterfactual), I find that the turnover rate would increase by 50% to 4.3% per year, and the rate at which firms change their size would remain at 16% per year. Moreover, I find that firms become far more sensitive to variation in demand. A market-fixed ef-

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[51] Dunne, Roberts, and Samuelson (1988) showed that entry and exit rates are highly correlated at the industry level, while I show that, in the ready-mix concrete industry, these are uncorrelated at the county-year level.

[52] See Collard-Wexler (2009) for the importance of productivity volatility in this industry.

fect regression of the number of plants on log construction employment yields a coefficient of 0.16 when firms use policies corresponding to variable demand, versus 0.30 when their policies correspond to constant demand. Thus the expectations of future changes in demand blunt the response to current demand shocks, and this is why we see such a small reaction, in terms of turnover and investment, to demand changes.

Using the estimates of the model in Table VI, I find that, in the base case, sunk entry costs are $132 million per year, and transition costs are $307 million per year. With the demand-smoothing policy, these costs rise to $137 million per year of sunk entry costs, and $496 million per year of size changing costs.

This 44% increase in investment is almost entirely due to the 39% increase in the number of plants in the industry under the demand-smoothing policy. In short, plants invest at the same rate, but there are more of them.

7.2. *Demand Smoothing and Industry Composition*

Table IX shows the effects of the demand-smoothing policy on the number of plants in the industry, fixed costs, plant size, and the industry's market structure. As in Table VIII, I show annual averages for the industry between 25 and 50 years after the policy was put into place. I compare constant demand to the unsmoothed case and then look at the effects of the five-year smoothing policy.

7.2.1. *Constant Demand*

The constant demand process predicts 16% more plants than the unsmoothed demand process (4264 versus 3645). Market structure also differs,

TABLE IX

DEMAND SMOOTHING AND INDUSTRY COMPOSITION

	Unsmoothed Demand	Constant Demand	5 Years of Smoothing
Total Plants	3645	4264	5433
Fixed Costs			
(per Period in Millions of $)	717	878	1109
Industry Composition			
Small Plants	54%	48%	49%
Medium Plants	23%	23%	24%
Big Plants	23%	29%	28%
Market Structure			
Markets With no Plants	5%	8%	1%
Markets With 1 Plant	43%	36%	25%
Market With 2 Plants	28%	24%	29%
Markets With More Than 2 Plants	25%	32%	46%

as the number of plants per market is more dispersed under constant demand, with 8% of markets having no plants, versus 5% in the unsmoothed case, and 32% of markets having more than two plants, versus 25% in the unsmoothed case. Constant demand spreads out the distribution of the net present value of demand, as a market with high demand will have high demand forever, and likewise, markets that have low demand retain it in perpetuity.

This difference in the cross-sectional distribution of demand also changes the industry's plant size distribution, as 29% of plants are large under constant demand, versus 23% under unsmoothed demand. Figure 3 showed that bigger markets have larger plants. Thus, a change in the distribution of market size alters the industry's plant size distribution.[53]

7.2.2. *Five Years of Smoothing*

Since demand is very volatile and shocks are short-lived, removing five-year changes in demand has a large effect on the intertemporal variance of demand. This policy increases the number of plants from 3645 to 5433, and raises fixed costs from $717 million to $1109 million per year.

If profits per consumer are either increasing or decreasing with demand (holding market structure fixed), then period profits are either a convex or concave function of demand. This has important implications on the effect of smoothing demand volatility. With a concave profit function (with respect to demand), by Jensen's inequality, less intertemporal volatility of demand raises the expected profitability of a market. I call this the "market expansion effect" of demand smoothing.

Figure 3 showed that the relationship between the number of plants in a market and construction demand is concave. This implies that profits per consumer are decreasing with demand.[54] I speculate that this effect is due to congestion costs for concrete deliveries when demand is particularly high. There are greater costs involved in making multiple deliveries because of labor and machinery shortages or because some deliveries cannot be made during the weeks of the year when demand peaks. Congestion is more likely when yearly demand is higher.

In contrast, in other industries, reducing demand volatility might *lower* the number of firms in the market. For instance, in the market for electric power, short-run profits are a convex function of short-run demand because aggregate

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[53]I find more large plants, even though, in principle, I could find either more small plants or more big plants given the distribution of demand in different markets.

[54]This implication can be tested by estimating the elasticity of profits (measured by sales minus all input costs) with respect to construction employment. I find a very inelastic response to construction employment when running this regression. However, attenuation bias is also a plausible explanation for this estimate.

bid curves typically take a highly convex "hockey stick" shape.[55] Thus, with lower demand volatility one might expect fewer power plants to be built.

The "market expansion effect" for the ready-mix concrete industry increases a market's profitability, and this raises the number of firms at which the free-entry condition binds. The number of markets served by more than one plant increases from 52% to 74%. As well, the increase in market size generated by the demand-smoothing policy's "market expansion effect" raises the share of large plants from 23% to 28%, while the share of small plants goes down from 54% to 49%, and the share of medium plants stays about the same.

Note that the five-year demand-smoothing policy has very different effects than the constant demand policy: It only reduces the intertemporal variance of demand, while the constant demand policy also increases the cross-sectional dispersion of demand. These two effects make it difficult to untangle the effects of a constant demand policy.

7.3. *Consumer and Producer Surplus*

Table X summarizes the differences in welfare between the five-year demand-smoothing policy and unsmoothed demand. I show these effects on the net present value of surplus (henceforth, NPV) for consumers, incumbents, and potential entrants.

For the 19% of markets that were formerly monopoly markets, but became competitive, prices would fall by 3%, based on the estimates in Figure 2. Taking into account all changes in market structure, decreases in price due to additional competition (holding purchases of concrete fixed) transfer $43 million per year, or $860 million in NPV, from producers to consumers. This number is a lower bound on the increase in consumer surplus, as any elasticity in the demand for concrete would add to it.

TABLE X

WELFARE EFFECTS OF DEMAND-SMOOTHING POLICIES[a]

Change in Net Present Value of	
Consumer Surplus	$860 Million
Producer Surplus for Incumbents	−$609 Million
Producer Surplus for Potential Entrants	−$36 Billion

[a]Numbers in this table refer to the difference in the net present value of surplus (using a 5% discount rate) between five years of smoothing and unsmoothed demand, averaged between 25 and 50 years after the policies were put into place, using 1976 as an initial state.

[55]See, for instance, the aggregate bid curves in Figure 2-1 on page 34 of http://www.monitoringanalytics.com/reports/PJM_State_of_the_Market/2010/2010-som-pjm-volume2-sec2.pdf.

In an oligopoly model with free entry, it is not clear how an increase in the number of firms in a market will affect producer welfare. I find that producer surplus for incumbents would decrease from $3.3 billion to $2.7 billion in NPV under the demand-smoothing policy, representing a 20% fall.[56] I also compute producer surplus for potential entrants, who represent 80% of the "firms" in the data. Their surplus falls from $134 billion to $98 billion in NPV when the demand-smoothing policy is implemented, a 31% decrease. However, the numbers for the surplus of potential entrants are suspect, since the vast majority of this surplus is derived from 98.7% of potential entrants who choose never to enter, yet receive a payoff from their private information shock ε_{a_0}. Surplus from firms that do not enter is truly an artifact of the model, since how do we interpret the profits of firms that choose not to enter?[57]

8. CONCLUSION

Due to the turbulence of local construction markets, the ready-mix concrete industry is subject to large fluctuations in demand. These fluctuations have substantial effects on the composition, size, and investment level in the industry. Specifically, I considered a policy in which the government would sequence its construction budgets in such a way as to eliminate five-year changes in demand, while retaining longer-run movements.

I estimated an oligopoly model of entry/exit and discrete investment and used it to evaluate the industry's response to this policy. This model allowed for considerable heterogeneity between plants, in terms of current and past size, as well as persistent differences between local markets.

Demand need not have a linear effect on plant profits, especially if marginal costs increase with the number of concrete deliveries. Absent linearity, any changes in the volatility of demand affect the profitability of a market, and hence, the number of plants it can support. For this industry, a reduction in intertemporal volatility of demand has a "market expansion" effect. This effect

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[56]To compute producer surplus, I reformulate the problem in terms of choice-specific value functions. Thus producer surplus is just

$$(14) \qquad PS = \sum_{i \text{ is incumbent}} V^i(x^{i0}) + \sum_{t=0}^{\infty} \beta^t \sum_{i \text{ is entrant}} V^i(x^{it}),$$

which is just the ex ante value function for incumbents, plus the discounted value of entrants in the future, which needs to be monitored, since I assume that if an entrant does not enter, they get a continuation value of 0. The ex ante value function is $V(x) = \sum_{j \in A_i} W(j|x) \Psi(j|x) + \gamma - \sum_{j \in A_i} \ln(\Psi(j|s)) \Psi(j|s)$.

[57]Potential entrants represent more than 80% of the players in the game, and potential entrants who choose to enter are 1.3% of all potential entrants, as is illustrated in the first row of Table II. These figures rely crucially on the assumption that there are 10 firms in each market, so the number of potential entrants is given mechanically as 10 minus the number of incumbents.

is similar to an increase in market size, and raises both the number and average size of plants in the industry.

This demand-smoothing policy lowers the amount of turnover in the industry by 25%, but leaves the rate at which firms change their size unaffected. In this industry, large sunk- and size-changing costs make it expensive to respond to demand shocks. Furthermore, firms are unlikely to react to demand shocks when demand is very volatile, since these demand shocks convey little information on future profitability.

High volatility of plant-level demand, and associated plant-level profitability, is a feature of many industries. As Collard-Wexler, Asker, and De Loecker (2011) showed, the volatility of plant profitability, driven in part by demand, differs substantially across similar industries in various countries. This paper indicates that the consequences of volatility may not be expressed by higher turnover or more volatile investment. Instead, demand volatility transforms the size and structure of the industry.

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Stern School of Business, New York University, New York, NY 10012, U.S.A.; wexler@stern.nyu.edu.