The Costs of Environmental Regulation in a Concentrated Industry *

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Abstract

The typical cost analysis of an environmental regulation consists of an engineering estimate of the compliance costs. In industries where fixed costs are an important determinant of market structure this static analysis ignores the dynamic effects of the regulation on entry, investment, and market power. I evaluate the welfare costs of the 1990 Amendments to the Clean Air Act on the US Portland cement industry, accounting for these effects through a dynamic model of oligopoly in the tradition of Ericson and Pakes (1995). Using a recently developed two-step estimator, I recover the entire cost structure of the industry, including the distribution of sunk entry costs and adjustment costs of investment. I find that the Amendments have significantly increased the sunk cost of entry. I solve for the Markov perfect Nash equilibrium (MPNE) of the model and simulate the welfare effects of the Amendments. A static analysis misses the welfare penalty on consumers, and may even obtain the wrong sign of the welfare effects on incumbent firms.

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1 Introduction

In the United States, the Environmental Protection Agency (EPA) is responsible for setting and enforcing regulations broadly consistent with national environmental policies, such as the Clean Air Act (CAA). The CAA gives the EPA a mandate to regulate the emissions of airborne pollutants such as ozone, sulfur dioxide (SO_2), and nitrogen oxides (NO_x), in the hopes of producing a healthier atmosphere. It also requires the Agency to assess the costs and benefits of a regulation before promulgating policy. The cost analysis is typically an engineering estimate of the expenditures on control and monitoring equipment necessary to bring a plant into compliance with the new regulations. However, this type of cost analysis misses most of the relevant economic costs in concentrated industries, in which sunk costs of entry and costly investment are important determinants of market structure. Shifts in the costs of entry and investment can lead to markets with fewer firms and lower production. The resulting increase in market concentration can have far-reaching welfare effects beyond the initial costs of compliance. This is a particularly acute problem for environmental regulators, as many of the largest polluting industries are also highly concentrated.[1]

In this paper, I measure the welfare costs of the 1990 Clean Air Act Amendments on the US Portland cement industry, explicitly accounting for the dynamic effects resulting from a change in the cost structure. Portland cement is the binding material in concrete, a primary construction material found in numerous applications, such as buildings and highways. The industry is typical of many heavy industries, consuming large quantities of raw materials and generating significant amounts of pollution byproducts. It is a frequent target of environmental activists and has been heavily regulated under the Clean Air Act. In 1990, Congress passed Amendments to the Clean Air Act, adding new categories of regulated emissions and requiring plants to undergo an environmental certification process. It has been the most comprehensive and important new environmental regulation affecting this industry in the last three decades since the original Clean Air Act.

My strategy for evaluating the effects of the Amendments on this industry proceeds in three distinct steps. First, I pose a theoretical model of the cement industry, where oligopolists make optimal decisions over entry, exit, production, and investment given the strategies of their competitors. Second, using a unique panel data set covering two decades of

[1]For example, the 1997 Economic Census reports that the Herfindahl-Hirschman Index (HHI) for many polluting industries exceeds 1,000, such as manufacturers of paper pulp, petrochemicals, soaps and detergents, tires, ceramic tiles, lime and gypsum, aluminum, and copper, among others. For comparison, the HHI for Portland cement, the industry studied in this paper, is 466. This national measure understates the effective degree of concentration since the industry is spatially segregated into regional markets.

the Portland cement industry, I recover parameters which are consistent with the underlying model. Third, I use the theoretical model to simulate economic environments with the cost structures recovered before and after the Amendments. I exploit a specific timing feature of the implementation of the Amendments to identify which changes in the cost structure were due to the regulations. By comparing the predictions of the model under these different cost structures, I can calculate the changes to a number of relevant policy quantities, such as producer profits and consumer surplus, that are the result of the regulation.

The backbone of my analysis is a fully dynamic model of oligopoly in the tradition of Ericson and Pakes (1995). I model the interaction of firms in spatially-segregated regional markets where firms are differentiated by production capacity. Firms are capacity constrained and compete over quantities in homogeneous good markets. Markets evolve as firms enter, exit, and adjust their capacities in response to variation in the economic environment. I incorporate sunk costs of entry, fixed and variable costs of capacity adjustment, and a fixed cost of exiting the industry. Given a richly-specified state space, I assume that firms optimize their behavior independently across periods, implying a Markov-perfect Nash equilibrium (MPNE).

My model is similar to several other applications of the Ericson-Pakes model.[2] However, I extend the model in several ways to tailor it to the Portland cement industry. First, I allow firms to fully adjust their capacity in each period, whereas previous models have looked at investment games where capital accumulates slowly. Additionally, I introduce fixed costs of adjustment to rationalize the lumpy investment behavior seen in the data, as firms tend to make very infrequent but large capacity adjustments. Second, I introduce private information into the model and allow for mixed strategy policy functions. Firms have private information about their fixed entry costs and marginal costs of production. Discrete adjustments in exit and adjustment naturally lead to the possibility of mixed strategies in the policy functions governing these actions. Third, I allow for multiple entry and exit in every period. Furthermore, potential entrants are as forward-looking as incumbent firms, as they are not restricted to begin operation at an exogenously imposed capacity level, but rather choose an optimal starting level given expectations about future market conditions.

The MPNE of the model leads to structural requirements on firm behavior which can be used as the basis of an estimator of the underlying primitives. Previously, the impediment to using these types of models for empirical work has been the computational burden of solving

[2] See, for example, Fershtman and Pakes (2000), Gowrisankaran and Town (1997), Besanko and Doraszelski (2004), Doraszelski and Satterthwaite (2005), and Benkard (2004).

for the MPNE, which makes nested fixed-point estimators (for example, Rust (1987)) impractical. However, a spate of recent papers has shown how to circumvent this problem using a two-step approach in which it is possible to estimate the dynamic model without solving for the equilibrium even once.[3] The first step simply describes *what* the firms do at every state, and the second step recovers parameters of the underlying model that explain *why* the firms behave as they do. In my application, the first step includes flexibly recovering the demand curve, production costs, and the policy functions governing entry, exit, and investment. These reduced-form policy functions describe what actions the firm will undertake given any state vector. The key to understanding the estimator is that these observed policy functions have to be optimal given the underlying theoretical model. Therefore, in the second second step, I find the remaining unknown parameters that best rationalize the observed policies as the equilibrium outcomes of profit-maximizing firms. Following the simulation-based minimum distance estimator proposed by Bajari, Benkard, and Levin (2006), I recover the fixed and variable costs of investment, the scrap value of exiting the market, and the distribution of entry costs. I recover these parameters before and after the 1990 Amendments in order to evaluate the changes in the underlying cost structure induced by the Amendments. As a testament to the flexibility and power of this approach, and the relatively clean institutional details of the cement industry, I am able to recover estimates of the cost of investment that are very close to accounting data from out-of-sample sources cited in Salvo (2005).

After recovering estimates for the underlying model primitives, I numerically solve for the MPNE of the theoretical model. This step provides policy functions which are used for the simulation of the welfare effects of the Amendments. I evaluate expected producer and consumer welfare, the number and size of firms, and the distribution of costs across incumbents and potential entrants before and after the regulations. In the baseline case of entry into a new market, I find that overall welfare has decreased at least $700M as a result of the Amendments, due to an increase in the average sunk cost of entry. More importantly, as my estimates show the costs of production have not statistically changed after the regulations, the welfare effect on producers depends critically on whether or not the firm is an incumbent. While potential entrants suffer welfare losses as the result of paying higher entry costs, incumbent firms benefit from increased market power due and reduced competition. A static analysis of this industry would preclude changes in barriers to entry, and may obtain the wrong sign for the welfare effects of the Amendments on incumbent

[3]See Bajari, Benkard, and Levin (2006), Aguirregabiria and Mira (2004), Pakes, Ostrovsky, and Berry (2005), and Pesendorfer and Schmidt-Dengler (2003).

firms.

I conclude by comparing the MPNE generated by an oligopoly to the social planner's problem. The social planner pursues policies that maximize the expected sum of both consumer and producer welfare, so it is the natural baseline for evaluating the efficiency of the observed equilibrium. The social planner's solution highlights that oligopoly markets have socially-inefficient low aggregate capacities. This is due to the fact that oligopolists fail to internalize the full welfare benefits of their investments. As a result, overall market capacity is larger under the social planner in both new and existing markets. In both cases, producers suffer moderate profit losses while consumers enjoy a three- to five-fold increase in surplus which more than offsets those losses.

This paper makes several contributions. First, I recover the entire cost structure of an industry, including the sunk costs of entry and exit, production costs, and investment costs. Recovering these parameters allows the measurement of a regulation's welfare effects in the presence of dynamics and market power for the first time.[4] These welfare cost estimates allow me to determine a lower bound of the value of clean air if the Amendments are to be efficient. One of the most important implications of my findings is that static engineering estimates of compliance costs miss most of the economic penalties associated with a regulation when there are significant sunk entry costs. The static analysis misses the penalty to consumer welfare due to lower production, and obtains a welfare cost of the wrong sign for incumbent producers. I also make a contribution to the investment literature by applying a generalized (S, s) model to a dynamic investment game.[5] My results suggest that both fixed and variable adjustment costs are an important determinant of investment behavior. I also highlight the importance that sunk costs of entry have on industry structure and evolution, since they are a primary determinant of market structure in this industry.

The paper is organized as follows. I give a brief overview of the Portland cement industry and relevant environmental regulations over the last 30 years in Section 2. I discuss the sources of the data and introduce the key variables of the model and estimation in Section 3. Section 4 introduces the theoretical model underpinning the estimation detailed in Section 5. I discuss the results in Section 6 and present the results of the counterfactual simulations in Section 7. Section 8 concludes with a summary of my results and a discussion of possible

[4]Mansur (2004) also examines the regulation of an industry with market power but is concerned with the effect of concentration on the quantity of pollution emissions. Benkard (2004) applies many of the ideas formalized in the BBL estimator in his examination of the widebody aircraft industry but does not recover estimates of fixed costs.

[5]Attanasio (2000) and Hall and Rust (2000) apply similar frameworks for modeling automobile purchase decisions and inventory control, respectively.

extensions.

2 Portland Cement Industry

Portland cement is a fine mineral dust with useful binding properties that make it the key ingredient of concrete. Water and cement form a paste that binds particulates like sand and stone together and makes a pourable material that hardens over time. The concrete is then used as a fill material, such as in highways and buildings, and in finished products like concrete blocks.

Producing cement requires two commodities in enormous quantities: limestone and heat. The limestone is usually obtained from a quarry located at the production site. Large chunks of limestone are pulverized before being sent to the centerpiece of cement operations: an enormous rotating kiln furnace. These kilns are the largest moving piece of industrial equipment in the world; they range in length from 450 to 1000 feet and have diameters of over 15 feet. The chemical process of converting limestone into cement requires temperatures equal to a third of those found on the surface of the sun, so one end of the kiln is heated with an intense flame produced by burning fossil fuels. The large scale nature of these installations is reflected in their raw materials and energy requirements: a large kiln can process up to 200 tons of limestone per hour, and cement kilns are the third largest consumer of energy in the world. These high energy requirements are what lead the cement industry, a tiny part of the US economy at under $10B a year in revenues, to have a large role in the environmental debate over emissions.

Cement is a difficult commodity to store, as it will gradually absorb water out of the air, rendering it useless. As a result, producers and distributors do not maintain large stocks. Also, I treat cement as a homogeneous good since producers in the United States adhere to the American Society for Testing and Materials Specification for Portland Cement. Cement's use as a construction material means that producers are held to strict conformity with these specifications.

As a result of cement's tendancy to spoil in storage, transportation costs are the most significant factors in determining Portland cement markets. Average transportation costs reported by U.S. producers for shipments within 50 miles of the plant were $5.79 per ton. These costs increased to $9.86 per ton for shipments within 51-100 miles, $14.53 per ton for 101-200 miles, and to $18.86 per ton for 201-300 miles. For shipments that are 500 miles or

Table 1: Cement Industry Summary Statistics

Year	Production	Imports	Consumption	Price	Capacity	Capacity Per Kiln
1980	68,242	3,035	70,173	111.90	89,561	239
1981	65,054	2,514	66,092	103.70	93,203	267
1982	57,475	2,231	59,572	95.76	89,770	287
1983	63,884	2,960	65,838	91.01	92,052	292
1984	70,488	6,016	76,186	89.70	91,048	297
1985	70,665	8,939	78,836	84.71	88,600	305
1986	71,473	11,201	82,837	81.48	87,341	305
1987	70,940	12,753	84,204	78.07	86,709	314
1988	69,733	14,124	83,851	75.50	86,959	327
1989	70,025	12,697	82,414	72.04	84,515	337
1990	69,954	10,344	80,964	69.02	83,955	345
1991	66,755	6,548	71,800	66.37	84,471	352
1992	69,585	4,582	76,169	64.25	85,079	357
1993	73,807	5,532	79,701	63.58	84,869	363
1994	77,948	9,074	86,476	68.06	85,345	364
1995	76,906	10,969	86,003	72.56	86,285	367
1996	79,266	11,565	90,355	73.64	85,687	376
1997	82,582	14,523	96,018	74.60	86,465	383
1998	83,931	19,878	103,457	76.45	87,763	393

Summary statistics for the Portland cement industry 1980-1998. The data is from Historical Statistics for Mineral and Materials Commodities in the United States, an online publication of the US Geological Survey. The units on quantities are thousands of metric tons, while prices are denoted in 1998 constant dollars.

more from the plant, transportation costs increased to $25.85 per ton.[6] These high costs, in conjunction with cement's low unit value, are the principal reasons the majority of cement is shipped locally. Jans and Rosenbaum (1997) quote a Census of Transportation report stating that 82.5 percent of cement was shipped under 200 miles, with 99.8 percent being shipped under 500 miles.

In 2000, the domestic Portland cement industry consisted of 116 plants in 37 states, run by one government agency and approximately 40 firms. The industry produced 86 million tons of Portland cement with a raw value of approximately $8.7 billion; most of this was used to make concrete, with a final value greater than $35 billion. Domestic cement production accounted for the vast majority of the cement used in the United States. According to the USGS (2001), about 73 percent of cement sales were to ready-mixed concrete manufacturers, 12 percent to concrete product producers, 8 percent to contractors, 5 percent to building materials dealers, and 2 percent for other uses. Cement expenditures in construction projects are usually on the order of less than 2 percent of total outlays.

Table 1 reports summary statistics for the industry over the period 1980-1998. One point

[6]These figures are taken from American University's Trade and Environment Database (TED) case study on Cemex.

of interest is that capacity utilization rates have risen since the passage of the Amendments. Production has increased while overall productive capacity has remained relatively steady. Imports grew as the production of domestic cement reached its maximum level, and firms chose to import instead of build new production facilities.[7]

The effects of imports on domestic producers are difficult to quantify due to the idiosyncracies associated with distributing cement from waterborne sources. For most markets, the economic impact is small and indirect, as few regions have the infrastructure and geography to profitably exploit the availability of imports. An examination of the import data provided in the USGS reports indicates that cement imports vary widely across markets and across time. Imported cement is actually shipped as clinker, the unground precursor of cement. In order to turn this raw material into cement, the importer must have a grinder and a supply of gypsum. Additionally, domestic cement producers have been highly successful in preventing large-scale imports through trade tariffs. For example, producers in states bordering the Gulf of Mexico have been successful in getting anti-dumping tariffs passed against imports from Mexico. This has limited the ability of importers to achieve greater penetration of local cement markets in these states. In large part, the response of potential importers has been to circumvent the tariffs through the acquisition of domestic facilities. In markets where imports do play a significant long-run role in the domestic market, such as around the Great Lakes region, I model this as a shift in the demand curve for domestically-produced cement.

There have been two major regulatory events of interest to the Portland cement industry in the last 30 years: the Clean Air Act of 1970 and its subsequent Amendments in 1990. The stated purpose of the Clean Air Act was to "protect and enhance the quality of the Nation's air resources so as to promote the public health and welfare and productive capacity of its population." To this end, Congress empowered the EPA to set and enforce environmental regulations governing the emission of airborne pollutants.

In 1990, Congress passed the Amendments to the Clean Air Act, which defined new categories of regulated pollutants and required major polluters to obtain a permit for operation. These Amendments mandated new monitoring, reporting, and emission requirements for the cement industry. The Amendments created a new class of emission restrictions governing hazardous air pollutants and volatile organic compounds. One key identifying feature of this legislation is that EPA did not promulgate final requirements for these new pollutants for 12 years. Therefore, there were no changes to firms' variable costs as a result of the

[7]Cement imports come primarily from Canada, China, Korea, Thailand, Spain, and Venezuela. Asian sources have become the dominant source of cement imports, with Thailand becoming the single-largest exporter in 2000.

Amendments, as they did not require the firms to adhere to any new emissions standards.[8]

There were two components of the legislation that began to bind immediately. Under Title V of the Amendments, all firms emitting significant quantities of pollutants had to apply for operating permits. The permits require regular reporting on emissions, which necessitate the installation and maintenance of new monitoring equipment. The Amendments also required firms to draw up formal plans for compliance and undergo certification testing. Industry estimates for the costs of compliance with these operating permits is on the order of five to ten million dollars. By 1996, virtually all cement plants had applied for their permits, which they are required to renew every five years. The EPA estimated that these certification costs should not exceed $5M per establishment.

The second aspect of the Amendments which is critical to understanding their welfare implications is that they required greenfield plants to undergo an additional, rigorous environmental certification and testing procedure. These additional fixed costs involved potential entrants contracting with environmental engineering firms to produce reports on their impact on local air and water quality as a result of the construction and operation of a new plant. Industry sources estimate that these costs would add approximately $5M to $10M to the cost of building a greenfield facility. It is this change to the sunk costs of entry which is going to drive many of the results that I find below.

3 Data

I collect data on the Portland cement industry from 1980 to 1999 using a number of different sources. I require market-level data on prices and quantities to estimate the demand curve for cement. The US Geological Survey (USGS) collects establishment-level data for all the Portland cement producers in the US and publishes the results in their annual Minerals Yearbook.[9] The USGS aggregates establishment-level data into regional markets to protect the confidentiality of the respondants. The Minerals Yearbook contains the number of plants in each market and the quantity and prices of shipped cement. There is occassional irregular

[8]To the best of my knowledge, as of 2005 no firm has made any changes to its production process as a result of the Amendments, due to opposition from the Portland Cement Association. Firms may also reasonably anticipate that changes to their marginal costs may ultimately be close to zero, as either they will be grandfathered into the legislation or the EPA may give pollution credits in return for adopting lower emissions standards.

[9]The Bureau of Mines had this responsibility prior to merging with the USGS in the 1990s. The data was collected by a mail survey, with a telephone follow-up to non-respondants. Typically the total coverage of the industry exceeded 90 percent; in some years, 100 percent response was indicated. The USGS attempted to fill in missing observations with data from other sources.

Table 2: Summary Statistics

Variable	Minimum	Mean	Maximum	Standard Deviation
Demand Data				
MARKETQ	186	2,835.84	10,262	1,565.34
PRICE	36.68	67.46	138.99	13.68
PLANTS	1	4.75	20	1.94
WAGE	20.14	31.72	44.34	4.33
COAL	15.88	26.64	42.33	8.13
ELECTRICITY	4.23	5.68	7.6	1.01
POPULATION	689,584	10,224,352	33,145,121	7,416,485
GAS	3.7	6.21	24.3	2.21
Production Data				
QUANTITY	177	699	2348	335
CAPACITY	196	797	2678	386
Investment				
INVESTMENT	-728	2.19	1,140	77.60

Demand data are from annual volumes of the USGS's Mineral Yearbook, 1981 to 1999. There are 517 observations in 27 regional markets. The unit for MARKETQ is thousands of tons per year, while PRICE is denoted in dollars per ton. WAGE is denoted in dollars per hour for skilled manufacturing workers, and taken from County Business Patterns. POPULATION is the total populations of the states covered by a regional market. The units are dollars per ton for COAL, dollars per kilowatt hour for ELECTRICITY, and dollars per thousand cubic feet for GAS. All prices are adjusted to 1996 constant dollars. The data on production and capacity are taken from the Portland Cement Association's annual Plant Information Summary, with full coverage from 1980 to 1999. Units on QUANTITY and CAPACITY are in thousands of tons per year.

censoring of data to ensure the confidentiality of individual companies, although this affects only a small number of observations representing a low percentage of overall quantity. Usually the USGS merges a censored region into a larger region in subsequent years to facilitate complete reporting.

I collect data on electricity prices, coal prices, natural gas prices, and manufacturing wages to use as instruments in the demand curve estimation. The data for fuel and electricity prices are from the US Department of Energy's Energy Information Administration.[10] Natural gas and electricity prices are reported at the state level from 1981 to 1999. Coal prices are only available in a full series over that time span at the national average level. I impute skilled manufacturing wages at the state level from the US Census Bureau's County Business Patterns. All prices are adjusted to 1996 constant dollars.

Table 2 shows summary statistics for the demand data. Most markets are characterized by a small number of firms, with the median market contested by four firms. The size of the markets varies greatly across the sample: the smallest market is 2 percent the size of

[10] http://www.eia.doe.gov.

the largest market. Price also varied substantially across markets, with Alaska and Hawaii generally being the most expensive markets. I account for market-specific factors in my analysis by adopting a fixed effect for each market.

Data on the plant-level capacities are from the Portland Cement Association's annual Plant Information Summary (PIS) and cover 1980 to 1998. These trade association databooks have complete coverage of all cement producers in the United States, and give detailed information on grinding and kiln capacity. For each establishment, the PIS reports daily and annual plant capacities. I interpret the daily capacity to be a boilerplate rating, as determined by the manufacturer of the kiln, of how much the kiln produces in a given 24-hour period of operation. I assume the yearly capacity is how much they actually produced in that year. This assumption is supported by the fact that plants operate continuously in runs lasting most of the year. Maintenance is performed during a single shutdown period, generally a month in duration, in which the plant produces nothing. If the firms are assumed to run at perfect efficiency on the days that they operate, then the boilerplate rating multiplied by the length of a year gives the theoretical maximum that a plant could have produced. The yearly capacity numbers never achieve this bound and fluctuate from year to year. Additionally, the yearly numbers add up to the rough market-level quantities reported in the USGS data. Therefore, I take the reported annual capacity of the kiln to be the amount of cement that it actually produced in that year. I emphasize, however, that this quantity is not a fixed percentage of the theoretical maximum capacity. Firms still choose how long to operate their kilns before performing maintenence, and are subject to idiosyncratic shocks affecting the duration of the maintenence period. More productive firms have shorter maintenence periods and therefore can produce more in a given year than less productive firms. Given that firms are at the edge of their maximum productive capacity during the sample period, capacity choice is clearly the most important strategic decision firms have to make, but it should be emphasized that they still face a tradeoff between production and maintenence. The last two rows of Table 2 give the summary statistics for production and capacity levels.

A key empirical fact of this industry is that most firms do not make adjustments to their capacity in most periods. The modal adjustment is zero, with a mean of just 2.9 thousand tons per year (TPY). This lumpy adjustment behavior is illustrated in Figure 1, which tracks the capacity levels of firms in the Colorado and Wyoming market over the course of the sample period. While there is some noise in the data, it is clear that most firms have relatively steady levels of capacity over time, with infrequent discrete adjustments. In addition to capacity investment, there are jumps in market-level capacity due to entry and

Figure 1: Capacity of Cement Plants in Colorado and Wyoming

exit.

To match the market-level demand data to the establishment data from the PIS, I combine some of the markets in the USGS data to form continuously-reported metamarkets. I then group all the plants into the appropriate metamarkets for every year of establishment data. The production data consists of an unbalanced panel of 2,233 observations.

4 Model

To evaluate the welfare effects of the Amendments, it is necessary to have a theoretical model that captures the salient features of the cement industry. The industry is characterized by simultaneous entry, exit, investment, and production decisions of a small number of firms in each market. The firms behave strategically and anticipate the future when making decisions. The structure within each regional market is primarily determined by the distribution of production capacities among active firms. I build on the work of Ericson and Pakes (1995), who provide an elegant theoretical framework of industry dynamics that can account for these features.

The fundamental idea of the model is that all of the economically-relevant characteristics of the firms in a market can be encoded into a state vector. Firms receive state-dependent revenues from a product market in each period, and can influence the evolution of the state vector through entry, exit, and adjustments to their capacity. Equilibrium obtains when firms follow strategies that maximize the expected discounted present value of their stream of revenues given the expected strategies of their competitors.

I adapt this general framework to account for the specific features of the cement industry, where the basic building block is a regional homogenous-goods market in which capacity is the most important strategic variable. In each period, incumbents compete over quantities in this market, subject to a private productivity shock which shifts the marginal cost of production. Firms are partially capacity constrained, as they experience smoothly increasing marginal costs as production approaches their theoretical maximum capacity.

Incumbent firms also make optimal decisions over whether to exit the market and pursue opportunities elsewhere. If a firm decides to exit the market, it receives revenues from both the product market and a final scrap value, before disappearing forever.[11] In addition to active incumbents, there is a pool of short-lived potential entrants who must decide whether or not to enter, paying a privately-known sunk cost of entry if they decide to do so.[12]

Entrants and active firms make capacity adjustment decisions based on the state vector and the expected strategies of their competitors. Investments today change the capital stock tomorrow, with firms paying both fixed and variable adjustment costs. The industry vector evolves over time as firms make entry, exit, and investment decisions.

To keep the model tractable, I assume that firm strategies depend only on the current state vector, generating a Markov-perfect Nash equilibrium. Specifically, the MPNE consists of a set of mutual best-response strategies governing entry (for potential entrants), production and exit (for incumbents), and investment (for both entrants and incumbents). In the following sections, I describe each component of the model in detail before deriving the ex-ante value functions for potential entrants and incumbents. The value function will play a crucial role in the counterfactual simulations I use to evaluate the welfare costs of the Amendments.

4.1 State Space

The state space is characterized by a set of M independent, geographically segregated markets, each with N_m firms. I restrict firms to behave independently across markets and drop the market-specific notation in what follows. Time is discrete and incumbent firms operate

[11]I do not restrict the scrap value to be positive, as it possible that a firm faces shutdown costs associated with cleaning up the site upon exit.

[12]Conceptually, it is straightfoward to allow long-lived potential entrants, who wait for a low enough draw from the distribution of sunk entry costs before entering. This requires labelling the composition of firms within a market, which becomes an intractible computational problem in the counterfactual simulations, even if it were possible to identify the set of all possible entrants.

with an infinite horizon. Each market is fully described by the $N \times 1$ state vector, s_t, where s_{it} is the capacity of the i-th firm at time t. I divide the firms into two groups: potential entrants ($s_{it} = 0$) and incumbents ($s_{it} > 0$). I assume that the potential entrants are short-lived; if a firm decides not to enter the market in one period, it gives up its slot and is replaced by a new potential entrant in the next period. Firms discount future profits at a constant rate of β, which I assume is equal to 0.9. For notational simplicity, I abuse notation slightly: in the expectations written below that are conditional on s, I assume that this also includes all the information available to a firm in the market. So when a firm projects the expected future market state, they build in the expected effects of entry, exit, and investment policies of all the firms in the market.

4.2 Timing

Each decision period is one year. The sequence of events in each period unfolds as follows:

- Potential entrants receive a draw from the distribution of entry values and make their entry decisions. Incumbent firms make their exit decisions.
- Incumbent firms and new entrants make investment decisions.
- Firms receive a private productivity shock and compete over quantities in the product market.
- Incumbents choosing to leave the market exit and receive their scrap payment. Entrants pay their entry fee.
- The state vector adjusts as investments mature and firms enter and exit.

Note that firms who decide to exit produce in this period before leaving the market, and that adjustments in capacity take one period to be implemented. A second feature of the game's timing is that firms make production and investment decisions without knowing the decisions of their competitors. Firms observe the state variable at the beginning of each period along with the entry, exit, investment, and production decisions of their rivals in the last period. Since shocks are drawn independently across periods from known common distributions, firms do not update their expectations of future behavior after observing the actions of their rivals.

4.3 Payoffs

The payoffs at each element of the state space are characterized by revenues from the product market, production costs, entry and exit costs, and investment costs.

4.3.1 Product Market Payoffs

Firms compete in quantities in a homogeneous goods product market. I assume within a given market firms face a constant elasticity of demand curve:

$$P(Q) = AQ^{1/\epsilon}, \tag{1}$$

where Q is the aggregate market quantity and ϵ is the elasticity of demand. I abstract away from any meaningful dynamics in the demand curve; for example, I rule out deterministic trends in demand growth.

Production costs consist of two parts: a constant marginal cost and an increasing function that binds as quantity approaches the capacity constraint. I assume that costs increase as the square of the percentage of capacity utilization, and parameterize both the penalty and the threshold at which the costs bind. Each firm also has a private productivity shock, SHOCK_i, drawn from a common distribution, that shifts the marginal cost of production in each period, giving rise to the following firm profit function:

$$\begin{aligned} \pi_i = \mathrm{Q}_i(\mathrm{PRICE}(\mathrm{MARKETQ}) - \mathrm{MC} + \mathrm{SHOCK}_i) \\ - 1(\mathrm{UTILPCT}_i > \nu)\left[\mathrm{CAPCOST} \cdot (\mathrm{UTILPCT}_i - \nu)^2\right], \end{aligned} \tag{2}$$

where Q_i is the firm's output quantity, ν is the threshold at which capacity costs bind, CAPCOST is the capacity penalty, $\mathrm{UTILPCT}_i$ is the fraction of capacity utilization, and SHOCK_i is the firm's private productivity shock. The second term accounts for the increasing costs associated with operating near maximum capacity, since firms have to cut into maintenence down time in order to expand production beyond a certain level. As the term SHOCK_i is private information, the appropriate solution concept for this game is Bayesian Nash equilibrium.

4.3.2 Entry, Exit, and Investment Costs

In addition to any profits or losses incurred in the product market, firms can make costly adjustments to their capacity levels. I allow adjustment costs to vary separately for positive and negative changes as a quadratic function of investment. This functional form allows for both fixed costs of adjustment and increasing marginal costs. The fixed costs capture the idea that firms may have to face significant costs, such as obtaining permits or doing feasibility studies, that accrue regardless of the size of the investment.

Divestment sunk costs can be positive as the firm may encounter costs in order to shut down the kiln and dispose of related materials and components. On the other hand, a negative cost of divestment encapsulates the idea that firms can receive revenues from selling off their infrastructure, either directly to other firms or as scrap metal.[13]

The per-period payoff function is composed of several parts, depending on the firm's status as a new entrant, continuing incumbent, or exiting incumbent. Potential entrants who choose not to enter receive a payment of zero and are never eligible to enter in the future. New entrants do not recoup any profits from the product market; they only pay an entry fee and the costs of their initial investments. The per-period payoff function for new firms in the period they enter is:

$$-\,\mathrm{SUNK}_i - \mathrm{ADJPOS} - \mathrm{INVPOS}\cdot\mathrm{INV}_i^e - \mathrm{INVPOS2}\cdot(\mathrm{INV}_i^e)^2, \tag{3}$$

where SUNK_i is the entrant's draw from $G(\cdot)$, the distribution of sunk entry costs, INV_i^e is the level of initial investment, ADJPOS is the fixed cost of positive investment, and INVPOS and INVPOS2 are variable costs of positive investment. Incumbent firms that choose to continue their operations in a market make production and investment decisions, so they receive revenues and have to account for investment decisions in that period. The per-period payoff function for these firms is:

$$\begin{aligned}\pi_i(s) - 1(\mathrm{INV}_i > 0)(\mathrm{ADJPOS} + \mathrm{INVPOS}\cdot\mathrm{INV}_i + \mathrm{INVPOS2}\cdot\mathrm{INV}_i^2)\\ - 1(\mathrm{INV}_i < 0)(\mathrm{ADJNEG} + \mathrm{INVNEG}\cdot\mathrm{INV}_i + \mathrm{INVNEG2}\cdot\mathrm{INV}_i^2),\end{aligned} \tag{4}$$

where ADJNEG is the firm's fixed cost of divestment, and INVNEG and INVNEG2 are the variable costs of divestment.

If an incumbent chooses to leave the market it obtains payoffs from the product market in addition to its scrap value:

$$\pi_i(s) + \mathrm{SCRAP}. \tag{5}$$

[13] There exists an active market for cement production equipment. For example, see Used Cement Equipment. While unit prices are typically very low, sometimes close to a nominal price of zero, transportation and cleanup costs are extremely high, occasionally into the millions of dollars depending on the size and type of equipment.

Together, Equations 3, 4, and 5 span the payoffs that a firm can achieve in a given state.

4.4 Transitions Between States

The last ingredient of the model is the transition process between states. The probability of moving from one state of the system to another is a combination of all the paths that can lead to that state. A key assumption I make regarding these transitions is that a firm's capacity vector is always equal to last period's capacity plus last period's investment.[14] The probability of achieving a state depends on investment, entry, and exit. The probability of each element of a new state vector is the linear combination of three probabilities:

$$\begin{aligned} Pr(s_i \rightarrow s_i') \quad = \quad & 1(s_i > 0)(1 - Pr(i \text{ exits}|s_i))Pr(s_i'|s_i, \text{INV}_i) \\ & +1(s_i > 0)\left[Pr(i \text{ exits}|s_i)Pr(j \text{ enters}|s_i, i \text{ exits})\cdot\right. \\ & \left. Pr(s_i'|i \text{ exits}, j \text{ enters}, \text{INV}_j)\right] \\ & +1(s_i = 0)Pr(j \text{ enters}|s_i)Pr(s_i'|j \text{ enters}, \text{INV}_j). \end{aligned}$$

The probability of observing an element of a new state is conditional on whether an incumbent is currently active in that slot. If there is an incumbent, there are two possible ways of obtaining the new state: either the incumbent stays in the market and moves to the new state, or the incumbent exits and is replaced by an entrant at the new state. If there is no incumbent, the probability of observing the new state is equal to the probability of a new firm entering at that state. So for any one change in the state vector, I have to account for the entry, exit, and investment decisions of incumbents and potential entrants. To find the probability of the entire state vector shifting to another, I simply multiply out the individual probabilities of each element of the state vector:

$$Pr(s \rightarrow s') = \prod_{i=1}^{N} Pr(s_i' \rightarrow s_i). \tag{6}$$

It is important to note that these transitions are conditionally independent given the choice of s_i, which is going to depend on the actions of the other firms in equilibrium.

As firms face a known, common distribution of entry costs in each period, the probability

[14] This abstracts away from depreciation processes, which do not appear to be significant in the data, and uncertainty in next period's capacity due to random completion times, etc. It is conceptually straightforward to incorporate these extensions in the model.

of entry and exit can be written in terms of the optimal entry and exit strategies:

$$Pr(\text{entry}|s_i) = \int \Theta(s_i, \text{SUNK}_i)\ dG(\text{SUNK}_i) \tag{7}$$

$$Pr(\text{exit}|s_i) = \Phi(s_i). \tag{8}$$

I denote the exit rule, which is a function of the state, as $\Phi(s_i)$. It is notable that the exit rule may reflect a mixed strategy equilibrium, as in the case where there are two incumbents and room for only one. Under these circumstances, $\Phi(s_i)$ is probability of exit derived from the mixed strategy equilibrium.

There exists an analogous entry rule, denoted by $\Theta(s_i, \text{SUNK}_i)$, which is a function of the firm's private draw from the distribution of sunk entry costs. Integrating out over the private information gives the probability that a firm enters at a given state. Under weak regularity conditions, Doraszelski and Satterthwaite (2005) prove that there always exists an MPNE in symmetric pure strategies where the entry policy will take the form of a cutoff rule: a firm will enter if and only if the entry cost is below a certain level. This boils down the expectation about competitors' entry and exit strategies to a probability that a competitor enters or exits in any given period. I revisit these policies after writing out the value functions describing the present values of both incumbents and potential entrants.

4.5 Equilibrium Concept

In each time period, player i makes entry, exit, production, and investment decisions, collectively denoted by Γ_i. Since the full set of dynamic Nash equilibria is unbounded and complex, I restrict the firms' strategies to be anonymous, symmetric, and Markovian. Therefore, I can write each firm's strategy, σ_{it}, as a mapping from states to actions:

$$\sigma_{it} : S_{it} \rightarrow \Gamma_{it}.$$

Each firm's strategy maps the current state of the system into a vector of actions. Since the time horizon is infinite, payoffs are bounded, the discount factor, β, is positive and less than one, and firms have Markovian strategies, I drop the time subscript and write the value of being in state $s \in S$ recursively:

$$V_i(s|\sigma(s)) = u_i(\sigma(s)) + \beta \int V_i(s'|\sigma)\ dP(s'|\sigma(s), s),$$

where $\sigma(s)$ is the vector of firm strategies, $u_i(\sigma(s))$ is the per-period payoff function, and $P(\cdot)$ is the conditional probability distribution governing the transition between states. Markov perfect Nash equilibrium requires each firm's strategy profile to be optimal given the strategy profiles of its competitors:

$$V(s|\sigma_i^*, \sigma_{-i}) \geq V(s|\sigma_i', \sigma_{-i}), \tag{9}$$

for all s and any alternative strategy σ_i'. This equilibrium concept places significant structure on the optimal behavior of firms, which I will exploit below to construct my empirical estimator. I assume that this MPNE is unique.[15]

4.6 Value Functions

Given the primitives of the model above, I can write down the ex-ante value functions for both the potential entrant and incumbent. These functions give the expected discounted present value, in dollars, of being at a given state vector. The value can be broken into two components: the per-period payoff function and the continuation value, which is the expected value of next period's state. For example, if there was no entry, exit, or investment, then the value of each state would simply be the expected discounted present value of obtaining the state-specific period payoffs in perpetuity. Firms use the value functions to find their optimal investment, entry, and exit policies. Each firm compares the marginal benefit of being at a new state against costs of achieving that new state when deciding on an investment strategy. Likewise, each firm evaluates the scrap value against its continuation value when deciding whether or not to exit. The potential entrant makes a comparison of its draw from the distribution of sunk entry costs against the expected value if it enters.

I integrate out all of the private information in the per-period payoff function when writing out the value functions. This is valid in the present context because the idiosyncratic shocks are iid, so conditioning on your present shock gives no additional information about the future. Therefore, firms base their optimal strategies on the ex-ante value functions of next period's potential states.[16]

[15] It may be that the addition of uncertainty at each step of the model (stage game, investment choice, entry and exit choice) could help purify the set of symmetric equilibria. Computing the set of admissable equilibria is an important, open research question. An important contribution in this direction is provided by Doraszelski and Satterthwaite, who demonstrate the conditions under which a symmetric, anonoymous MPNE exists in pure strategies. Verifying their conditions with the current model is straightforward. However, enumerating the set of equilibria remains an important area for future research.

[16] This distinction is not made in the baseline Ericson-Pakes model because there is no private information or uncertainty in the per-period payoff function. For example, in the canonical example of firms investing in product quality the only uncertainty enters in the transition function between states. Given that the ex-ante

A second point is also in order about why it is necessary to solve for the value function in the first place, given that I have recovered the policy functions and underlying primitives above, and could construct the value function directly. The reason is that the policy functions, and thus the value functions associated with them, are valid only for the specific set of primitives that I recovered in the estimation. To perform any counterfactuals, it is necessary to re-solve for the policy functions, and thus the value functions, for the new set of parameters, as firms will generically alter their optimal strategies in response to changes in the economic environment. If I was interested in questions that did not require changing the underlying primitives, then it would not be necessary to re-solve for the optimal policies numerically.[17]

I first consider the potential entrant, who simply checks the expected value of entering against the draw of entry costs it receives. Since I assumed that these potential entrants live for only one period, they do not solve an optimal stopping problem, where a firm with a high draw in this period may delay entering until it receives a more favorable draw in the future. Conditional on the current state and the draw from the sunk cost of entry, SUNK_i, the value function for potential entrants who decide to enter in the next period can be written as:

$$V_i^e(s, \mathrm{SUNK}_i) = \max_{\mathrm{INV}_i^e} \{-\mathrm{SUNK}_i - \mathrm{ADJPOS} - \mathrm{INVPOS} \cdot \mathrm{INV}_i^e \\ -\mathrm{INVPOS2} \cdot (\mathrm{INV}_i^e)^2 + \beta E(V(s')|s)\}. \quad (10)$$

Note that the value function for the entrant includes the optimal choice for an initial investment. The potential entrant is forward-looking and rational, so the expected value of entering accounts for the investments of other firms and their entry or exit decisions. Also note that solving for the optimal investment does not depend on SUNK_i, so firms solve for INV_i^e by finding the optimal investment conditional on entering. For a given state and optimal investment, there exists a draw from the sunk cost distribution such that a firm is indifferent between entering and not. Denoting the optimal investment conditional on

and ex-post value functions both integrate out the uncertainty arising from the transitions between states, these two functions will be the same. In the present model I have multiple sources of private information, some of which enter the per-period payoff function, which results in differences between the ex-ante and ex-post value functions.

[17] If the policy functions and parameters are recovered precisely enough in the first stage, and the model is not misspecified, then solving for the MPNE policy functions would reproduce those recovered from the data. As a check on the robustness of the model, I find the predicted policy functions closely mimic their empirical counterparts.

entering as INV_i^{e*}, the draw at which a firm is indifferent is:

$$\overline{\text{SUNK}}_i = -\text{ADJPOS} - \text{INVPOS} \cdot \text{INV}_i^{e*} - \text{INVPOS2} \cdot (\text{INV}_i^{e*})^2 + \beta E(V(s')|s). \tag{11}$$

In equilibrium, the entry policy function will be a cutoff rule where a firm enters the industry if its draw from the distribution of sunk entry costs is less than or equal to this value. I denote the entry policy function by $\Theta(s_i, \text{SUNK}_i)$.

The derivation of the value function for the incumbent firm is similar to the potential entrant, except it has two parts corresponding to whether or not the firm decides to exit the industry. If the firm decides to leave the market, it obtains its product-market payoffs, $\pi_i(s)$, and its scrap payment, SCRAP. If a firm decides to remain active, it also receives product market revenues. However, instead of receiving a scrap payment, it obtains the following payoff, which is composed of the costs of its optimal investment and the continuation value:

$$\begin{aligned} V_i^{STAY}(s) = \max_{\text{INV}_i} & -1(\text{INV}_i > 0)(\text{ADJPOS} + \text{INVPOS} \cdot \text{INV}_i + \text{INVPOS2} \cdot \text{INV}_i^2) \\ & - 1(\text{INV}_i < 0)(\text{ADJNEG} + \text{INVNEG} \cdot \text{INV}_i + \text{INVNEG2} \cdot \text{INV}_i^2) + \beta E(V(s')|s). \end{aligned} \tag{12}$$

Combining the payoffs of firms that stay and firm that exit, and integrating over the distribution of productivity shocks, results in the ex-ante value function for an incumbent firm:

$$V_i(s) = \int \pi_i(s_i)\ dS + (1 - \Phi(s_i))V_i^{STAY}(s) + \Phi(s_i)\text{SCRAP}_i. \tag{13}$$

The value functions in Equations 10 and 13 are the basis for my empirical strategy, which I discuss next.

5 Empirical Strategy

5.1 Overview

The empirical goal of this paper is to estimate all of the parameters in the theoretical model described above. I follow the two-step empirical strategy laid out in Bajari, Benkard, and Levin (BBL) (2006). In the first step, I recover the policy functions governing entry, exit, and investment along with the product market profit function. In the second step, I take these functions and impose the restrictions of the MPNE to recover the dynamic parameters governing the costs of capacity adjustment and exit. This then allows me to simulate the value of a new firm entering the market, which can be used to recover the distribution of the sunk costs of entry.

Before getting into the details, it is useful to consider the mapping between the theoretical model above and the empirical estimates below. In the first step the relevant empirical objects that I need to recover are the parameters of the product market profit function and the policy functions that describe what actions the firm will undertake at any state. The model specifies a specific functional form for the parameters that enter into the product market profit function; in this case it is straightforward to write down an estimator consistent with the underlying assumptions. The theoretical model also provides some guidance for the form of the estimators of the policy functions. The entry decisions is a cutoff rule, where a firm will enter when its private draw on sunk entry costs is low enough relative to the expected dollar value of entering at a given state. The exit decision reflects the outcomes of a potentially mixed strategy equilibrium, which is also a function of the state vector. This suggests that to recover the policy functions governing entry and exit, I should fit some function of the observable state variables against the observed probability of entry and exit. Under ideal circumstances a nonparametric regression would asymptotically recover the true underlying policy functions. Due to data limitations, I estimate both the entry and exit policy functions using probits.

The theoretical model also suggests that the empirical policy function should be a function of the state variables and should be flexible enough to account for lumpy investment behavior. One model that satisfies both of these requirements is the (S, s) rule of investment, introduced by Scarf (1959), where firms tolerate deviations from their optimal level of capacity due to fixed adjustment costs.[18] In the language of the (S, s) rule, firms have a target level bounded on either side by an adjustment band, both of which can be functions of observable variables. When the actual level of capacity hits one of the bands, the firm will make an adjustment to the target level. The target level and bands are only observed when the firm makes adjustments, and are flexibly parameterized to be functions of the underlying state variables. This model also nests the model of continuous investment, and is thus quite flexible in its ability to capture a range of investment behavior.

[18]Deriving this rule as the explicit solution to an optimization problem is involved—see Hall and Rust (2000) for an example of the optimality of this rule in an inventory setting.

5.2 Identification

It is useful to consider the identification of the structural parameters in this setting. One of the benefits of the two-step approach is that identification is intuitive and follows directly from moments in the reduced form equations. The first empirical object, the demand curve for cement, is identified through functional form (constant elasticity of demand) and the usual excluded cost-side shifters.

The cost curves for firms, which has initially flat and then increasing, are identified off differences in output across markets which vary with the number of firms, the vector of plant capacities, and the level of demand in the market. Intuitively, the demand curve provides us with an estimate of the marginal revenues a firm would receive from producing a marginal unit of cement. Variation in these marginal revenues trace out the best-response functions for firms, as a function of their own capacities, which in turn can be inverted to recover estimates of the marginal cost curve. In principle, these cost curves are nonparametrically identified, as we simply need enough variation in marginal revenues, for a fixed set of capacities in a market, to trace out the marginal cost curve.

The reduced form policy functions are simply descriptions of the equilibrium behavior of firms, conditioning on the state vector. Therefore, the only identification requirement for these objects is that there is sufficient variation in the right-hand side variables to trace out the equilibrium responses of firms to changes in the economic environment. While data limitations force me to adopt some parametric forms for the policy functions, I retain as much flexibility as possible by using semiparametric estimators for the investment policy functions. With richer data a completely nonparametric approach is feasible.

The reduced form policy functions are subsequently projected onto the underlying theoretical model to recover the primitives governing the cost of entry, exit, and investment. While the model itself may be quite complex, the intuition about the identification of these parameters is straightforward. Essentially we find parameters such that the policy functions recovered in the data are as close to profit-maximizing as possible. Therefore, the fixed cost of investment is identified through variation in when firms make investment decisions, conditional on the state. We can compute the amount of money left on the table by investing too early, or delaying investment for too long. If firms were to invest more frequently than implied by the investment policy function, it has to be the case that the fixed costs of investment are sufficiently large to make this a poor strategy. Conversely, if firms are too slow to make adjustments, the model gives an estimate of how much money was left on the table. The parameter that estimate is going to balance these two forces in such a manner as to replicate the observed frequency of investment in the data as close as possible. Variation in the expected revenues of investment thus identify this parameter.

Identification of the variable costs of investment follows from an analogous argument. The model provides an estimate of the discounted present value of additional revenues accruing to an expansion in capacity. Firms choose investments such that the marginal cost of investment equals the marginal NPV dollar. Therefore, it is possible to identify those investment parameters from variation in these expected revenues. As was the case with the production costs above, it is possible to nonparametrically estimate this relationship if the data were rich enough.

Lastly, entry and exit costs are identified from variation in expected revenues from becoming an active firm, and exiting the market, respectively. The data provides variation in entry rates, and the model provides an estimate of the foregone profits lost by not entering, so it is possible to match these two objects together to nonparametrically identify entry costs. A similar argument holds in the other direction for exit costs. As a practical matter, nonparametric estimation is weak in this case, since the entry data is relatively scarce.

5.3 First-Stage Estimates

The first step has two goals: recover as many parameters as possible without needing to resort to a specific dynamic model, and describe the behavior of firms at every state. This means recovering the parameters of the demand curve, production costs, and the policy functions governing firm investment, entry, and exit, in that order. The period profit function from the product market, encompassing the demand curve and production function, is independent from any dynamic considerations in my model and can be estimated as stand-alone objects. The policy functions describe the empirical behavior of the firms for any given state vector. Under the assumption that the firms in the data play the same equilibrium across different markets, these observed policy functions have to be consistent with firms maximizing their outcomes under the theoretical model.

5.3.1 Demand Curve

The first step is estimating the demand curve. I use a static demand system in my model, so I can recover these parameters from the USGS market-level data independently of any dynamic considerations. I form the following moments:

$$m_1(\alpha) = \frac{1}{MT}\sum_{t=1}^{T}\sum_{i=1}^{M}\frac{1}{N_m}\sum_{j=1}^{N_m} Z'_{ijt}(\log \text{MARKETQ}_{ijt} - \alpha_0 - \alpha'_1 \log \text{PRICE}_{ijt} + \alpha'_2 \text{REGION}_i), \tag{14}$$

where Z_{it} is a vector of instruments. In this specification, the coefficient on market price, α_1, is the elasticity of demand. To account for endogeneity of prices and quantities, I form instruments using supply-side cost shifters: coal prices, gas prices, electricity rates, and wage rates. The indicator variable REGION proxies for unobserved heterogeneity across markets. For notational clarity I denote the vector of parameters associated with the region fixed effects by α_2. Shifts in market demand are measured relative to the baseline market of Alabama.

5.3.2 Production Parameters

The predicted quantities for each firm in each market, conditional on the vector of production costs, $\hat{Q}_{it}(\alpha)$, are defined by the system of first-order conditions associated with the firms' profit maximization problem. I form a vector of moments from the gradient vector of the difference between the actual and predicted quantities. There are six production parameters: CAPCOST, MC, the level at which capacity costs begin to bind (ν), and late period dummy shifters for each, which generate six associated sample moment conditions:

$$m_2(\alpha) = (nT)^{-1}\sum_{i=1}^{N}\sum_{j=1}^{T}\nabla_\alpha(Q_{it} - \hat{Q}_{it}(\alpha)). \tag{15}$$

I restrict the threshold at which capacity costs bind to be between 0 and 1 with a logit transformation: $\nu = \exp(\tilde{\nu})/(1.0 + \exp(\tilde{\nu}))$. Note that it is possible to back out the productivity shock, SHOCK_i, from the observed quantities and their predicted counterparts, conditional on the estimated parameters, using an inversion of the first-order condition for optimal pricing. I condition on this shock in the investment and exit policies, which I estimate next.[19]

[19] Cooper and Haltiwanger (2005) have shown the importance of idiosyncratic shocks as a determinant of investment behavior. See Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg and Caves (2004) for a recent strand of the literature dealing with the empirical implications and identification of productivity shocks on firm behavior.

5.3.3 Investment Policy Function

I follow Attanasio's (2000) model of the (S, s) rule, with the exception that I only model firms with positive capacity levels at the start and end of each period, treating the entry and exit process separately. This is acceptable in this context because I am only interested in what the investment behavior of a firm will be given a specific state. Firms have a target level of capacity that they adjust to when they make an investment:

$$\text{TARGET}_{it} = \alpha_4' s_1(\text{CAP}_{it}) + \alpha_5' s_2(\text{SUMCAP}_{-it}) + \alpha_6 \text{SHOCK}_{it} + u_{it}^d \tag{16}$$

where the desired level of capacity is a function of the firm's own capacity, the sum of its competitors capacities (SUMCAP_{-it}), its productivity shock from the product market, and a mean zero error term. The functions s_1 and s_2 are approximated using cubic B-splines. For notational simplicity I again denote the vector of parameters associated with these functions as α_4 and α_5.

The critical aspect of the (S, s) rule that generates lumpy investment behavior is that firms only adjust CAP_{it} to TARGET_{it} when it is sufficiently far from the desired level. I model this type of adjustment behavior by assuming that there are upper and lower "bands" which dictate when the firm will make an adjustment. As soon as the actual level of capacity is above the upper band or below the lower band, the firm adjusts to its target level. These bounds are assumed to be a symmetric function of the same state variables as the target and a mean-zero error term,

$$\text{BAND}_{it} = \text{TARGET}_{it} \pm \exp(\alpha_7' s_1(\text{CAP}_{it}) + \alpha_8' s_2(\text{SUMCAP}_{-it}) + \alpha_9 \text{SHOCK}_{it} + u_{it}^b) \tag{17}$$

This specification ensures that the desired level of adjustment is always in between the bands. This model also nests a model of continuous adjustment in the limit as the bands go to zero. I assume that the residuals in the bands are iid normal with zero mean and equal variance, and are independent of the error in the target. I derive the likelihood function for this model in the Appendix.

I estimate the policy function parameters in a two-step procedure. Since I assume that the change in capacity reveals the size of the band, I use a first-stage OLS estimator to recover initial guesses for α in Equations 16 and 17 above. I use these parameters as starting values in a GMM estimator formed from the score vector of the log-likelihood function derived above:

$$m_3(\alpha) = (n(T-1))^{-1} \sum_{i=1}^{N} \sum_{j=2}^{T} \nabla_\alpha \log L(\alpha). \tag{18}$$

5.3.4 Entry and Exit Policy Functions

I estimate entry and exit policies conditional on the state vector. As discussed above, I parameterize these probabilities with a probit model. Explanatory variables in both estimations are a constant, the sum of competitors' capacities, and a dummy variable for before and after 1990. I add the firm's capacity and productivity shock to the exit equation. I denote the moments corresponding to the exit probit as $m_4(\alpha)$.

5.3.5 Standard Errors

The motivation for using GMM to estimate these initial stages is that I have to correct the variance matrix to account for error introduced by using the results of one estimation as inputs into the next stage. Fortunately, there is a relatively simple and straightforward method to do this, starting with the consistent but inefficient estimates obtained by running each stage separately. Following Newey and McFadden (1994), I stack the moments $m_1(\alpha)$, $m_2(\alpha)$, $m_3(\alpha)$ and $m_4(\alpha)$ and form the following one-step estimator:

$$\tilde{\alpha} = \bar{\alpha} - (\bar{G}'\hat{W}\bar{G})^{-1}\bar{G}'\hat{W}\hat{g}_n(\bar{\alpha}), \tag{19}$$

where $\hat{g}_n(\bar{\alpha})$ is the stacked vector of moments evaluated at $\bar{\alpha}$, an initial parameter vector found by estimating each stage above separately, $\bar{G}$ is a consistent estimator of plim $[\nabla_\alpha \hat{g}_n(\alpha_o)]$, and $\bar{W}$ is a consistent estimator of the inverse variance matrix. I use an efficient weighting matrix, $\bar{\Omega}$, to ensure that $\tilde{\alpha}$ has the same asymptotic variance as the full (iterated) GMM estimator with optimal efficient matrix.[20] Once I have obtained $\tilde{\alpha}$ using the one-step formula, I find a consistent estimate of the covariance matrix using $(G'WG)^{-1}$, where G and W are evaluated at $\tilde{\alpha}$.

[20] There is one complication due to the fact that my moments are defined over data series of differing lengths. Denoting the subvector of moments defined over data set j as $g_j(z_i, \bar{\alpha})$, I construct a block-diagonal covariance matrix, $\bar{\Omega} = \bar{\omega} \otimes I_3$, where each element of $\bar{\omega}$ is $\bar{\omega}_j = \sum_{i=1}^{n_j} g_j(z_i, \bar{\alpha}) g_j(z_i, \bar{\alpha})'$. Similarly, I evaluate $\bar{G}$ piecewise with its sample analogue: $n_j^{-1} \sum_{i=1}^{n_j} \nabla_\alpha g_j(z_i, \bar{\alpha})$. This matrix of derivatives is lower block triangular, as each successive stage has more parameters.

5.4 Second-Stage Estimates

The first step has provided functions that describe both how the state vector evolves over time and what product market profits are at each state. The second step is concerned with finding parameters that make these observed policy functions optimal, given the underlying theoretical model.

Given a starting state configuration, I simulate the evolution of the state vector forward 200 periods, far enough in the future that payoffs from that period have a very low discounted present value. I update the state vector from period to period by reading off the various policy functions. For example, if the slot is currently empty, then I draw from $U[0,1]$ and compare it to the probability given the the entry probit conditional on the current state. If the draw is low enough, then the firm makes the appropriate investment, as described by the (S, s) rule, and becomes an active firm at that capacity in the next period. By collecting the actions of the firm through time, I can calculate the present-value payoffs to that path for a given set of parameters. By perturbing the policy functions a little bit I generate different paths and different present-value payoffs for a given parameter vector. The key insight of this estimator is that the observed policy functions were generated by profit-maximizing firms who chose the path with the highest expected discounted stream of payoffs. Therefore, at the true parameters, the payoffs generated by the observed policies should be greater than those generated by any other set of policies. This intuition is the heart of the second step, where I recover of the fixed and variable costs of investment and the distributions of sunk entry costs and exit scrap values.

5.4.1 Investment Parameters and Distribution of Scrap Values

To derive the estimator for investment costs and the distribution of scrap values, recall the firm's optimal decision, written recursively:

$$\max_{\sigma_i} u_i(\sigma(s), s) + \beta \int V_i(s'|\sigma) dP(s'|\sigma(s), s), \tag{20}$$

Note that, given the parameters estimated in the first step described above, I can decompose u_i into a linear function of its known and unknown components:

$$
\begin{aligned}
u_i = \pi_i - 1(x > 0)(\text{ADJPOS} + \text{INVPOS} \cdot \text{INV}_i + \text{INVPOS2} \cdot (\text{INV}_i)^2) \\
- 1(x < 0)(\text{ADJNEG} + \text{INVNEG} \cdot \text{INV}_i + \text{INVNEG2} \cdot (\text{INV}_i)^2) \\
+ 1(\text{i exits})\text{SCRAP}, \quad (21)
\end{aligned}
$$

where the per-period payoff function, π_i, capacity adjustment, and exit decision have been recovered in previous steps. The unknowns are the costs of capacity adjustment and the scrap value received upon exit from a market. Note that the unknown parameters, denoted by the vector α, enter linearly into the payoffs of the firm in the current period and all future periods. It is therefore possible to decompose the value function into the vector of parameters and the vector of expected discounted payoffs and actions, $W(s_o; \sigma_i, \sigma_{-i})$:

$$
W(s_o; \sigma_i, \sigma_{-i}) = E_{\sigma_i, \sigma_{-i}|s_o} \sum_{t=0}^{\infty} \beta^t \zeta(s_{it}), \tag{22}
$$

where $\zeta(s_i)$ is the vector of functions corresponding to the dynamic parameters:

$$
\begin{aligned}
\zeta(s_i) = \big\{ \pi_i, -1(\text{INV}_i > 0), -1(\text{INV}_i > 0)\text{INV}_i, -1(\text{INV}_i > 0)\text{INV}_i^2, \\
-1(\text{INV}_i < 0), -1(\text{INV}_i < 0)\text{INV}_i, -1(\text{INV}_i < 0)\text{INV}_i^2, 1(\text{i exits}) \big\}. \quad (23)
\end{aligned}
$$

Note that the α vector contains a 1 in the first position, as the profits from the per-period payoff function enter in for each state irrespective of the unknown parameters. I impose the Markov perfect equilibrium condition (see Equation 9) for all alternative policies σ' to obtain:

$$
W(s_o; \sigma_i^*, \sigma_{-i}) \cdot \alpha \geq W(s_o; \sigma_i', \sigma_{-i}) \cdot \alpha, \tag{24}
$$

where the value function has been replaced by the explicit sum defined in Equation 22. At the true parameters the above relation should hold for all alternative policies. Exploiting the linearity of the unknown parameters, I can rewrite the above equation in terms of profitable deviations from the optimal policy:

$$
g(x, \alpha) = [W(s; \sigma_i', \sigma_{-i}) - W(s; \sigma_i^*, \sigma_{-i})] \cdot \alpha. \tag{25}
$$

Intuitively, I want to find parameters such that profitable deviations from the optimal policies are minimized. Formally, I draw alternative policies from a distribution H over all policies to generate a set of n_k inequalities, X_k. The true parameter minimizes:

$$\min_{\alpha} \int 1\left(g(X_k, \alpha) > 0\right) g(X_k, \alpha)^2 dH(X_k). \tag{26}$$

To form the estimator, I replace the above with its sample counterpart:

$$Q_n(\alpha) = \frac{1}{n_k} \sum_{i=1}^{n_k} 1\left(g(X_{ki}, \alpha) > 0\right) g(X_{ki}, \alpha)^2. \tag{27}$$

Implementing this estimator proceeds in two separate steps. In the first step, I find W for both the observed and alternative policies. I generate the alternative policies by adding noise to the observed policy functions. For example, to permute the exit policy function I add an error drawn from the standard normal to the terms inside the exit probit. I generate many W to find the terms in 27. The linearity of the unknown parameters becomes useful during the minimization, as I do not have recompute separate outcome paths for each set of parameters. Note that the function is not trivially minimized at zero because the profits from the product market enter in each time period. Due to potential flat spots in the objective function, I use the Laplace-type estimator of Chernozhukov and Hong (2003). This estimator is robust to non-smooth functions and also has the nice feature of jointly estimating the mean and variance of the unknown parameters.

5.4.2 Distribution of Sunk Entry Costs

Having recovered the policy functions, which describe how the firm will act at each state, and the underlying primitives of the model, which quantify the costs and benefits of those actions, it is possible to find the distribution of sunk costs. Knowing how the firm will act if it enters, along with stream of revenues associated with those behaviors, allows me to compute the expected value of entering a market. If a firm does not enter when these expected profits are positive, it must be because it received a sufficiently large draw on sunk entry costs to make it unprofitable to do so. By matching the cumulative distribution of the sunk costs to the predicted probability of entry I can recover the distribution of sunk costs.

Formally, the value of entering at a state is:

$$V_i^e(s, \text{SUNK}_i) = \max_{\text{INV}_i^e} \{-\text{SUNK}_i - \text{ADJPOS} - \text{INVPOS} \cdot \text{INV}_i^e \\ -\text{INVPOS2} \cdot (\text{INV}_i^e)^2 + \beta E(V(s')|s)\} . \quad (28)$$

The optimal investment is given by the policy function, and I have all the parameters that enter the initial outlay and future stream of revenues save for SUNK_i. Recalling Equation 11, the firm will enter the market when its draw is lower than the value of entering the market, $EV^e(s)$, as defined by the terms to the right of SUNK_i in the above equation. As in the recovery of the dynamic parameters, I simulate many forward paths of possible outcomes given the firm entered. Averaging over these paths gives the expected value of entry, which I then can match against the observed rates of entry at different states. Formally, the probability of entering the market is the probability of receiving a draw that is less than the value of entry:

$$Pr(\text{SUNK}_i \leq EV^e(s)) = G(EV^e(s); \mu_G, \sigma_G^2), \quad (29)$$

where $G(\cdot)$ is the cumulative distribution function of sunk entry costs. The left-hand side is given by the entry probit. I simulate $EV^e(s)$ for NS different states and match $G(EV^e(s))$ at those values to the observed probability of entry:

$$\min_{\{\mu_G, \sigma_G^2\}} (NS)^{-1} \sum_i^{NS} \left[Pr(\text{entry}|s) - G\left(EV^e(s)\right)\right]^2 . \quad (30)$$

I recover the parameters of the distribution of sunk entry costs before and after the 1990 Amendments.

With the conclusion of this estimation stage, I have recovered all of the parameters of the underlying theoretical model. Next, I present the results of these estimations before performing the counterfactual policy simulations.

6 Empirical Results

Demand Curve I first recover the demand curve for Portland cement. I use market-level data on prices and quantities to determine the parameters in Equation 1, with several cost-side shifters serving as instruments to account for the endogeneity of prices. The results are presented in Table 3. In order to account for differing levels of demand across markets,

Table 3: Constant Elasticity of Demand Results

Variable	Coefficient	Standard Error
Elasticity	-2.954	(0.378)
Intercept	20.362	(1.564)
Alaska, Hawaii, Oregon, and Washington	-0.345	(0.219)
Arizona, Nevada, and New Mexico	0.296	(0.197)
Arkansas and Oklahoma	-0.577	(0.175)
California North	0.172	(0.188)
California South	1.047	(0.184)
Colorado and Wyoming	-0.130	(0.193)
Florida	0.366	(0.177)
Georgia and Tennessee	-0.406	(0.173)
Idaho, Montana, and Utah	-0.366	(0.186)
Illinois	-0.623	(0.176)
Indiana	-0.529	(0.183)
Iowa, Nebraska, and South Dakota	-0.294	(0.171)
Kansas	-0.574	(0.178)
Kentucky, Mississippi, North Carolina, and Louisiana	-0.307	(0.174)
Maryland, Virginia, and West Virginia	-0.472	(0.177)
Michigan and Wisconsin	0.295	(0.174)
Missouri	-0.020	(0.178)
New York and Maine	-0.116	(0.175)
Ohio	-0.755	(0.177)
Pennsylvania East	0.283	(0.175)
Pennsylvania West	-0.917	(0.175)
South Carolina	-0.430	(0.183)
Texas North	0.242	(0.181)
Texas South	-0.221	(0.186)

All market-specific fixed effects are relative to Alabama. Instruments were gas prices, coal prices, electricity prices, and skilled labor wage rates. There are a total of 517 observations. Parameters were estimated using a LIML specification.

Table 4: Production Function Estimation Results

Parameter	Coefficient	Standard Error
CAPCOST	0.829	6.004
BINDING LEVEL (ν)	1.896	0.024
MARGINAL COST	35.322	0.327
CAPCOST LATE DUMMY	-0.753	5.711
BINDING LATE DUMMY	0.023	0.053
MARGINAL COST DUMMY	-1.303	0.615

This table reports the estimated parameters for the production function. The binding threshold at which the capacity costs become important is restricted to $[0, 1]$ by estimating a logit probability: $\nu = \exp(\tilde{\nu})/\left(1.0 + \exp(\tilde{\nu})\right)$. At the estimated value of 1.9, this implies that capacity costs start to bind at an approximately 87 percent utilization rate. I fail to reject the hypothesis that there is no difference in the parameters before and after 1990 at the 95 percent level.

I incorporate market-specific fixed effects. These coefficients have the expected signs, with markets like Alaska and Hawaii having the highest prices.

I find that the elasticity of demand for cement is -2.95. While this seems quite high, I appeal to a simple out-of-sample test below which strongly suggests that the elasticity has to be somewhere in this neighborhood. If the elasticity was much lower than 2.95, implied profit margins would be incorrect and, in particular, the implied investment costs would be much too high. I return to this discussion after recovering the rest of the parameters, as they are necessary for constructing that argument. I also test this simple specification against several alternatives, such as adding in predictable components of demand growth, which I discuss below.

To verify that the instruments used in the demand estimation are both correlated with the endogenous regressor and orthogonal to the error term, I evaluate both the fits of the instruments on the endogenous regressor and the Anderson-Rubin statistic. The F-statistic of an OLS regression of the instruments on the endogenous regressor results is 17.83, which is significant at the 99.9 percent level and well above the rule-of-thumb threshold of 10. The Anderson-Rubin statistic is 52.62, which is also significant at the 99.9 percent level. I conclude that the tests fail to reject the hypothesis that the instruments were both well-correlated with prices and orthogonal to the error terms.

Production Costs Having estimated the demand curve, I recover the production cost parameters by matching predicted quantities as closely as possible to their empirical counterparts. I estimate six parameters: marginal cost, capacity cost, the capacity binding level, and post-1990 dummies for each. The results are shown in Table 4. I bootstrapped the

Table 5: Implied Prices, Revenues, Costs, and Profits

Variable	Value	Standard Deviation
Price	15,773	10,607
Revenues	39,539	18,697
Costs	23,765	11,520
Profit	15,773	10,607
Margin	38.5 percent	14 percent

This table reports the summary statistics of the implied prices, revenues, costs, and profits for every firm in my sample at the estimated demand and production parameters. Prices, revenues, costs, and profits are measured in thousands of dollars. Margin is the implied profit margin calculated as profits divided by revenues.

estimator 500 times with subsamples of 100 markets to obtain confidence intervals. The estimates indicate that capacity costs become important as firms increase production beyond 87 percent of their boilerplate capacity. Once firms cross this threshold they experience large, linearly increasing marginal costs as they cut into the normal period of maintenence downtime. The penalty for cutting out your maintenence is significant, preventing most producers from exceeding 90 percent of their stated production capacity.

I test for differences in the cost parameters before and after 1990. I find that there have been slight increases in productive efficiency after 1990. However, I fail to reject the null hypothesis that the coefficients on the dummy variables for post-1990 are all zero at the 90 percent confidence level. This helps strengthen the argument that the Amendments did not have an influence on marginal costs. This is also a positive result in another regard, as it is necessary evidence to reject the idea that there was an additional, unobserved shock to the industry's costs structure over this time period.

The relationship between CAPCOST and its post-1990 shifter is also of interest. Due to the increasing nature of costs at the margin where these parameters bind, they are poorly identified relative to each other. It was typically the case that when one was large, the other was small. This tends to inflate the variance and understate the significant of those capacity costs. Restricting the late dummy for capacity costs to be zero results in the same numbers for pre-1990 costs, with much lower variances and statistical significance for CAPCOST. In this restricted case, I also fail to reject the null hypothesis that costs are equal across the two time periods at the 90 percent level.

As a check on the estimated parameters, I compute the market price, revenues, costs, and profit margin for every firm in my sample. The summary statistics for these values are shown in Table 5. The prices are well within the range seen in the data, with the average firm grossing slightly less than \$40M a year. Profits average just under \$16M a year, which is little less than a 40 percent profit margin. This is a plausible gross return, as public financials for major cement producer Lafarge North America report an 33 percent average gross profit margin for the three-year period 2002-2004.[21] These findings foreshadow my results below, in that there must be extensive sunk costs in order to sustain such high profit margins. However, before uncovering these costs directly, I estimate the policy functions governing how firms invest, enter, and exit.

Investment Policy I model the investment policy function as an (S, s) rule. Under the assumption that the bandwidth and target level are observable when a firm makes an adjustment, it is possible to obtain consistent estimates for the parameters in Equations 16 and 17 using a simple OLS regression. The bandwidth is determined by a regression of shocks, own capacity, and the capacity of a firm's competitors on the size of the change. The target level coefficients are determined by regressing the same state variables on the post-adjustment capacity. In order to estimate this policy function as flexibly as possible I use cubic B-splines as basis functions for the capacity variables. I use the OLS resuls as starting values for the full maximum likelihood estimator. The results are presented in Table 6.

The (S, s) rule does a good job of fitting the investment behavior observed in the data, partly because of the flexibility of the target and band functions. Interpreting the B-spline coefficients is difficult, since the approximation of the relationship of the covariate to the response variable is a superposition of several piecewise polynomials. The productivity shock does not have a statistically significant effect on the size of the band. This is somewhat surprising, as higher levels of efficiency in production is in part due to better administration and organization, qualities which would also translate to efficiencies in investment. On the other hand, this may reflect the fact that more efficient firms are able to make better use of their existing capacity, and so have higher deviation thresholds before making permanent adjustments.

The productivity shock also has no statistically significant effect on the target. This can be due to the fact that being more efficient has two countervailing effects. On one hand, the more efficient firms have less incentive to engage in "precautionary" overinvestment, putting downward pressure on the target level. At the same time, they operate more efficiently, which can have a positive influence on the desired level of capacity. The results suggest that

[21] Sales and profit data are from Hoover's Online "Annual Financials" fact sheet for Lafarge S.A., 2002-2004. http://www.hoovers.com.

Table 6: Policy Function Results

Parameter	Coefficient	Standard Error
BAND SUMCAP B-spline 1	5.444	1.236
BAND SUMCAP B-spline 2	6.239	1.367
BAND SUMCAP B-spline 3	6.19	1.551
BAND SUMCAP B-spline 4	5.871	1.721
BAND SUMCAP B-spline 5	5.99	2.174
BAND SUMCAP B-spline 6	8.519	2.852
BAND CAP B-spline 1	-3.016	1.769
BAND CAP B-spline 2	-2.485	1.398
BAND CAP B-spline 3	-2.373	1.155
BAND CAP B-spline 4	-0.803	1.664
BAND CAP B-spline 5	-2.887	0.757
BAND Shock	-0.01	0.01
TARGET SUMCAP B-spline 1	2,247.638	2.007
TARGET SUMCAP B-spline 2	2,203.819	3.294
TARGET SUMCAP B-spline 3	2,256.723	2.392
TARGET SUMCAP B-spline 4	2,202.157	2.156
TARGET SUMCAP B-spline 5	2,293.337	2.623
TARGET SUMCAP B-spline 6	2,190.144	1.129
TARGET CAP B-spline 1	-2,014.84	3.063
TARGET CAP B-spline 2	-1,756.918	3.661
TARGET CAP B-spline 3	-1,217.592	2.866
TARGET CAP B-spline 4	-431.08	2.03
TARGET CAP B-spline 5	222.511	0.602
TARGET Shock	0	0.002
σ^2_{BAND}	1.037	0.338
σ^2_{TARGET}	213.721	8.96

Number of capacity changes = 774. Initial parameters estimates selected through OLS before being estimated by maximum likelihood. SUMCAP refers to the summed capacity of a firm's competitors, while CAP refers to a firm's own capacity, both measured at the time the firm makes an investment decision.

Table 7: Entry and Exit Policy Results

Parameter	Coefficient	Standard Error
Exit Policy		
Constant	-1.306	0.183
CAP	-1.55×10^{-3}	2.81×10^{-3}
SHOCK	-4.60×10^{-5}	8.80×10^{-5}
SUMCAP	4.50×10^{-5}	1.70×10^{-5}
Late Dummy	-0.301	0.081
Entry Policy		
Constant	-1.68	0.210
SUMCAP	3.71×10^{-5}	3.60×10^{-5}
Late Dummy	-0.491	0.242

Sample size for exit policy function = 2233; sample size for entry policy function = 414.

the two effects have roughly equal magnitudes, leading to an empirically indistinguishable effect of productivity on target level.

Entry and Exit Policy The entry and exit policy function results are presented in Table 7. For the most part, the marginal effect parameters have the desired sign in the exit equation. As would also be expected, a firm has a marginally lower probability of exiting a market given a higher capacity, which is a measure of the firm's staying power and the strength of market demand. The productivity shock parameter has the correct sign, as more productive firms have a lower incentive to leave the market in any given period. As a firm's competitors become larger it has an increased chance of leaving the market. Firms have a significantly lower probability of leaving the market in the later period.

Interestingly, the capacity of extant firms is not a significant explanatory variable in the entry equation. One explanation for this is that the relationship between extant capacity and the expected value upon entry is complicated by the nonlinear response of competing firms to any entry. For less-capitalized markets, competitors may be more likely to actively respond to the entry of a new firm, leading to a profit-reducing capacity buildup. When faced by a set of larger firms, that entrant may be able to enter as a smaller firm and not face any response from the incumbents. Sometimes this reduced intensity of competition leads to a higher probability of entering the market, just at a lower overall level of capacity, which it is important to emphasize is completely separate from the choice to enter or not.

A second set of confounding factors is that larger markets may have higher demand, in which case the capacity of competitors would proxy for this. The addition of market-level

Table 8: Investment Costs and Scrap Values

Parameter	Median	Standard Error
Early Period		
ADJPOS	5,846	2,878
INVMCPOS	160	19.72
INVMCPOS2	-0.009	0.011
ADJNEG	9,665	4,305
INVMCNEG	-428	105
INVMCNEG2	0.88	0.534
SCRAP	185,351	2,362
Late Period		
ADJPOS	4,745	1,913
INVMCPOS	229	17.9
INVMCPOS2	-0.024	0.012
ADJNEG	8,390	6,259
INVMCNEG	-427	153
INVMCNEG2	0.623	0.752
SCRAP	192,012	8,666

Point estimates and confidence intervals were obtained using 100,000 simulated outcomes of 4 firms with 200 year lifetimes each. Each simulation path was replicated 100 times and averaged to obtain expected values. The estimated mean cost of a 1,500,000 TPY investment is $226M before the Amendments and $286M after.

fixed effects to account for demand heterogeneity changes the sign on the sum of competitor's capacity. However, the effect was still statistically insignificant and resulted in much less precise estimates of the other parameters. The relatively small size of the relevant data set leads me to use the most parsimonious specification, as the magnitude of the coefficients on the constant and late period dummy are similar across specifications, and more precisely identified in the model with fewer regressors.[22]

The most important variable in the entry model is the dummy for the 1990 Amendments, which is significantly negative. This directly contrasts to the effect of the Amendments on the probability of exit, which is lower after 1990. To get some sense of these results, consider that there were 15 entries and 51 exits in the period before 1990, corresponding to entry and exit rates of 6.55 percent and 3.70 percent, respectively. From 1990 onward, these rates drop off dramatically. There were four entries and six exits, corresponding to entry and exit rates of 2.16 percent and 0.70 percent, respectively. This results in the stark empirical fact that entry rates were 67 percent lower, and exit rates 81 percent lower, after the passage of the Amendments in 1990.

[22]To check the robustness of the dynamic parameters to these specifications, I ran the estimation scheme using both sets of parameters, with negligible differences.

Investment and Exit Costs The estimates for the costs of investment and the scrap value of exiting a market are presented in Table 8. The results suggest that both fixed and variables costs of adjustment play a significant role in determining the investment behavior of firms in this industry. The fixed costs are high enough that firms are willing to tolerate deviations from their desired level of capacity. When I simulate the MPNE of the model below, I find that the magnitude of the fixed adjustment costs are sufficient to induce lumpy investment behavior. The variable costs of investment are also high enough to greatly restrict the capacity of firms. The overall cost of investment is also reasonable when compared against out-of-sample estimates of adjustment costs, as I discuss in the following section on specification testing.

As a second check of the plausibility of these estimates, note that the benefits of selling off capacity are lower than the costs of acquiring the capacity. This is a necessary condition to prevent firms from obtaining arbitrage profits through investment. The exit values are high, which is in line with the large size of the average per-period profits in this industry. The scrap value only has appeal for marginal firms on the edge of large markets facing many competitors. This is consistent with the empirical regularity that exit is fairly rare.

Distribution of Entry Costs I assume that the sunk costs of entry are independent draws from a normal distribution that is common across markets. I match the empirical probability of entry for a given state, given by the probit policy function, against the cumulative distribution function evaluated at the expected value of entering at that state. The results of the estimation are presented in Table 9. One of the main results of this paper is that I find the Amendments increased the sunk costs of entry. The mean of the entry cost distribution increased by about 1 percent while the variance decreased by approximately 35 percent. These two shifts work together to significantly decreases the chance of a firm receiving a small enough draw on the sunk cost of entry to warrant building a new facility.

To illustrate this point, it is useful to consider the expected sunk costs conditional on entering. The average cost shifts from roughly \$46M to \$58M after 1990, an increase of more than 25 percent. The magnitude of these numbers is also in line with the costs estimated by the EPA for undergoing the environmental review and certification processes, which were in the ballpark of \$10M to \$15M. I stress that this shift in the distribution of sunk costs is the single most important determinant of market structure in the second period. As I demonstrate in the counterfactual, this increase in sunk costs led to significant welfare penalties on consumers which would be missed by a static analysis.

Table 9: Sunk Cost of Entry Distribution Results

Parameter	Median (000 $)	Standard Error
Early Period		
Mean	669,216	95,430
Variance	6.63E10	2.33E10
Late Period		
Mean	674,657	99,543
Variance	4.32E10	1.72E10

Parameters were estimated by matching the cumulative distribution function of a normal distribution to the empirical probabilities of entry. States were varied by the capacity of incumbent firms from 500,000 TPY to 3M TPY in 5,000 TPY increments. The expected value of entry was computed using 250 replications at each state.

Table 10: Announced Plant Costs

Company	Plant Location	Size (000 TPY)	Reported Cost ($M)	$\epsilon = 2.9$ ($M)	$\epsilon = 1.64$ ($M)
St. Lawrence Cement	Greenport, NY	2,000	350	342	1084
GCC America	Pueblo, CO	1,000	150	177	542
Florida Rock	Brooksville, FL	819	100	146	443
Florida Rock	Newberry, FL	750	80	135	406
Sawanee American Cement	Brandford, FL	750	130	135	406
Ash Grove	Las Vegas, NV	1,500	200	261	813
Sum of Squared Errors				9.87E3	1.37E6

This table contains the costs for several new plants, as reported in trade periodicals and local newspapers.

To summarize, I estimate the changes in the cost structure of the cement industry due to the Amendments. I find that production costs remained the same across the two periods, which is consistent with the underlying story that the Amendments did not affect variable costs. I also find that they led to an increase in the sunk costs of entry. Before evaluating the welfare effects of this change in the cost structure, I discuss the overall fit of the model and several alternative empirical specifications.

6.1 Specification Tests

While the estimated elasticity of 2.95 seems large at first, there is an out-of-sample test that indicates that the elasticity has to be somewhere in that neighborhood. It is straightforward to impose lower elasticities and investigate the changes to the predicted costs of investment. For example, when using an elasticity of 1.64[23] the costs of investment are too high to be reconciled with the announced plant prices given in Table 10. Due to the nonlinearity of the demand curve, further decreasing the elasticity of demand leads to increasingly worse estimates of investment costs. Lower elasticities also lead to unreasonable estimates of production costs, which in turn means that the model cannot reproduce observed market prices.

In principle, given enough data on profit margins and plant costs, one could invert the problem to obtain an estimate of the elasticity. As these investment costs demonstrate, that elasticity has to be somewhere in the neighborhood of the estimate of 2.95 in order for the rest of the model to match observed behavior. Finally, Salvo (2005) has accounting data on the investment costs of cement plants in Brazil. To the extent that costs are comparable across countries, his estimates of $200 per ton of capacity are consistent with the estimated investment costs I recover using an elasticity of 2.95.

I investigate the underlying assumptions in the demand system's functional form. I test for the presence of time trends in each of the markets, as it is critical that firms are not conditioning on expected increases or decreases in the average level of demand over time. The distance metric (DM) test (see Table 2 in Newey-McFadden (1994)) overwhelmingly fails to reject the null hypothesis that the market-specific time trends are all equal to zero at the 99.9 percent confidence level.

I also tested for time trends in the policy functions. I failed to reject the null hypothesis that there were no time trends in the investment, entry, and exit policies at the 90 percent level. I estimated the investment policy functions separately across the two periods, but also failed to reject the null hypothesis that those parameters were the same across the two periods.

It is useful to consider the implications if demand was growing over time. Demand growth would increase the expected value of being active in the future; if I estimate the policy functions ignoring this fact then I will tend to underestimate the costs of investment and entry, as these have to be ever higher than given here to prevent firms from capitalizing on expected future revenues. In the policy experiments below, I would also tend to underestimate the effect that the Amendments have had on welfare, as the increase in barriers to entry would be even more important in a growing industry. In effect, the estimates in this paper are more conservative than they would be with precise estimates of growing demand, if such a

[23] I ran a number of instrumental variables estimators to evaluate the small-sample variability of the estimates to various techniques. This suite of estimation procedures produced a range of elasticities; 1.64 is from GMM and 2.9 is from LIML.

trend was significant and long-lived.

7 Policy Experiments

The benefit of estimating a structural model is the ability to simulate counterfactual policy experiments once a researcher knows the underlying primitives. My primary interest is to evaluate the welfare effects of the Amendments, so a natural investigation is to determine the differences across cost structures for quantities of economic interest, including welfare measures for both producers and consumers. To achieve this, I compute the MPNE of the theoretical model with two sets of parameters: the observed post-Amendments cost structure, and the post-Amendments cost structure with the distribution of sunk entry costs taken from before the regulation. To deal with potential mixed strategy equilibria in the computed MPNE, I use a techniques developed in Doraszelski and Satterthwaite (2005). They show it is possible to approximate the a mixed strategy MPNE as the limiting outcome of a game of private information as the uncertainty about the other player's actions goes to zero. This technique also helps achieve convergence in the value function iteration used to solve for the MPNE, as it smooths out a player's response to changes in an opponent's strategy.

With policy functions from these equilibria it is possible to simulate hypothetical markets given some starting configuration. I examine the distribution of producer profits and consumer surplus under two different starting states: a new market with no incumbent firms, and a market with two incumbents and space for two entrants. Ideally, one could solve out for the MPNE of every market in the US and simulate welfare changes for each one. Computational constraints, however, prevent this approach, and I have to restrict the number of active firms to be four, which is the median size of a cement market in the United States. While this is restrictive, the results with four firms indicate that the possibility of a fifth firm entering this market is very low. It is therefore reasonable to conclude that this restricted specification captures the essential dynamics of the average market.

Table 11 presents the results of the counterfactual simulations. In the case of a new market, where the initial state vector is four empty slots waiting for entrants, overall welfare has decreased significantly due to the Amendments. The new market serves as a natural bound for the upper limit of welfare damages; it is the market configuration that would be most affected by a change in sunk entry costs. Indeed, the driving factor for changes in welfare across both simulated markets is the change in entry rates. With the higher sunk

Table 11: Counterfactual Policy Experiments

	Post-Amendments (High Sunk Costs)	Counterfactual (Low Sunk Costs)	Social Planner (Low Sunk Costs)
New Market			
Producer profit	293,627.77	180,720.27	-1,433,854.25
Consumer welfare	278,981.72	1,081,812.47	5,888,001.63
Periods with no firms	26.74	5.51	2.06
Periods with one firm	262.58	191.05	347.94
Periods with two firms	60.10	147.14	0.00
Periods with three firms	0.56	5.54	0.00
Periods with four firms	0.02	0.76	0.00
Total welfare	572,609.49	1,262,532.73	4,454,147.38
Profits of firm 1	294,158.99	178,771.62	-1,433,854.25
Average size of active firm	747.90	1,301.05	7,952.91
Average market capacity	934.51	1,862.23	7,952.91
Average market quantity	814.16	1,622.72	7,150.67
Average market price	96.22	81.69	39.03
Market with Two Incumbents			
Producer profit	290,798.04	288,092.02	175,521.07
Consumer welfare	2,256,603.91	2,285,601.13	6,908,995.41
Periods with no firms	0.00	0.00	0.00
Periods with one firm	0.00	0.00	0.00
Periods with two firms	347.56	326.65	350.00
Periods with three firms	2.44	23.35	0.00
Periods with four firms	0.00	0.00	0.00
Total welfare	2,547,401.95	2,573,693.15	7,084,516.48
Profits of firm 1	265,583.73	265,582.15	64,333.19
Average size of active firm	1,146.03	1,334.40	4,804.54
Average market capacity	2,299.12	2,736.13	9,609.08
Average market quantity	2,003.32	2,384.19	8,502.02
Average market price	75.55	71.44	35.79

Industry distributions were simulated along 25,000 paths of length 200 each. All values are present values denominated in thousands of dollars. The new market initially has no firms and four potential entrants. The incumbent market is started with one 750,000 TPY incumbent and one 1.5M TPY incumbent and two potential entrants.

costs of entry, there are a significant number of periods where the market is not served by any firms. Futher, periods with two, three, and four active firms have decreased by 59, 90, and 97 percent, respectively. Prices are 18 percent higher and quantities are 50 percent lower. The lower number of firms translates into better outcomes for producers, for whom profits are \$112M higher, an increase of 62 percent. Overall, as a result of higher entry costs, total welfare has decreased by 55 percent, or a little under \$700M. Consumers in particular are hurt by this policy, losing out on more than \$800M in foregone surplus.

The second market I consider has two incumbents with capacities of 750,000 TPY and 1.5M TPY. The new entry market is an extreme case of what could have happened under the Amendments. A market with incumbents of over 2M TPY capacity is a close approximation of a mature, fully capitalized cement market of average size in the United States. As such, this should provide a lower bound to welfare penalties, as this market will be least affected by a change in entry rates. Here, the differences are smaller, but still significant. Prices increase by 6 percent and quantities decrease by 16 percent, once again driven by lower entry rates. Under the higher entry costs, entry is 90 percent lower than with the lower costs. Consumers take a welfare penalty of almost \$29M, while producers benefit modestly, increasing their present values by a little less than \$3M. Note that this implies that if the costs of obtaining the operating permits was lower than \$3M for the average firm, then incumbents are actually better off under the Amendments than before 1990. In this case, the static analysis of the engineering costs would not only ignore the dynamic costs to consumers, but also obtain welfare costs to suppliers of the wrong sign. Extrapolating these costs to the entire US, under the assumption welfare losses can be summed equally across all 27 markets, leads to an estimate of over \$700M as a lower bound. The corresponding upper bound (\$21.6B) clearly has little merit when extrapolated to the entire US, as it would be an estimate of the costs of starting the entire industry over from scratch under the two different sunk cost distributions.

An interesting application of the structural model is to examine the differences between the oligopolist's MPNE to that of the social planner. The social planner sums the profits of all firms and consumer welfare and finds the optimal evolution of the industry given those state values. I calculate the social planner's MPNE with the same cost structure as the oligopoly counterfactual. This solution gives an upper bound for the welfare losses under the regulation, as this would have been the best possible welfare outcome in the absence of the Amendments. The third column compares the social planner's solution to the oligopoly solution.

The key characteristic of the social planner's solution is that it exploits lost welfare gains due to inefficiently low investment to increase overall welfare. The social planner is willing to inflict losses on the firms, through costly, expansive investment, in order to drastically increase consumer surplus. As a result, the average market size is over three times larger under the social planner than oligopoly. Prices are half as much as under the oligopoly, and overall welfare is three times larger. The social planner solves the maximization problem by having one extremely large firm. This follows from the linearity of adjustment costs. The social planner's problem with two incumbent firms is similar. The difference in market capacity, as compared to the no-firm case, is almost exactly equal to the 2,250 TPY of starting capacity. The results suggest that the oligopoly solution is not very close to the social optimum, even given some starting capacity. In the case of two incumbents, a social planner would result in a 72 percent, or approximately \$3B, increase in total welfare.

8 Conclusion

In this paper, I have estimated the welfare costs of the 1990 Amendments to the Clean Air Act on the Portland cement industry. My principal finding is that a static analysis of the costs of the regulation will not only underestimate the costs to consumers, but will actually obtain estimates of the wrong sign for incumbent firms. Exploiting the timing structure of the implementation of the Amendments, I identify that the most significant economic change in the Portland cement industry was a large increase in the sunk costs of entry. As a result of lower entry rates, overall welfare decreased by at least \$700M. These results highlight the importance of estimating the welfare consequences of regulation using a dynamic model to account for all relevant changes to the determinants of market structure. A static model would also be incapable of calculating the counterfactual benefits to producers of paying higher entry costs but facing lower ex-post competition. The estimates that the certification process would at most cost \$5M per installation would underpredict the welfare costs by at least \$200M.

I find that the (S, s) investment rule is a flexible and powerful method for characterizing the lumpy investment behavior of firms, as these choices are partially governed by significant fixed adjustment costs. I am able to recover estimates of the investment costs which are consistent with out-of-sample accounting estimates. This is a natural omnibus check on the fit of the model, as the estimates of the investment costs are dependent on every aspect of the model save the fixed costs. The interplay between market power, investment, and production choice is particularly interesting. For smaller markets, firms find it optimal to produce near the socially efficient level due to capacity constraints. However, there are too many firms and they under underinvest relative to the social planner. As a result, the oligopoly outcomes are far inside the socially optimal frontier.

An interesting extension of the present work would be to examine the effects of a "cap-and-trade" market-based emissions control program, similar to the trading program for SO_2 in the electricity industry. In this environment the regulatory authority removes all specific point-source control requirements and instead places an overall cap on the level of emissions in a regional area. Firms are endowed with pollution rights that they are free to trade among each other. This type of policy has the benefit of achieving the most efficient configuration of production within the industry for a given level of pollution. However, it may have other consequences with respect to market power and the concentration to pollution to a subset of firms within the market. By coupling emissions data, reported in many states at the yearly level, to production data I can back out a pollution production function. One question I can then address is whether efficiency obtains in this environment, as some of the more inefficient firms may buy pollution rights in return for additional market power. There are clearly a number of other interesting dynamic questions in this framework, from the nonlinear health effects of pollution concentration to the investment incentives of heterogeneous firms in a region, that are left for future research.

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A Appendix

A.1 Likelihood Function for (S, s) Rule

To derive the likelihood function of observed investments, it is necessary to consider three cases: positive, negative, and no change in capacity. In the derivation that follows, I assume that when firms make adjustments that they reveal both the size of the band and the desired target level.[24] Therefore, the likelihood of a firm making a positive or negative adjustment is simply the joint probability of observing the band and target level:

$$f(u_{it}^d, u_{it}^b) = f(u_{it}^d)f(u_{it}^b) = f(\text{CAP}_{it} - \alpha^T x_{it}^T)f(\log(|\Delta\text{CAP}_{it}|) - \alpha^B x_{it}^B), \tag{31}$$

where ΔCAP_{it} is the change in capacity, and I have economized on notation by collapsing the parameters and covariates in the target and band to $\alpha^T x_{it}^T$ and $\alpha^B x_{it}^B$, respectively. This probability is the product of two normal probabilities due to the independence of the errors in the band and target.

The likelihood of observing no change in capacity is slightly more complicated since I do not observe either the target or band in that period. The probability of observing no change is:

$$\begin{aligned}
& Pr(\text{BAND}_{it}^{lower} < \text{CAP}_{it} < \text{BAND}_{it}^{upper}) \\
= \;& Pr\left(\text{TARGET}_{it} - \exp(\alpha^B x_{it}^B + u_{it}^b) < \text{CAP}_{it} < \text{TARGET}_{it} + \exp(\alpha^B x_{it}^B + u_{it}^b)\right) \\
= \;& \int Pr\left(\text{TARGET}_{it} - \exp(\cdot) < \text{CAP}_{it} < \text{TARGET}_{it} + \exp(\cdot)|u_{it}^b\right) dF(u_{it}^b) \\
= \;& \int Pr\left(\alpha^T x_{it}^T + u_{it}^d - \exp(\cdot) < \text{CAP}_{it} < \alpha^T x_{it}^T + u_{it}^d + \exp(\cdot)|u_{it}^b\right) dF(u_{it}^b) \\
= \;& \int \left(\int_{\psi_1}^{\psi_2} dF(u_{it}^d)\right) dF(u_{it}^b) \\
= \;& \int [F(\psi_2) - F(\psi_1)]\, dF(u_{it}^b),
\end{aligned}$$

where $\psi_1 = \text{CAP}_{it} - \alpha^T x_{it}^T + \exp(\cdot|u_{it}^b)$, $\psi_2 = \text{CAP}_{it} - \alpha^T x_{it}^T - \exp(\cdot|u_{it}^b)$, and $F(\cdot)$ is the normal cumulative distribution function. The integral in the last term is easily computed using Gauss-Hermite quadrature.

[24] It is a straightforward extension to estimate the model assuming that the size of the band is unobservable.