# Technology and Market Power: The United States Cement Industry, 1974-2019*

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June 29, 2023

**Abstract**

We examine the evolution of market power in the cement industry over more than four decades using a structural model of procurement. The model matches aggregated outcomes in the data, and implies transportation costs, shipping distances, and demand elasticities that are consistent with external sources. Evaluating county-level outcomes throughout the contiguous United States, we find that market concentration and markups increase but that prices do not rise. We attribute these patterns to a technological innovation—the precalciner kiln—that lowered variable costs, increased plant-level capacities and economies of scale, and contributed to an industry shakeout in which many plants closed.

JEL Codes: L11, L13, L41, L61
Keywords: markups, concentration, market power, economies-of-scale, antitrust, cement

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*The analysis and conclusions set forth are those of the authors and do not indicate concurrence by other members of the Board research staff or by the Federal Reserve Board of Governors. We thank Alex MacKay, Jeremy Sandford, Paul Scott, Chenyu Yang, and Ron Yang for helpful discussions and comments. We also thank seminar and conference participants at APIOC, Georgetown University, IIOC, NBER Summer Institute (scheduled), University of Connecticut, University of Michigan, University of North Carolina, University of Rochester, and University of Virginia. We have benefited from conversations with Ashley Hatfield and Hendrik van Oss of the United States Geological Survey and with industry participants. Miller and Osborne received support for the research through an Equitable Growth grant.

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# 1 Introduction

Innovations in production technology can have wide-ranging consequences for economic outcomes. Within a firm, technology determines the efficient level of production and the availability of scale economies. Within a market, it shapes the number of firms that can profitably coexist and the extent to which firms can exercise market power. This paper considers a major technological advance in the portland cement industry—the modern precalciner kiln—and analyzes its effects on economic outcomes as it came to dominate production in the late twentieth and early twenty-first centuries. We document that the number of plants nearly halved over a 46-year window spanning 1974-2019, even as consumption, production, and industry capacity increased. We apply structural modeling techniques to understand how this transformation has affected market concentration, markups, prices, and economies of scale throughout the United States.

Motivating our effort is a growing literature on what sometimes is referred to as *The Rise of Market Power*. There are two main strands. First, De Loecker et al. (2020) combine accounting data with production function estimates for a large number of firms in the U.S. and determine that a significant increase in markups has occurred in recent decades.[1] Second, a string of articles document rising concentration across a number of industries in the U.S., at least at the national level (e.g, Peltzman, 2014; Barkai, 2016; Grullon et al., 2019; Ganapati, 2021a; Autor et al., 2020; Kwon et al., 2023).[2] We complement this literature by providing an industry study that traces the evolution of market power in a specific context and explores the mechanisms that give rise to these changes.

The results of our analysis indicate that local market concentration and markups increase over the sample period. Nonetheless, real prices do not rise. At the local level, there is a tight relationship between concentration and markup changes, but not between concentration and price changes. A decomposition reveals that precalciner adoption and plant closures largely account for these empirical patterns. In our model, these factors contribute to rising markups by reducing marginal cost and lessening competition. For the same reasons, they exert opposing effects on price. Furthermore, as scale-increasing technology can induce an industry shakeout in the long run, our interpretation is that the plant closures themselves are attributable to precalciner technology. Consistent with this hypothesis, we evaluate plant-level economies of scale and show that the adoption of precalciner technology creates an impetus for significant output expansion for plants that adopt it.

[1] Subsequent research probes the production function methodology used to recover markups (e.g. Bond et al., 2021; Doraszelski and Jaumandreu, 2021; Raval, 2023; De Ridder et al., 2022; Foster et al., 2022).

[2] The level of aggregation can matter: evidence indicates that concentration may be *decreasing* in markets that are defined narrowly, either in geographic space (Rossi-Hansberg et al., 2020) or product space (Benkard et al., 2021).

Our methodological approach is to estimate an oligopoly model of supply and demand using data on prices and quantities. This allows us to recover markups and the market shares of plants as they vary across the U.S., even though these objects are not observed in data. At a high level, our approach has been standard in Industrial Organization since at least Berry et al. (1995). However, a number of challenges arise in the application of existing models to business-to-business markets. Chief among these is that prices can be transaction-specific and specified in confidential business contracts. As a result, researchers may not observe the prices that are available to buyers or the terms-of-trade that ultimately are realized. This challenge is present in our application, as we observe decades of data on plant-level technologies but coarsely aggregated prices and quantities.

To make progress, we develop an empirically tractable model of procurement that nonetheless preserves the richness of the institutional setting. We assume that buyers conduct "second-score" auctions in which suppliers are evaluated based on their bid and a number of fixed attributes, the buyer with the highest score wins the auction, and price is pinned down by the score of the second-best supplier (e.g., Che, 1993; Laffont and Tirole, 1987; Asker and Cantillon, 2008, 2010). As a second-score auction can be recast as a quality-adjusted descending-price auction, it can be a reasonable representation of procurement events in which buyers play prospective suppliers off against each other in order to obtain more favorable prices. In the model, suppliers maximize profit by bidding at marginal cost. Under a parametric assumption proposed in Miller (2014), we obtain expressions for the market shares and the average markups and prices that each supplier obtains in each county of the U.S.[3] We specify the model to incorporate the salient features of the industry, including the transportation costs associated with shipping cement, the availability of imports, and kiln-specific fuel costs and capacity constraints.

We estimate the model using a generalized method-of-moments (GMM) approach that accommodates aggregated data. The basic idea is that a loss function can be constructed by comparing the data to the (aggregated) equilibrium predictions that arise under different parameters.[4] Implementation therefore requires that equilibrium be computed for each set of parameters considered. This is feasible because equilibrium in the second-score auction is characterized by plant-level quantities—which pin down marginal costs and thus bids—rather than by plant-county-level prices.[5] The key identifying assumption is that plant

[3]Miller (2014) shows how a second-score auction can be calibrated for the purpose of merger review. The approach has been used by expert economists testifying on behalf of antitrust authorities in the merger trials of Anthem/Cigna (2016), Wilhemsem/Drew Marine (2018), Secure/Tervita (2022), and Penguin Random House/Simon & Schuster (2022). Sheu and Taragin (2021) extend the model for vertical merger simulations.

[4]A similar GMM approach is used Miller and Osborne (2014b) and Jung et al. (2022) to estimate models of Bertrand competition in the context of cement and corn markets, respectively. D'Haultfoeuille et al. (2019) estimate a related model of automobile markets in which consumers may negotiate prices.

[5]Miller and Osborne (2014b) instead calculate prices for each plant-county during estimation. However,

heterogeneity can be accounted for with observables, which we view as reasonable in our specific context. Nonetheless, we validate our estimates by comparing the transportation costs and demand elasticities that we obtain to external evidence. With the structural parameters in hand, we bound kiln-level fixed costs using the approach of Eizenberg (2014), which allows us to obtain average cost functions and to assess scale economies.

The modeling results that we obtain are at least partially consistent with *The Rise of Market Power* in the cement industry, as local market concentration and markups increase over the sample period. Looking across the counties in the contiguous U.S., we find that the quantity-weighted median Herfindahl Hirschman Index (HHI) increases from 2171 to 2895, a change that is equivalent to a reduction in the number of symmetric firms from 4.6 to 3.5. Thus, by the end of the sample, most consumption occurs in counties that would be deemed "highly concentrated" under the thresholds of the 2010 *Horizontal Merger Guidelines* of the Department of Justice and Federal Trade Commission. The increase in the quantity-weighed median markup is more modest, at either 4.2% or 5.4%, depending on how the markup is measured, well less than the estimates of De Loecker et al. (2020). The average real price per metric tonne of cement is similar in 1974 and 2019.

In the model, equilibrium outcomes are affected by many market factors, including plant closures, technology adoption, entry, mergers, factor prices, and demand conditions. We use counterfactual simulations to understand how much each of these factors contributes to changes in concentration, markups, and prices. The results of this decomposition exercise indicate that plant closures largely explain the increase in concentration, though mergers and entry also have meaningful, offsetting effects. Markups rise mainly due to plant closures and mergers, which lessen competition. Precalciner technology also increases markups but to a much smaller degree. Finally, a number of factors impact prices, with plant closures and precalciner technology having large, opposing effects.

These results are consistent with the main short run effect of precalciner technology being marginal cost reductions that are passed through to cement buyers in the form of lower prices. To the extent that the adoption of precalciner technology contributes to rising concentration and markups, it appears to be through an effect on long run decisions, including on plant closures. However, it may be reasonable to attribute the bulk of plant closures to precalciner technology because precalciners not only lower marginal costs but also increase significantly productive capacity. For a sense of magnitudes, the average plant-level capacity in 2019 is more than double that of 1974. Put simply, with modern technology it takes far fewer plants to meet the same amount of demand.

To explore this hypothesis in greater quantitative detail, we evaluate economies of scale for each plant and year in the sample, using the fixed cost bounds and an engineering esti-

they restrict attention to only one region in the U.S., which limits the dimensionality of their problem.

mate of capital costs. We focus on the ratio of average costs to marginal costs—a standard measure of scale economies also known as the *scale elasticity* (Syverson, 2019)—and find that it increases over the sample period due to the shift toward modern precalciner technology. If evaluated at average 1974 plant-level quantities, the quantity-weighted median scale elasticity increases from 1.15 in 1974 to 2.18 in 2019. Thus, the amount of additional output that can be generated by incurring a given increase in costs nearly doubles (evaluated at the same level of output). Finally, we compute the ratio of price to average cost for plants with modern technology. If evaluated at 1974 plant-level quantities, it remains well below one throughout the sample period, which implies that output expansion is necessary for precalciner adoption to be profitable. We interpret these results as demonstrating the impetus for output expansion that precalciner technology creates, and as consistent with a central role of precalciner technology in explaining the industry shakeout that has occurred over the previous four decades.

The articles closest to ours use structural models to examine specific industries over long time horizons. Collard-Wexler and De Loecker (2015) examine the steel industry over 1963-2002, when the advent of the minimill greatly reduced fixed costs. This facilitated entry, lowered markups, and induced some vertically-integrated plants to exit. Ganapati (2021b) determines that investments by wholesalers over 1992-2012 in information technology increased scale economies and improved service quality; markups increased but consumers benefited nonetheless. Grieco et al. (2022) study automobile manufacturing and find that markups have decreased over time due to competitive pressures, despite significant improvements in marginal cost and product quality. Brand (2021), Döpper et al. (2023), and Atalay et al. (2023) examine consumer packaged goods and determine that markups have increased due to marginal cost reductions that are not passed through to consumers.[6] Consistent with our research, all of these articles highlight the role of technology in shaping the long-term economics of industries. They also point to important heterogeneity across industries in technological change and its impacts.[7]

Modern precalciners allow firms to invest in a higher fixed cost, lower marginal cost production technology. Thus, our research also relates to a large number of empirical articles that explore the implications of fixed costs for market outcomes. Among the important contributions are Bresnahan and Reiss (1991) on local small business markets, Berry (1992), Ciliberto and Tamer (2009), Ciliberto et al. (2021), and Li et al. (2022) on the airlines

[6]Each of these articles find that the elasticity of demand has decreased over time. Brand (2021) attributes this to the growing popularity of "niche" products whereas Döpper et al. (2023) point to broader changes in consumer shopping habits.

[7]Conlon et al. (2023) present evidence that there is no apparent correlation between the markup changes of De Loecker et al. (2020) and real price changes, which also points toward cost reductions as an explanation for rising markups. One study that fits this narrative less well is Bet (2021), which finds rising markups in the airlines industry over 1990-2019 and attributes them to softer competitive conduct.

industry, Berry and Waldfogel (1999) and Berry et al. (2016) on radio broadcasting markets, Seim (2006) on video retail markets, Eizenberg (2014) on personal computers, and Wollmann (2018) on the commercial vehicle market. Among these, Eizenberg (2014) is the most similar to our research thematically, as it considers the impacts of innovation, specifically the development and introduction of Intel's Pentium M computer chip.[8]

There is a substantial literature on the economics of the portland cement industry. In part this reflects the scale of the industry. For 2019, the USGS places domestic production at more than 87 million metric tonnes and total domestic expenditure on cement at more than $12 billion.[9] Its share of global anthropogenic $CO_2$ emissions is estimated to be around five percent (van Oss and Padovani, 2003b). However, the cement industry also is attractive for research because data are available and it is amenable to modeling. Steven Berry has proposed it as a "model industry" in Industrial Organization.[10] Recent contributions using data from the U.S. explore environmental regulation (Ryan, 2012; Fowlie et al., 2016; Miller et al., 2017), the patterns of spatial price discrimination (Miller and Osborne, 2014b), how firms approach strategic entry decisions (Perez-Saiz, 2015), and the determinants of technology adoption (Macher et al., 2021). Outside of the U.S., Kusaka et al. (2022) show that the precalciner kiln led to a reduction in the labor share in Japan, Song (2022) examines environmental regulation in China, and Leone et al. (2022) examine whether high fixed costs limit competition in developing countries.

We structure the paper as follows. We first describe the cement industry and our data sources (Section 2). We then present the model and our empirical specification (Section 3). Next, we develop the GMM estimator and discuss identification, how to assess credibility, and the computational burdens associated with estimation (Section 4). We then present the results (Section 5) and conclude with a discussion of limitations and directions for future research (Section 6).

# 2 The Portland Cement Industry

## 2.1 Background Facts

Portland cement is a finely ground dust that forms concrete when mixed with water and coarse aggregates such as sand and stone. Production involves feeding limestone and other raw materials into large, capital-intensive rotary kilns. The output of the kilns is cooled,

[8]This literature continues to grow. Two recent working papers that develop new methods for bounding fixed costs are Fan and Yang (2023) and Garrido (2023).

[9]Statistics are from the 2019 *Minerals Yearbook* of the USGS.

[10]Berry, Steven [@steventberry]: "I was reading about "model organisms" in biology research. Maybe RTE cereal, airlines and cement are IO's model industries–our versions of mice, fruit flies and tapeworms." (Twitter, January 26, 2021).

mixed with a small amount of gypsum, and ground to form cement. The variable costs of production are mainly attributable to raw materials, fuel costs, electricity costs, labor, and kiln repair and maintenance (EPA (2009)). The limestone is usually obtained from a quarry adjacent to the plant, and most plants use coal or natural gas for their fuel. Plants run at full capacity except for a single period that is typically 4-6 weeks each year, during which kiln maintenance is conducted. The main way that plants adjust output is by shortening, lengthening, or skipping this maintenance period.

Cement producers typically sign short-term contracts with buyers, predominantly construction firms and ready-mix concrete plants.[11] The contracts specify a mill price (or a "free-on-board" price) and can include discounts that reflect the ability of buyers to substitute to other producers. Buyers are responsible for the cost of transportation. Trucks are the most common method of transport but trains and river barges also can be used. Because the production of cement conforms to standards published by the American Society for Testing and Materials (ASTM), which helps assure reliability and consistency of the product, differentiation among cement plants is largely spatial in nature. Transportation can account for a meaningful portion of buyers' total acquisition costs, and cement producers tend to locate their plants near urban areas, interstate highways, and the Mississippi River System in order to be accessible for their customers.

Demand is pro-cyclical because cement is used nearly exclusively in the construction sector. With favorable macroeconomic conditions, consumption can outstrip production due to domestic capacity constraints. Figure 1 plots total consumption and production in the contiguous U.S. Gaps between consumption and production are filled by importers, who supply domestic customers through a number of customs districts located around the periphery of the country. Most imports arrive via transoceanic freighter, especially after freighter technology improved in the early 1980s. Some imports are trucked from Canada and Mexico. Exports from the U.S. are negligible. Finally, cement cannot be stored for any meaningful period of time because it gradually absorbs moisture from the air, rendering it unusable.

## 2.2 Precalciner Technology

The focus of our study is on the economic implications of the precalciner kiln. For context, throughout most of the twentieth century, cement manufacturers relied on "wet" and "long dry" kilns that typically were 100 yards or longer in length.[12] Raw materials would

[11] There is a some vertical integration in the industry. Syverson and Hortaçsu (2007) report that 30% of cement plants and 11% of ready-mix concrete plants were (partially) vertically integrated as of 1997.

[12] Wet kilns process raw materials that are wet-ground into a slurry, whereas long dry kilns process raw materials that are dry-ground into a powder. Modern preheater and precalciner kilns use the dry process.

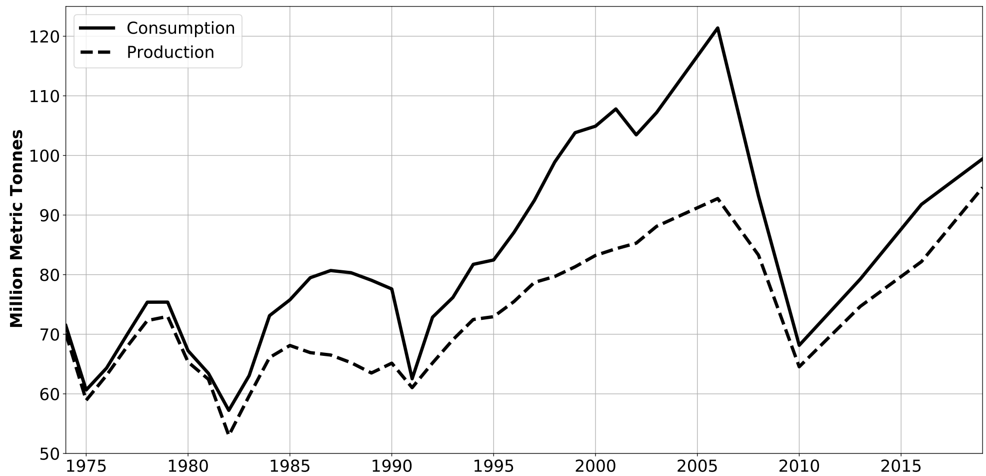


Figure 1: Consumption and Production, 1974-2019

Notes: Consumption and production are calculated based on data from the *Minerals Yearbook*.

enter at one end of the kiln and undergo chemical reactions as they approach the burning zone on the other end. An inherent inefficiency with this process is that some heat (i.e., energy) escapes with the exhaust gases of the kiln and also due to kiln radiation. Modern precalciner technology significantly mitigates this inefficiency. The basic idea is that the raw materials can be preheated before they enter the kiln using exhaust gases and heat from a supplementary combustion chamber. As the raw materials then need less time in the kiln for the chemical reactions, the rotary kiln is shorter in length, and this in turn reduces inefficiency due to kiln radiation. A modern precalciner kiln is typically 25-40 yards in length and 25-35% more fuel efficient than a wet or long dry kiln.

A second characteristic of the modern precalciner kiln is that it allows for greater productive capacity than the older wet and long dry kilns. Thus, the trend toward precalciner technology that has occurred over the previous 50 years has coincided with a reduction in the total number of plants and kilns manufacturing cement. This sets up a tension commonly associated with increasing scale economies: more efficient production can go hand-in-hand with a loss of competition.

Figure 2 decomposes industry capacity (top panel) and the number of plants (bottom panel) by technology type. We refer to wet and long dry kilns as "Old Technology" and preheater and precalciner kilns as "Modern Technology."[13] Over 1974-2019, total industry capacity increases by 20%, from 91 to 109 million metric tonnes, with old technology accounting for nearly all of this capacity at the beginning of the sample and modern technology accounting for nearly all of this capacity at the end. Over the same period, the

[13]Preheater kilns do not have the supplementary combustion chamber of precalciner kilns.

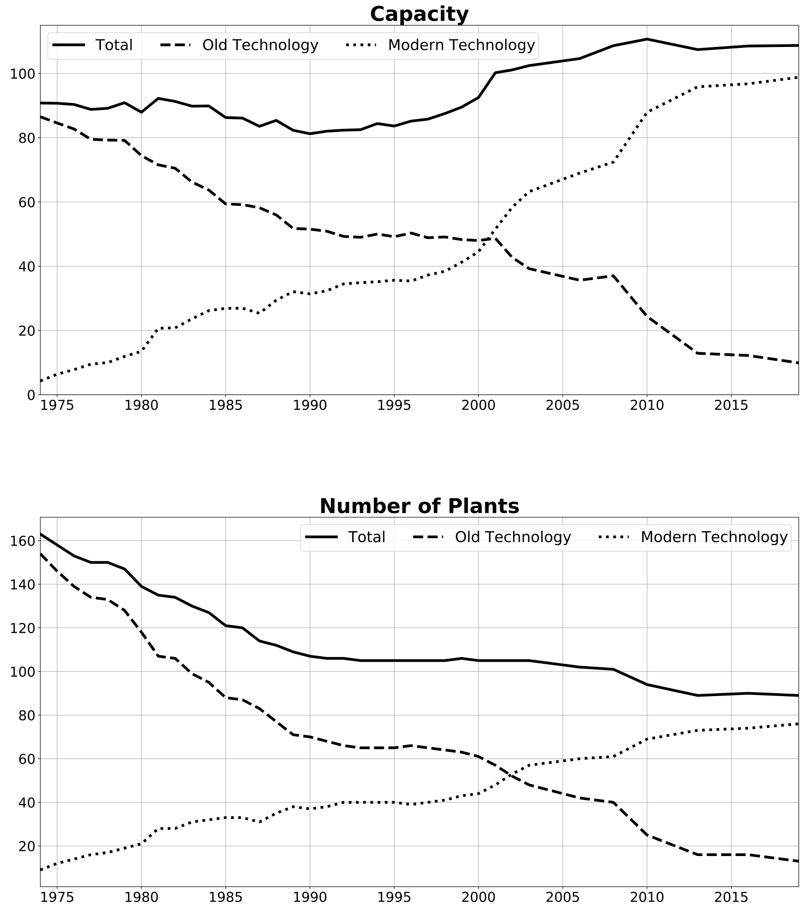


Figure 2: Industry Capacity and the Number of Cement Plants, 1974-2019

Notes: In the top panel, capacity is in millions of metric tonnes. We designate plants as using "Old Technology" if their least efficient kiln is a wet kiln or a long dry kiln, and as using "Modern Technology" if their least efficient kiln uses a precalciner or a preheater. Plants are excluded from the graphs if they are temporarily idled (e.g., due to maintenance or low demand). Data are from the *Plant Information Summary* of the Portland Cement Association.

number of plants falls by 45%, from 163 to 89. (This incorporates 13 new plants that were constructed during the sample period.) As with capacity, nearly all plants use the old technology at the beginning of the sample and the new technology at the end. Modern kilns have far greater capacities than older kilns. Indeed, in 2019 the average annual capacity of a modern technology kiln was nearly double that of a old technology kiln.[14]

The pace of technological adoption reflects that firms must incur significant capital costs

[14]The data in Figure 2 also imply that the average plant-level capacity in 2019 is more than double the average plant-level capacity in 1974. We provide a graph of plant-level capacity in the Appendix (Figure D.1). That figure also plots the number of kilns and the average number of kilns per plant over the sample period.

to upgrade their technology to a precalciner kiln. The European cement association, CEMBUREAU, has placed the construction costs of a modern plant with one million metric tonnes of annual capacity at €150-200 million, or approximately three years of revenue, and states that this ranks cement "among the most capital intensive industries."[15] Previous research has sought to identify the conditions that are conducive for precalciner technology (Macher et al., 2021). The results indicate that adoption is more likely if fuel prices are high, there are few nearby competitors, and local demand conditions are strong. The latter two effects are consistent with the benefits of cost-reducing technology increasing with plant output (e.g., Gilbert, 2006). By contrast, Macher et al. (2021) find that plants are more likely to retire their kilns if fuel costs are high, there are many nearby competitors, and demand conditions are weak.

Figure 3 plots the national average price over the sample period. A remarkable feature of the data is the degree of similarity between the real price per metric tonne in 1974 and 2019: $102.16 and $104.83, respectively. Thus, the greater efficiency of precalciner kilns has not obviously created significant benefits for buyers, just as the loss of competition has not obviously created significant harm. The fluctuations in the price within the sample coincide with changes in fossil fuel prices (especially in the 1970s) and with macroeconomic conditions. We use modeling to explore in greater detail how the adoption of precalincer kilns has affected producers' costs, markups, and profits, as well as the prices that are negotiated by buyers and the market concentration that results.

## 2.3 Data Sources

### The *Minerals Yearbook* and other USGS data

The USGS conducts an annual census of cement firms and summarizes the results in a publication called the *Minerals Yearbook*. This provides data on free-on-board prices, production, consumption, imports, and transportation methods that we use to estimate the model. The response rate to the census typically exceeds 90% and USGS staff imputes missing values based on other data and their institutional knowledge. Our understanding is that imputation is required for prices more than for consumption and production because some firms are more reticent to share price information. The *Minerals Yearbook* has been published every year going back into the early twentieth century.

[15] Cement producers outsource kiln design to one of several industrial architecture firms with expertise in cement. Installation is not technically demanding, and many industrial construction firms can manage the steel plates, refractory linings, and duct work. Nonetheless, the total design and installation costs are significant. The authors can provide the CEMBUREAU estimates upon request. Alternatively, see `http://www.cembureau.be/about-cement/cement-industry-main-characteristics`, which must be accessed using the Wayback Machine, and `https://www.cembureau.eu/about-our-industry/key-facts-figures/`.

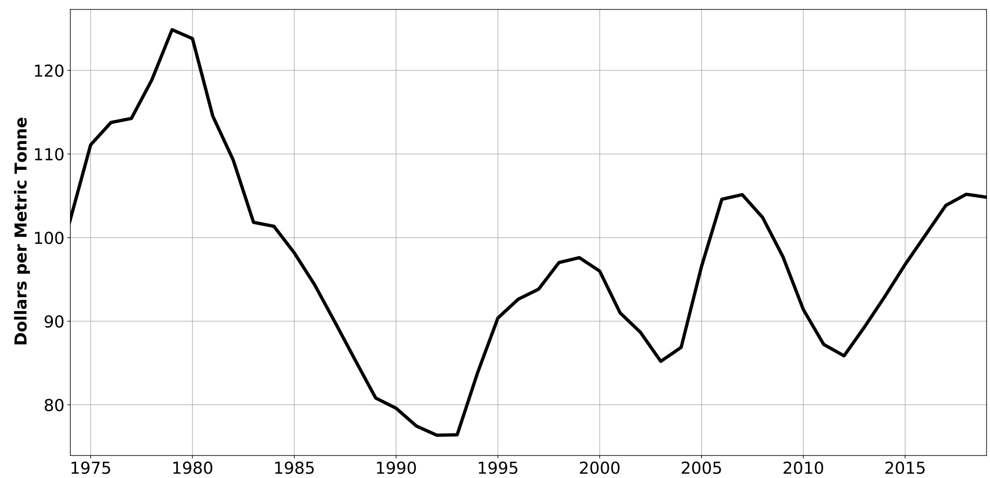


Figure 3: National Average Price per Metric Tonne, 1974-2019

Notes: The national average price is obtained from the *Minerals Yearbook* and deflated to real 2010 dollars using the CPI.

The data in the *Minerals Yearbook* are aggregated in order to protect the confidential business data of census respondents. We observe average price and total production by region, with the regions satisfying a "rule-of-three" that they contain data from at least three independent plants. This ensures that no firm can infer the data of another using the *Minerals Yearbook*. The regions are not intended to approximate economic markets. For example, as the number of plants decreases over 1974-2019, the USGS increases the size of regions simply to satisfy the rule-of-three. Thus, there are 26 price regions in 1974 but only 20 in 2019. Production regions nearly always conform with price regions. We observe total consumption within a different set of regions. The consumption regions are smaller and more stable over time; there are 53 in 1974 and 55 in 2019.

The *Minerals Yearbook* also provides the proportion of cement that is produced by plants with a wet kiln and data on transportation methods, including the proportion of cement that is shipped using a river barge. Finally, we obtain the quantity and value (inclusive of insurance, freight, and delivery charges) of imported cement at each customs district.

The other USGS publication that we use is the *California Letter*, which tracks the destination of cement shipments that originate at plants in California. No other publicly-available data links the locations of cement producers to the locations of their customers. Points of origination are aggregated to northern California, southern California, or California (in its entirety). Points of destination are aggregated to the same regions and also to Arizona and Nevada. Unlike the *Minerals Yearbook*, data are available only over 1990-2010, and even within that window some data points are withheld to preserve confidentiality.[16]

### The *Plant Information Summary* and other PCA data

The Portland Cement Association (PCA) conducts phone surveys of plants and reports the results in a publication called the *Plant Information Summary*. Data are available annually over 1973-2003 and also for 2004, 2006, 2008, 2010, 2013, 2016, and 2019.[17] The data provide an end-of-year snapshot on the location, owner, and primary fuel of each cement plant in the U.S., as well as the age, capacity, and type (wet/dry/precalciner) of each kiln. Capacity is reported as an annual number that incorporates a prescribed allotment for maintenance downtime, and as a daily boilerplate rating that reflects the maximum possible production. The *Plant Information Summary* also reports whether each kiln was operated during the year. The other PCA publication that we use is the *U.S. and Canadian Portland Cement Labor-Energy Input Survey*, which is published intermittently and contains information on the energy requirements of cement production and the energy content of fossil fuels burned in kilns. We use those data along with supplementary data on fossil fuel prices to construct engineering estimates of plant-specific fuel costs (Appendix A.1).

### Other Data Sources

We use county-level data on construction employment from the County Business Patterns of the Census Bureau (NAICS Code 23 and SIC Code 15) in order to help model the location of demand for cement. We obtain the data for 1974-1985 from the University of Michigan Data Warehouse and the data for 1986-2019 from the Census Bureau website. We use data on fossil fuel prices from the State Energy Database System (SEDS) of the Energy Information Administration (EIA) to help construct the engineering estimates of fuel costs (Appendix A.1). Finally, we obtain the latitude and longitude of the cement plants and the centroid of every county using Google Maps, and the latitude and longitude of the mile markers along the Mississippi River System from the Army Corps of Engineers. We calculate the straight-line distances between plants, counties, and the Mississippi River System. This helps us model transportation costs in a realistic manner.

[16] Using NCA, SCA, CA, AZ, and NV to refer to northern California, southern California, California, Arizona, and Nevada, respectively, we observe: CA to NCA over 1990-2010, NCA to NCA over 1990-1999, SCA to NCA over 1990-1999, CA to SCA over 2000-2010, SCA to SCA over 1990-1999, CA to NV over 2000-2010, SCA to NV over 1990-1999, CA to AZ over 1990-2010, and SCA to AZ over 1990-1999.

[17] Most years are available at the Yale University library. We purchased the most recent books from the PCA.

## 3 Empirical Model

### 3.1 Demand

We examine a model in which buyers use scoring auctions to purchase cement for use in their construction projects. Each buyer chooses to purchase cement from a domestic plant or from an importer. They can also select the outside good, which we conceptualize as representing asphalt, steel, wood, or some other alternative input. We apply a nested logit structure in which the cement options are closer substitutes for one another than they are for the outside good.[18]

We assume that buyers are atomistic and dispersed throughout the more than 3,000 counties of the United States, allowing for differences in the density of buyers across counties. Let the *indirect gross utility* that a buyer receives from an option be the non-price value of the option to the buyer. We decompose the indirect gross utility of option $j$ for buyer $i$ (in county $n$ and year $t$) according to

$$u_{ijnt} = \overline{u}_{jnt}(\boldsymbol{X}_t, \boldsymbol{\theta}) + \zeta_{int} + (1-\sigma)\epsilon_{ijnt} \tag{1}$$

where $\overline{u}_{jnt}(\cdot)$ is a common component that is the same for all buyers in the same county-year and $\zeta_{int}$ and $\epsilon_{ijnt}$ are buyer-specific preference shocks. The common component depends on data, $\boldsymbol{X}_t$, and parameters, $\boldsymbol{\theta}$. The indirect gross utility for the outside good ($j=0$) is $u_{i0jt} = \epsilon_{i0nt}$. We assume that each $\epsilon_{ijnt}$ is distributed iid type 1 extreme value and that $\zeta_{int}$ has the unique distribution such that $\epsilon^*_{ijnt} \equiv \zeta_{int} + (1-\sigma)\epsilon_{ijnt}$ also is type 1 extreme value (Berry, 1994; Cardell, 1997). Given these distributional assumptions, $\sigma \in [0,1)$ determines the extent to which preference shocks for different cement options are correlated. Higher values of $\sigma$ imply greater differentiation between cement and the outside good, and if $\sigma = 0$ then preferences collapse to those of a logit model.

Buyers score their options based on the indirect gross utilities of equation (1) and the "bids" that they receive. Higher scores are assigned to those options that provide greater gross utility and those that submit more attractive (i.e., lower) bids. The option with the highest score is selected. The scoring rule is additively separable in gross utility and the bid, such that

$$score_{ijnt} = u_{ijnt} - \phi b_{ijnt} \tag{2}$$

where $b_{ijnt}$ is the bid and $\phi > 0$ is a parameter. Because $\phi$ will scale equilibrium markups (and thus prices), we sometimes refer to it as the "price parameter." The bid of the outside

[18] The three alternative materials that we mention—asphalt, steel, and wood—are the primary substitutes to cement for transportation projects (e.g., roads), commercial applications, and residential construction, respectively (EPA, 2009). However, cement has significant advantages in most of the projects for which it is used because it is cheap, locally available, and has low maintenance costs (van Oss and Padovani, 2003a).

option equals zero. Assumptions that we place on the supply-side of the model imply that each option submits the same bid to every buyer in a given year, so we have $b_{ijnt} = b_{jt}$ for all $i$ and $n$.

Given the stochastic assumptions on the buyer-specific preference shocks, the probability with which option $j = 1, 2, \dots, J_t$ is selected in county $n$ and year $t$ is given by

$$s_{jnt}(\boldsymbol{b}_t; \boldsymbol{X}_t, \boldsymbol{\theta}) = \frac{\exp\left(\frac{\overline{u}_{jnt}(\boldsymbol{X}_t,\boldsymbol{\theta}) - \phi b_{jt}}{1-\sigma}\right)}{\sum_{k\neq 0}\exp\left(\frac{\overline{u}_{knt}(\boldsymbol{X}_t,\boldsymbol{\theta}) - \phi b_{kt}}{1-\sigma}\right)} \times \frac{\left(\sum_{k\neq 0}\exp\left(\frac{\overline{u}_{knt}(\boldsymbol{X}_t,\boldsymbol{\theta}) - \phi b_{kt}}{1-\sigma}\right)\right)^{1-\sigma}}{1+\left(\sum_{k\neq 0}\exp\left(\frac{\overline{u}_{knt}(\boldsymbol{X}_t,\boldsymbol{\theta}) - \phi b_{kt}}{1-\sigma}\right)\right)^{1-\sigma}} \tag{3}$$

where $\boldsymbol{b}_t$ contains all the bids submitted in year $t$. In this expression, the first ratio is the probability that option $j$ ($j \neq 0$) is selected conditional on cement being selected, and the second ratio is the probability that cement is selected. The probability with which the outside good is selected is $s_{0nt}(\boldsymbol{b}_t; \boldsymbol{X}_t, \boldsymbol{\theta}) = 1 - \sum_{j\neq 0} s_{jnt}(\boldsymbol{b}_t; \boldsymbol{X}_t, \boldsymbol{\theta})$. Often we refer to these choice probabilities as market shares. The quantity of cement sold by plant $j$ in county $n$ is $q_{jnt}(\boldsymbol{b}_t; \boldsymbol{X}_t, \boldsymbol{\theta}) = s_{jnt}(\boldsymbol{b}_t; \boldsymbol{X}_t, \boldsymbol{\theta}) M_{nt}$, where $M_{nt}$ is a measure of the county's size.

In a second-score auction, the price that a buyer pays makes it indifferent between transacting with its first-best option (at the price) and its second-best option (at that option's bid). If plant $j$ has the highest score then this indifference condition can be written:

$$u_{ijnt} - \phi p_{ijnt} = \max_{k \notin \mathbb{J}_{f(j)}} \{u_{iknt} - \phi b_{kt}\}$$

and the price is

$$p_{ijnt} = \frac{1}{\phi}\left(u_{ijnt} - \max_{k \notin \mathbb{J}_{f(j)}} \{u_{iknt} - \phi b_{kt}\}\right) \tag{4}$$

where $\mathbb{J}_{f(j)}$ is a set that contains the plants owned by the same firm as plant $j$. This embeds that plants operated by the same firm do not bid against each other, a result that obtains under an assumption we place on the supply-side of the model.

Average prices vary across counties due to differences in the common component of gross utility. Holding bids fixed, buyers in counties with more well-positioned suppliers tend to obtain lower prices, all else equal. Prices also vary within counties because buyers are heterogeneous in the gross utility that they obtain from suppliers (due to the stochastic term). The latter source of price dispersion is driven by our distributional assumptions, and we do not focus on it in our empirical results.

The demand derivatives that obtain from our model are analogous to those of nested logit models with posted prices. Suppressing subscripts for the county and year for notational brevity, the derivatives of the market shares with respect to the bid of plant $j$ are given by:

$$\frac{\partial s_k}{\partial b_j} = \begin{cases} -\frac{\phi}{1-\sigma} s_j(1-\sigma\hat{s}_{j|g} - (1-\sigma)s_j) & \text{if } j = k \\ \phi s_j \left( s_k + \frac{\sigma}{1-\sigma}\hat{s}_{k|g} \right) & \text{if } j \neq k \text{ and } k \neq 0 \\ \phi s_j s_0 & \text{if } k = 0 \end{cases} \tag{5}$$

where $\hat{s}_{j|g} \equiv s_j / \sum_{k \neq 0} s_k$ is the probability with which plant $j$ is selected conditional on cement being selected. Bid elasticities of demand can be obtained by multiplying the demand derivative by the bid and dividing by the choice probability. Diversion among the cement options is in proportion to their county-specific conditional choice probabilities. Thus, the model accommodates that two plants may be strong substitutes in one county but weak substitutes in another. Diversion between cement and the outside option is mediated by the value of the nesting parameter.[19]

## 3.2 Supply

We model the bidding behavior of cement firms as they compete for customers in each county. The variable profit function of firm $f$ with plants in the set $\mathbb{J}_f$ is given by

$$\pi_{ft}(\boldsymbol{b}_t; \boldsymbol{X}_t, \boldsymbol{\theta}) = \sum_{j \in \mathbb{J}_f} \sum_n \overline{p}_{jnt}(\boldsymbol{b}_{nt}; \boldsymbol{X}_t, \boldsymbol{\theta}) q_{jnt}(\boldsymbol{b}_{nt}; \boldsymbol{X}_t, \boldsymbol{\theta}) - \sum_{j \in \mathbb{J}_f} \int_0^{Q_{jt}(\boldsymbol{b}_t; \boldsymbol{X}_t, \boldsymbol{\theta})} c_{jt}(Q; \boldsymbol{X}_t, \boldsymbol{\theta}) dQ \tag{6}$$

where $\overline{p}_{jnt}(\cdot)$ is the expected price obtained by plant $j$ conditional on winning an auction, $Q_{jt}(\boldsymbol{b}_t; \boldsymbol{X}_t, \boldsymbol{\theta}) = \sum_n q_{jnt}(\boldsymbol{b}_{nt}; \boldsymbol{X}_t, \boldsymbol{\theta})$ is the total amount of cement sold by plant $j$ across all counties, and $c_{jt}(\cdot)$ is a non-decreasing, convex marginal cost function. We provide an analytical expression for expected price below. We refer to $\pi_{ft}(\cdot)$ as the *variable profit* of the firm because fixed costs are required to operate kilns. As fixed costs do not affect outcomes in the second-score auction, we defer them to Section 5.3, where they are relevant for our analysis of scale economies.

If marginal costs were constant in quantity then it would be at least a weakly dominant strategy for each firm to submit a single "at cost" bid to each buyer from the plant that creates the most economic surplus. By "at cost" we mean a bid that equals the plant's

[19] We conceptualize diversion in this context as being due to a change in a bid, rather than a change in price. Conlon and Mortimer (2021) provide a useful overview of the economics of diversion. Section 3.4 addresses diversion to the outside good in greater detail.

marginal cost. Thus, plant $j$ operated by firm $f(j)$ would submit a bid, $b_{ijnt} = c_{jt}$, to buyer $i$ if

$$u_{ijnt} - \phi c_{jt} \geq \max_{k \in \mathbb{J}_{f(j)}} \{u_{iknt} - \phi c_{kt}\} \tag{7}$$

where our measure of economic surplus is the difference between the buyer's gross utility and (transformed) marginal cost. Such strategies are not strictly dominant if the bids of losing firms do not affect their own profit. However, if firms perceive a positive probability of winning an auction, for example due to imperfect information about buyers' preference shocks for competitors, then submitting a single "at cost" bid from the highest-surplus plant is a strictly dominant strategy, following the standard logic for second-price auctions.[20]

With increasing cost functions the analysis of equilibrium is more complicated. We proceed by positing bidding strategies and then examining the conditions under which those strategies constitute an equilibrium. In particular, let each firm submit a single "at cost" bid to each buyer from the plant that can create the most economic surplus, as defined in equation (7). Then a vector of plant-level quantities, $\boldsymbol{Q}_t^* = (Q_{1t}^*, Q_{2t}^*, \ldots, Q_{Jt}^*)$, clears the market in year $t$ if and only if

$$Q_{jt}(\boldsymbol{c}_t(\boldsymbol{Q}_t^*; \boldsymbol{X}_t, \boldsymbol{\theta}); \boldsymbol{X}_t, \boldsymbol{\theta}) = Q_{jt}^* \tag{8}$$

for every plant $j$, where $\boldsymbol{c}_t = (c_{1t}, c_{2t}, \ldots, c_{Jt})$ contains the implied marginal costs of each plant. In words, this requires that when plants submit bids equal to the marginal cost implied by $\boldsymbol{Q}_t^*$, those bids imply the plant level quantities in $\boldsymbol{Q}_t^*$. By Brouwer's fixed point theorem, a solution to this system of equations exists under our maintained assumptions.[21]

Therefore, it is possible for all firms to submit an "at cost" bid and have the market clear. We now examine whether these bids characterize an equilibrium. First, if firms have perfect information then it is easy to verify that no firm has a profitable deviation, again following the standard logic for second-price auctions. However, losing bidders can make small enough changes to their bids such that their payoffs do not change. It follows that "at cost" bids constitute a weak Nash equilibrium under perfect information. Second, suppose instead that firms have perfect information except that they do not observe the preferences

[20] Interpreted strictly within the second-score framework, a scenario in which a firm does not have the information to determine which of its plants creates the most surplus with a given buyer presents thornier issues. However, we view the second-score model as a useful reformulation of a quality-adjusted descending price auction. In that setting, a firm would not allow buyers to play its plants off against each other once other rivals have dropped out of the auction. Therefore, it is reasonable think that whether firms can accurately rank their plants would not affect outcomes.

[21] To verify that the conditions for Brouwer's fixed point theorem are satisfied, it is convenient to recast equation (8) in terms of plant-county level market shares:

$$s_{jnt}(\boldsymbol{c}_t(\boldsymbol{s}_t^*; \mathbf{M}_t, \boldsymbol{X}_t, \boldsymbol{\theta}); \mathbf{M}_t, \boldsymbol{X}_t, \boldsymbol{\theta}) = s_{jnt}^*$$

where the function $s(\cdot)$ is a continuous function that maps a convex and compact domain onto itself.

that buyers have for their competitors. As the preference shocks have unbounded support, every firm perceives a positive probability of winning the auction. Thus, any deviation strictly reduces expected profit, and "at cost" bids constitute a strict Nash equilibrium.

Whether these strategies are dominant may be a matter of interpretation. A firm can do no better than bidding "at cost," and this is unaffected by the bids of its competitors. However, others' bids can effect the firm's marginal cost (through quantities) and thus the bid it would submit under an "at cost" bidding strategy. Henceforth, we assume that each firm submits an "at cost" bid from the plant that generates the most surplus in the auction.

### 3.3 Equilibrium Outcomes

An implication of equation (8) is that equilibrium can be characterized by a vector of plant-specific quantities. This provides critical computational savings in estimation, as we describe later. Another feature of the model is that, conditional on plant-specific quantities, analytical expressions are available for market shares, average prices, and average markups, all at the plant-county level. We provide those expressions in this section.

Denote the marginal costs that are associated with the market-clearing quantities as $c^*_{jt}(\boldsymbol{X}_t, \boldsymbol{\theta}) \equiv c_{jt}(Q^*_{jt}; \boldsymbol{X}_t, \boldsymbol{\theta})$. Plugging these into equation (3) yields equilibrium market shares:

$$s^*_{jnt}(\boldsymbol{X}_t, \boldsymbol{\theta}) = \frac{\exp\left(\frac{\overline{u}_{jnt}(\boldsymbol{X}_t,\boldsymbol{\theta}) - \phi c^*_{jt}(\boldsymbol{X}_t,\boldsymbol{\theta})}{1-\sigma}\right)}{\sum_{k\neq 0}\exp\left(\frac{\overline{u}_{knt}(\boldsymbol{X}_t,\boldsymbol{\theta}) - \phi c^*_{kt}(\boldsymbol{X}_t,\boldsymbol{\theta})}{1-\sigma}\right)} \times \frac{\left(\sum_{k\neq 0}\exp\left(\frac{\overline{u}_{knt}(\boldsymbol{X}_t,\boldsymbol{\theta}) - \phi c^*_{kt}(\boldsymbol{X}_t,\boldsymbol{\theta})}{1-\sigma}\right)\right)^{1-\sigma}}{1+\left(\sum_{k\neq 0}\exp\left(\frac{\overline{u}_{knt}(\boldsymbol{X}_t,\boldsymbol{\theta}) - \phi c^*_{kt}(\boldsymbol{X}_t,\boldsymbol{\theta})}{1-\sigma}\right)\right)^{1-\sigma}} \tag{9}$$

The equilibrium market share of a plant increases with the (non-price) value it creates for buyers and decreases with its marginal cost. It decreases with the other plants' values and increases with other plants' marginal cost. One difference from models of Bertrand price competition is that the second-score auction is efficient because buyers always select the highest-surplus plant in equilibrium. An implication is that multi-plant ownership does not affect the equilibrium market shares of individual plants.

The expected price that a plant receives in equilibrium conditional on winning an auction in a given county-year can be decomposed into marginal cost and an expected markup:

$$\overline{p}^*_{jnt}(\boldsymbol{X}_t, \boldsymbol{\theta}) = c^*_{jt}(\boldsymbol{X}_t, \boldsymbol{\theta}) + \overline{m}^*_{jnt}(\boldsymbol{X}_t, \boldsymbol{\theta}) \tag{10}$$

The markup that the winning firm receives in a given auction is determined by the incremental surplus it provides, defined as the surplus that it can create less the maximum surplus that could be created by a competitor. This can be seen by subtracting marginal cost from both sides of equation (4) and assuming equilibrium bidding strategies:

$$m_{ijnt}(\boldsymbol{X}_t, \boldsymbol{\theta}) \equiv p_{ijnt} - c^*_{jt}(\boldsymbol{X}_t, \boldsymbol{\theta}) = \frac{1}{\phi}\left(u_{ijnt} - \phi c^*_{jt}(\boldsymbol{X}_t, \boldsymbol{\theta}) - \max_{k \notin \mathbb{J}_{f(j)}} \{u_{iknt} - \phi c^*_{kt}(\boldsymbol{X}_t, \boldsymbol{\theta})\}\right) \quad (11)$$

where we have assumed that firm $j$ is the winning supplier. Applying the nested logit inclusive value formulas and simplifying using the equation for equilibrium market shares yields the expression for the expected markup conditional on winning an auction:

$$\overline{m}^*_{jnt}(\boldsymbol{X}_t, \boldsymbol{\theta}) = -\frac{1}{\phi} \frac{1}{\sum_{k \in \mathbb{J}_{f(j)}} s^*_{knt}} \log \left[1 - (1 - s^*_{0nt}) \left(1 - \left(1 - \sum_{k \in \mathbb{J}_{f(j)}} \frac{s^*_{knt}}{1 - s^*_{0nt}}\right)^{1-\sigma}\right)\right] \quad (12)$$

By inspection, the right-hand-side does not vary across plants owned by the same firm. Thus, the "common markup" property that arises with Bertrand pricing and logit demand extends to our formulation of the second-score auction. Another shared property is that a firm that has a larger market share (summing across its plants) in equilibrium also obtains a larger markup. While less visually apparent, this is easy to confirm numerically.

## 3.4 Empirical Specification

### 3.4.1 Demand

We specify the model to capture the salient features of the cement industry. On the demand-side, we assume that the common component of gross utility reflects the disutility of transportation and whether the supplier is a domestic plant or the importer. We allow for shipments to go by truck or rail directly from the plant to the buyer, or to go by barge utilizing the Mississippi River System. Our specification is:

$$\begin{aligned} \overline{u}_{jnt}(\boldsymbol{X}_t, \boldsymbol{\theta}) = \min\{&\beta_1 d_{j \to n}\ ,\ \beta_1 \left(d_{j \to R} + d_{R \to n}\right) + \beta_2\} \\ &+ \beta_3 TREND_t + \beta_4 IMPORT_j + \beta_0 \end{aligned} \quad (13)$$

The first line on the right-hand-side is the disutility of transportation, where $d_{j \to n}$ is the distance between the plant and the county, $d_{j \to R}$ is the distance between the plant and the Mississippi River System, and $d_{R \to n}$ is the distance between the Mississippi River System and the county. The parameters $\beta_1$ and $\beta_2$ capture, respectively, the per-mile disutility associated with overland transportation and a fixed disutility associated with barge transportation. We choose this form because barge transportation is much more cost efficient than overland transportation on a per-mile basis but requires users to pay loading charges.[22] We assume that the preferred form of transportation is used. The second line incorporates a demeaned time trend ($TREND_t$), an indicator for the importer ($IMPORT_j$), and a constant for the inside goods.

Thus, we incorporate transportation costs through buyer preferences, reflecting our understanding that buyers typically bear the burden of these costs. This is not an economically consequential assumption because the same shares and markups would obtain in equilibrium if transportation costs loaded instead on the marginal costs of suppliers. One limitation of the model is that we do not distinguish between truck and rail transportation, and so interpret $\beta_1$ as a "blended" disutility of overland transportation (in the average year, 18% of shipments make use of rail). Another limitation is that we do not incorporate that the disutility of overland transportation likely varies with diesel prices. We make this choice based on publicly-available reports from the *American Transportation Research Institute*, which indicate that fuel costs accounted for only 24% of per-mile trucking costs in 2019, with previous years being similar. However, we obtain similar results if we model the disutility of overland transportation using the product of distance and the diesel price.

Finally, we detail our approach to modeling buyer substitution to the outside good. In the model, this depends on the nesting parameter ($\sigma$) and the county sizes ($M_{nt}$). To see this, equation (5) can be manipulated to obtain an expression for the diversion from plant $j$ to the outside good:

$$DIV_{j\to 0} \equiv \frac{\frac{\partial s_0}{\partial b_j}}{\left|\frac{\partial s_j}{\partial b_j}\right|} = \frac{1-\sum_{k\neq 0} s_k}{\frac{1}{1-\sigma}(1-\sigma \hat{s}_{j|g} - (1-\sigma)s_j)} \tag{14}$$

where the county sizes convert quantities into market shares (holding quantities fixed, a larger county size implies lower market shares for inside goods). We have found it difficult to pin down outside good diversion econometrically given the publicly-available data on the industry. Therefore, we choose an approach that *imposes* relatively little outside diversion, consistent with our understanding that alternatives to cement are weak substitutes in most applications (e.g., van Oss and Padovani, 2003a). To do so, we first define "region sizes" as twice the observed consumption in the region, and allocate these region sizes to county sizes in proportion to observed county-level construction employment. Aggregating across counties, this implies a market share of the outside good of 50%.[23] Thus, there is little

[22] One industry expert claimed to us that the marginal per-mile cost of barge transportation is negligible and we simply ignore it in the modeling.

[23] The assumption that the average market share of the outside good is the same in every year motivates our inclusion of the trend in the demand equation. The trend allows the model to accommodate both the invariance

empirical variation with which to identify the nesting parameter, and we set $\sigma = 0.90$, high enough to significantly damp substitution to the outside good.[24]

### 3.4.2 Marginal Cost

On the supply-side, we assume that plants operate one or more kilns.[25] The marginal cost of production at any kiln $l$ (operated by plant $j$ in year $t$) is given by

$$c_{jt}^{(l)}\left(Q_{jt}^{(l)}; \boldsymbol{X}_t, \boldsymbol{\theta}\right) = \boldsymbol{w}_{jt}^{(l)}\boldsymbol{\alpha} + \gamma\left(\frac{Q_{jt}^{(l)}(\cdot)}{CAP_{jt}^{(l)}} - 0.5\right)^2 \mathbb{1}\left\{\frac{Q_{jt}^{(l)}(\cdot)}{CAP_{jt}^{(l)}} > 0.5\right\} \tag{15}$$

where $Q_{jt}^{(l)}$ is the output of the kiln, $\boldsymbol{w}_{jt}^{(l)}$ is a vector of kiln-specific cost-shifters, $CAP_{jt}^{(l)}$ is the capacity of the kiln, and the parameters include $(\boldsymbol{\alpha}, \gamma)$. The cost-shifters include a constant, a demeaned time trend, and the fuel cost of production, the latter of which captures that modern kilns are more efficient than older wet or long dry kilns. We construct the fuel cost for each kiln using the approach of Miller et al. (2017), as we describe in the Appendix. We measure capacity using the boilerplate rating of the kiln, which provides the theoretical maximum amount that could be produced with no downtime for maintenance.[26]

Kiln-level marginal costs increase in output once the utilization rate, i.e., the ratio of output to capacity, exceeds 50%. Producing at capacity results in a marginal cost increase of $\gamma/4$ relative to producing at a utilization rate less than 50%. In principle, it is possible to *estimate* the threshold utilization rate at which costs begin to increase (e.g., Ryan, 2012; Miller and Osborne, 2014b) but this slows estimation significantly because the threshold and $\gamma$ affect model predictions similarly. There are two reasons that marginal costs may slope up in the cement industry. The first is that high utilization rates create financial costs due to deferred maintenance and a greater chance of breakdowns. The second is that operating near a binding capacity constraint creates opportunity costs in that selling to one buyer may preclude selling to another. We do not seek to disentangle these explanations because they have similar equilibrium effects.

We assume that each plant allocates output across its kilns to minimize cost. For low-

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of the outside good share with the changes in the industry that are observed to occur (e.g., plant closures and the greater shipping distances caused by them).

[24] We obtain similar but somewhat noisier results using county sizes that depend *only* on construction employment, following Miller and Osborne (2014b). Cement prices are unlikely to affect construction activity much because cement accounts for a small fraction of total construction expenditures (e.g., Syverson, 2004).

[25] Multi-kiln plants are more common earlier in the sample. The reason is that plants using old technology often have two or more kilns, whereas plants with modern technology usually have a single kiln. In the Appendix, we plot the average number of kilns per plant over the sample period (Figure D.1).

[26] If we also include kiln age as a cost-shifter, we find that it has a positive but negligible effect on marginal cost, so we exclude it from the main specification to reduce computational burden (see Section 4.3).

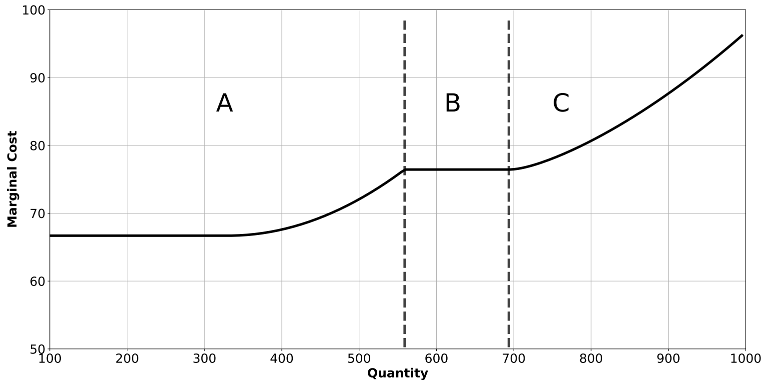


Figure 4: Plant-Level Marginal Cost per Metric Tonne (Illustrative Example)

Notes: The figure plots the marginal cost function of the Flintkote plant (Kosmodale, Kentucky) in 1974, taking as given our parameter estimates. The plant has two kilns. It initially uses the more efficient kiln to produce marginal output (region A), then it uses the less efficient kiln (region B), and finally it splits marginal output between the kilns (region C). The vertical axis is in dollars per metric tonne and the horizontal axis is in thousands of metric tonnes.

enough production, this entails producing only from the most efficient kiln. However, as that kiln reaches higher levels of utilization, production from less efficient kilns may become economical, and cost minimization dictates that the plant equate the kiln-specific marginal costs of any kiln that it uses. In this manner, we construct a continuous and weakly upward sloping *plant-level* marginal cost function, $c_{jt}(Q_{jt}; \boldsymbol{X}_t, \boldsymbol{\theta})$, from the kiln-level marginal cost function of equation (15). Figure 4 shows the marginal cost function that we obtain for one of the multi-kiln plants in our data.[27]

Finally, we assume that imported cement is provided by a competitive fringe that ships into each of the active customs districts (Appendix A.2). The fringe submits bids equal to the customs value of imported cement, inclusive of insurance, freight, and other delivery charges to the port of entry, which we observe in the data. This may not align precisely with marginal cost, but any discrepancy is accounted for because the demand-side includes a separate intercept for imports.

[27] Among the 4,202 plant-year observations in our data, 2,428 have multiple kilns. (See also Figure D.1 in the appendix.) In 528 of these observations, kiln heterogeneity creates nonconvexity in the plant-level marginal cost functions, as in the illustrative example of Figure 4. With nonconvexity, Brouwer's fixed point theorem does not guarantee that market-clearing quantities exist. However, we are able to find market-clearing quantities to numerical precision in our application.

# 4 Estimation

## 4.1 Estimation Strategy

We assume a data generation process in which each observed endogenous outcome—average price among plants in Northern California, for example—is generated by the following:

$$y_{mt} = h_{mt}(\boldsymbol{X}_t; \boldsymbol{\theta}_0) + \omega_{mt} \tag{16}$$

where $y_{mt}$ is outcome $m$ in year $t$, $h_{mt}(\boldsymbol{X}_t; \boldsymbol{\theta}_0)$ is a known function defined by the model that returns the analogous model prediction given data and parameters, and $\omega_{mt}$ is a stochastic term that satisfies $\mathbb{E}[\omega_{mt}|\boldsymbol{X}_t] = 0$. We enumerate the endogenous outcomes later in this section. The exogenous data in $\boldsymbol{X}_t$ includes the county sizes, the customs value of imported cement, the locations of the customs offices, the locations, kiln fuel costs, and kiln capacities of cement plants, and the location of the Mississippi River System. The parameters to be estimated are $\boldsymbol{\theta}_0 = (\boldsymbol{\beta}, \boldsymbol{\alpha}, \phi, \gamma)$.

We interpret the stochastic term as measurement error that arises due to less than perfect response rates to the USGS surveys from which the data on endogenous outcomes are created. We construct the following empirical moments:

$$g_m(\boldsymbol{\theta}; \boldsymbol{X}) \equiv \frac{1}{||\mathbb{T}_m||} \sum_{t \in \mathbb{T}_m} \kappa_t \left( y_{mt} - h_{mt}(\boldsymbol{X}_t; \boldsymbol{\theta}) \right) \tag{17}$$

where $\mathbb{T}_m$ includes the years in which outcome $m$ is observed and $\kappa_t$ is the weight that we put on year $t$. Although our data span a 46-year window, we use only 36 years in estimation because the plant-level data are unavailable for many of the more recent years. Accordingly, we place greater weight on the more recent years for which we have complete data in order to ensure that our results are not overly dominated by the empirical variation that exists in the first half of the sample.[28]

We construct moments based on the following endogenous outcomes:

1. Average price of plants by region. There are 63 price regions and the average number of years each is observed is 14.29. The average year has 25 price regions.

2. Total production by region. There are 62 production regions and the average number of years each is observed is 14.56. The average year has 25 production regions.

[28] In estimation we use the following 36 years: 1974-2003, 2006, 2008, 2010, 2013, 2016, and 2019, which reflects the availability of the *Plant Information Summary*. We weight observations in year $t$ based on the number of years since the last observation. For example, observations from 2006 receive a weight that is three times greater than the weight for consecutive observation years because the most recently observed data is from 2003.

3. Total consumption by region. There are 57 consumption regions, and they are observed for an average of 34.42 years. The average year has 54.5 consumption regions.
4. The proportion of production that is accounted for by plants with a wet kiln. This is observed in 35 years of the estimation sample (there are no data for 1991).
5. The proportion of cement that is shipped using river barges. This is observed in all of the 36 years in the estimation sample.
6. The proportion of cement shipped from regions in California to regions in California, Arizona, and Nevada. There are 88 observations overall (see Section 2.3).

Stacking these empirical moments into a vector, $\boldsymbol{g}(\boldsymbol{\theta};\boldsymbol{X})$, our estimate of $\boldsymbol{\theta}_0$ is

$$\hat{\boldsymbol{\theta}}(\boldsymbol{\Sigma}) = \underset{\boldsymbol{\theta}\in\Theta}{\text{argmin}}\ \boldsymbol{g}(\boldsymbol{\theta};\boldsymbol{X})'\boldsymbol{\Sigma}^{-1}\boldsymbol{g}(\boldsymbol{\theta};\boldsymbol{X}) \tag{18}$$

where $\boldsymbol{\Sigma}$ is a positive definite, diagonal weighting matrix. We employ a one-step estimator. An efficient two-step estimator (e.g., Hansen (1982)) appears infeasible in our setting because different moments are observed in different time periods. Given that, the literature does not appear to provide clear guidance about how to calculate the off-diagonal elements of the efficient weighting matrix.[29] In the weighting matrix we use, each element of the diagonal is the sample variance of the endogenous outcome that corresponds to the moment (e.g., the variance of region-year prices for any price moment). This ensures that the different types of data receive similar weight in estimation. We also scale the weights placed on consumption and production by 50% as an adjustment for likely correlation between the two sets of moments. In Appendix B, we discuss informally how the moments we use pin down the different structural parameters.

## 4.2 Identification

Price endogeneity is a primary threat to consistency in the estimation of many oligopoly pricing models. Strictly interpreted, it does not arise in our application because price data are not used to construct the right-hand-side of equation (16). Instead, price predictions arise endogenously from the model, and parameters are selected so that the predictions match the data. Nonetheless, if prices and quantities covary for reasons that are not explicitly modeled then our estimates may exhibit a *misspecification bias* that is similar in spirit to price endogeneity bias. For example, if one region exhibits higher prices and greater output

[29] Lynch and Wachter (2013) evaluate strategies for reweighting when there are two sets of moments, with a longer time series being available for one set than the other. What distinguishes our application is that many of our moments are observed over very different time frames, and some moments have no overlap at all with which to calculate covariances.

because its plants provide higher unobserved quality then this could lead us to understate the price sensitivity of buyers. Similarly, if plants in a region have higher marginal costs due to unobservables then the region may exhibit relatively higher prices and lower output, leading us to overstate price sensitivity.

Therefore, in assessing the credibility of our estimates, a relevant consideration is the extent to which heterogeneity exists in ways not captured by the model. On the demand-side, the cement itself is an unlikely source of unobserved heterogeneity because it is produced in accordance with ASTM standards. Some plants may have a reputation for good customer service, or for being reliable in their production schedule, but we have not seen evidence that such factors are of first-order importance. Considerations that are specific to a plant-buyer pair (e.g., relationships) can be conceptualized as subsumed by the preference shocks and thus would not contribute to any unobserved quality. On the supply-side, we use a wealth of information about the technologies, capacities, and fuel costs of the kilns in our sample to help model marginal cost. Thus, we believe the model accounts for much of the heterogeneity that exists in the cement industry.

Still, previous studies have documented significant heterogeneity in plant-level productivity (e.g., Syverson, 2004), and the possibility that important unobserved heterogeneity could remain motivates additional validity checks on the magnitude of the price parameter. First, we compare the implied willingness-to-pay for overland proximity (i.e., $\beta_1/\phi$) to external estimates of transportation costs. As we develop later, the model fits the production, consumption, and cross-region shipments moments quite well. Therefore, our estimate of $\beta_1$ is likely accurate, and the transportation cost comparison is useful for assessing the price parameter ($\phi$). Second, we compare the demand elasticities that we estimate to those obtained elsewhere in the literature. Both sets of comparisons are favorable and suggest that our parameter estimates are in a reasonable range.

## 4.3 Computational Burden

The main computational challenge in estimation is that equilibrium must be computed for every candidate parameter vector. In most years of our sample there are more than 300,000 prices and shares at the plant-county level. We exploit the properties of the second-score auction model to make computation tractable. The key insight is that equilibrium can be characterized by plant-level quantities (equation (8)). In our estimation sample, the maximum number of plants in a given year is 179. Thus, by formulating equilibrium in terms of a plant-level strategies, the length of the vector being targeted by our nonlinear equation solver is reduced by more then two orders of magnitude relative to what would be required for an analogous Bertrand model of price competition.[30] To implement, we use the large-scale nonlinear equation solver of La Cruz et al. (2006) and parallelize by assigning each of the 36 years in the estimation sample to a different processor.

Another challenge is that equilibrium outcomes are nonlinear in the demand and cost parameters. This limits the number of parameters that reasonably can be incorporated. Without plant-level data on prices and quantities, it is not possible to "concentrate out" some parameters from the objective function, as is standard for models of Bertrand competition and random coefficients logit demand (e.g., Berry et al., 1995; Nevo, 2001). Our specification features ten parameters. We benefit from the empirical setting because it is possible to capture the salient features of the cement industry with a sparsely parameterized model. We minimize the objective function using Nelder-Mead and then apply Levenberg-Marquardt to confirm that convergence occurs at a local minimum. We use different starting points and find that they converge to the same parameter estimates.

# 5 Results

## 5.1 Parameter Estimates

Table 1 provides estimates of the model's parameters and derived statistics on transportation costs and demand elasticities. On the demand-side of the model, buyers prefer lower prices and nearby cement plants, all else equal. The disutility that buyers receive from overland transportation is sufficient to ensure that most shipments are local. In the equilibrium implied by the estimates, 89% of shipments use overland transportation exclusively (i.e., they do not use a river barge) and, of these, the median shipment is 74 miles and 84% travels less than 200 miles. This aligns with a Census Bureau (1977) study that reports that more than 80% of cement is transported within 200 miles. By contrast, for the 11% of shipments that use a river barge for transportation, the median distance between a plant and the buyer is 523 miles. The Mississippi River System allows buyers to purchase at significantly greater distances than economical with overland transportation alone.

On the supply-side, marginal costs increase with fuel costs and as production approaches capacity. The fuel cost parameter of 1.78 implies that fuel costs are more than fully passed through to bids, consistent with recent studies of cost pass-through in the cement industry (Miller et al., 2017; Ganapati et al., 2020). One explanation is that fossil fuel prices are correlated with the electricity prices that plants pay to grind clinker into cement and perform various other functions. The constant implies that other inputs (e.g., materials, labor)

[30] Two of us applied a brute-force approach to estimate a Bertrand/logit model of the cement industry (Miller and Osborne, 2014b). We focused exclusively on Arizona, California, and Nevada in order make the problem manageable. The typical year featured around 1,000 prices and market shares at the plant-county level.

Table 1: Parameter Estimates and Derived Statistics

| Parameter | | Estimates | Std. Error |
|---|---|---|---|
| *Demand* | | | |
| Price Parameter | $\phi$ | 0.007 | (0.000) |
| Constant | $\beta_0$ | 0.597 | (0.050) |
| Overland Miles (000s) | $\beta_1$ | -2.511 | (0.107) |
| River Barge Used | $\beta_2$ | -0.471 | (0.007) |
| Time Trend | $\beta_3$ | 0.003 | (0.001) |
| Imported Cement | $\beta_4$ | 0.164 | (0.021) |
| *Marginal Cost* | | | |
| Constant | $\alpha_0$ | 35.80 | (1.67) |
| Fuel Cost | $\alpha_1$ | 1.78 | (0.05) |
| Time Trend | $\alpha_2$ | 0.182 | (0.027) |
| Capacity Cost | $\gamma$ | 81.57 | (5.35) |
| *Transportation Costs* | | | |
| Overland Cost ($ per Tonne-Mile) | $\beta_1/\phi$ | 0.38 | |
| Barge Cost ($ per Tonne) | $\beta_2/\phi$ | 70.32 | |
| *Bid Elasticity of Demand* | | | |
| Plant-Level Demand | | -4.00 | |
| Demand for Domestic Cement | | -0.20 | |
| Demand for Cement | | -0.13 | |

Notes: The results are based on GMM estimation. The fuel cost variable and the time trends are demeaned.

contribute \$35.80 to marginal cost per metric tonne in the average year. The capacity cost parameter implies that producing at capacity increases marginal cost by \$20.39 per metric tonne relative to producing at a utilization rate less than 50%. To give a sense for changes over time, Figure D.2 in the appendix plots marginal cost over the sample period, averaging across plants, along with a decomposition that separates the constant portion and the portion due to capacity constraints.

We validate that the price parameter is in a reasonable range by comparing the transportation costs and demand elasticities that derive from our model to those provided in external sources. On the former, we obtain an overland transportation cost of \$0.38 per tonne-mile, blending truck and train shipments. The 1974 *Minerals Yearbook* reports \$0.43 per tonne-mile on average for trucking. Miller and Osborne (2014b) obtain \$0.57 per tonne-mile over 1983-2003 using an estimation approach that is similar to ours, but with data on a region of the country for which rail transportation is less prevalent. As a third point of comparison, data from *The Bureau of Transportation Statistics* indicate that the average revenue per tonne-mile of general freight common carriers is \$0.12 over 1985-2019. The price for trucking cement is likely to be significantly higher than this average because cement shipments require specialized trailers and an empty return trip.[31]

We estimate the quantity-weighted median plant-level bid elasticity to be -4.00. We obtain this by converting the demand derivative of equation (5) into an elasticity and evaluating it at equilibrium bids (which equal marginal costs). Thus, the bid elasticity also has the interpretation as a cost elasticity. The price elasticities reported in the literature are sometimes higher and sometimes lower. On one hand, Miller and Osborne (2014b) estimate a median firm-level price elasticity of -3.22 and Ganapati et al. (2020) estimate a plant-level demand elasticity of -2.90. One the other hand, Chicu (2012) estimates a median plant-level price elasticity of -6.55 and Fowlie et al. (2016) estimate a market-level price elasticity of -2.05 that implies an average plant-level price elasticity of -7.35.[32] Our interpretation is our estimates imply a reasonable degree of price sensitivity.

Figure 5 shows the fit of the model to the time-series of total consumption, total production, and average price. The solid lines show the data and the dashed lines show the model predictions. In each case, the model tracks the broad patterns in the data. One notable feature is that the model under-predicts average price in 2019. In some of the following analyses, we make an adjustment that centers the model-implied prices around observed prices. Appendix D provides additional figures that show the fit of the model to the *Califor-*

[31] We have adjusted all estimates in this section to be in real 2010 dollars.

[32] The demand system of Chicu (2012) is estimated with older data that span 1949-1969. For Fowlie et al. (2016), we obtain -7.35 by multiplying the market-level price elasticity of -2.05 by the average number of firms in the geographic markets that they delineate, which is 3.625. The calculation is valid for their model of Cournot competition.

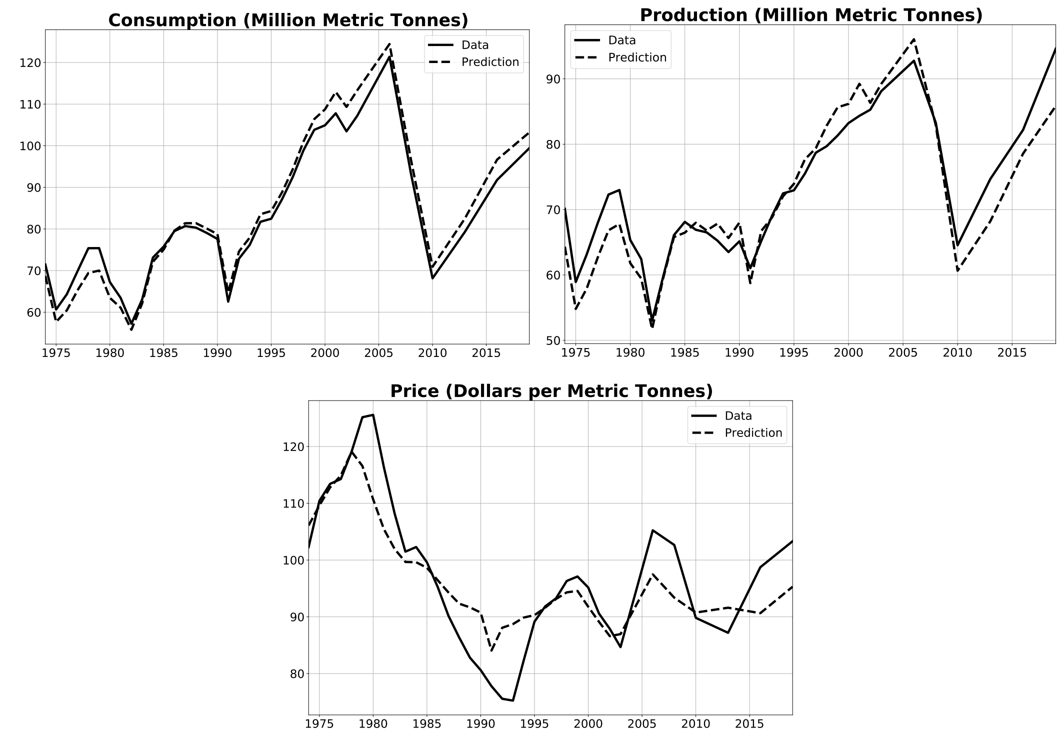


Figure 5: Model Fits for Consumption, Production, and Prices

*nia Letter* data on cross-region shipments, the panel data on consumption, production, and prices, and the time-series of production by wet kilns and the prevalence of barge shipments (Figures D.3 and D.4). Overall, our interpretation is that the model fits the data well.

Table 2 summarizes the quantity-weighted median markups that we obtain from the model. We report the Lerner Index ($(p-c)/p$), the additive markup ($p-c$), and the "price-over-cost" markup ($p/c$). We calculate these markups using both marginal cost and average variable cost. Using marginal costs, we obtain a median Lerner Index of 0.19, a median additive markup of $16.99 per metric tonne, and a median price-over-cost markup of 1.23. Using average variable cost, these statistics are 0.31, $28.74, and 1.46, respectively.

Underlying these markups are a rich set of county-plant specific prices and a correspondingly rich set of shipment patterns. Exploring the spatial patterns in detail is beyond the scope of this paper. To give some sense, however, in Appendix D we show that plants obtain both higher markups and greater market shares in nearby counties, with the degree of markup dispersion depending on the presence of competitors (Figure D.5). We also provide a map of plants and buyers that transport over the Mississippi River System (Figure D.6).

Table 2: Implied Median Markups

| | | Marginal Cost | Average Variable Cost |
|---|---|---|---|
| Lerner Index | $(p-c)/p$ | 0.19 | 0.31 |
| Additive Markup | $p-c$ | \$16.99 | \$28.74 |
| "Price-Over-Cost" Markup | $p/c$ | 1.23 | 1.46 |

Notes: The table reports quantity-weighted median markups calculated using marginal costs and average variable costs. The additive markups are in dollars per metric tonne.

## 5.2 The Rise of Market Power in Cement

We now examine how market concentration and markups have changed in the model over the sample period, relate those changes to each other and to prices, and explore mechanisms. To measure market concentration, we use county-level HHIs that reflect the localized competition that is relevant for buyers of cement.[33] Our construction of the HHIs excludes the outside good and treats imports as being provided by one distinct supplier of cement. For each county and year, we obtain

$$HHI_{nt} = 10,000 \times \sum_f \left( \sum_{j \in \mathbb{J}_f} \frac{s_{jnt}}{1 - s_{0nt}} \right)^2 \tag{19}$$

where $s_{jnt}/(1-s_{0nt})$ is the probability that plant $j$ wins an auction in county $n$ and year $t$, conditional on cement being purchased. Results are similar if we instead treat imports as being sold by infinitesimally small firms. For markups, we focus on the additive markup and the price-over-cost markup, as trends in the Lerner Index resemble those of the price-over-cost markup.

Figure 6 summarizes how these objects have changed over time. The top panel shows that the quantity-weighted median HHI increases from 2171 to 2895 over the sample period. To put this in context, it is equivalent to a reduction in the number of symmetric competitors from roughly 4.6 to 3.5. Counties differ significantly in their HHI and the HHI change that they experience. Applying the classifications of the 2010 *Horizontal Merger Guidelines*, the proportion of consumption that occurs in "unconcentrated" counties falls tenfold, from 31% to 3%, whereas the proportion of consumption that occurs in "highly concentrated" counties increases from 42% to 62%. Consumption in counties with near-monopoly levels of the HHI increases somewhat less dramatically, consistent with antitrust

[33]This is consistent with the approach described in the 2010 *Horizontal Merger Guidelines* for geographic market definition in the presence of spatial price discrimination.

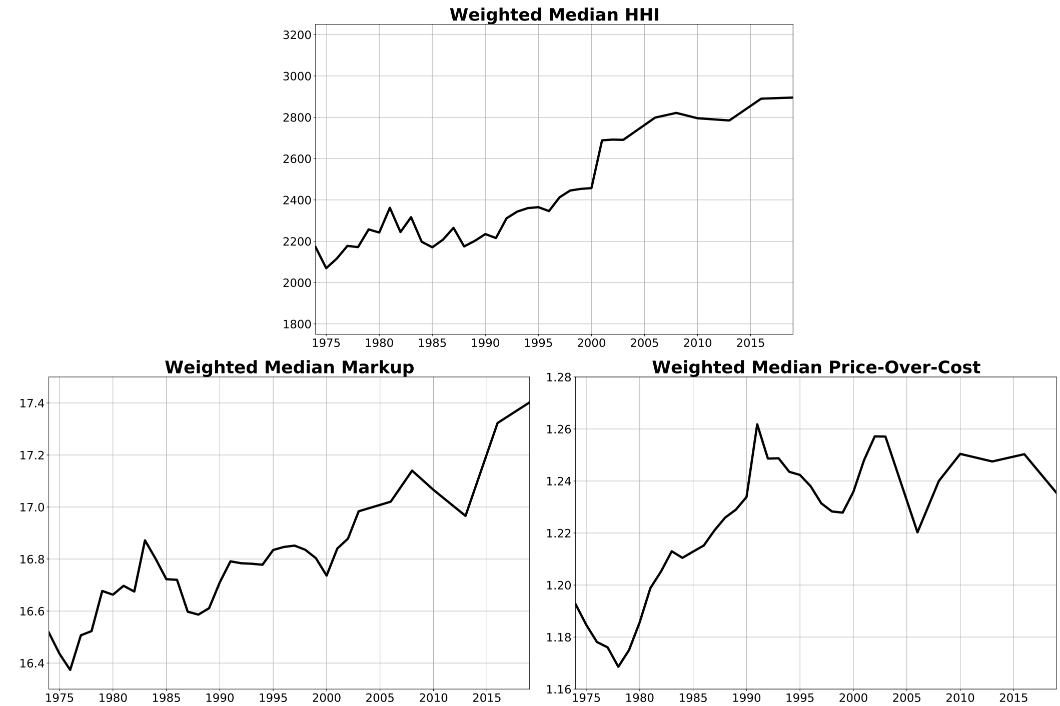


Figure 6: Rising Concentration and Markups, 1974-2019

Notes: The figure plots the quantity-weighted median county-level HHI (top panel), the quantity-weighted median county-level additive markup, in dollars per metric tonne (bottom left panel), and the quantity-weighted median county-level price-over-cost markup (bottom right panel). The county-level HHIs and markups are obtained from the model. In constructing the median, we weight by equilibrium quantities.

enforcement actions of the Federal Trade Commission.[34] In the Appendix, we provide these and other tabulations (Table D.1) and also examine a measure of the national-level HHI that does not reflect the localized nature of competition in the cement industry (Figure D.7).[35]

The figure also plots the quantity-weighted median additive markup (bottom left) and price-over-cost (bottom right). The additive markup trends upward over the sample period, moving from \$16.52 in 1974 to \$17.40 in 2019, an increase of 5.4%. The price-over-cost rises from roughly 1.19 to 1.24, an increase of 4.2%, with most of the change occurring in the 1980s. The relative flatness in more recent years is due to the combination of rising additive markups and rising prices (Figure 3). That we find rising markups is consistent with the results of De Loecker et al. (2020) for the manufacturing sector, although the

[34] We have identified six mergers that received an antitrust challenge over 1996-2019 using a publicly-available Federal Trade Commission database. Of these, one was consummated subject to a behavioral remedy, four were consummated subject to plant divestitures to preserve local competition, and one was abandoned.

[35] The 2010 *Horizontal Merger Guidelines* classify markets with an HHI under 1500 as "unconcentrated," markets with an HHI between 1500 and 2500 as "moderately concentrated," and markets with an HHI above 2500 as "highly concentrated." For the purposes of illustration, the table uses 5000 and 6000 as HHI thresholds for "near-monopoly."

magnitude of change that we estimate is smaller.[36]

We now analyze the panel variation in the model predictions, and in particular explore whether changes in concentration are correlated with changes in markups and prices. Figure 7 shows scatter plots of the county-level HHI changes against county-level average markup changes (top panel) and county-level average price changes (bottom panel). Each circle represents one county, and the areas of the circles are proportional to county-level consumption. There is a clear positive correlation between the HHI and markup changes—those counties that experienced the greatest increase in concentration also experience the greatest increase in markups. The line of best fit has an $R^2$ of 0.658, consistent with a tight relationship. In contrast, the relationship between the HHI and price changes is less obvious. Although there is a positive correlation, many counties experience an HHI increase with a price decrease, or vice-versa. This is reflected in the smaller $R^2$ of 0.127.

These broad patterns are consistent with an effect of precalciner kilns. Technology that expands capacity and lowers marginal cost can increase concentration by inducing the exit of some firms, just as it can increase markups by lowering marginal cost and reducing competition (due to induced exit). Yet the implications for price can be ambiguous to the extent that marginal cost reductions and the loss of competition have opposing effects.[37]

Still, a number of alternative mechanisms can generate similar relationships between concentration, markups, and prices, and we conduct decomposition exercises to extend the analysis. In the data, we observe changes in a wide range of market factors that bear on equilibrium outcomes: plant closures, technology adoption, entry, mergers, fuel prices, and so on. To examine which of these matter most, we start with the 1974 data and introduce changes in sequence, computing equilibrium with each change, until we obtain the 2019 data. We then examine how concentration, markups, and prices shift as we move from 1974 to 2019 conditions.

The specific sequencing of the counterfactuals that we use is as follows:

(i) Use the 2019 county sizes, fossil fuel prices, and the 2019 value of the demand and cost time trends.

(ii) Apply (i) and remove all plants that are not present in the 2019 data. We interpret this as measuring of the short run influence of plant closures.

(iii) Apply (ii) and use the 2019 kiln technologies, including the primary fuel choice. We interpret this as measuring the short run influence of technology adoption.

[36] See Table 12.1 in the appendix of De Loecker et al. (2020).

[37] Our analysis illustrates in a particular empirical setting how both price and the HHI are equilibrium outcomes that are determined by demand and supply factors. The correlation between them can be positive or negative, depending on what gives rise to the empirical variation, and the sign of the correlation need not inform the extent to which competition matters for price (e.g., Miller et al., 2022).

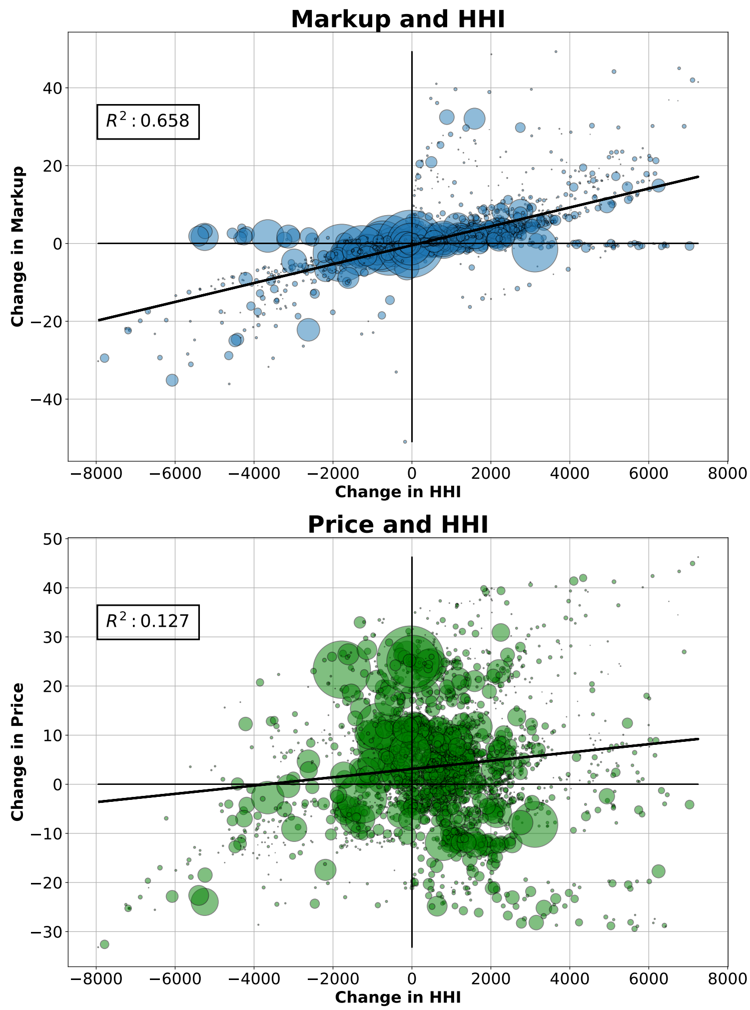


Figure 7: Markup and Price Changes Plotted Against HHI Changes, 1974 to 2019

Notes: The figure plots the county-level changes in average additive markups (top panel) and average prices (bottom panel) against the county-level changes in the HHI. The vertical axes are in dollars per metric tonne. The circles are proportional to consumption. The county-level changes are those predicted by the model, although we recenter the price changes so that the average price change between 1974 and 2019 match with changes in the average national-level price that are observed in the data. Also shown are lines of best fit and the $R^2$ of the fits.

(iv) Apply (iii) and add plants that are present in 2019 but not 1974. We interpret this as measuring the short run influence of entry.

(v) Apply (iv) and also use the 2019 plant ownership structure. We interpret this as measuring the short run influence of mergers and acquisitions.

With the final step, we reproduce the 2019 data. The interpretations we offer represent short run effects because the incentives for technology adoption, exit, entry, and mergers are intertwined in long run equilibrium. One relationship that is particularly relevant in our application is that the adoption of a cost-reducing, scale-increasing technology by some plants is likely to induce others to exit. Thus, what is isolated in step (ii) likely incorporates a long run effect of technology adoption, a matter that we revisit in the next section.[38]

Figure 8 summarizes the results of the decomposition exercise. Three waterfall graphs are provided, one each for the quantity-weighted median country-level HHI (top panel), the quantity-weighted median county-level additive markup (bottom left panel) and the quantity-weighted median county-level price (bottom right panel). The gray bars on the left and right provide the values in 1974 and 2019, respectively. The bars in the middle provide the incremental effect of each sequenced change in the market, as enumerated above. We shade these bars blue for increases and red for decreases.

We find that plant closures contribute 761 points to the median HHI. Other meaningful factors include mergers, which contribute 337 points to the median HHI, and plant entry, which reduces the median HHI by 298 points. For markups, the main contributing factors are plant closures ($0.59) and mergers ($0.50). The adoption of modern technology also increases markups but to a much smaller degree ($0.03). All of the changes in markups are small relative to average prices. Finally, we find that changes in demand and cost conditions contribute to higher prices ($14.80), as do plant closures ($19.15). Plant closures have a bigger affect on prices than markups because they increase the utilization (and thus the marginal costs) of the remaining plants. Offsetting these factors, we obtain price reductions from the adoption of modern technology ($28.00) and plant entry ($6.57). The effect of modern technology on prices is mainly due to better fuel efficiency and greater capacity, both of which reduce the marginal cost of production. Mergers increase prices by a much smaller amount ($0.35) that is roughly commensurate with their effect on markups.

These results are consistent with the main *short run* effects of technology adoption in the cement industry being marginal cost reductions that are passed through to cement buyers in the form of lower prices. To the extent that technology adoption contributes to rising concentration and markups, our analysis indicates that it is through its effect on long run

[38]We scale the plant capacities in step (i) so that total capacity aligns with that of 2019, which avoids mismatches in supply and demand that could mask more interesting mechanisms. We then use the true capacities of the plants in 2019 starting in step (iii). With these adjustments, the results more usefully summarize the economics at play. We also apply a centering correction in our analysis of price so that the total change between 1974 and 2019 matches the change in the average national-level price that is observed in the data.

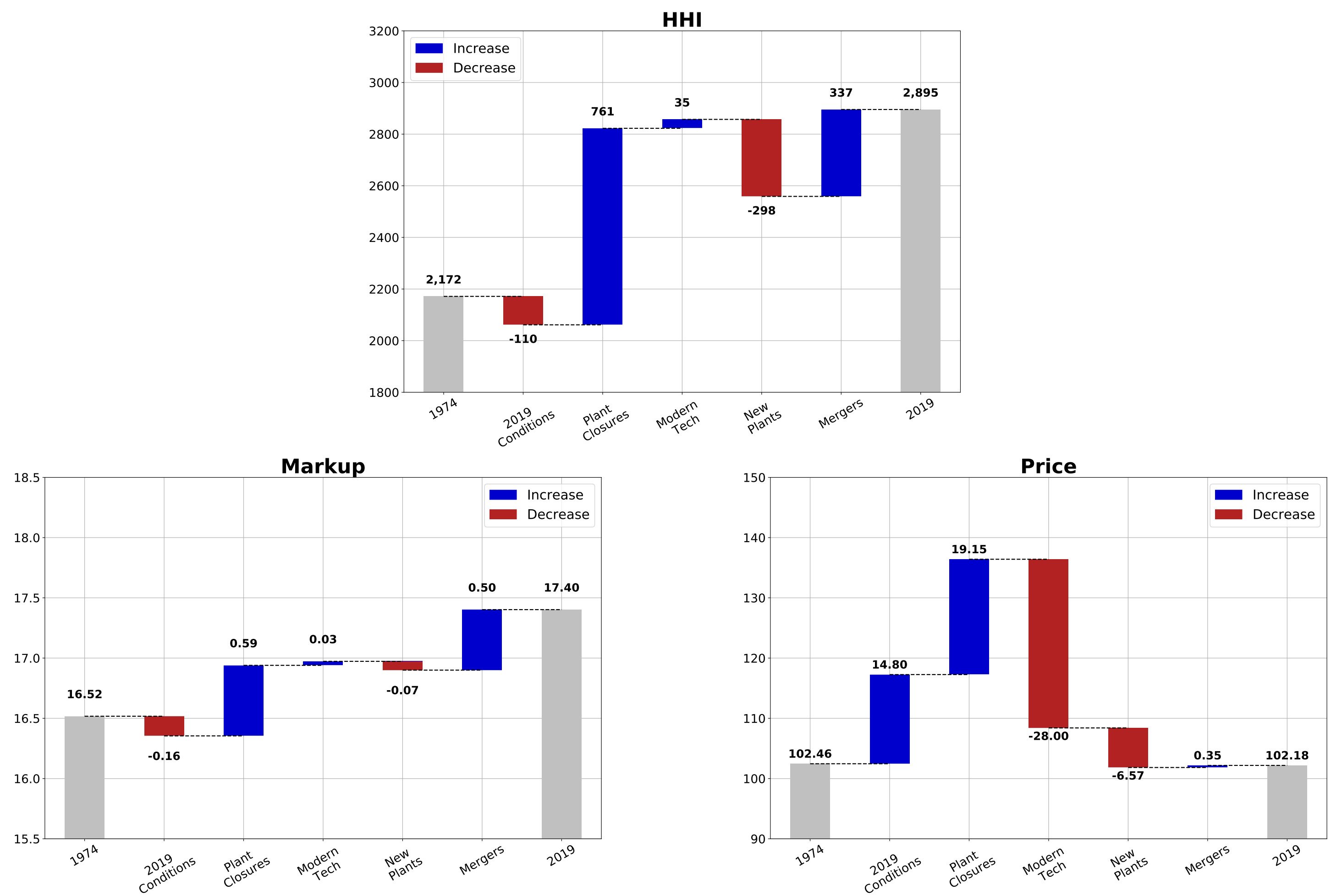


Figure 8: Short Run Determinants of HHI, Markup, and Price Changes

Notes: The figure provides waterfall graphs for the quantity-weighed median county-level HHI (top panel), the quantity-weighed median county-level additive markup (bottom left panel), and the quantity-weighed median county-level price (bottom right panel). Markups and prices are in dollars per metric tonne.

decisions, including on plant closures. However, the stylized facts presented in Section 2 suggest that it is indeed reasonable to attribute the bulk of plant closures to technology adoption.[39] Plants with modern precalciner kilns are more fuel efficient and have capacities that are much greater than those of plants with wet or long dry kilns. It takes fewer modern plants to meet the same level of demand. In such a setting, it makes sense that technology adoption would go hand-in-hand with plant closures. We explore the scale advantage of modern plants in greater quantitative detail in the next section.

### 5.3 Economies of Scale and the Role of Modern Technology

One explanation for rising concentration and markups in the cement industry is that a cost-reducing, scale-increasing technology (precalciner kilns) became available and this led to a shakeout in which some plants invested in the new technology and others exited. In this section, we explore the implications of precalciner technology for plant-level economies of scale. Results already obtained provide the marginal cost functions of each plant. We take additional steps to inform the fixed costs of production and obtain the average cost functions that are relevant for scale economies. The results we obtain indicate that precalciner technology creates an impetus for significant output expansion for plants that adopt it, and are consistent with the hypothesis that precalciner technology was a main driver of the industry shakeout observed in the data.

We take the perspective of a plant that has one or more old kilns. The plant pays operational fixed costs for each kiln due to associated salaried labor, the cost of ramping the kiln after its previous maintenance period, and any future maintenance costs. The capital costs associated with installing the old kilns are sunk. The plant can replace its old kilns with a precalciner kiln. If it does so, it incurs an upfront capital cost and then must pay an operational fixed cost in each future year. Under these assumptions, the annualized total fixed cost can be represented as:

$$TFC = \begin{cases} F & \text{if keep old kiln} \\ (1-\delta)E + F' & \text{if adopt precalciner} \end{cases} \tag{20}$$

where $\delta$ is the discount factor, $F$ and $F'$ are the operational fixed costs of the old and new technologies, respectively, and $E$ is the capital cost required for the new technology. To obtain this expression, we assume that both technologies are infinitely-lived, which is a

[39] Other factors surely contributed to plant closures. One candidate is that environmental regulation became more stringent along some dimensions over the course of the sample period (e.g., Ryan, 2012; Fowlie et al., 2016). However, some empirical patterns in the data seemingly are inconsistent with environmental regulation being the primary driver of the plant closures, including the 13 instances of new plant entry and industry-wide capacity increases (Section 2).

Table 3: Numerical Analysis of Fixed Costs

| | Operational Fixed Cost Bounds | Capital Cost (Annualized) | Total Fixed Cost Bounds | Total Fixed Cost Midpoint |
|---|---|---|---|---|
| Wet and Long Dry Kilns | [0.11 , 3.75] | sunk | [0.11 , 3.75] | 1.93 |
| Modern Preheater/Precalciner Kilns | [0.47 , 11.01] | 23.27 | [23.74 , 34.28] | 29.01 |

Notes: For the operational fixed costs, we provide a 95% confidence interval for the estimated set, based on the two-sided bounds approach of Eizenberg (2014). The annualized capital cost incorporates a discount factor of $\delta = 0.90$ and a capital cost of $233 million. Total fixed cost is the sum of operational fixed cost and capital cost. Units are in millions of dollars.

reasonable approximation given that kilns tend to operate for many decades.

To make progress, we assume a discount factor of $\delta = 0.90$. For the capital cost, we make assumptions based on the CEMBUREAU estimates of construction costs (Section 2.2). Specifically, we assume that the capital cost is €175 million, and we convert that to dollars using the average closing price of the exchange rate in 2010, which is 1.33. This implies a capital cost ($E$) of $233 million.[40] Finally, for the operational fixed cost, we apply the two-sided bounds approach of Eizenberg (2014). In doing so, we exploit 175 instances in which we observe that a kiln is not operated during a year. This is referred to as "idling" or "mothballing" a kiln and it is often done when demand conditions are unfavorable. In Appendix C, we develop the bounds formally and provide details on implementation.

Table 3 summarizes our numerical analysis of fixed costs. For the operational fixed costs, we obtain an estimated set that provides model-implied bounds, separately for old kilns and modern kilns. We report a 95% confidence interval around those estimated sets. For each old kiln the confidence interval is [0.11, 3.75], and for each modern kiln it is [0.47, 11.01], where units are in millions of real 2010 dollars. These confidence intervals overlap but we cannot rule out the operational costs are significantly higher for modern kilns.[41] Putting these together with capital costs, we obtain an interval of [23.74, 34.28] for the total fixed cost of modern kilns. Finally, for the analyses below, we assume that total fixed costs are at the midpoint of the bounds. This provides $1.93 million per kiln-year for old kilns and $29.01 million per kiln-year for modern kilns.

With this quantification of fixed costs, we recover an average cost function for each plant and year in the sample. This allows us to examine how the adoption of modern kiln technology affects average costs, economies of scale, and the efficient level of production.

[40] In the Appendix, we recreate the main figures of this section using capital costs of $116 million (50% lower) and $349 million (50% higher). See Figure D.8.

[41] If we restrict the sample of idled kilns to those that also imply that the entire *plant* idles then the lower bound on the operational fixed cost for modern kilns increases to $3.1 million, whereas the other numbers do not change much.

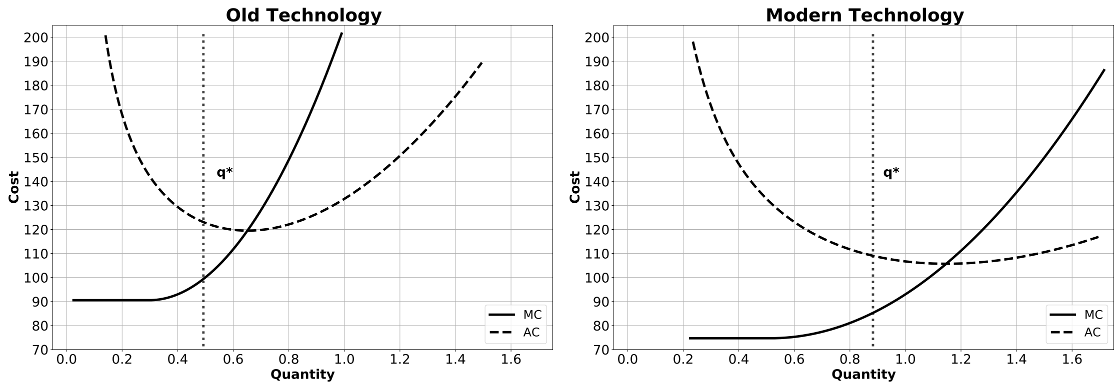


Figure 9: Plant-Level Cost Functions (Illustrative Example)

Notes: The figure plots marginal cost (MC) and average total cost (AC) functions at an Essroc plant in Nazareth, Pennsylvania. The left panel provides the cost functions in 1976, the final year before the plant adopted precalciner technology. The right panel corresponds to the year 1977. In both panels, the vertical axis is in dollars per metric tonne and the horizontal axis is in millions of metric tonnes. The vertical dotted lines show the equilibrium plant quantities ($q^*$).

Figure 9 provides an illustrative example using the Essroc plant in Nazareth, Pennsylvania, which replaced its eight older, long dry kilns with a single precalciner kiln in 1977. The left panel shows the average cost and marginal cost functions of the plant in 1976, prior to adoption, and the right panel shows those functions in 1977, after adoption. Equilibrium quantities ($q^*$) are marked with the vertical dotted lines. The efficient level of production—defined by the quantity that minimizes average costs—increases from 0.65 million metric tonnes to 1.15 million metric tonnes due to the adoption of modern technology. Average cost evaluated at the efficient level of production decreases from \$120 to \$106 per metric tonne. This is a particularly meaningful reduction given national average prices around \$114 per metric tonne (Figure 3). Therefore, technology adoption seemingly is an attractive proposition for this plant. However, the profitability of adoption *requires* a significant expansion of output. To see this, if the plant were to hold its output fixed at the 1976 equilibrium level of 0.49 million metric tonnes, then adoption would be unprofitable, as it would increase average cost from \$123 to \$134 per metric tonne. We find that equilibrium output does indeed increase with adoption, to 0.88 million metric tonnes, which allows the plant to realize a sizeable reduction in average cost.

To generalize across plants, we use the ratio of average cost to marginal cost, which is a standard measure of scale economies (Syverson, 2019). If the ratio is greater than one then average costs are decreasing in output, meaning economies of scale exist. If it is less than one then diseconomies of scale exist, and if it equals one then output is at the efficient level. Furthermore, as the ratio of average cost to marginal cost equals the inverse of the elasticity of total cost with respect to quantity, its value has the interpretation as being the

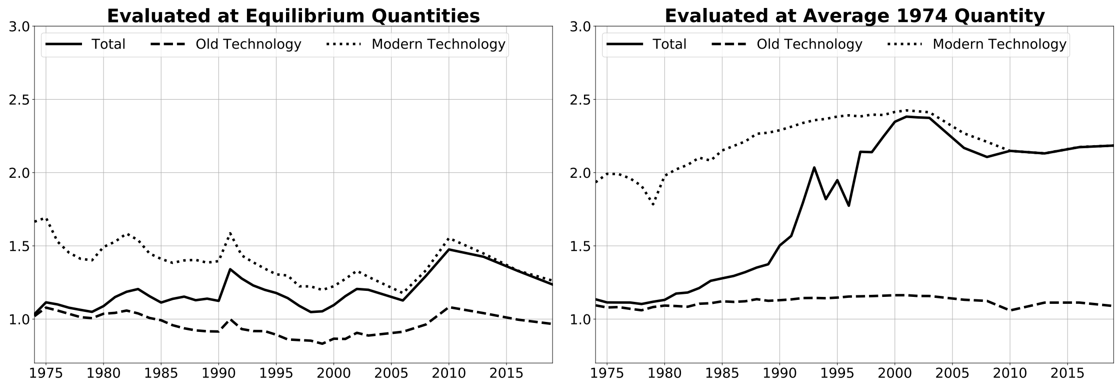


Figure 10: Scale Elasticities in the Cement Industry, 1974-2019

Notes: The figure plots the ratio of average cost to marginal cost (the "scale elasticity"). The ratios shown are quantity-weighted medians across plants. The left panel evaluates the average cost and marginal cost functions at equilibrium quantities. The right panel evaluates the functions at the average output of a plant in 1974, which we obtain from the model. Medians are shown for all plants, plants with old technology, and plants with modern technology.

percentage change in quantity that can be obtained from a one percent increase in cost, and we sometimes refer to it as the *scale elasticity*.[42] We calculate the ratio for every plant and year, and examine how scale economies have evolved.

Figure 10 summarizes the results. The left panel plots the quantity-weighted median scale elasticity, evaluated at the equilibrium quantities that we obtain from the model. Among all plants, the median scale elasticity increases from 1.03 in 1974 to 1.23 in 2019. The scale elasticity is greater for plants with modern technology than it is for plants with old technology, and the upward trend in the industry-wide number is mainly due to a compositional shift toward modern technology.

The increase in the scale elasticity over the sample period is consistent with a meaningful impact of modern kiln technology. However, the left panel understates this impact. Economies of scale are equilibrium outcomes in models with fixed costs and increasing marginal costs because they depend on how much firms choose to produce. Returning to the illustrative example, the scale elasticity of the Essroc plant in Nazareth is 1.24 with old technology (in 1976) and 1.28 with modern technology (in 1977). The change is modest because it reflects the decision of the plant to expand output. If one evaluates the scale elasticity of the Essroc plant in 1977, but under the counterfactual that output is at its 1976 level, the scale elasticity is 1.79. In our view, this better demonstrates that modern kiln technology allowed the plant to increase output in a cost-efficient manner.

We extend this thought experiment to the full sample in the right panel of Figure 10, which plots the quantity-weighted median scale elasticity evaluated at the average plant-

[42]For any differentiable total cost function $C(Q)$, we have $C'(Q)(Q/C) = MC/AC$.

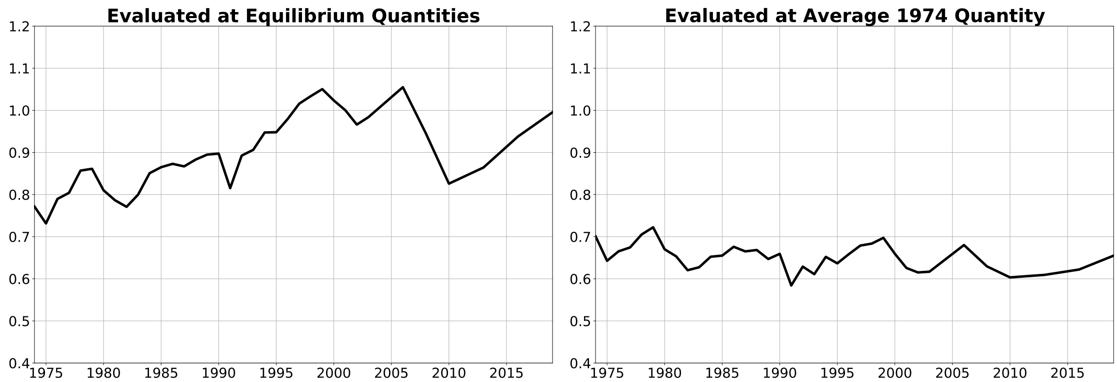


Figure 11: Ratio of Price to Average Cost, 1974-2019

Notes: The figure plots the quantity-weighted median ratio of price to average cost for plants with modern technology. The left panel evaluates the ratio at equilibrium quantities. The right panel evaluates the ratio at the average output of a plant in 1974.

level output of 1974.[43] Among all plants, we find that the median scale elasticity increases from 1.15 in 1974 to 2.18 in 2019, with the change again mainly being due to a compositional shift toward modern technology. Thus, the amount of additional output that can be generated by incurring an increase in costs nearly doubles (evaluated at the same level of output). This demonstrates the impetus for output expansion that precalciner technology creates for plants that adopt it, and supports the centrality of precalciner technology in explaining the industry shakeout that occurred over the sample period.

As a final exercise, we examine the ratio of price to average cost, which is a standard measure of economic profitability. We focus on plants with modern kilns because we have a measure of capital costs for those kilns. Figure 11 plots the quantity-weighted median ratio evaluated at equilibrium quantities (left panel). The ratio starts below one, but then increases over time until it stabilizes around one for the back half of the sample.[44] This suggests that the variable profit that plants obtain with modern kilns may be just enough to recover the fixed costs associated with adopting and operating the new technology.[45] However, if the ratio of price to average cost is evaluated at the average 1974 quantity (right panel), then it is well less than one throughout the sample period. This again supports that output expansion is necessary for precalciner adoption to be profitable.

[43]To be clear, we evaluate the ratio of average to marginal costs for every plant-year observation under the counterfactual that output is 0.39 metric tonnes, which is the mean plant-level output predicted by our model for 1974. In constructing the quantity-weighted median, we use the equilibrium quantities from the model. Therefore, the weights applied in the top and bottom panels of Figure 10 are the same.

[44]The dip in profitability in 2010 is due to the recession, which significantly reduced purchases (Figure 1).

[45]Alternatively, if one has a prior that the cement industry is characterized by free entry and exit in the long run, then the results corroborate that our estimates of fixed costs are in a reasonable range.

# 6 Conclusion

In this paper, we have sought to trace out the effects of a major technological advance in the cement industry—the precalciner kiln—and connect our results to the literature on *The Rise of Market Power*. Our results indicate that local market concentration and markups increased over 1974-2019. Nonetheless, real prices do not rise. These empirical patterns can be understood through the economics of precalciner technology, which lowered the marginal cost of production and significantly increased plant-level capacities, thereby contributing to an industry shakeout in which many plants closed. Our findings demonstrate the importance of accounting for technological change when considering the possible implications of rising market concentration.

Our analysis advances the literature along multiple dimensions, but it also is subject to a number of limitations. We highlight three here. First, although we present evidence consistent with precalciner technology contributing to the shakeout that occurred during the sample period, we do not model that dynamic process formally because it would require sacrificing some of the modeling realism that lends credibility to our results. With our results in hand, however, there is an improved ability for future research to extend in that direction (e.g., as in Igami, 2017; Igami and Uetake, 2020). Second, as with any industry study, the external validity of the results that we obtain needs to be treated carefully. There is an important role for research that takes a broader perspective and pulls together results that have been obtained across industries. In the context of *The Rise of Market Power* this is increasingly likely to be fruitful, as studies have now been conducted in a number of different contexts. Finally, our methodological approach uses modeling to infer objects of interest, such as local market concentration and markups. To the extent that more detailed data can be obtained—in the United States or elsewhere—a more data-driven analysis could provide useful insights that could corroborate (or contradict) our findings.

Other possibilities for future research involve extending our model to examine new research questions. For example, one could study the efficacy of merger policy or the approach that antitrust authorities take to defining geographic markets, leveraging that the Federal Trade Commission has filed four complaints against mergers between cement producers in the past decade, resulting in three consent decrees and one abandoned transaction. Alternatively, additional research could be conducted on the environmental impact of the cement industry and how market power affects the efficacy of regulation.

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# Appendix Materials

## A Data Details

### A.1 Measuring Fuel Costs

We take a similar approach to that in Miller et al. (2017) to measure fuel costs of each kiln, which we calculate based on fossil fuel prices and kiln energy requirements. The calculation is

$$\text{Kiln Fuel Cost}_{jt} = \text{Primary Fuel Price}_{jt} \times \text{Energy Requirements}_{jt}$$

where the primary fuel price is in dollars per mBtu and the energy requirements are in mBtu per metric tonne of clinker.

We use the state-level average prices of coal, natural gas, and distillate fuel oil paid by the industrial sector, which we obtain from the State Energy Database System (SEDS). Some kilns list multiple primary fuels in the *Plant Information Summary*. As the mix of primary fuels is unknown, we treat such kilns as follows: We calculate fuel costs with the price of coal if coal or petroleum coke are among the primary fuels. If not, we use natural gas prices if natural gas is among the multiple fuels. We use oil prices only if oil is the only fossil fuel listed.

We calculate the energy requirements of each kiln technology based on the *U.S. and Canadian Portland Cement Labor-Energy Input Survey*. There is no discernible change in the energy requirements of production, conditional on the kiln type, over 1990-2010. We calculate the average mBtu per metric tonne of clinker required in 1990, 2000, and 2010, separately for each kiln type, and apply these averages over 1990-2016. These requirements are 3.94, 4.11, 5.28, and 6.07 mBtu per metric tonne of clinker for precalciner kilns, preheater kilns, long dry kilns, and wet kilns, respectively. A survey of the USGS accords with our calculations (Van Oss (2005)). Technological improvements within kiln type are evident over 1974-1990. The labor-energy surveys indicate that in 1974 the energy requirements were 6.50 mBtu per metric tonne of clinker at dry kilns (a blended average across dry kiln types), and 7.93 mBtu per metric tonne of clinker at wet kilns. We assume that technological improvements are realized linearly over 1974-1990 and scale the energy requirements accordingly. Lastly, we scale down our calculated energy requirements by five percent to reflect that a small amount of gypsum is ground together with the kiln output to form cement.

Appendix Figure D.9 plots the fraction of industry capacity that uses each fossil fuel as its primary source of energy, based on this methodology (top panel). In the early years of the sample, natural gas and fuel oil are used as the primary fuel by some kilns. In the middle years, coal and petroleum coke are the only primary fuels used. In the final year, some kilns switch back to natural gas. The figure provides the prices of these fuels (bottom panel). Usage tracks relative prices.

### A.2 Customs Districts

In the model we assume that buyers can purchase imported cement from the nearest active customs district. We implement in a manner that addresses a number of stylized facts about trade flows: First, there is a great deal of heterogeneity in the throughput of the customs districts. Second, the amount of cement that flows through specific customs districts is often small or negligible through the early years of the sample, then grows later in the sample. Third, in some years with low demand, the quantity of imports can fall to nearly zero even in the largest customs districts.

Our approach is to identify the customs districts that provide the greatest access to imported cement. To that end, we take the following steps:

1. For each customs district, we calculate the maximum quantity of imported cement that arrives within a year over 1974-2019.
2. We rank the customs districts according to this maximum, and select the top 20.
3. We designate these top 20 ports as "active" once import quantities reach 30% of the port's maximum level, and in every subsequent year.
4. We assume that imported cement is available only at the top 20 customs districts, and only in years in which they are active.

We find that this allows the model to match the quantity of imports over time (Figure D.4). The top 20 customs districts, in descending order of the maximum quantity of imported cement received in a year, are: New Orleans LA, Tampa FL, Los Angeles CA, Houston TX, San Francisco CA, Detroit MI, Miami FL, Seattle WA, New York City NY, Charleston SC, Columbia-Snake / Portland OR, Nogales AZ, Cleveland OH, Buffalo NY, Norfolk VA, Mobile AL, Ogdensburg NY, Providence RI, San Diego CA, and El Paso TX.

The customs districts that we exclude, again in descending order of the maximum quantity of imported cement received in a year, are: Philadelphia PA, Milwaukee WI, Savannah GA, St. Albans VT, Baltimore MD, Wilmington NC, Boston MA, Duluth MN, Pembina ND, Chicago IL, Great Falls MT, Laredo TX, Minneapolis MN, Portland ME, and Bridgeport CT.

## B Connecting Empirical Variation to Parameters

In this appendix, we describe informally how the different moments that we use can pin down different parameters. To do so transparently, we consider an alternative parameterization of the model in which demand is logit ($\sigma = 0$), marginal cost is constant in output, and the gross utility and marginal cost functions are $\overline{u}_{jnt}(\boldsymbol{X}_t, \boldsymbol{\theta}) = \boldsymbol{x}_{jnt}\boldsymbol{\beta}$ and $c_{jt} = \boldsymbol{w}_{jt}\boldsymbol{\alpha}$, respectively, where $\boldsymbol{x}_{jnt}$ is an $M$ dimensional vector of demand covariates and $\boldsymbol{w}_{jt}$ is an $L$-vector of cost shifters. There are $M + L + 1$ parameters to be identified: the demand parameters in $\boldsymbol{\beta}$, the price parameter $\phi$, and the cost parameters in $\boldsymbol{\alpha}$.

We start under the baseline assumption that the econometrician observes market shares and average prices at the plant-county level, and return to the implications of having more aggregate data later. The equations for shares and average prices are:

$$s_{jnt} = \frac{\exp(\boldsymbol{x}_{jnt}\boldsymbol{\beta} - \phi \boldsymbol{w}_{jt}\boldsymbol{\alpha})}{1 + \sum_k \exp(\boldsymbol{x}_{knt}\boldsymbol{\beta} - \phi \boldsymbol{w}_{kt}\boldsymbol{\alpha})} \tag{B.1}$$

and

$$\overline{p}_{jnt} = \boldsymbol{w}_{jt}\boldsymbol{\alpha} + \frac{1}{\phi}\frac{1}{s_{jnt}} \log\left(\frac{1}{1 - s_{jnt}}\right) \tag{B.2}$$

Consider first the cost and price parameters. It is possible to solve equation (B.2) for both $\boldsymbol{\alpha}$ and $\phi$ under mild conditions because both market shares and average prices are data. To see why, stack the prices into a vector $\overline{\boldsymbol{p}}$ and let the matrix $\boldsymbol{W}$ to combine the cost shifters and the markup terms, such the the row corresponding to plant $j$, county $n$, and period $t$ is given by

$$\left[\boldsymbol{w}_{jnt}, \quad \frac{1}{s_{jnt}} \log\left(\frac{1}{1 - s_{jnt}}\right)\right]$$

With this notation in place, we can write

$$\overline{\boldsymbol{p}} = \boldsymbol{W}\left[\boldsymbol{\alpha}, \quad \frac{1}{\phi}\right]$$

A sufficient condition for a unique solution is that $\boldsymbol{W}$ has full column rank and there are at least $M+1$ equations. The intuition is identical to the identification necessary for regression coefficients.

For the demand parameters, once $\boldsymbol{\alpha}$ and $\phi$ have been recovered, they can be plugged into equation (B.1), and this allows a solution for $\boldsymbol{\beta}$ to be obtained under mild conditions. In particular note that the usual share inversion holds:

$$\log(s_{jnt}) - \log(s_{0nt}) = \boldsymbol{x}_{jnt}\boldsymbol{\beta} - \phi \boldsymbol{w}_{jt}\boldsymbol{\alpha} \tag{B.3}$$

where $s_{0nt}$ is the share of the outside good. Let $\boldsymbol{y}$ be a vector with the element corresponding to plant $j$, county $n$, and period $t$ being given by

$$\left[\log(s_{jnt}) - \log(s_{0nt}) + \hat{\phi}\boldsymbol{w}_{jt}\boldsymbol{\alpha}\right]$$

and let $\boldsymbol{X}$ be a matrix with the same row given by $\boldsymbol{x}_{jnt}$. Identification is obtained if $\boldsymbol{Y} = \boldsymbol{X}\boldsymbol{\beta}$ can be solved for $\boldsymbol{\beta}$. A sufficient condition is that there are at least $L$ equations and that $\boldsymbol{X}$ has full column rank, with intuition again identical to the case of regression.

These identification arguments reveal an important property of the second-score auction model: estimation based on the market share inversion of equation (B.3) alone does not separate the price parameter from the cost parameters, as these enter only through there multiplicative products. Furthermore, each demand parameter is identified only to the extend that the corresponding demand shifter is not also a cost shifter. Thus, price moments are necessary to separately identify all of the parameters of the model.

In cases for which estimation is based on aggregated moments, as in our application, global identification typically must be assumed. Miller and Osborne (2014a) provides a discussion that covers identification and the conditions under which asymptotic consistency and normality are obtained in that context. Among the moments we use in this application, all but the price moments can be calculated from equilibrium market shares. These cannot disentangle the cost parameters from the price parameter, and they cannot separately identify the demand and cost coefficients for any variable that enters demand and cost (which in our case is the time trend and the constant). Still, they do pin down the demand parameters that characterize the disutility of distance and they also help determine the multiplicative products of the cost parameters and the price parameter. The price moments we use are necessary then to separately identify all of the parameters.

# C Two-Sided Bounds on Operational Fixed Costs

This appendix details our approach to estimating two-sided bounds for operational fixed costs, which follows Eizenberg (2014). Adapting the Eizenberg notation to our setting, let the operational fixed cost associated with operating kiln $r$ be given by

$$F_{rt} = F^d + \nu_{rt}$$

where $F^d$ takes one value for wet and long dry kilns and another value for modern preheater and precalciner kilns (we use the $d$ to distinguish technologies), and $\nu$ is mean-zero stochastic term with bounded support. We suppress time subscripts for the remainder of this section.

Let firms simultaneously determine which kilns to operate each year, with payoffs then being determined by the second-score auction model of Section 3. The key identifying assumption is that observed outcomes satisfy the equilibrium condition that no firm can improve its profit by idling a kiln observed to be active, or by operating a kiln observed to be idle, taking as given the status of all other kilns. Consistent with this assumption is that idling is often observed when demand conditions are unfavorable. For instance, in the average year we observe that 2% of kilns idle, but in 2010—just after the Great Recession—19 of 155 kilns (12%) idle.

The identifying assumption would be violated if some kilns are idled due to unanticipated breakdowns, and indeed we understand that breakdowns can occur. Such a violation of the identifying assumption ends up being benign for the bounds that we construct, however. The reason is that idled kilns are used to construct the lower bound of operational fixed cost, and the main ingredient to the lower bound is the minimum profit that any idled kiln would have earned had it operated (as we show mathematically below). That minimum is most likely to come from a kiln that satisfies the assumption that it is idled due to unfavorable conditions.

Because fixed costs have bounded support, the following bounds obtain:

$$L_r(\boldsymbol{X}, \boldsymbol{\theta}) \leq F_r \leq U_r(\boldsymbol{X}, \boldsymbol{\theta}) \tag{C.1}$$

These are trivially satisfied for any small enough $L_r(\cdot)$ and big enough $U_r(\cdot)$. The central methodological contribution of Eizenberg (2014) is in using data to inform how tight the bounds can be made. The first step is to obtain the incremental gain to variable profit that a firm obtains (or would obtain) by operating a kiln. For kiln $r$ owned by firm $f(r)$, we denote the incremental gain as

$$\Delta_r(\boldsymbol{X}, \boldsymbol{\theta}) \equiv \pi^*_{f(r)}(\boldsymbol{X}, \boldsymbol{\theta} | r \text{ operates}) - \pi^*_{f(r)}(\boldsymbol{X}, \boldsymbol{\theta} | r \text{ idles})$$

where we hold fixed the observed status of other kilns. For any kiln that operates, the first term on the right-hand-side can be obtained from the observed equilibrium, and the second term is obtained with a counterfactual simulation. This is reversed for any kiln that is idle. Thus, to recover $\Delta_r(\boldsymbol{X}, \boldsymbol{\theta})$, we simulate one counterfactual equilibrium for each kiln-year in the data.

One-sided bounds are possible to compute without additional assumptions.[46] To inform the two-sided bounds of equation (C.1), Eizenberg assumes that the variation in incremental gain across observations is likely to exceed the variation in fixed costs, and describes why assumption is reasonable in many settings. We adopt that assumption here. Letting

[46]For any kiln that operates, $F_r \leq \Delta_r(\cdot)$. For any kiln that is idle, $F_r \geq \Delta_r(\cdot)$.

$A_d^0$ and $A_d^1$ be the sets of kilns that idle and operate, respectively, and separately by kiln technology, the bounds then can be expressed:

$$L_r(\boldsymbol{X},\boldsymbol{\theta}) = \begin{cases} \min_{m\in A_d^0} \Delta_m(\boldsymbol{X},\boldsymbol{\theta}) & r \in A_d^1 \\ \Delta_r(\boldsymbol{X},\boldsymbol{\theta}) & r \in A_d^0 \end{cases} \tag{C.2}$$

and

$$U_r(\boldsymbol{X},\boldsymbol{\theta}) = \begin{cases} \Delta_r(\boldsymbol{X},\boldsymbol{\theta}) & r \in A_d^1 \\ \max_{m\in A_d^1} \Delta_m(\boldsymbol{X},\boldsymbol{\theta}) & r \in A_d^0 \end{cases} \tag{C.3}$$

The final step is to average across these bounds to gain knowledge of the $F^d$ terms. Taking unconditional expectations obtains

$$\mathbb{E}[L_r(\boldsymbol{X},\boldsymbol{\theta})] \leq F^d \leq \mathbb{E}[U_r(\boldsymbol{X},\boldsymbol{\theta})]$$

which defines the identified set for $F^d$. The estimated set is $\left[\bar{l}^d(\boldsymbol{X},\hat{\boldsymbol{\theta}}), \bar{u}^d(\boldsymbol{X},\hat{\boldsymbol{\theta}})\right]$ where the elements are sample averages:

$$\bar{l}^d(\boldsymbol{X},\hat{\boldsymbol{\theta}}) = \frac{1}{N^d}\sum_{m=1}^{N^d} L_m(\boldsymbol{X},\hat{\boldsymbol{\theta}}) \qquad \bar{u}^d(\boldsymbol{X},\hat{\boldsymbol{\theta}}) = \frac{1}{N^d}\sum_{m=1}^{N^d} U_m(\boldsymbol{X},\hat{\boldsymbol{\theta}})$$

with $N^d$ being the number of kilns of type $d$. Because far more kilns operate than idle, the lower bound is mostly determined by the $\min$ function (equation (C.2)) whereas the upper bound is not much affect by the $\max$ function (equation (C.3)).

Following Eizenberg and Imbens and Manski (2004), we report a $(1-\alpha)\times 100\%$ confidence interval for $F^d$ by constructing one-sided intervals for the sample averages:

$$\left[\bar{l}^d(\boldsymbol{X},\hat{\boldsymbol{\theta}}) - \frac{S_l(\boldsymbol{X},\hat{\boldsymbol{\theta}})}{\sqrt{N^d}} z_{1-\alpha}\ ,\ \bar{u}^d(\boldsymbol{X},\hat{\boldsymbol{\theta}}) + \frac{S_u(\boldsymbol{X},\hat{\boldsymbol{\theta}})}{\sqrt{N^d}} z_{1-\alpha}\right] \tag{C.4}$$

where $S_l(\boldsymbol{X},\hat{\boldsymbol{\theta}})$ and $S_u(\boldsymbol{X},\hat{\boldsymbol{\theta}})$ are standard deviations of $L_r$ and $U_r$. Our confidence intervals do not account for statistical uncertainty from auction model estimation.

We implement using 8552 kiln-year observations. Of these, we observe 175 in which a kiln is idled in a given year—140 involving old technology kilns and 25 involving modern kilns. Our counterfactual simulations indicate that $\Delta_r$ equals zero for 732 observations (9%), and we exclude those from our subsequent calculations. One limitation of our analysis is that, among the 25 instances in which a modern kiln idles, 24 involve preheater kilns that do not have the supplementary combustion chamber of a precalciner kiln. Thus, our bounds estimates may reflect the operation fixed cost of preheater kilns more than the broader set of modern preheater and precalciner kilns.

# D Additional Figures and Tables

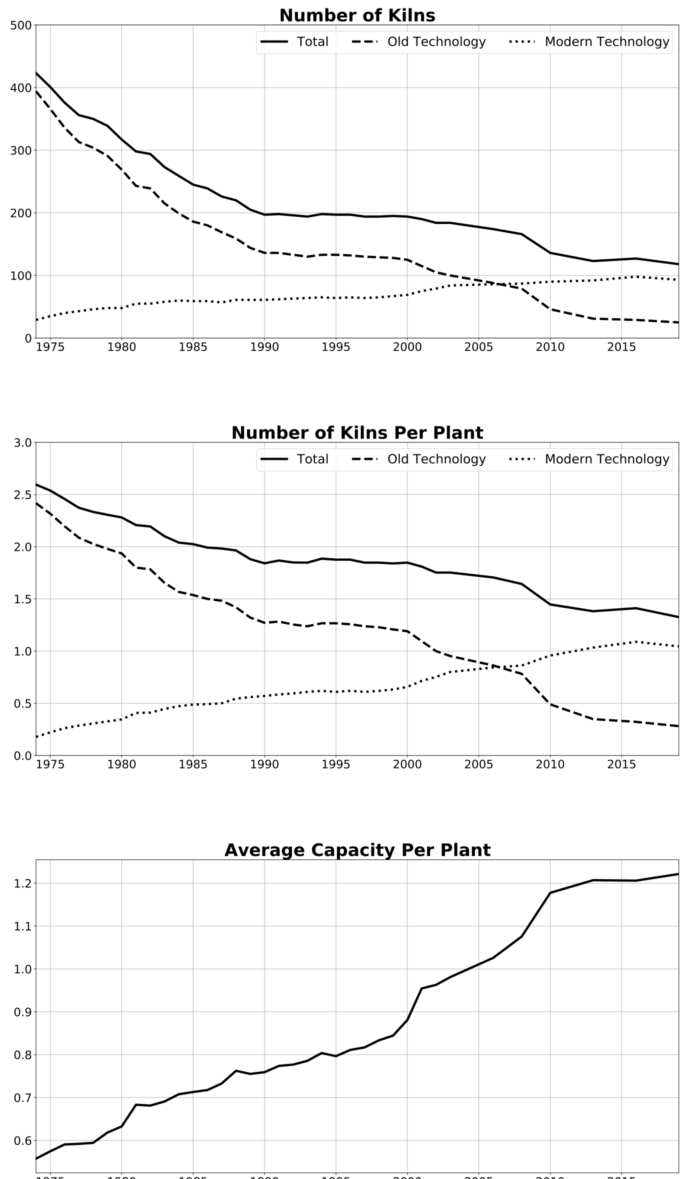


Figure D.1: Additional Kiln-Level and Plant-Level Statistics, 1974-2019

Notes: The figure shows the number of kilns (top panel), the average number of kilns per plant (middle panel), and the average plant capacity in millions of metric tonnes (bottom panel) over the sample period. We designate kilns as using "Old Technology" if the kiln is a wet kiln or a long dry kiln, and as using "Modern Technology" if the kiln uses a precalciner or a preheater. Data are from the *Plant Information Summary* of the Portland Cement Association.

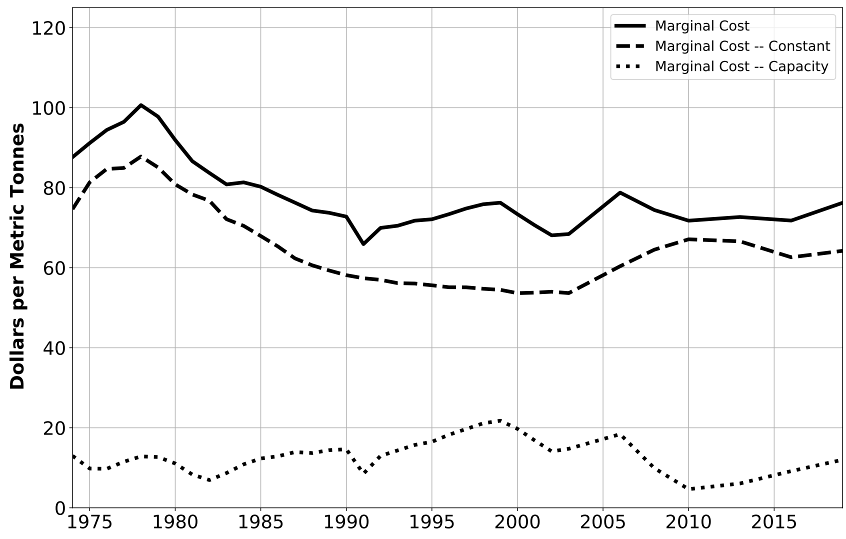


Figure D.2: Marginal Cost and Marginal Cost Components, 1974-2019

Notes: The figure plots the average plant-level marginal cost over the sample period, as well as a decomposition that separates marginal cost into a constant portion and a portion that is due to capacity constraints. Variation in the constant portion of marginal cost is predominately due to changes in fossil fuel prices (e.g., Figure D.9) and changes in kiln technology that improve fuel efficiency. Variation in the portion due to capacity constraints is predominately attributable to macroeconomic demand-side fluctuations that affect the utilization rates of domestic kilns.

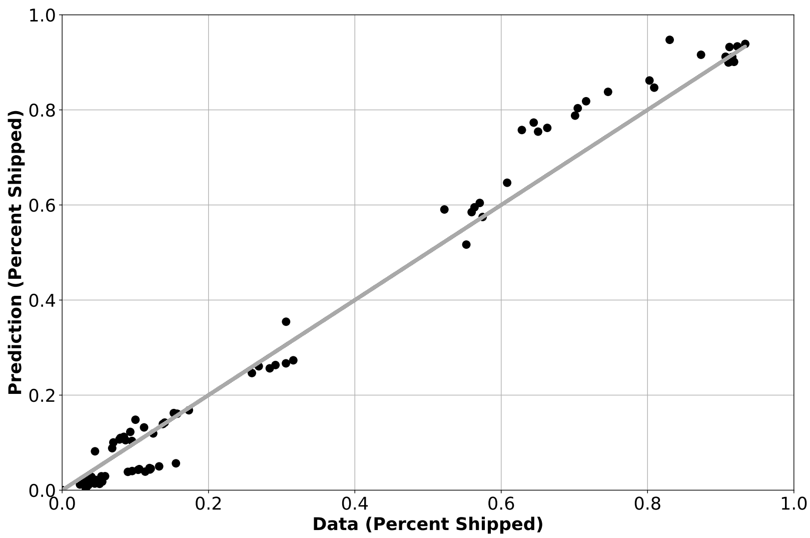


Figure D.3: Model Fit for Observed Cross-Region Shipments

Notes: The dots in the scatter plot represent the fraction of shipments from Northern California, Southern California, or California that go to the same regions, Arizona, and Nevada. Section 2.3 describes the *California Letter* data in greater detail. The horizontal location of each dot provides the value in the data and the vertical location provides the value in the model. The dots are clustered around the 45-degree line, illustrating the fit of the model.

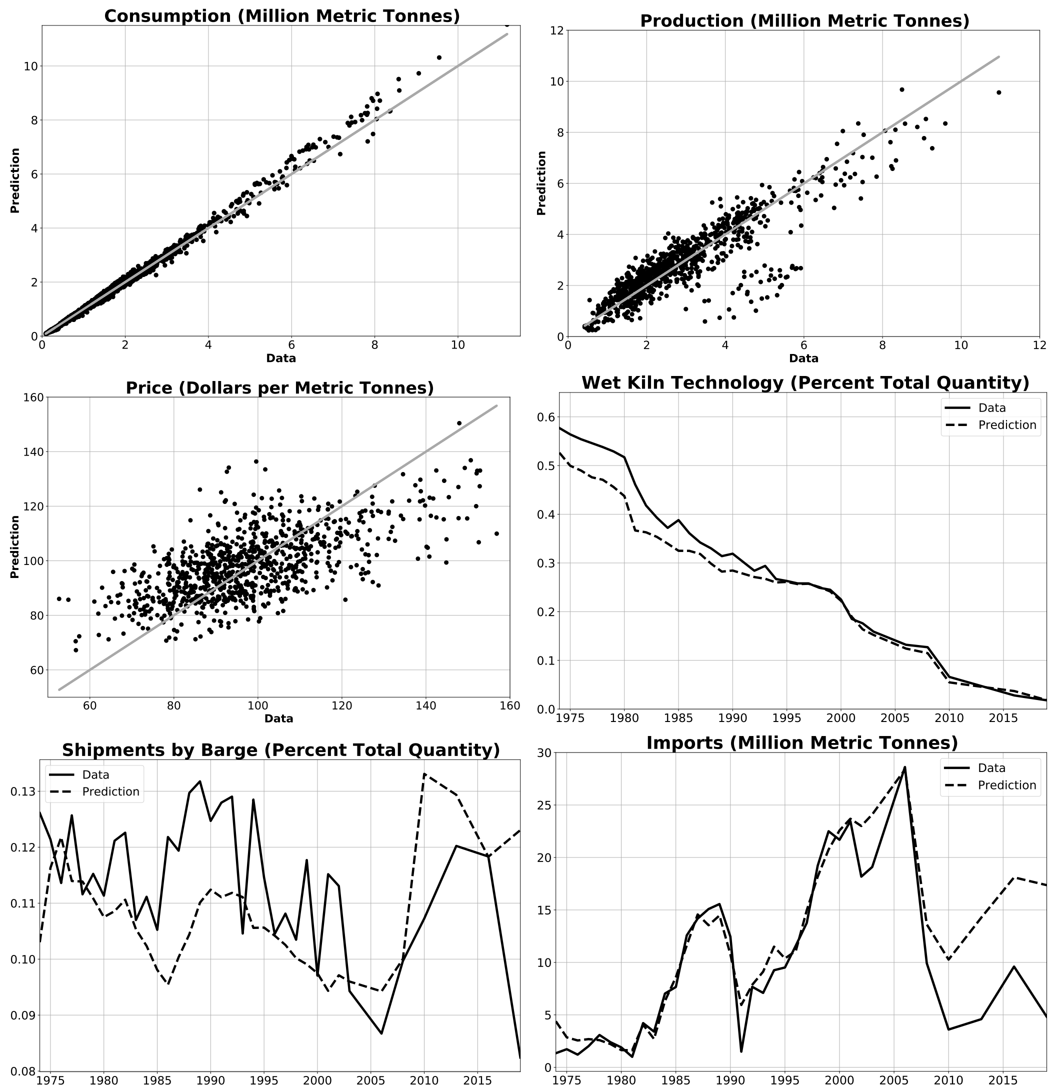


Figure D.4: Additional Model Fits

Notes: The first three panels show the panel fit to region-year specific consumption, production, and average prices. The other panels show time-series fits for the proportion of production by plants with a wet kiln, the proportion of shipments that use a river barge, and the quantity of imports. A 45-degree line is provided in all scatter plots. In the panel for production, the dots for which the model significantly understates the data correspond to Colorado, Wyoming, and Kansas. The model may understate the ability of plants in those states to reach distant buyers using rail transportation.

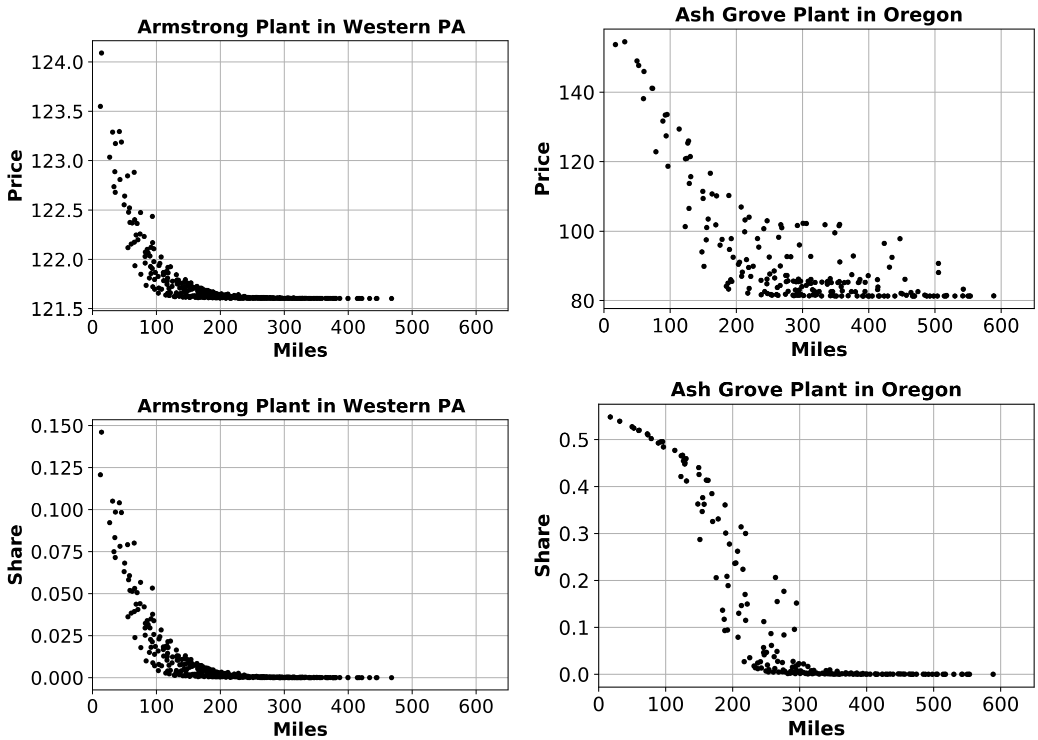


Figure D.5: Illustration of Spatial Differentiation and Price Discrimination

Notes: The top panels show county-specific average price per metric tonne charged by an Armstrong plant in Western Pennsylvania (left) and an Ash Grove Plant in Oregon (right). The horizontal axis show the miles between the county and the plant. The bottom panels display the market shares for the same plants in every county. Prices and market shares are obtained from the model for the year 2019. Comparing the two plants, note that the scales of the vertical axes are quite different. Whereas both plants obtain higher prices and greater market shares from nearby counties, these patterns are more pronounced for the Ash Grove plant, which is more isolated from competitors.

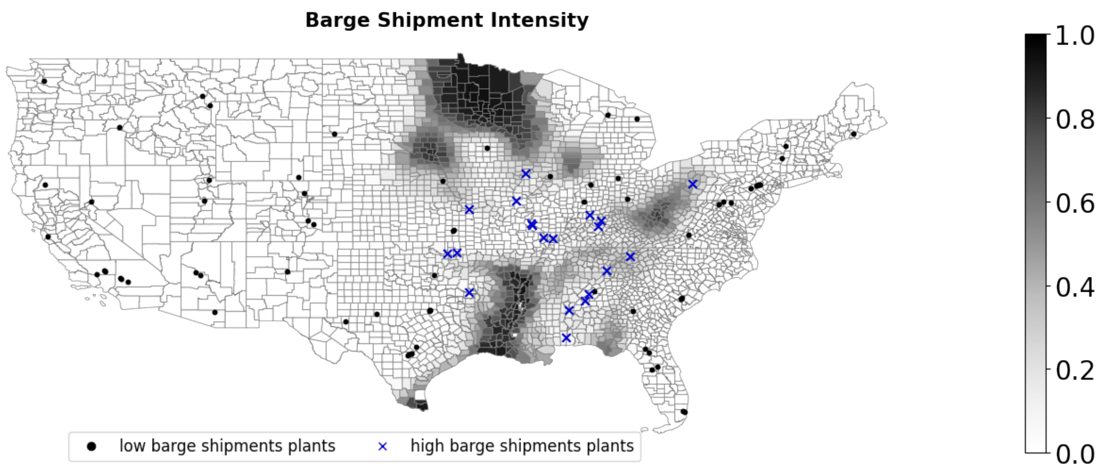


Figure D.6: Barge Shipment Sources and Destinations

Notes: The county-level shading depicts the proportion of cement consumption in 2019 for which barge transportation is utilized. Plants are identified as high barge shipment plants if more than 15 percent of their cement is shipped using a barge. All statistics are based on the modeling results for 2019. The counties and plants that use barge transportation heavily are near the Mississippi River System, but differ in where along the river they are located.

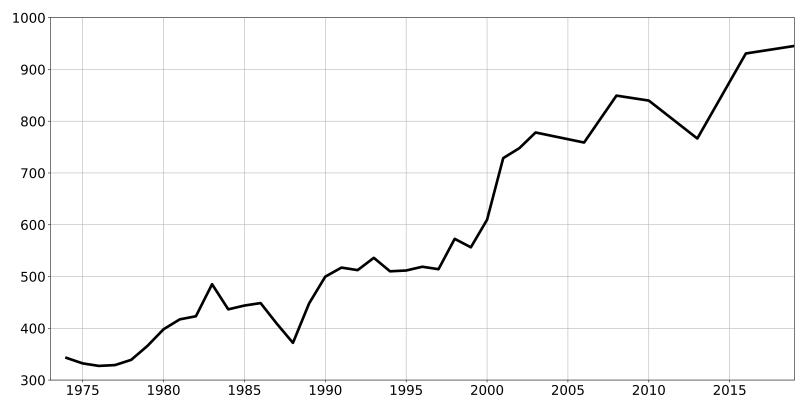


Figure D.7: The National Capacity-Based HHI, 1974-2019

Notes: The figure plots a measure of the national-level HHI that we calculate using data on the capacity shares of domestic firms obtained from the *Plant Information Summary* of the Portland Cement Association. At the national level, concentration is increasing, just as it is locally (Figure 6). However, the national-level HHI is significant lower than average county-level HHIs, and does not capture the local competition that matters for cement buyers.

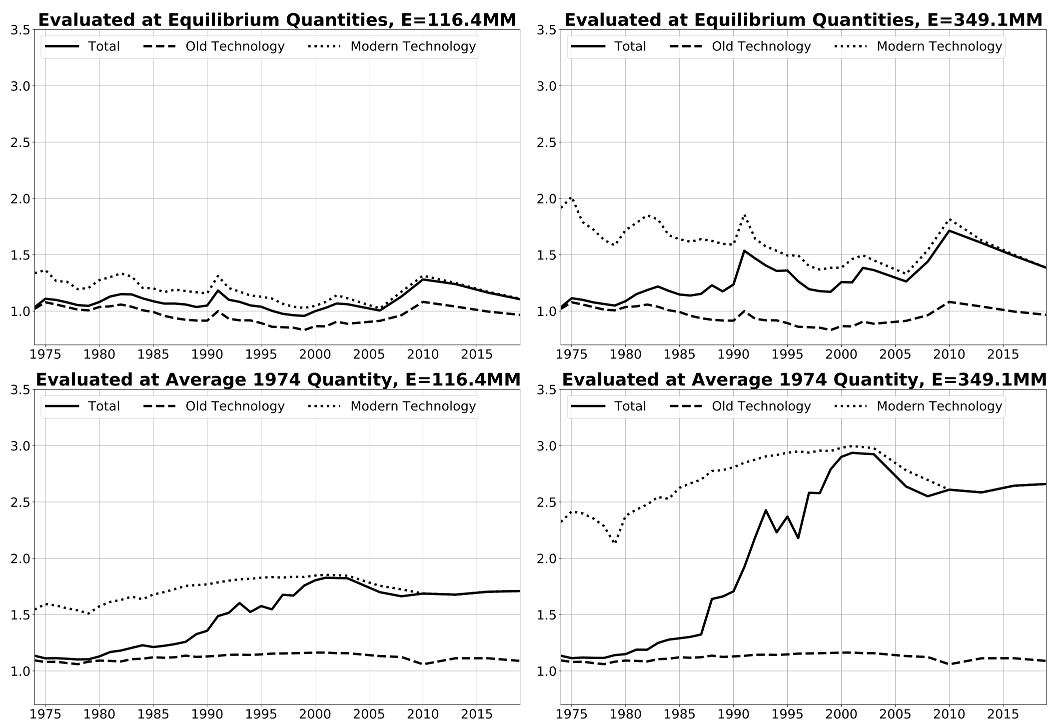


Figure D.8: Robustness Analysis for the Scale Elasticities

Notes: The figures show the quantity-weighted median ratio of average cost to marginal cost for alternate fixed cost values. The top panels evaluate the average cost and marginal cost functions at equilibrium quantities with a 50% reduction in fixed costs (left, $E = 116.4$) and a 50% increase in fixed costs (right, $E = 349.1$), relative to our baseline analysis. The bottom panels evaluate the functions at the average output of a plant in 1974, which we obtain from the model. Medians are shown for all plants, plants with old technology, and plants with modern technology.

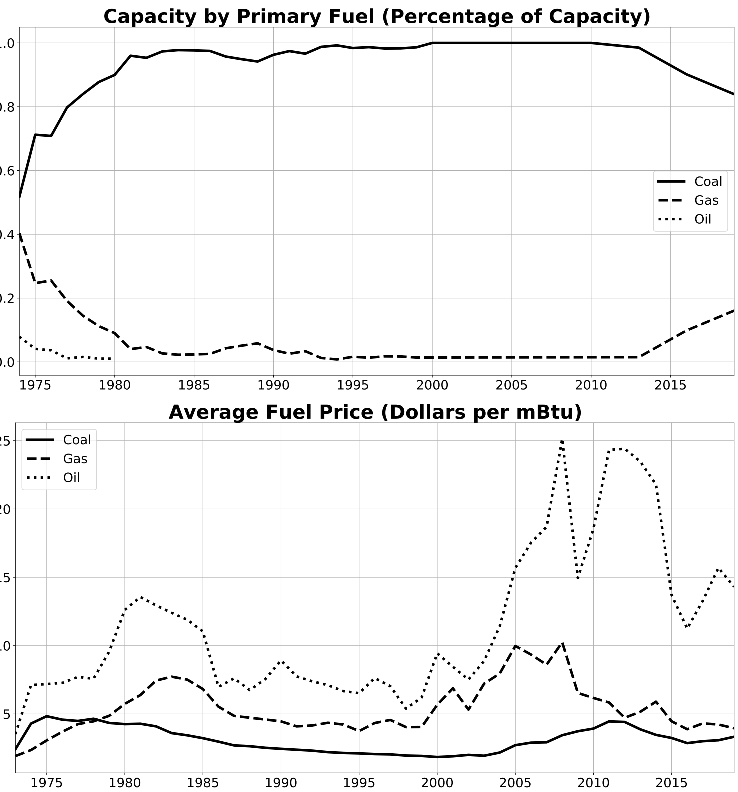


Figure D.9: Primary Fuels and Fuel Prices

Notes: The top panel plots the fraction of kiln capacity that burns as its primary fuel (i) coal or petroleum coke, (ii) natural gas, and (iii) fuel oil. Data are from *Plant Information Summary*. The bottom panel plots the average national prices paid for these fuels by the industrial sector in real 2010 dollars per mBtu. Data are from the State Energy Data System (SEDS). The figure demonstrates that plants tend to select a primary fuel that has a low price. It also illustrates the sustained dip in fossil fuel prices that occurred in the 1990s and surrounding years.

Table D.1: County-Level Concentration in 1974 and 2019

| | 1974 | | 2019 | |
|---|---|---|---|---|
| | Number of Counties | Proportion of Consumption | Number of Counties | Proportion of Consumption |
| HHI<1500 | 853 | 31.0% | 171 | 3.2% |
| 1500≤HHI<2500 | 885 | 26.7% | 898 | 35.1% |
| HHI≥2500 | 1,292 | 42.4% | 1,962 | 61.7% |
| HHI≥5000 | 528 | 8.2% | 639 | 12.2% |
| HHI≥6000 | 383 | 6.1% | 459 | 6.3% |

Notes: County-level HHIs are obtained from the model. The 2010 *Horizontal Merger Guidelines* classify markets with HHI under 1500 as "unconcentrated," markets with HHI between 1500 and 2500 as "moderately concentrated," and markets with HHI above 2500 as "highly concentrated."