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

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Abstract

We examine the evolution of concentration and markups in the cement industry over more than four decades in the United States. We estimate a model in which buyers use a second-score auction to procure cement from spatially differentiated plants. The model matches aggregated outcomes in the data, and the implied transportation costs and shipping distances are consistent with external sources. We infer local market concentration and markups from the model. At the county-level, the median HHI rises from 1,890 to 2,660 during the sample period. Average markups increase modestly, but prices do not rise. We attribute these changes to a technological innovation—the precalciner kiln—that lowered variable costs, increased plant-level capacities, and also 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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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 gain an understanding of how this transformation has affected scale economies, prices, markups, and market concentration 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) combines accounting data with production function estimates for a large number of firms in the U.S. and determines 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 change.

Our methodological approach is to estimate an oligopoly model of supply and demand using publicly-available, aggregated data on prices and quantities. At a high level, this 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 often are transaction-specific and specified in confidential business contracts. As a result, researchers often do not observe the prices that are available to buyers or the terms-of-trade that ultimately are realized. This challenge is present in the present application, as we observe decades of data on plant-level technologies and coarsely aggregated prices and quantities.

To make progress, we develop an empirically tractable model of procurement that nonetheless preserves the richness of the institution 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). Suppliers maximize profit by bidding at marginal cost. Under a parametric assumption proposed in Miller

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

(2014), we obtain closed-form expressions for the equilibrium market shares and average 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. The key identifying assumption is that plant 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 demand and marginal cost parameters in hand, we bound kiln-level fixed costs using the approach of Eizenberg (2014), which allows us to obtain average cost functions and evaluate scale economies.

The modeling results indicate rising concentration at the local market level that can be attributed to the adoption of precalciner kilns and the associated industry shakeout. Weighting by a measure of county size, we find that the median county-level HHI increases from 1,890 to 2,660 during the sample period, a change that is equivalent to a reduction in the number of symmetric firms from 5.3 to 3.8. By 2019, the majority of counties have an HHI above the threshold that the *Horizontal Merger Guidelines* of the DOJ and FTC uses to delineate markets that are "highly concentrated." Most consumption also occurs in such counties. We conduct a decomposition exercise and determine that nearly two-thirds of the change is due to plant closures (itself a product of increasing scale economies), with the remainder attributable to mergers and other changes in plant ownership.

The evolution of markups requires a more nuanced treatment. Our marginal cost specification incorporates that capacity constraints can create opportunity costs for cement plants operating at high levels of utilization. As these do not reflect financial costs, whether they should be incorporated into markups may depend on the purpose for which markups are being calculated. Measuring markups using average variable cost, to which opportunity costs contribute little, we find modest markup increases. The median Lerner Index, for instance, increases from 0.27 in 1974 to 0.33 in 2019. Thus, the average unit of cement produced becomes more profitable over time.[5]

[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).

[4] A similar GMM approach is used Miller and Osborne (2014) 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) introduce some modifications and estimate a model of automobile markets in which consumers may negotiate prices.

[5] Markups calculated using marginal costs are flatter, reflecting that utilization increases especially in 1970s and 1980s. Thus, the marginal unit is not much more *economically* profitable at the end of the sample than at the beginning, even if

A striking feature of the data is that the average real price per metric tonne of cement is nearly identical in 1974 and 2019. Thus, the greater efficiency of precalciner kilns has not obviously created benefits for buyers, just as the loss of competition has not obviously created harm. Indeed, the data suggest these two changes—both of which point to greater markups—may offset each other in their affects on price. In a final analysis, we examine the relationship between county-specific changes in HHI over 1974-2019 and the corresponding changes in county-specific average price. We find virtually no correlation between HHI changes and price changes at this level.

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, where the advent of the minimill allowed for economical production at much lower fixed costs. This facilitated entry, reduced markups, and induced some vertically-integrated plants to exit. Ganapati (2021b) examines wholesalers over 1992-2012 and determines that investments in information technology increased scale economies and improved service quality; markups increased but consumers benefited nonetheless. Grieco et al. (2022) examines automobile manufacturing and finds that markups have decreased over time due to competitive pressures, despite significant improvements in marginal cost and product quality. Brand (2021) and Döpper et al. (2022) 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]

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.[8] Its share global anthropogenic CO2 emissions may be around five percent (Van Oss and Padovani, 2003). However, the cement industry also is attractive to research because data are available and it is amenable to modeling. Professor Berry has proposed it as a "model industry" in Industrial Organization.[9] 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, 2014), 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, and Leone et al.

it is more financially profitable.

[6]Both articles find that the elasticity of demand has decreased over time. Brand (2021) attributes this to the growing popularity of "niche" products and Döpper et al. (2022) 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.

[8]Statistics are from the 2019 *Minerals Yearbook*.

[9]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).

(2022) examines 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 the estimator (Section 3). Next, we provide the estimation results, evaluate the fit to the data, and validate our estimates to the extent possible (Section 5). Finally, we consider the implications of the model for the evolution of market concentration and markup (Section 6) and conclude (Section 7).

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, 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 during what typically is a single 4-6 week period each year, during which kiln maintenance is conducted. The main way that plants adjust output is by shortening or lengthening (or skipping) this maintenance period.

Cement producers typically sign short-term contracts with buyers, predominantly construction firms and ready-mix concrete plants.[10] 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. to illustrate this pattern. 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 improvements in freighter

[10]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.

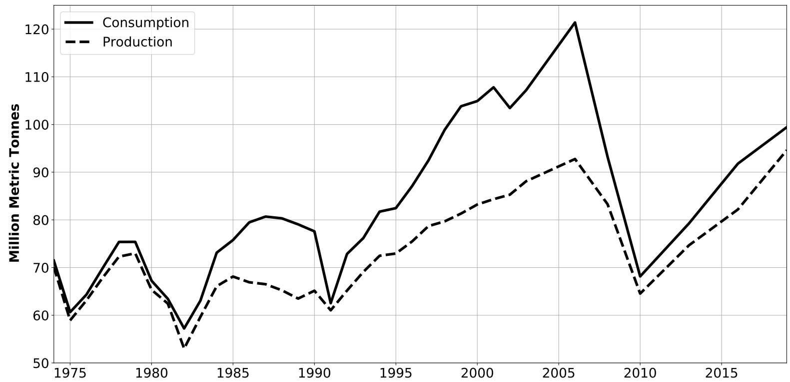

Figure 1: Consumption and Production, 1974-2019

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

technology were made 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, the cement manufacturers relied on "wet" and "long dry" kilns that typically were 100 yards or longer in length.[11] Raw materials would 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 simply 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 must be 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)

[11] 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.

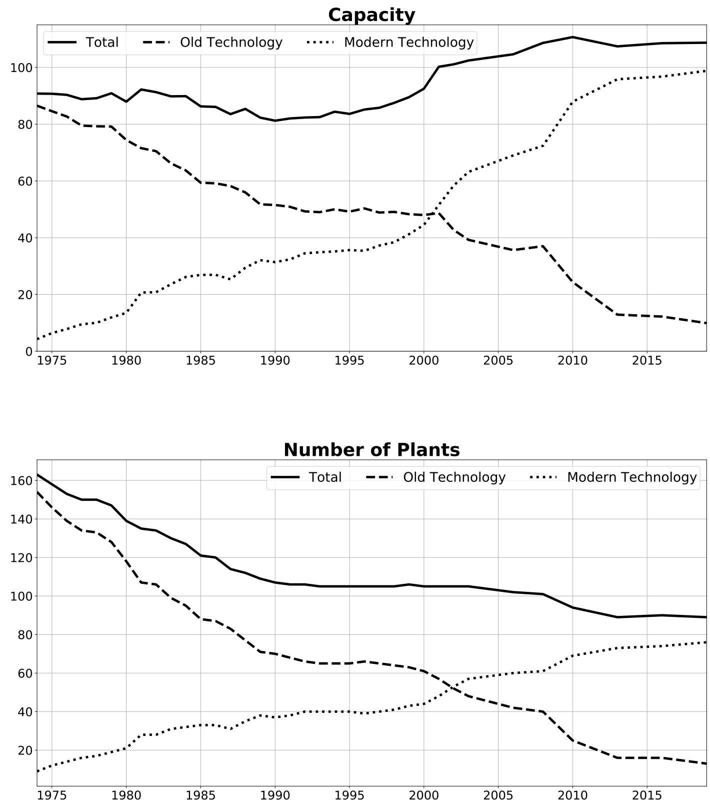

Figure 2: Industry Capacity and the Number of Cement Plants, 1974-2019

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.

by technology type. We refer to wet and long dry kilns as "Old Technology" and preheater and precalciner kilns as "Modern Technology."[12] 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 new technology accounting for nearly all of this capacity at the end. Over the same period, the number of plants falls by 45%, from 163 to 89. As with capacity, nearly all plants used the old technology at the beginning of the sample and the new technology at the end. Reconciling these two trends is that modern kilns are simply much larger (in capacity) than older kilns. Indeed, in 2019 the average annual capacity of a modern technology kiln was nearly double that of a old technology kiln.

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

[12] A preheater kiln does not incorporate the supplementary combustion chamber of a precalciner kiln, but otherwise is similar.

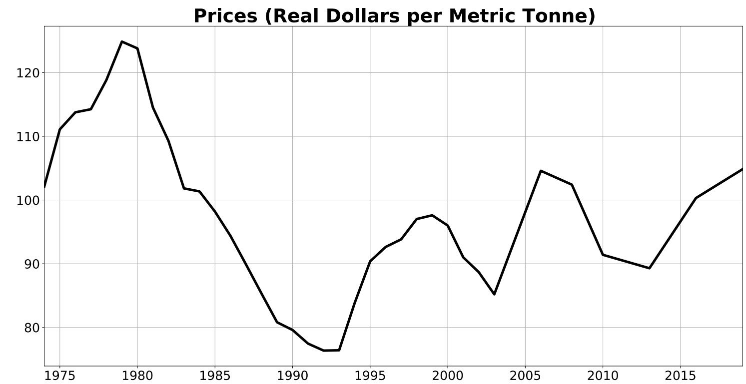

Figure 3: National Average Price, 1974-2019

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

upgrade their technology to a precalciner kiln. To benchmark the plausible magnitude of these costs, publicly available estimates appear to place the total cost of building a modern cement plant at around $800 million.[13] Previous research has sought to identify the conditions that are most conducive for the adoption of precalciner technology (Macher et al., 2021). The results of that study 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 technology that reduces marginal cost 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 that real price per metric tonne is nearly identical in 1974 and 2019: $102.16 and $104.83, respectively. Thus, the greater efficiency of precalciner kilns has not obviously created benefits for buyers, just as the loss of competition has not obviously created 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.

[13]The European cement association, CEMBUREAU, places construction costs for a one million metric tonne plant at around three years of revenue and estimates annual total costs of around $200 million. A (2011) study by The Carbon War Room, an environmental action group, places profit margins at 33 percent given a per-tonne price of $100. Combining this information yields $\$200 \times 1.33 \times 3 = \$798 \approx \$800$ million. See `http://www.cembureau.be/about-cement/cement-industry-main-characteristics` for the CEMBUREAU estimate.

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.

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.[14] The regions do not necessarily approximate local economic markets. As the number of plants decreased over 1974-2019, the USGS increased the size of regions accordingly. 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. To our knowledge, no other publicly-available data directly 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). Point 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.[15]

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-

[14] This ensures that no firm can infer the data of another from what is reported in the *Minerals Yearbook*.

[15] 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.

2003 and also for 2004, 2006, 2008, 2010, 2013, 2016, and 2019.[16] 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.

3 Empirical Model

As a second-score auction can be recast as a quality-adjusted descending-price auction, it can be a reasonable representation of procurement events—such as those in the cement industry—in which buyers play prospective suppliers off against each other in order to obtain more favorable prices.

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 wood, asphalt, 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.

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

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 common to all buyers in the same county-year and ζ_{int} and ϵ_{ijnt} are buyer-specific preference shocks. The indirect gross utility for the outside good ($j = 0$) is $u_{i0jt} = \epsilon_{i0nt}$. We assume that each ϵ_{ijnt} is distributed iid Type 1 extreme value and that ζ_{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 σ 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. We assume the bid of the outside 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 county and year, so we have $b_{ijnt} = b_{jnt}$ for all i.

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

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

where $\boldsymbol{b}_{nt}$ contains all the bids submitted for county n in year t. In this expression, the first ratio gives the probability that option j ($j \neq 0$) is selected conditional on cement being selected, and the second ratio gives the probability that cement is selected. The probability with which the outside good is selected is $s_{0nt}(\boldsymbol{b}_{nt}; \boldsymbol{X}_t, \boldsymbol{\theta}) = 1 - \sum_{j\neq 0} s_{jnt}(\boldsymbol{b}_{nt}; \boldsymbol{X}_t, \boldsymbol{\theta})$. Often we will refer to these choice probabilities as market shares. The quantity of cement sold by plant j in county n is

$q_{jnt}(\boldsymbol{b}_t; \boldsymbol{X}_t, \boldsymbol{\theta}) = s_{jnt}(\boldsymbol{b}_{nt}; \boldsymbol{X}_t, \boldsymbol{\theta}) M_{nt}$, 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:

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

and the implied price is

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

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. Prices are buyer-specific even within a given county and year, and even for cement from the same plant.

The demand derivatives are no different than 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 $\hat{s}_{j|g} \equiv \frac{s_j}{\sum_{k \neq 0} s_k}$ is the probability with which plant j is selected conditional on cement being selected. Furthermore, 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.[17]

[17] 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.

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

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

where $\overline{p}_{jnt}(\cdot)$ is the expected price obtained by plant j conditional on winning an auction, $c_{jt}(\cdot)$ is a non-decreasing, convex marginal cost function, and $Q_{jt}(\boldsymbol{b}_t; \boldsymbol{X}_t, \boldsymbol{\theta}) = \sum_n q_{jnt}(\boldsymbol{b}_{nt}; \boldsymbol{X}_t, \boldsymbol{\theta})$ is the total amount of cement sold by plant j across all counties. 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 a plant. As fixed costs do not directly affect outcomes in the second-score auction we defer discussion of them to Section 4.3, where we also cover estimation.

If marginal costs were constant in quantity then it would be at least a weakly dominant strategy each firm submit a single "at cost" bid to each buyer from the plant that can create the most economic surplus. By "at cost" we refer to a bid that equals the plant's marginal cost. Thus, plant j operated by firm $f(j)$ would submit a bid, $b_{ijnt} = c_{jt}$, to buyer i if

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

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 some 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 emerges as a strictly dominant strategy, following the standard logic for second-price auctions.[18]

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

[18]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.

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.[19]

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 that buyers have for their competitors. As the preference shocks have unbounded support, every firm perceives some 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. The reason is that 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 analytical expressions are available for market shares, average prices, and average markups, all the plant-county level. We provide those expressions in this section.

Denote the marginal costs that are associated with the market-clearing quantities as $c_{jt}^*(\boldsymbol{X}_t, \boldsymbol{\theta}) \equiv$

[19] 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.

$c_{jt}(Q^*_{jt}; \boldsymbol{X}_t, \boldsymbol{\theta})$. Plugging these 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 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 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:

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

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:

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

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.

3.4 Empirical Specification

We now specify the model to match 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:

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

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 β_1 and β_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.[20] We assume that the preferred form of transportation is used. The second line incorporates an indicator for the importer ($IMPORT_j$), a demeaned time trend to help account for changes in import availability over time ($TREND_t$), and a constant.

Thus, we incorporate transportation costs through buyer preferences, reflecting our understanding that buyers 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 β_1 as a "blended" disutility of overland transportation. In most years, less than 18% of shipments make use of rail.

To finish the demand-side of the model, we measure county size using data on construction employment. Because cement accounts for a small fraction of total construction expenditures (e.g., Syverson, 2004), cement prices are unlikely to have meaningful effects on the overall level of construction activity. To construct county size, we allocate cement consumption—again, observed at the region level—to individual counties in the region in proportion to their construction employment, and then double that amount. As this ensures the outside good share is always 50%, there is no empirical variation with which to identify the nesting parameter. Thus, we assume $\sigma = 0.90$, which is consistent with our understanding that at prevailing prices there is relatively little substitution between cement and the outside option.

[20] One industry expert claimed to us that the per-mile cost of barge transportation is approximately one-seventieth that of trucking, which we interpret as being close enough to zero to ignore in the modeling.

On the supply-side, we specify the marginal cost function as:

$$c_{jt}(Q_{jt}; \boldsymbol{X}_t, \boldsymbol{\theta}) = \boldsymbol{w}'_{jt}\boldsymbol{\alpha} + \gamma \, 1\left\{\frac{Q_{jt}(\cdot)}{CAP_{jt}} > 0.5\right\}\left(\frac{Q_{jt}(\cdot)}{CAP_{jt}} - 0.5\right)^2 \tag{14}$$

where $\boldsymbol{w}_{jt}$ is a vector of cost-shifters, CAP_{jt} is plant capacity, and the parameters include $(\boldsymbol{\alpha}, \gamma)$. Similar marginal cost functions are used in Ryan (2012) and Miller and Osborne (2014). The cost-shifters include a constant and the fuel costs 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 described in the appendix. For plants that have multiple kilns, we use the fuel costs of the least efficient kiln.[21]

Marginal costs start to increase in output once utilization exceeds 50%. Producing at capacity raises marginal costs by $\gamma/4$ relative to producing at a utilization less than 50%. 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. However, their relative importance would affect the extent to which our marginal cost estimates are reflected in accounting data.[22]

Finally, we assume that imported cement is being 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.

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:

$$y_{mt} = h_{mt}(\boldsymbol{X}_t; \boldsymbol{\theta}_0) + \omega_{mt} \tag{15}$$

where y_{mt} is outcome m in year t, $h_{lt}(\boldsymbol{X}_t; \boldsymbol{\theta}_0)$ is a known function defined by the model that returns the analogous model prediction given data and parameters, and ω_{mt} is a stochastic term that satisfies

[21] 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 4.2.3).

[22] For the purposes of the model, we measure capacity using the boilerplate rating of the plant's kiln(s). This provides the maximum possible production and does not account for routine downtime that may be skipped with high demand.

$\mathbb{E}[\omega_{mt}|\boldsymbol{X}_t] = 0$. 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, fuel costs, kiln ages, 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:

$$g_m(\boldsymbol{\theta}; \boldsymbol{X}) \equiv \frac{1}{||\mathbb{T}_m||} \sum_{t \in \mathbb{T}_m} \kappa_t \left(y_{mt} - h_{mt}(\boldsymbol{X}_t; \boldsymbol{\theta}) \right) \tag{16}$$

where $\mathbb{T}_m$ includes the years in which outcome m is observed and κ_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.[23]

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.

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 is 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

$$\hat{\boldsymbol{\theta}}(\boldsymbol{\Sigma}) = \operatorname*{argmin}_{\boldsymbol{\theta} \in \Theta} \boldsymbol{g}(\boldsymbol{\theta}; \boldsymbol{X})' \boldsymbol{\Sigma}^{-1} \boldsymbol{g}(\boldsymbol{\theta}; \boldsymbol{X}) \tag{17}$$

[23] 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 of three because the most recently observed data is from 2003.

where $\boldsymbol{\Sigma}$ is a positive definite, diagonal weighting matrix. We employ a one-step estimator. 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. An efficient two-step estimator (e.g., Hansen (1982)) appears infeasible in our setting because moments are observed over many different time periods. To our knowledge, the literature does not provide clear guidance about how to calculate the off-diagonal elements of the efficient weighting matrix when moments are observed over different time frames.[24]

4.2 Discussion

4.2.1 Identification

Among the moments that we use in estimation, the price moments are unique in that they are necessary to separately identify many of the parameters of the model. To see this, consider a simpler parameterization with logit demand ($\sigma = 0$) and gross utility and marginal cost functions of $\overline{u}_{jn}(\boldsymbol{X}_t, \boldsymbol{\theta}) = \boldsymbol{x}_j'\boldsymbol{\beta}$ and $c_j = \boldsymbol{x}_j'\boldsymbol{\alpha}$, respectively, where we have suppressed time subscripts. Equilibrium market shares and average prices then are given by

$$s_{jn} = \frac{\exp(\boldsymbol{x}_j'(\boldsymbol{\beta} + \phi\boldsymbol{\alpha}))}{1 + \sum_k \exp(\boldsymbol{x}_k'(\boldsymbol{\beta} + \phi\boldsymbol{\alpha}))} \tag{18}$$

and

$$\overline{p}_{jn} = \boldsymbol{x}_j'\boldsymbol{\alpha} + \frac{1}{\phi}\frac{1}{s_{jn}}\log\left(\frac{1}{1 - s_{jn}}\right) \tag{19}$$

The non-price moments that we use are constructed as aggregations of plant-county market shares. Given equilibrium market shares, we can calculate consumption within a region, the proportion of production that occurs at plants with a wet kiln, and the shipments from Northern California to Arizona. Yet by inspection of equation (18), this does not disentangle the marginal cost parameters ($\boldsymbol{\alpha}$) from the price parameter (ϕ) because these enter only through their multiplicative product. Furthermore, it identifies demand parameters only insofar as they are excluded from the marginal cost function (so β^k, the k^{th} element of $\boldsymbol{\beta}$, is identified iff $\alpha^k = 0$).

By contrast, the price moments are constructed as aggregations of average plant-county prices. From equation (19), these moments separately identify all of the structural parameters (as the demand parameters enter through the market shares). Indeed, in a finite sample with sufficient price variation, estimation could exploit *only* price moments. In our application, the price data are sub-

[24]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.

stantially aggregated and the non-price moments provide valuable information about the combinations of parameters that minimize the objective function.

4.2.2 Assessment of Credibility

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 (15). 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 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 kiln technology, capacity, and fuel cost to help model marginal cost. Thus, we believe the model accounts for much of the heterogeneity that exists in the cement industry, and that our assumptions are reasonable given the setting.

Still, the possibility that important unobserved heterogeneity could remain motivates additional validity checks on the magnitude of the price parameter.[25] First, we compare the demand elasticities that we estimate to those obtained elsewhere in the literature. Second, we compare the implied willingness-to-pay for overland proximity (i.e., β_1/ϕ) to engineering estimates of transportation costs and to estimates in the academic literature. Both sets of comparisons are favorable.

4.2.3 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

[25]Previous studies have documented significant heterogeneity in plant-level productivity (e.g., Syverson, 2004).

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.[26] 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 nine 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.

4.3 Fixed Costs

Information about fixed costs is required to characterize the economies-of-scale associated with cement production. We use the bounds approach of Eizenberg (2014), exploiting 173 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 most often is done when demand conditions are weak. Adapting the Eizenberg notation to our setting, let the 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 ν is mean-zero stochastic term with bounded support. We suppress time subscripts hereafter.

We assume that firms simultaneously determine which kilns to operation, taking as given the implications for subsequent competition in the second-score auctions. We make the further assumption that no firm can improve its profit by idling a kiln observed to be active, or by operating a kiln observed to be idle. That is, there is no unilateral deviation from observed choices that would improve a firm's profit. Because fixed costs have bounded support, these assumptions imply the

[26]Two of us applied a brute-force approach to estimate a Bertrand/logit model of the cement industry (Miller and Osborne, 2014). 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.

following bounds:

$$L_r(\boldsymbol{X},\boldsymbol{\theta}) \leq F_r \leq U_r(\boldsymbol{X},\boldsymbol{\theta}) \tag{20}$$

These inequalities are trivially satisfied for any small enough $L_r(\cdot)$ and big enough $U_r(\cdot)$. A central contribution of Eizenberg (2014) is showing how data can inform how tight the bounds can be made while retaining a specified amount of statistical certainty that the bounds are satisfied.

The first step is to obtain the incremental gain to variable profit that firm obtains 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 all other kilns. For any kiln that operates, the first term on the right-hand-side can be obtained from the model at the estimated equilibrium, and the second term must be obtained with a counterfactual simulation. This is reversed for any kiln that is idle. Thus, to recover $\Delta_r(\boldsymbol{X},\boldsymbol{\theta})$ it is necessary to simulate a counterfactual for every kiln-year in the data. To reduce computational burden, we estimate the fixed cost bounds taking as given the demand and marginal cost estimates, rather then estimating them jointly.

This is sufficient to provide one-sided bounds for each kiln.[27] To construct two-sided bounds (20), Eizenberg (2014) argues that in many settings, the variation in incremental gain across observations will exceed the variation in fixed costs. We adopt that assumption for our application. Letting A^0_d and A^1_d be the sets of kilns that idle and operate, respectively, and separately by kiln technology, the bounds then can be expressed:

$$L_r(\boldsymbol{X},\boldsymbol{\theta}) = \begin{cases} \min_{m\in A^0_d} \Delta_m(\boldsymbol{X},\boldsymbol{\theta}) & r \in A^1_d \\ \Delta_r(\boldsymbol{X},\boldsymbol{\theta}) & r \in A^0_d \end{cases}$$

and

$$U_r(\boldsymbol{X},\boldsymbol{\theta}) = \begin{cases} \Delta_r(\boldsymbol{X},\boldsymbol{\theta}) & r \in A^1_d \\ \max_{m\in A^1_d} \Delta_m(\boldsymbol{X},\boldsymbol{\theta}) & r \in A^0_d \end{cases}$$

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 $\left[\bar{l}^d(\boldsymbol{X},\hat{\boldsymbol{\theta}}), \overline{u}^d(\boldsymbol{X},\hat{\boldsymbol{\theta}})\right]$ where the ele-

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

ments 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. Following Eizenberg (2014) 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:

$$\left[\bar{l}^d(\boldsymbol{X}, \hat{\boldsymbol{\theta}}) - \frac{S_l(\boldsymbol{X}, \hat{\boldsymbol{\theta}})}{\sqrt{N^d}} z_{1-\alpha}\ ,\ \bar{u}^d(\boldsymbol{X}, \hat{\boldsymbol{\theta}}) + \frac{S_u(\boldsymbol{X}, \hat{\boldsymbol{\theta}})}{\sqrt{N^d}} z_{1-\alpha}\right] \tag{21}$$

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. We apply the finite-sample adjustment of Hall and Park (2002), as discussed in footnote 30 of Eizenberg (2014).

The bounds that we report in this version of the paper are preliminary. We find that some values for $\Delta_r(\boldsymbol{X}, \boldsymbol{\theta})$ are negative, and that this arises as an artifact of the plant-specific marginal cost function that we use. We are updating the paper with kiln-specific marginal costs—a cost minimizing plant with multiple kilns will allocated production across them to equate marginal costs—which should allow for better inference on fixed cost. In the meantime, we implement by using the 5th and 95th percentiles of $\Delta_r(\boldsymbol{X}, \boldsymbol{\theta})$ to construct $L_r(\boldsymbol{X}, \boldsymbol{\theta})$ and $U_r(\boldsymbol{X}, \boldsymbol{\theta})$.

5 Estimation Results

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 in particular 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 81 miles and 86% travels less than 200 miles.[28] By contrast, for the 11% of shipments that use a river barge for transportation, the median distance between a plant and the buyer is 540 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 1.62 aligns with recent studies of the cement industry indicating that fuel costs are more than fully passed through to prices (Miller et al., 2017; Ganapati et al., 2020). The capacity cost parameter indicates that producing at capacity increases marginal cost by $26.13

[28]This aligns with a Census Bureau (1977) study that reports that more than 80% of cement is transported within 200 miles, and Miller and Osborne (2014) find that 90% of cement travels less than 200 miles.

Table 1: Parameter Estimates and Derived Statistics

Parameter		Estimates	Std. Error
Demand			
Price Parameter	ϕ	-0.006	(0.000)
Overland Miles (000s)	β_1	-2.156	(0.088)
River Barge Used	β_2	-0.447	(0.006)
Imported Cement	β_3	0.053	(0.017)
Imported Cement $\times$ Trend	β_4	-0.007	(0.001)
Constant	β_0	0.555	(0.046)
Marginal Cost			
Constant	α_0	38.97	(1.57)
Fuel Cost	α_1	1.62	(0.04)
Capacity Cost	γ	104.54	(6.92)
Fixed Cost			
Wet and Long Dry Kilns	F^{old}	[64 , 2,897]	
Modern Preheater/Precalciner Kilns	F^{new}	[2,057 , 10,266]	
Transportation Costs			
Overland Cost ($ per Tonne-Mile)	β_1/ϕ	0.33	
Fixed Cost of Barge ($ per Tonne)	β_2/ϕ	68.90	
Bid Elasticity of Demand			
Plant-Level Demand		-4.04	
Demand for Domestic Cement		-0.23	
Demand for Cement		-0.12	

Notes: The demand and marginal costs results are based on GMM estimation. For fixed costs, we report 95% confidence intervals using on the bounds approach of Eizenberg (2014).

per metric tonne relative to producing at a utilization rate less than 50%. The constant implies a contribution of other inputs (e.g., materials, labor, electricity) to marginal cost of $38.97 per metric tonne. Our preliminary estimate of fixed cost bounds indicate that fixed costs likely are higher for modern preheater and precalciner kilns than for wet and long dry kilns.

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 $0.33 per tonne-mile. The 1974 *Minerals Yearbook* reports $0.43 per tonne-mile on average, *Transportation in America* (2007, 20th Edition) reports revenues per tonne-mile of Class I general freight common carriers of $0.36-$0.43 over 1983-2003, and Miller and Osborne (2014) estimate $0.57 per tonne-mile. (We have adjusted all of these estimates to be in real 2010 dollars.) It makes sense that our estimate would be somewhat lower because it is based on a "blended" disutility of truck and rail transportation.[29]

We obtain a quantity-weighted median plant-level bid elasticity of -4.04. We obtain this by converting the demand derivative of equation (5) into an elasticity and evaluating it at equilibrium bids (which equal marginal cost). 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 (2014) estimates a median firm-level price elasticity of -3.22 and Ganapati et al. (2020) estimates a plant-level demand elasticity of -2.90. One the other, Chicu (2012) estimates a median plant-level price elasticity of -6.55 and Fowlie et al. (2016) estimates a market-level price elasticity of -2.05 that implies an average plant-level price elasticity of -7.35.[30] Our interpretation is our estimates imply a reasonable degree of price sensitivity.

Figure 4 shows selected model fits. The first three panels plot total consumption, total production, and average price over the sample period. The solid lines show the data and the dashed lines show the model predictions. In each case the model tracks the broad pattern in the data. The fourth panel is a scatter plot with the data and predictions on the cross-region shipments from Northern and Southern California to Northern and Southern California, Arizona, and Nevada. The dots fall along the 45-degree line, indicating that that the model fits these shipments well. In Appendix B, we provide additional fits to the panel data on consumption, production, and prices, as well as to the time-series of production by wet kilns and the prevalence of barge shipments.

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 multiplicative markup (p/c). We calculate these markups using marginal cost, the constant portion of marginal cost, average variable cost, and average fixed cost. Each of these is interesting in its own way. Our motivation

[29] Again, in most years, less than 18% of shipments make use of rail. The Miller and Osborne (2014) model is estimated on data from the U.S. Southwest, where rail transportation is less common.

[30] 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.

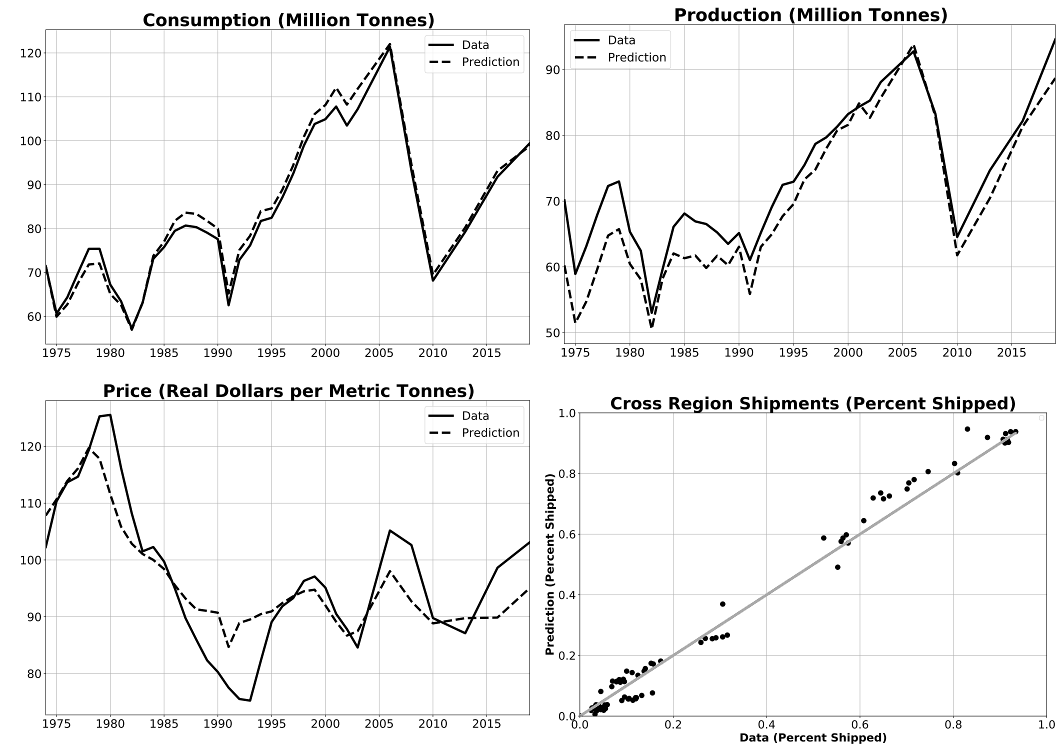

Figure 4: Selected Model Fits

Notes: The left panels show the time series of consumption, production, and prices. The right panels show region-year fits for consumption, production, and prices. A 45-degree line is plotted in all scatter plots.

for examining the constant portion of marginal cost is that (as already discussed) producing near capacity may create opportunity costs rather than physical costs. Focusing on the constant portion of marginal cost strips away the influence of any such opportunity costs and may isolate the financial gain associated with the marginal unit.

Focusing on average variable cost, we obtain a median Lerner Index of 0.32, a median additive markup of \$30.91 per metric tonne, and a multiplicative markup of 1.44. Markups roughly halve if marginal costs are used instead of average variable cost, due to the influence of the capacity constraints. Finally, if average fixed costs are used, the values are of 0.28 for the Lerner Index, \$27.30 for the additive markup, and 1.34 for the multiplicative markup. These latter results are based on preliminary estimates of fixed cost but suggest the production is profitable, as one would expect given the capital investment associated with buildin a new cement plant.

Underlying these average markups are prices that are unique to each plant and county and a corresponding rich set of shipment patterns. Exploring these in detail is beyond the scope of this paper. To give some sense, however, in Appendix B we illustrate that plants tend to obtain both higher markups and greater market shares in nearby counties, with the degree of markup dispersion depending on the presence of competitors. We also provide a map of plants and buyers that rely on

Table 2: Implied Median Markups

		Cost Measure Used			
		MC	$\overline{MC}$	AVC	ATC
Lerner Index	$(p-c)/p$	0.19	0.34	0.32	0.28
Additive Markup	$p-c$	17.31	33.45	30.91	27.30
Multiplicative Markup	p/c	1.22	1.49	1.44	1.34

Notes: The table reports median markups, weighted by quantities. Four different cost measures are used: marginal costs (MC), the constant portion of marginal cost ($\overline{MC}$), average variable costs (AVC), and average total costs (ATC). We calculate total costs using the midpoint of the fixed cost bounds.

the Mississippi River System for transportation.

6 Technology and Market Power

We focus now on the evolution of concentration and markups over 1974-2019. In the next version of the paper, as we make progress pinning down fixed costs, we also will analyze the evolution of scale economies. We calculate the county-level HHIs based on the market shares of every supplier of cement to the county:

$$HHI_{nt} = 10,000 \times \sum_f \left(\sum_{j \in \mathbb{J}_f} \frac{s_{jnt}}{1 - s_{0nt}} \right)^2 \tag{22}$$

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. For the purposes of the calculation, we treat imports as being provided by one distinct supplier of cement. An alternative approach that treats imports as a competitive fringe that does not contribute to HHI obtains similar results.

Figure 5 shows that the distribution of HHI across counties shifts up during the sample period. The median HHI, represented as the solid line, steadily increases from 1,890 to 2,660. To help put this in context, with symmetry the same change would be produced by a reduction in the number of competitors from 5.3 to 3.8. The figure also plots the 10th, 25th, 75th, and 95th percentiles. All of these increase over time but the changes are more pronounced at the bottom of the distribution.

Table 3 shows the number of counties and the proportion of consumption that falls into various concentration tiers. We choose the tiers based on the *Horizontal Merger Guidelines* of the DOJ and FTC, which describe markets with an HHI less than 1,500 as being "unconcentrated," markets with an HHI between 1,500 and 2,500 as being "moderately concentrated," and markets with an HHI above 2,500 as being "highly concentrated." Between 1974 and 2019, the number of unconcentrated counties fell from 1,056 (36.8% of consumption) to 205 (4.1% of consumption). The number of

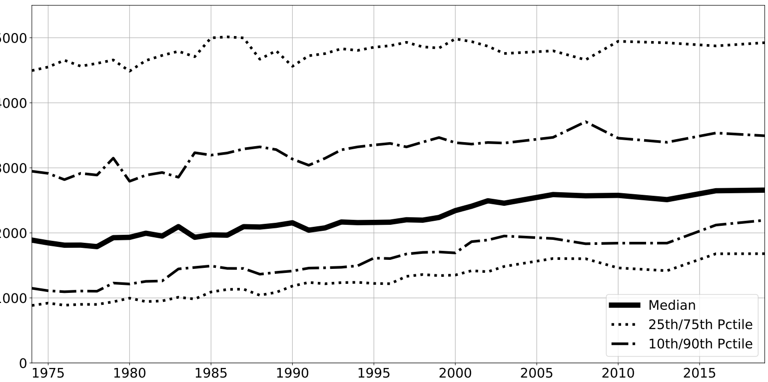

Figure 5: HHI Distribution Across Counties, 1974-2019

Notes: County-level HHIs are calculated from the county-level market shares that are obtained from the model. The order statistics are weighted by our measure of county size.

Table 3: County-Level Concentration in 1974 and 2019

	1974		2019	
	Number of Counties	Proportion of Consumption	Number of Counties	Proportion of Consumption
HHI<1500	1,056	36.8%	205	4.1%
1500≤HHI<2500	782	27.8%	1,040	39.1%
HHI≥2500	1,193	35.4%	1,786	56.8%
HHI≥5000	496	6.1%	500	8.6%
HHI≥6000	358	4.9%	336	5.0%

moderately concentrated counties increased from 782 (30.2% of consumption) to 1,040 (39.1% of consumption). The number of highly concentrated counties also increased from 1,193 (35.4% of consumption) to 1,786 (56.8% of consumption). An interesting feature of the modeling results is that the number of exceptionally concentrated markets has remained relatively constant. For instance, the number of counties with an HHI above 5,000 is 496 (6.1% of consumption) in 1974 and 500 (8.6% of consumption) in 2019 and the number of counties above 6,000 is 358 (4.9% of consumption) in 1974 and 336 (5.0% of consumption) in 2019.

We conduct a decomposition exercise to explore why these changes occur. Starting with the 1974 data, we recompute equilibrium as follows:

(i) Using the 2019 market sizes, fossil fuel prices, and value of the import trend.

(ii) Applying (i), using the 2019 capacities and also removing all plants that are not present in the 2019 data.

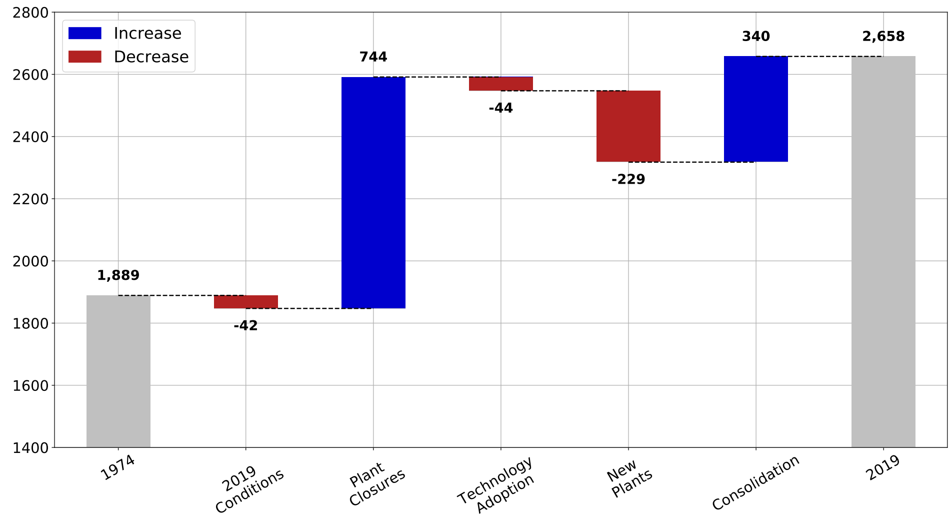

Figure 6: Decomposition of Changes in the Median County-Level HHI

Notes: The bars on the left and right show the 1974 and 2019 median county-level HHI, weighted by county-level quantities. The middle bars show changes that occur in counterfactual simulations that, cumulatively, move from the 1974 equilibrium to the 2019 equilibrium.

(iii) Applying (ii), using the 2019 primary fuels and also allowing for kiln upgrades.

(iv) Applying (iii) and also adding plants that are present in 2019 but not 1974.

(v) Applying (iv) and also using the 2019 plant ownership structure.

The final step reproduces the 2019 data. In the first step we scale the plant capacities so that total capacity aligns with that of 2019, which avoids mismatches in supply and demand that could mask more interesting mechanisms. In the subsequent steps we use the true capacities of the plants in 2019. Of particular interest are steps (ii), (iv), and (v), which isolate the competitive effects of exit, entry, and mergers, respectively. Each of our scenarios capture a particular short run equilibrium.

Figure 6 summarizes how the weighted-average median HHI changes with each of these steps. Plant closures increase the median HHI by 744, and consolidation increases the median HHI by 340; these effects are partially offset by competition from new plants, which reduces the median HHI by 229. We interpret this as evidence that most of the increase in local market concentration is due to changes in technology—specifically, the precalciner kiln—that increase the minimum efficient scale of production and thereby reduce the number of plants over time. Nonetheless, mergers and acquisitions also have an impact on local market concentration.

Figure 7 plots the distribution of markups for domestic plants over 1974-2019. The measure that we use is the Lerner Index calculated with average variable cost. We find that, by this measure,

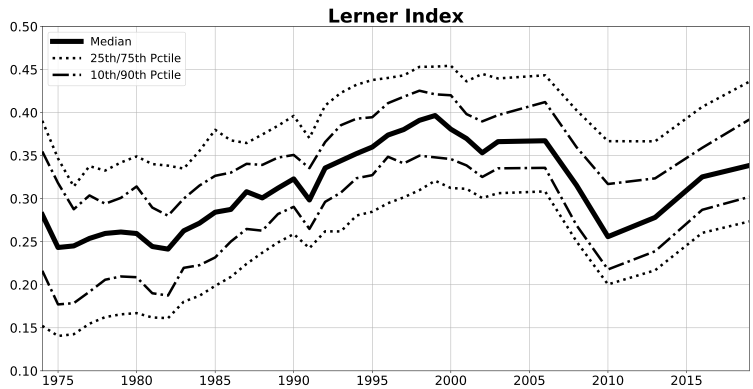

Figure 7: Weighted Average Markups over 1974-2019

Notes: We calculate markups using average variable cost.

markups increase through most of the sample, dip with the Great Recession, and then partially recover by the end of the sample. The median is 0.27 in 1974 and 0.33 in 2019. As there is no commensurate increase in average prices (Figure 3), the increase in markups reflects predominantly lower average variable cost.

We repeat the decomposition exercise to examine why markups change between 1974 and 2019 as they do. Figure 8 summarizes the results using the additive markup. The results indicate that plant closures and consolidation increase the markup by \$1.21 and \$0.59, respectively, and that competition from new plants decreases the markup by \$0.65. Also notable is that the adoption of modern precalciner technology by incumbents increases markups by \$0.09. A main effect of technology adoption on markups, then, comes through its affect on market structure.

In our final analysis, we compare the changes in average county-level prices to the changes in the county-level HHI, again focusing on 1974 and 2019. The bottom panel shows that the relationship between price changes and HHI changes is more complicated. We believe this reflects that modern kiln technology lowers the cost of production but also increases the minimum efficient scale of production, and so reduces competition in the long run. Whereas the former effect benefits buyers in the form of lower prices, the latter does the opposite. The net of the two effects depends on local supply and demand conditions.

7 Conclusion

In this paper, we have used structural modeling techniques to interpret publicly-available data on the United States cement industry over 1974-2019 and, specifically, to estimate the extent of local market concentration and the magnitude of price-cost markups. The model, though parsimonious, contains a number of elements appropriate to the cement industry, including spatially differentiated

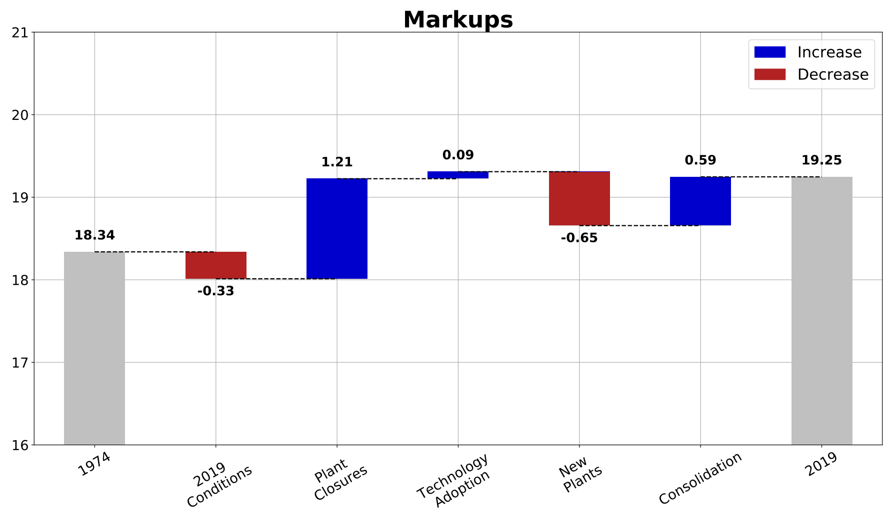

Figure 8: Decomposition of Markup Changes

Notes: The bars on the left and right show the 1974 and 2019 average additive markup, measuring using variable cost. The middle bars show changes that occur in counterfactual simulations that, cumulatively, move from the 1974 equilibrium to the 2019 equilibrium.

preferences, multi-modal transportation options, and supply that allows for capacity constraints and technological change. We estimate this model using aggregated data and are able to replicate patterns of production and consumption over time and across regions.

Our results imply that the industry experienced a notable increase in local market HHIs during the sample period, but we also find that average markups increase only modestly and that prices do not rise. We attribute these changes to the adoption and diffusion of the precalciner kiln, which lowered marginal costs and increased capacity while simultaneously driving an industry shakeout in which many plants closed. Although mergers also contributed to the trends in HHIs and markups, we show that the largest impact comes from plant exit. Our findings demonstrate the importance of accounting for technological change when considering the possible outcomes of increases in concentration and their effects on consumers.

An interesting area for future research would be to study the efficacy of merger policy in the cement industry. In the past decade alone, the Federal Trade Commission has filed four complaints against mergers between cement producers, resulting in three consent decrees and one abandoned transaction. Our model could allow us to assess the impact of these enforcement actions and perhaps could suggest additional policies that may benefit consumers.

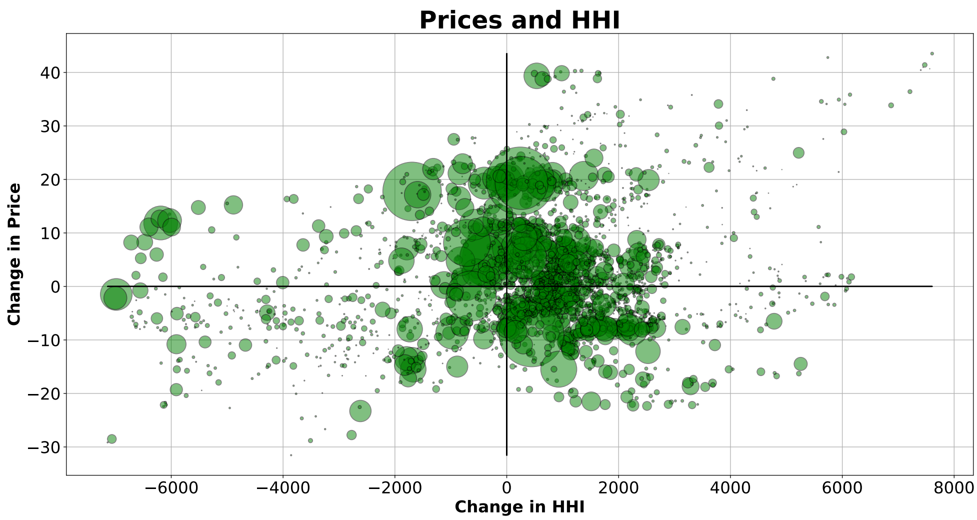

Figure 9: Price Changes Plotted Against HHI Changes, 1974 to 2019

Notes: The figure plots the county-level changes in average prices against the county-level changes in the HHI. The circles are proportional to county-level consumption.

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Appendix Materials

A Data Details

A.1 Measuring Fuel Costs

We follow the approach of Miller et al. (2017) to measure fuel costs of each plant, which we calculate based on fossil fuel prices and the energy requirements of the plant's least efficient kiln.[31] The calculation is

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

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 plants list multiple primary fuels in the *Plant Information Summary*. As the mix of primary fuels is unknown, we treat such plants 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 B.4 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 plants. In the middle years, coal and petroleum coke are the only primary fuels used. In the final year, some plants switch back to natural

[31] We view the least efficient kiln as most likely to produce the marginal output.

gas. The figure provides the prices of these fuels (bottom panel). Usage tends to track the relative prices.

A.2 Customs Districts

In the model we assume that buyers can purchase cement from the nearest active customs district. Implementing this assumption in an empirically-grounded way is challenging for a number of reasons. First, there is a great deal of heterogeneity in the size 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 near 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 approach allows the model to match the quantity of imports over time (Figure B.1). The top 20 customs districts, in descending order of the maximum quantity of imported cement received in a year, are: 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 AZ, Buffalo NY, Mobile AL, 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 Additional Figures and Tables

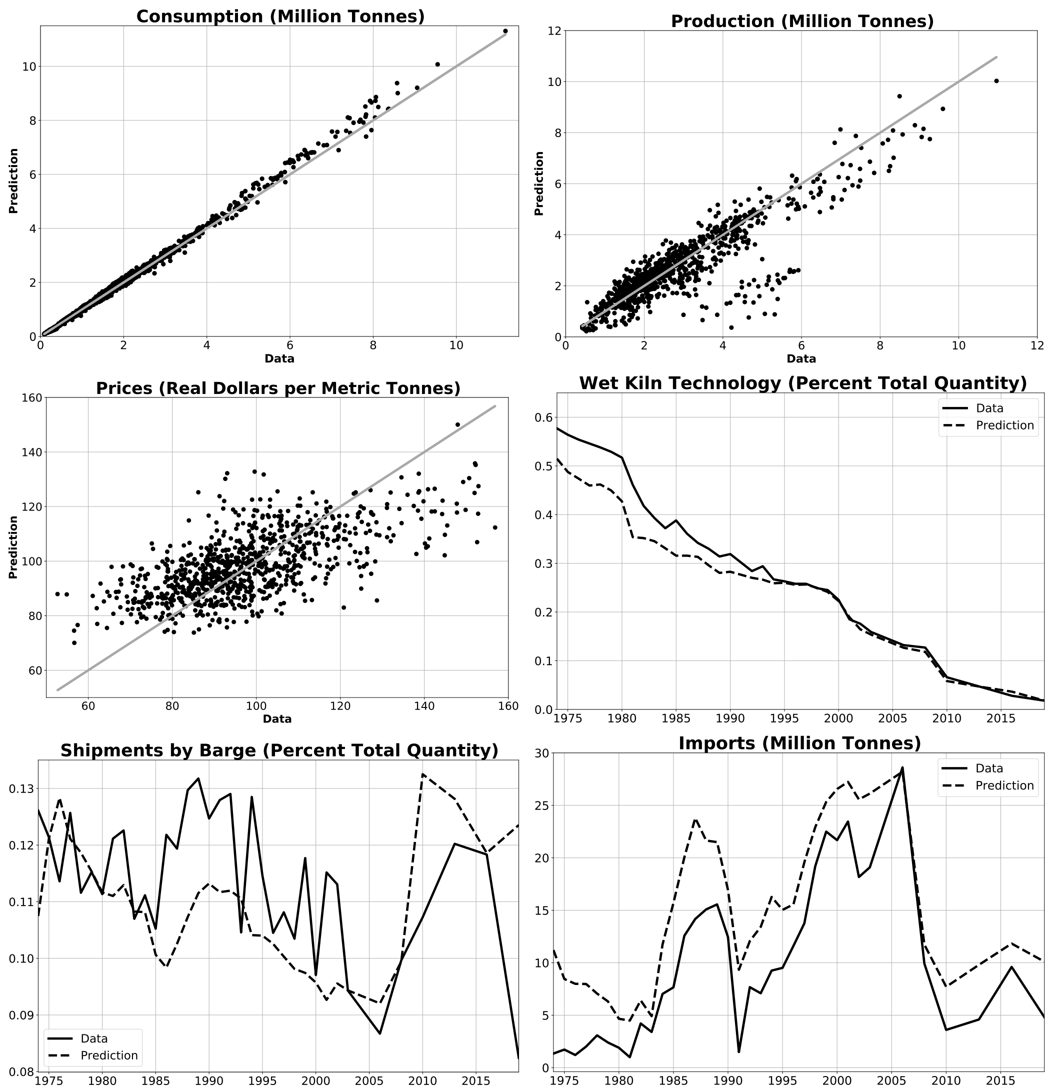

Figure B.1: Additional Model Fits

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 plotted in all scatter plots.

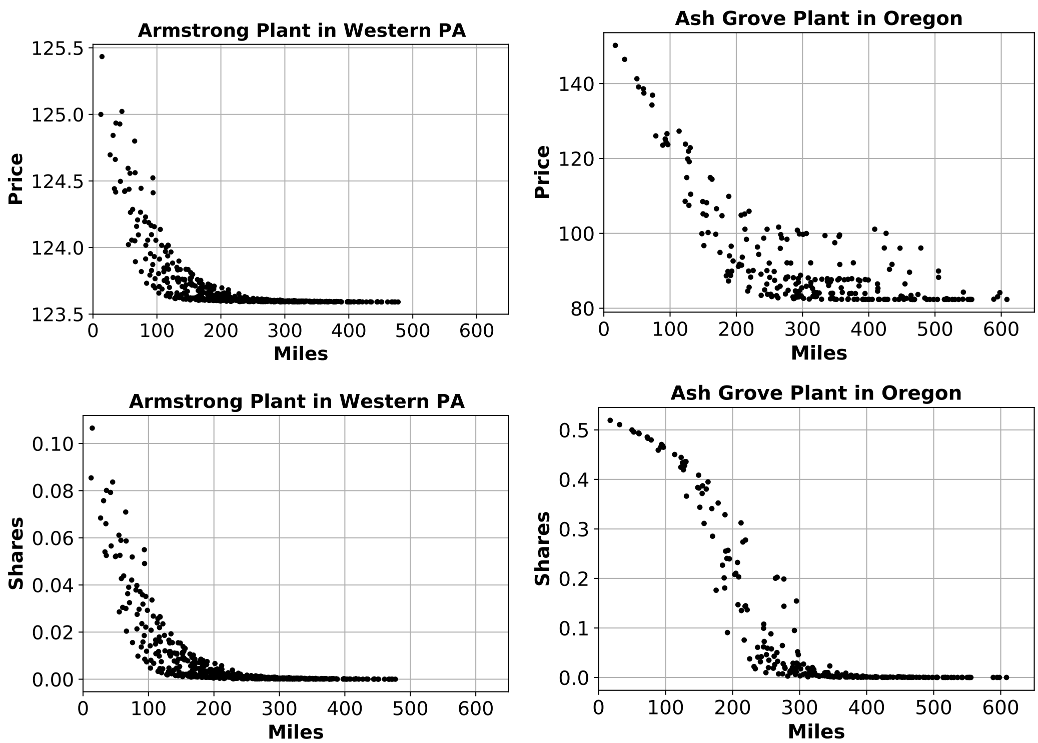

Figure B.2: Illustration of Spatial Differentiation and Price Discrimination

Notes: The top panels display the price charged in every county by an Armstrong plant in Western Pennsylvania (left) and an Ash Grove Plant in Oregon (right). The horizontal axis is the miles between each county and the plant. The bottom panels display the market shares for the same plants in every county. The prices and market shares between each plant-county combination 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.

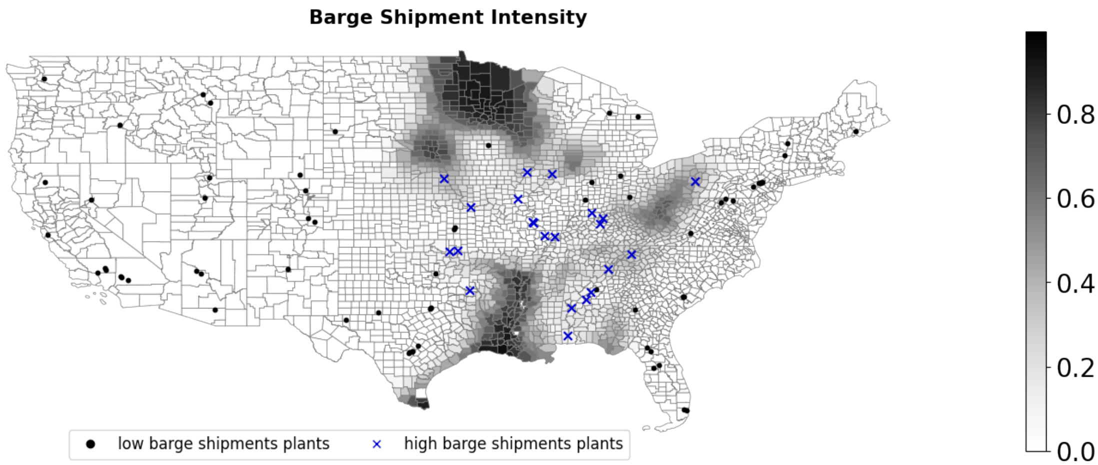

Figure B.3: Barge Shipment Sources and Destinations

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 plant that use barge transportation heavily are near the Mississippi River System, but differ in where along the river they are located.

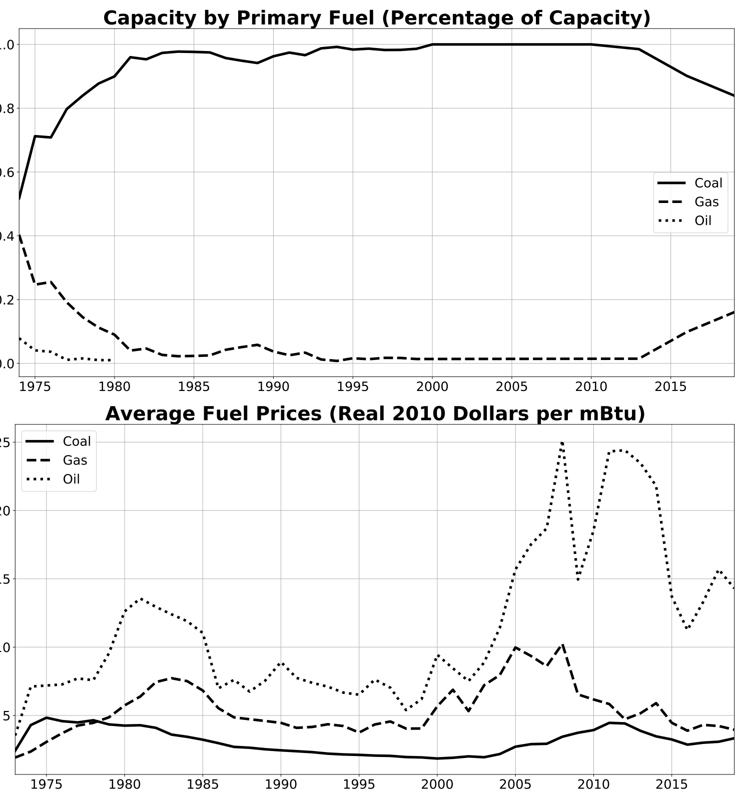

Figure B.4: Primary Fuels and Fuel Prices

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).