Technology and Market Power in the Cement Industry*

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Abstract

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

JEL Codes: L11, L13, L41, L61
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1 Introduction

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

Motivating our effort is a growing literature on what sometimes is referred to as *The Rise of Market Power*. There are two main strands. First, De Loecker et al. (2020) combine accounting data with production function estimates for a large number of firms in the U.S. and determine that a significant increase in markups has occurred in recent decades.[1] Second, a string of articles document rising concentration across a number of industries in the U.S., at least at the national level (e.g, Peltzman, 2014; Barkai, 2016; Grullon et al., 2019; Ganapati, 2021; Autor et al., 2020; Kwon et al., 2024).[2] We complement this literature by providing an industry study that traces the evolution of market power in a specific context and explores the mechanisms that give rise to these changes.

The results of our analysis indicate significant increases in local market concentration, but markups increase only modestly, and real prices do not rise. At the local level, there is a tight relationship between concentration and markup changes, but not between concentration and price changes. A decomposition reveals that precalciner adoption and plant closures largely account for these empirical patterns. In our model, these factors contribute to rising markups by reducing marginal cost and lessening competition. For the same reasons, they exert opposing effects on price. As scale-increasing technologies can induce exit in the long run, the plant closures themselves may be due to precalciner technology. We evaluate plant-level economies of scale and find that the adoption of precalciner technology creates an impetus for significant output expansion for plants that adopt it.

Thus, our results support a nuanced view of *The Rise of Market Power* in the cement industry. Technological change, rather than weak antitrust enforcement or a lax regulatory

[1] Subsequent research probes the production function methodology used to recover markups (e.g. Bond et al., 2021; Doraszelski and Jaumandreu, 2021; Raval, 2023; De Ridder et al., 2024; Foster et al., 2022).

[2] 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., 2023).

environment, is the primary explanation for changes in concentration and markups. Furthermore, buyers of cement do not appear to have been harmed on average. Two literature reviews that cite our research indicate that, looking across industries, nuances similar to the ones we identify are the norm (Shapiro and Yurukoglu, 2024; Miller, 2025).

Methodologically, we develop an oligopoly model of supply and demand to recover local market outcomes from aggregated data on prices and quantities. We assume buyers conduct second-score auctions in which suppliers are evaluated based on their bid and a number of other 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). The model is strategically equivalent to a multi-attribute English auction, which makes it appropriate for settings in which buyers play prospective suppliers off against each other to obtain favorable terms. We incorporate upward-sloping marginal cost functions and prove that a Nash equilibrium exists in which suppliers maximize profit by bidding at marginal cost. An important property of the model is that, if buyers have heterogeneous preferences, markups and prices are specific to buyer-supplier pairs, even though equilibrium bids are determined by plant-level marginal costs.

We specify the model to incorporate spatial differentiation among plants, allowing it to generate the rich variation we observe in outcomes as, over time, plants in different locations enter and exit, and demand shifts across geographic locations. We assume transportation costs depend on the distance between each plant and small geographic areas—in practice, counties. This, in turn, allows the closeness of competition between plants to depend on their relative proximity to buyers, as the prices generated from the second-score auction depend on how buyers rank plants, inclusive of transportation costs. Under a parametric assumption proposed in Miller (2014) and Allen et al. (2019), we derive closed-form solutions for the market share, average markup, and average price of each plant in each county. These analytical solutions distinguish our model from the Bertrand models used previously for spatial differentiation (e.g., Thomadsen, 2005; Miller and Osborne, 2014b; Elickson et al., 2020).[3] They vastly speed up the computation of equilibrium because the nonlinear search is over plant-level bids rather than plant-county-level prices and quantities.

We estimate the model using nonlinear least squares, exploiting comprehensive microdata on cement plants that includes their kiln technology and productive capacity. The objective function is based on squared differences between (aggregated) equilibrium predictions and analogous endogenous data. As implementation requires that we compute equilibrium for each candidate parameter vector, the computational savings that we obtain from the second-score framework are crucial. An identifying assumption is that plant-level

[3] Our framework is more flexible than assuming all trade occurs within local markets and there is no differentiation among plants in the same market, an assumption that has been used productively in research on the cement industry that addresses different questions (e.g. Ryan, 2012; Fowlie et al., 2016).

heterogeneity can be accounted for using observables, which we consider reasonable for our setting, given the plant-level micro-data. We validate our estimates by comparing the transportation costs and demand elasticities that we obtain to external evidence. With the structural parameters in hand, we bound kiln-level fixed costs following Eizenberg (2014), which allows us to obtain average cost functions and to assess scale economies.

The modeling results that we obtain are partially consistent with *The Rise of Market Power* in the cement industry, as local market concentration and markups increase over the sample period. Looking across the counties in the contiguous U.S., we find that the quantity-weighted median Herfindahl Hirschman Index (HHI) increased from 1876 to 2727, equivalent to a reduction in the number of symmetric firms from 5.3 to 3.7. However, the increase in the quantity-weighed median markup is more modest, at 5.3%, much less than the estimates of De Loecker et al. (2020). Perturbations to the model, such as small increases in buyers' bargaining power or price sensitivity, can eliminate the rise in markups. Buyer surplus increased by three percentage points from 1974 to 2019, while the variable profit of cement firms decreased by seven percentage points; total welfare did not change.

In the model, equilibrium outcomes are affected by many factors, including plant closures, technology adoption, entry, mergers, factor prices, and demand conditions. We use counterfactual simulations to understand how much each of these factors contributes to changes in concentration, markups, and prices. The results of this decomposition exercise indicate that plant closures largely explain the increase in concentration, though mergers and entry also have meaningful, offsetting effects. Markups rise mainly due to plant closures and mergers, which lessen competition. Finally, a number of factors impact prices, with plant closures and precalciner technology having large, opposing effects. An examination of the panel variation indicates that proximity to the Mississippi River System is a moderating influence, as it connects a large number of buyers and suppliers, and helps produce equilibrium outcomes that are less extreme and more stable over time.

Overall, these results are consistent with the main short run effect of precalciner technology being marginal cost reductions that are passed through to cement buyers in the form of lower prices. To the extent that the adoption of precalciner technology contributes to rising concentration and markups, it is through an effect on long run decisions, including on plant closures. However, it may be reasonable to attribute the bulk of plant closures to precalciner technology because they increase productive capacity significantly.

To explore this hypothesis in greater quantitative detail, we evaluate economies of scale using the fixed cost bounds and an engineering estimate of capital costs. We find that the scale elasticity increases over the sample period due to the shift toward precalciner technology. Evaluated at fixed quantities, the median scale elasticity rises from 1.12 in 1974 to 2.38 in 2019, implying that the amount of additional output that can be generated by incurring a given increase in costs nearly doubles. We also compute the ratio of price to average cost for plants with modern technology. Evaluated at 1974 quantities, it remains well below one throughout the sample, implying output expansion is necessary for precalciner adoption to be profitable. The results are consistent with a central role of precalciner technology in explaining the industry shakeout that has occurred over the previous four decades.

The insights we generate highlight the value of using an equilibrium model to interpret economic data. The contours of some of our results can be found in raw data—for example, the technological transition toward modern kiln technology, the plant closures, and the price trends. Yet the implications for local-market concentration, markups, welfare, and scale economies, both in how they change over time and their distribution across space, are not readily apparent from data alone. Simpler measures, such as national-level HHI statistics, do not inform the local market outcomes that matter for the buyers and sellers of cement. A production approach to markup estimation using firm-level accounting data (e.g., De Loecker et al., 2020) does not inform, for example, whether rising markups are due to higher prices or lower costs, which have meaningfully different interpretations.

The articles closest to ours use structural models to examine specific industries over long time horizons. Collard-Wexler and De Loecker (2015) examine the steel industry over 1963-2002, when the advent of the minimill reduced fixed costs, resulting in entry, lowered markups, and the exit of some vertically-integrated plants. Ganapati (2025) determines that investments by wholesalers over 1992-2012 in information technology increased scale economies and improved service quality; markups increased, but consumers benefited nonetheless. Grieco et al. (2024) study automobile manufacturing and find that markups have decreased over time due to competitive pressures, despite significant improvements in marginal cost and product quality. Brand (2021), Döpper et al. (2024), and Atalay et al. (2025) examine consumer packaged goods and determine that markups have increased due to marginal cost reductions that are not passed through to consumers. Kusaka et al. (2022) examine precalciner kilns in Japan and find that they reduced the labor share. Each of these articles highlight the role of technology in shaping the long-term economics of industries. Together, they point to heterogeneity in technological change and its impacts.

Our research also relates to a large number of empirical articles that explore the implications of fixed costs for market outcomes. Among the contributions are Bresnahan and Reiss (1991) on small businesses, Berry (1992), Ciliberto and Tamer (2009), Ciliberto et al. (2021), and Li et al. (2022) on airlines, Berry and Waldfogel (1999) and Berry et al. (2016) on radio broadcasting, Seim (2006) on video retail markets, Eizenberg (2014) on personal computers, Wollmann (2018) on commercial vehicles, and Fan and Yang (2024) on mergers and entry in beer markets. Among these, Eizenberg (2014) is the most similar to our research thematically, as it considers the impacts of innovation, specifically the development and introduction of Intel's Pentium M computer chip.

We structure the paper as follows. We first describe the cement industry and our data sources (Section 2). We then present the model and our empirical specification (Section 3). Next, we develop the estimator and discuss our baseline estimates (Section 4). We examine the evolution of market outcomes over the sample period (Section 5), and conclude with a discussion of limitations and directions for future research (Section 6). In the appendices, we provide additional detail on proofs (Appendix A), model extensions (Appendices B and C), data and estimation (Appendix D), and the robustness of our results (Appendix E).

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 raw materials enter at one end of the kiln and undergo chemical reactions as they approach the burning zone on the other end. The output of the kilns—clinker—is cooled, mixed with a small amount of gypsum, and ground to form cement. Variable costs include raw materials, fuel costs, electricity costs, labor, and kiln repair and maintenance (EPA (2009)). Plants run at full capacity except during an annual maintenance period.

Most cement is sold under short-term contracts with construction firms and ready-mix concrete plants that specify a mill price (or a "free-on-board" price) and can include buyer-specific discounts. Some cement firms operate one or more ready-mix concrete plants and sell cement and concrete to construction firms through these plants. Although fewer than 100 cement plants now operate in the US, there are thousands of ready-mix concrete plants.[4] Differentiation among cement plants is predominantly spatial, as cement is costly to ship and must conform to quality standards published by the American Society for Testing and Materials (ASTM). Trucks, trains, and river barges can transport cement; buyers typically pay the costs. Cement plants tend to locate outside cities, along interstate highways, and near the Mississippi River System.

Figure 1 plots total consumption and production. Both are pro-cyclical because cement is used in construction. Consumption tends to outstrip production when macroeconomic

[4] Syverson and Hortaçsu (2007) analyzes vertical integration using data from the US Census. For 1997, the final year of their sample, they report that 30.5% of cement plants, accounting for 55.4% of cement sales, were at least partially vertically integrated. In the same year, 10.6% of ready-mix concrete plants, accounting for 14.2% of concrete sales, were vertically integrated. We interpret these numbers as indicating that most sales even from vertically-integrated cement plants are made to independent ready-mix concrete plants. We discuss the modeling implications of vertical integration in Appendix C.

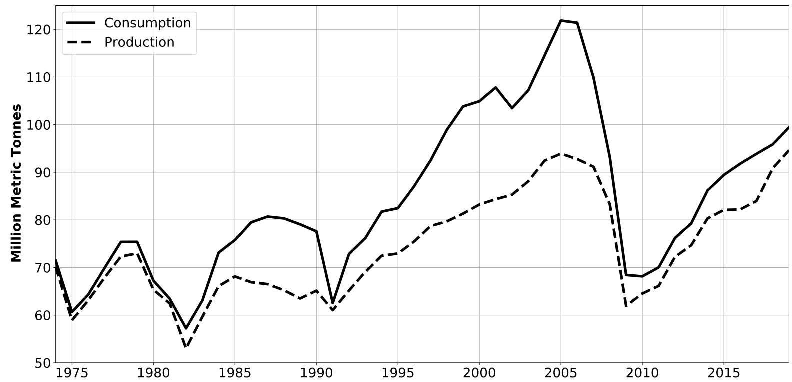

Figure 1: Consumption and Production, 1974-2019

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

conditions are favorable, due to domestic capacity constraints. Importers make up the difference. Since freighter technology improved in the early 1980s, most imports have arrived via transoceanic freighters. Some imports are trucked from Canada and Mexico. Exports from the U.S. are negligible.

2.2 Kiln Technology

Modern precalciner kilns mitigate two inefficiencies of the "wet" and "long dry" kilns that dominated production through most of the twentieth century. First, with older kiln technology, heat escaped with the kiln's exhaust gases. Second, the length of the older kilns—more than 100 yards—amplified heat loss due to radiation. With modern kilns, raw materials are preheated before they enter the kiln with exhaust gases and heat from a supplementary combustion chamber. Less time is needed in the kiln, so modern kilns are shorter in length—typically only 25-40 yards—which reduces kiln radiation. They are 25-35% more efficient than wet and long dry kilns and have greater productive capacity.

Figure 2 plots industry capacity (top panel) and the number of plants (bottom panel) by technology type. We refer to wet and long dry kilns as "Old Technology" and precalciner kilns as "Modern Technology."[5] Over 1974-2019, total industry capacity increased by 20%, from 91 to 109 million metric tonnes, with old technology accounting for most of this capacity at the beginning of the sample and modern technology accounting for most of this capacity at the end. The number of plants fell by 45%, from 163 to 89. (This incorporates 13 new plants constructed during the sample period.) Reconciling the increase in capacity

[5]We also classify preheater kilns—which do not have the supplementary combustion chamber of precalciner kilns—as modern technology. There are far fewer preheater kilns than precalciner kilns.

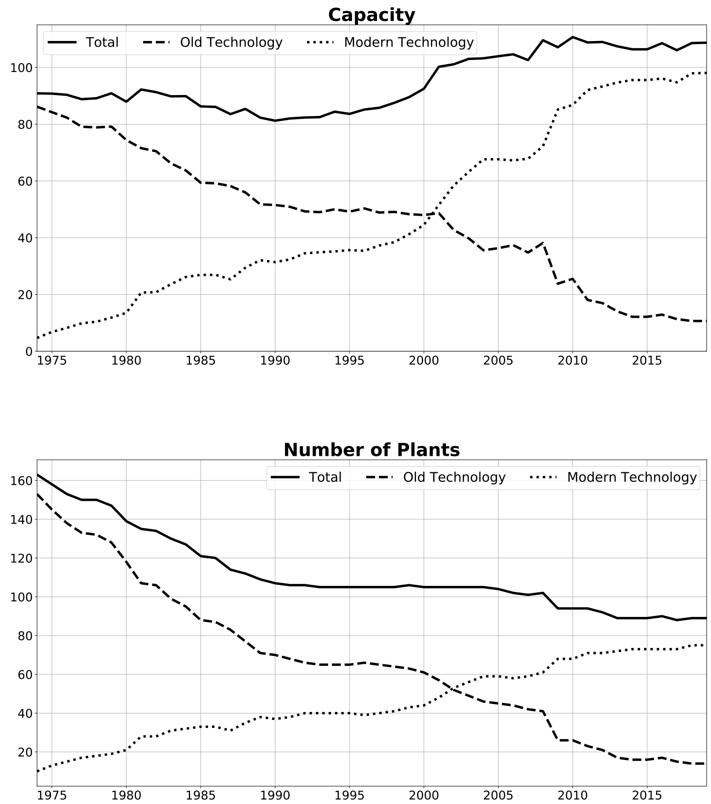

Figure 2: Industry Capacity and the Number of Cement Plants, 1974-2019

Notes: 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 temporarily idled (e.g., due to maintenance or low demand). Data are from the *Plant Information Summary* of the Portland Cement Association.

with the decrease in plants is the greater capacity of modern kiln technology.[6]

Firms must incur significant capital costs to upgrade their technology to a precalciner kiln. The European cement association, CEMBUREAU, has placed the construction costs of a modern plant with one million metric tonnes of annual capacity at €150-200 million, or approximately three years of revenue, and states that cement ranks "among the most capital intensive industries."[7] Previous research has sought to identify the conditions that

[6]Appendix Figure G.1 plots the average capacity per plant, which more than doubles over the sample period; it also plots the number of kilns and the number of kilns per plant.

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

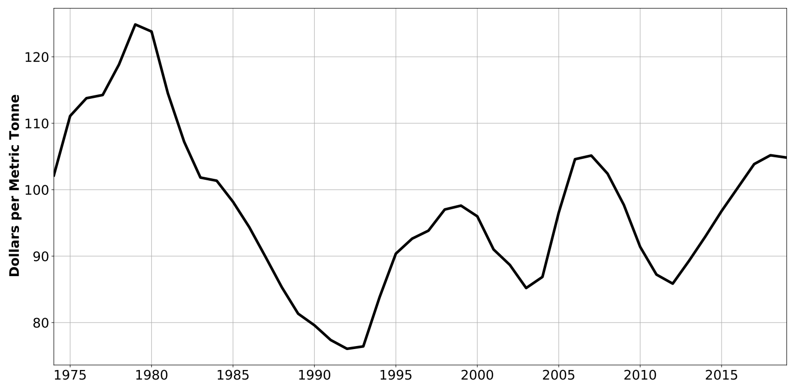

Figure 3: National Average Price per Metric Tonne, 1974-2019

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

are conducive for precalciner technology (Macher et al., 2021). The results indicate that adoption is more likely if fuel prices are high, there are few nearby competitors, and local demand conditions are strong. The latter two effects are consistent with the benefits of cost-reducing technology increasing with plant output (e.g., Gilbert, 2006).

Figure 3 plots the national average price over the sample period. The real price per metric tonne is similar in 1974 and 2019: $102.16 and $104.83, respectively. The fluctuations within the sample period coincide with changes in fossil fuel prices (especially in the 1970s) and macroeconomic conditions. We use modeling to explore in greater detail how the adoption of precalincer kilns affected producers' costs, markups, and profits, as well as the prices negotiated by buyers and the market concentration that results.

2.3 Data Sources

The *Minerals Yearbook* and other USGS data

The USGS conducts an annual census of cement plants and summarizes the results in a publication called the *Minerals Yearbook*. It contains data on free-on-board prices, production, and consumption that are aggregated to the region level. The regions are not intended to approximate economic markets, and their number varies over time to satisfy a "rule-of-three" that they include at least three independent plants. There were 26 price regions in 1974, but only 20 in 2019. Production regions nearly always conform to price regions. The consumption regions are smaller; there were 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

ing the Wayback Machine, and `https://www.cembureau.eu/about-our-industry/key-facts-figures/`.

that is shipped using a river barge. Finally, we use the data it provides on the quantity and value (inclusive of insurance, freight, and delivery charges) of imported cement.

The other USGS publication that we use is the *California Letter*, which tracks the destination of cement shipments that originate at plants in California. No other publicly available data links cement producers' locations to their customers' locations. Depending on the year, points of origination are aggregated to northern California, southern California, or California (in its entirety). Points of destination are aggregated to the same regions, Arizona and Nevada. Unlike the *Minerals Yearbook*, data are available only for 1990-2010, and even within that window, some data points are withheld to preserve confidentiality.[8]

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 from 1973 to 2003 and also for 2004, 2006, 2008, 2010, 2013, 2016, and 2019. 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, as explained in further detail in Appendix D.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.

[8]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.

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, county centroids, and the Mississippi River System.

3 Empirical Model

We use a private value second-score auction to represent the decentralized negotiation process through which buyers play cement producers off against each other to obtain more favorable terms of trade. In the model, buyers choose the supplier with the best-scoring bid, and the second-best bid determines the price. The model is strategically equivalent to a descending multi-attribute English auction, which makes it appropriate for decentralized negotiations (e.g., as used in Allen et al., 2013, 2019; Miller, 2014; Aryal et al., 2021; Slattery, 2024; Beckert et al., 2024). It extends naturally to a setting in which price is determined by *ex post* Nash bargaining between the buyer and the winning bidder (Appendix B).

3.1 The Second-Score Auction

Let there be a set $\mathcal{J}$ of cement plants indexed by j that supply cement to a continuum of buyers indexed by i. The plants belong to a set of firms $\mathcal{F}$ indexed by f, each of which may own one or more plants, with the set owned by firm f denoted by $\mathcal{J}^f$. The total mass of buyers is given by the market size, M.

The gross utility—utility not accounting for price—that buyer i receives from plant j is

$$u_{ij} = \overline{u}_{ij} + e_{ij} \tag{1}$$

where $\overline{u}_{ij}$ captures buyer and plant characteristics that are observable to the econometrician and e_{ij} is an unobservable preference shock. We assume that the characteristics are deterministic and constitute common knowledge among all agents. The preference shocks are independently and identically distributed with a continuous distribution function H^e. Our first assumption is about the information agents have about these shocks.

Assumption 1. *(Information) Given the preference shocks $\{e_{ij}\}_{j\in\mathcal{J}}$ $\forall i$,*

1. *Each buyer i has perfect information about the value of $\{e_{ij}\}_{j\in\mathcal{J}}$,*

2. *Each firm f has perfect information about the value of $\{e_{ij}\}_{\forall j\in\mathcal{J}^f}$ $\forall i$, and*

3. *Each firm f has perfect information about the distribution, H^e, of the buyer/plant-level shocks for other firms, $\{e_{ik}\}_{\forall k \notin \mathcal{J}^f}$*

Thus, buyers know their preference shocks for every plant, and each firm knows the preference shocks associated with its plants. Firms do not know the preference shocks associated with the plants of other firms, but they do know how these shocks are distributed.

Firms submit plant-level bids simultaneously. Suppose a buyer i faces a vector of bids $\{b_{ij}\}_{j\in\mathcal{J}_i}$, where $\mathcal{J}_i$ is the set of plants that have submitted bids. Our second assumption introduces the second-score auction.

Assumption 2. *(Second-Score Auction) Given a set of bids, $\{b_{ij}\}_{j\in\mathcal{J}_i}$, received by buyer i, the second-score auction takes the following form:*

1. *Buyer i scores the bidding plants according to a rule given by*

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

where the parameter ϕ converts the bid from units of currency to utils.

2. *The winning plant is the one with the highest score. That is, plant j is the winner if and only if*

$$score_{ij} = \max_{k\in\mathcal{J}_i}\{u_{ik} - \phi b_{ik}\}. \tag{3}$$

3. *The price is set such that the buyer is indifferent between transacting with the winning plant at the price and transacting with the second-best option at that option's bid. That is, if plant j is the winning plant,*

$$u_{ij} - \phi p_{ij} = \max_{k\in\mathcal{J}_i\setminus\{j\}}\{u_{ik} - \phi b_{ik}\}, \tag{4}$$

where p_{ij} is the transaction price.

The transaction price is a function of bids in a manner that is similar to what occurs in a second price auction, where the price paid equals the bid of the second ranked firm. All else equal, higher scores are assigned to those plants that provide greater gross utility and those that submit more attractive (i.e., lower) bids. The buyer uses the second-best alternative to determine the price. Solving equation (4) for the price gives

$$p_{ij} = \frac{1}{\phi}\left(u_{ij} - \max_{k\in\mathcal{J}_i\setminus\{j\}}\{u_{ik} - \phi b_{ik}\}\right) \tag{5}$$

in the case where plant j wins. The model can be generalized to incorporate Nash bargaining between the buyer and the winning firm after the scoring auction (Appendix B). In that alternative setting, equation (5) obtains if sellers have all of the bargaining power.

We now characterize market shares and quantities. Let $\mathcal{A}_j(\mathbf{b})$, a function of $\mathbf{b}$, the vector of all bids, denote the combinations of characteristics and preference shocks (as in equation (1)) for buyers for whom plant j has the highest score, and let the observable buyer characteristics have the empirical distribution H^D. The proportion of buyers choosing plant j is

$$s_j(\mathbf{b}) = \int_{\mathcal{A}_j(\mathbf{b})} dH^D(D)dH^e(e), \tag{6}$$

and the plant-specific demand functions are given by

$$q_j \equiv q_j(\mathbf{b}, M) = s_j(\mathbf{b})M, \tag{7}$$

where, again, M is the market size.

Turning to the supply side, we assume that each plant j has a marginal cost function given by $c_j(q_j)$. Our third assumption establishes the form the cost functions can take.

Assumption 3. *(Marginal Costs) Let $c_j(q_j)$ be a continuous plant marginal cost function. For any two quantities q_j^1 and q_j^2 where $q_j^1 < q_j^2$, we have that $c_j(q_j^1) \leq c_j(q_j^2)$.*

That is, the marginal cost functions are continuous and non-decreasing in quantity. Firm profits are

$$\pi_f = \sum_{j\in\mathcal{J}^f} \left[\int_{\mathcal{A}_j(\mathbf{b})} p_{ij} dH^D(D)dH^e(e)M - \int_0^{q_j} c_j(q)dq \right], \tag{8}$$

which adds up revenue from the auctions won and subtracts production costs.

Our main theorem establishes that marginal cost bidding is a Nash equilibrium of the simultaneous-move game defined by the auction format in Assumption 2.

Theorem 1. *(Second-Score Auction Equilibrium) The following bidding strategies constitute a Nash equilibrium of the auction described in Assumption 2:*

$$b_{ij} = \begin{cases} c_j(q_j) & \text{if } u_{ij} - \phi c_j(q_j) = max_{k\in\mathcal{J}^f}\{u_{ik} - \phi c_k(q_k)\} \geq 0 \\ \infty & \text{otherwise} \end{cases} \tag{9}$$

$\forall j \in \mathcal{J}$, $\forall f \in \mathcal{F}$, and $\forall i$.

Proof. See Appendix A.1. □

We refer to the difference between gross utility and marginal cost, measured in units of currency (i.e., $(1/\phi)(u_{ij} - \phi c_j(q_j))$, as the *surplus* that would be created if buyer i selects plant j. In equilibrium, each firm submits a finite bid to each buyer only from the plant that can create the most surplus; this prevents the firm's other plants from driving down price through the buyer playing them off of each other. For its highest surplus plant, the firm submits a bid equal to the marginal cost of the plant.

For a given set of cost functions, the equilibrium bids solve a fixed point problem. There must be some vector of marginal costs such that, when firms bid at those marginal costs, the quantities that obtain imply the same marginal costs. Equivalently, there must be market shares that generate costs and bids that obtain the same market shares. We formalize using market shares. A solution to the fixed point problem is defined by a vector of market shares, $\{s_j^*\}_{j\in\mathcal{J}}$, that solves

$$s_j^* = s_j(\{c_j(s_j^* M)\}_{j\in\mathcal{J}}) \quad \forall j \in \mathcal{J}, \tag{10}$$

where $c_j(\cdot)$ is the marginal cost function from Assumption 3 and $s_j(\cdot)$ is the market share function from equation (6).

An additional assumption on demand ensures that a fixed point exists.

Assumption 4. *(Continuous Demand) The market share function of equation* (6) *is continuous in terms of bids* $\mathbf{b}$.

The assumption requires that the gross utilities of buyers—incorporating the distributions of observables and the preference shocks—are such that any arbitrarily small change in a bid does not generate discrete changes in market shares. A number of standard functional forms, such as those of logit or nested logit demand, satisfy this assumption. Because marginal cost functions are continuous (Assumption 3), continuous demand ensures that the combined function of equation (10) is continuous. We now examine the fixed point.

Theorem 2. *(Fixed Point Existence) A fixed point for the problem defined by equation* (10) *exists.*

Proof. Equation (10) is a continuous vector-valued function in $\mathbb{R}^{|\mathcal{J}|}$-space that maps the set $\mathcal{S} = \{\{s_j \in [0,1]\}_{j\in\mathcal{J}} | \sum_{j\in\mathcal{J}} s_j \leq 1\}$ into itself. The set $\mathcal{S}$ is nonempty, compact, and convex. Therefore, by Brouwer's Fixed Point Theorem, a fixed point of this function exists. □

As written, this theorem assumes the presence of a non-strategic outside good that is not part of the set $\mathcal{J}$. This outside good forms the residual share when $\sum_{j\in\mathcal{J}} s_j < 1$, so that the shares sum up to 1. For a market with only two plants present, the set $\mathcal{S}$ is the triangle with vertices at (0,0), (1,0), and (0,1) in $\mathbb{R}^2$-space, including the boundary.

In equilibrium, the surplus created by the winning plant is split between the seller and the buyer, where, again, the surplus is given by $(1/\phi)(u_{ij} - \phi c_j(q_j))$. The seller's surplus is given by its markup, $m_{ij} \equiv p_{ij} - c_j(q_j)$. Seller surplus does not fully account for variable profit, as sellers also earn rent on infra-marginal sales with lower marginal costs. Subtracting $c_j(q_j)$ from both sides of equation (5) and evaluating at equilibrium bids yields:

$$m_{ij} = \frac{1}{\phi}\left(u_{ij} - \phi c_j(q_j) - \max_{k \in \mathcal{J}_i \setminus \{j\}} \{u_{ik} - \phi c_k(q_k)\}\right), \tag{11}$$

where plant j is the winner of the auction. Thus, the seller's surplus is the difference between the surplus created by its best plant and the surplus that its competitors' best plant could have created. Restated, the incremental surplus created by the winning seller determines the markup and the split of surplus. The buyer's surplus is the residual; it equals the maximum surplus that could have been created by the plants of the losing firms.

3.2 Nested Logit Demand

We use a nested logit demand system to make estimation tractable in the presence of aggregated data. In doing so, we strengthen our assumption on the distribution of preference shocks. We also assume that the observable portion of gross utility, $\overline{u}_{ij}$, is the same within sufficiently similar groups of buyers.[9] We use county boundaries to delineate the groups. Thus, gross utility comprises a component common to all buyers in the same county and a preference shock that captures buyer-specific deviations. Finally, we incorporate an outside good (e.g., steel, asphalt, or wood) that is supplied at a constant marginal cost.

Assumption 5. *(Nested Logit Demand) The gross utility that buyer i, located in county n, receives from plant j is*

$$u_{ij} = \overline{u}_{jn} + \zeta_i + (1-\sigma)\epsilon_{ij}, \tag{12}$$

where each ϵ_{ij} is distributed iid type 1 extreme value, ζ_i has the unique distribution such that e_{ij} also is type 1 extreme value, and $\sigma \in [0, 1)$ is a nesting parameter (Berry, 1994; Cardell, 1997). The gross utility provided by the outside good, labeled $j = 0$, is $u_{i0} = (1-\sigma)\epsilon_{i0}$.

This assumption places all cement plants in one nest and the outside good in another nest. Higher values of σ imply greater differentiation between cement plants and the outside good; if $\sigma = 0$ then a multinomial logit demand system obtains. An important empirical advantage of the nested logit demand system is that analytical expressions exist for market shares and markups, given a solution to the fixed point problem of equation (10).

Theorem 3. *(Equilibrium Outcomes) Let $\{c_j^*\}_{j \in \mathcal{J}}$ be plant-level marginal costs that provide a solution to the fixed point problem of equation* (10). *Then the market share, average markup,*

[9] That is, for a given set of buyers within one of these groups, H^D is a degenerate distribution that puts all the probability weight on a single value.

and average price of cement plant j in county n are given by:

$$
\begin{aligned}
s_{jn}^{*} &= \frac{\exp\left(\frac{\overline{u}_{jn}-\phi c_{j}^{*}}{1-\sigma}\right)}{\sum_{k\in\mathcal{J}}\exp\left(\frac{\overline{u}_{kn}-\phi c_{k}^{*}}{1-\sigma}\right)} \frac{\left(\sum_{k\in\mathcal{J}}\exp\left(\frac{\overline{u}_{kn}-\phi c_{k}^{*}}{1-\sigma}\right)\right)^{1-\sigma}}{1+\left(\sum_{k\in\mathcal{J}}\exp\left(\frac{\overline{u}_{kn}-\phi c_{k}^{*}}{1-\sigma}\right)\right)^{1-\sigma}}, && (13)\\
\overline{m}_{jn}^{*} &= -\frac{1}{\phi}\frac{1}{\sum_{k\in\mathcal{J}^{f(j)}} s_{kn}^{*}} \log\left[1-(1-s_{0n}^{*})\left(1-\left(1-\sum_{k\in\mathcal{J}^{f(j)}}\frac{s_{kn}^{*}}{1-s_{0n}^{*}}\right)^{1-\sigma}\right)\right], && (14)\\
\overline{p}_{jn}^{*} &= \overline{m}_{jn}^{*}+c_{j}^{*}, && (15)
\end{aligned}
$$

where $\mathcal{J}^{f(j)}$ is the set of plants owned by the firm that owns plant j. Furthermore, in county n, the market share of the outside good, s_{0n}^{*}, and average buyer surplus, $\overline{CS}_{n}^{*}$, are given by:

$$
\begin{aligned}
s_{0n}^{*} &= \frac{1}{1+\left(\sum_{k\in\mathcal{J}}\exp\left(\frac{\overline{u}_{kn}-\phi c_{k}^{*}}{1-\sigma}\right)\right)^{1-\sigma}}, && (16)\\
\overline{CS}_{n}^{*} &= -\frac{1}{\phi}\ln\left(s_{0n}^{*}\right)-\sum_{j\in\mathcal{J}} s_{jn}^{*}\overline{m}_{jn}^{*}. && (17)
\end{aligned}
$$

Proof. See Appendix A.2. □

Each plant obtains heterogeneous markups and prices from its buyers, even those within the same county (see equation (11)), reflecting buyer-specific preference shocks and their role in driving auction outcomes. The buyer surplus created in each transaction is likewise heterogeneous. A property of nested logit demand is that the expected values of these objects are functions of equilibrium market shares. We use the bar superscript for these objects to indicate expected value, and refer to the expected values as averages to invoke integration over a continuum of realized preference shocks.

3.3 Baseline Empirical Specifications

We now describe the baseline specifications for marginal cost and the common component of gross utility. We also discuss import competition and how we measure market size. To start, we build the plant-level marginal cost functions accounting for the reality that many plants operate multiple kilns, especially early in the sample. We add notation for a time dimension in the data given by t. We assume that the marginal cost of production at any kiln l (operated by plant j in year t) is given by

$$c_{jt}^{(l)}\left(Q_{jt}^{(l)};\boldsymbol{X}_{t},\boldsymbol{\theta}\right)=\boldsymbol{w}_{jt}^{(l)}\boldsymbol{\alpha}+\gamma\left(\frac{Q_{jt}^{(l)}(\cdot)}{CAP_{jt}^{(l)}}-\nu\right)^{2}\mathbb{1}\left\{\frac{Q_{jt}^{(l)}(\cdot)}{CAP_{jt}^{(l)}}>\nu\right\}, \qquad (18)$$

where $Q_{jt}^{(l)}$ is the output of the kiln, $\boldsymbol{X}_t$ contains the exogenous data, $\boldsymbol{w}_{jt}^{(l)}$ is a vector of kiln-specific cost-shifters, $CAP_{jt}^{(l)}$ is the capacity of the kiln, and the parameters in the vector $\boldsymbol{\theta}$ include $(\boldsymbol{\alpha}, \gamma, \nu)$. The cost-shifters include a constant, a time trend, and the fuel cost of production. We demonstrate the robustness of our results to additional controls and region and time fixed effects in Appendix E.[10] Kiln-level marginal costs increase in output once utilization exceeds ν. Ryan (2012) and Miller and Osborne (2014b) use similar cost functions.

We assume plants allocate output across kilns to minimize cost. For low-enough output, this entails using the most efficient kiln. However, as higher levels of utilization are reached, production from less efficient kilns becomes economical, and cost minimization dictates that plants equate the kiln-specific marginal costs of the kilns they use. We construct a continuous and weakly increasing *plant-level* marginal cost function, $c_{jt}(Q_{jt}; \boldsymbol{X}_t, \boldsymbol{\theta})$, from the kiln-level marginal cost function of equation (18). Appendix Figure G.2 shows the marginal cost function obtained for one of the multi-kiln plants in our data.

On the demand side, we assume that the common component of gross utility reflects the disutility of transportation and whether the supplier is an importer. Shipments go by truck directly from the plant to the buyer, or by barge utilizing the Mississippi River System—whichever is less costly. The baseline specification is:

$$\begin{aligned}\overline{u}_{jnt}(\boldsymbol{X}_t, \boldsymbol{\theta}) = \min\{&\beta_1 d_{j\to n}\ ,\ \beta_1\left(d_{j\to R} + d_{R\to n}\right) + \beta_2\} \\ &+ \beta_3 TREND_t + \beta_4 IMPORT_j + \beta_5 IMPORT_j \times TREND_t + \beta_0 \quad (19)\end{aligned}$$

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 the per-mile disutility associated with overland transportation and a fixed disutility associated with barge transportation. We include a time trend, an indicator for imports, a time trend for imports, and a constant for the inside goods. Thus, the specification accommodates that barge transportation is more efficient per mile, but imposes upfront costs. It also allows the relative desirability of domestic plants, importers, and the outside good to shift over time. We show the robustness of our results to additional specifications in Appendix E.

We assume imports are provided by a competitive fringe that ships into each of the active customs districts (Appendix D.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

[10]The results without fixed effects are our preferred specification due to computational constraints, as the fixed effects take a significant time to estimate.

entry, which is in the data. If actual bids differ, the import dummy in gross utility provides an adjustment. We allow buyers to purchase from any active customs district. Finally, we measure market size at the county-year level using data on construction employment, following Miller and Osborne (2014b). Details are in Appendix D.3.

4 Estimation and Estimation Results

4.1 Objective Function

Our estimation strategy involves selecting parameters that minimize the distance between data on endogenous outcomes (e.g., aggregated price and quantity data) and corresponding model predictions. This approach is used in Miller and Osborne (2014b) and Elickson et al. (2020), which also estimate models of spatial differentiation. We assume a data generation process in which each observed endogenous outcome is generated as follows:

$$y_{mt} = h_{mt}(\boldsymbol{X}_t; \boldsymbol{\theta}_0) + \omega_{mt}, \tag{20}$$

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

We use nonlinear least squares to estimate the parameters. The loss function is

$$L(\boldsymbol{\theta}; \boldsymbol{X}) = \sum_m \kappa_m \frac{1}{||\mathbb{T}_m||} \sum_{t \in \mathbb{T}_m} \left(y_{mt} - h_{mt}(\boldsymbol{X}_t; \boldsymbol{\theta})\right)^2, \tag{21}$$

where $\mathbb{T}_m$ includes the years in which outcome m is observed and κ_m is the weight we place on the endogenous outcome, which we set based on its (inverse) sample variance. To evaluate the loss function for a candidate parameter vector, we compute equilibrium by solving the fixed point problem of equation (10), and then aggregate the equilibrium predictions to the level of the data. We target the following endogenous outcomes in estimation:

1. Average price of plants by region. There are 63 price regions. The average region is observed for 18 years, and the average year has 25 price regions.

2. Total production by region. There are 62 production regions. The average region is observed for 18 years, and the average year has 24 production regions.

3. Total consumption by region. There are 57 consumption regions. The average region is observed for 44 years, and the average year has 55 production regions.

4. The proportion of production accounted for by plants with a wet kiln. This is observed in 45 years of the 46 years in the estimation sample (there are no data for 1991).

5. The proportion of cement that is shipped using river barges. This is observed in all of the 46 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).

We discuss identification, the computational burden of estimation, and consistency in Appendix D. We also provide additional details about implementation.

4.2 Estimation Results

Table 1 summarizes the estimation results we obtain with the baseline specification. On the demand-side, buyers incur disutility from transportation; the overland transportation cost is \$0.42 per tonne-mile (β_1/ϕ), and the per-tonne barge loading cost is \$82 (β_2/ϕ). Most shipments are local. In equilibrium, 89% of shipments use overland transportation exclusively (i.e., they do not use a river barge), and, of these, the median shipment is 78 miles, and 84% travels less than 200 miles. Conditional on a barge being used, the median distance between a plant and the buyer is 532 miles. Buyers prefer cement to the outside good; buying cement is worth \$86.40 more to a buyer (β_0/ϕ), all else equal. The time trend is small and not statistically significant. We also find that buying imported cement is worth \$17.40 to a buyer (β_4/ϕ). This preference grows over time, consistent with better reliability or availability of imported cement.

We find that marginal costs increase with fuel costs and as production approaches capacity. The fuel cost parameter of 1.75 implies that fuel costs are more than fully passed through to bids, consistent with recent studies of cost pass-through in the cement industry (Miller et al., 2017; Ganapati et al., 2020). The constant implies that other inputs (e.g., materials, labor) contribute \$30.95 to marginal cost per metric tonne in the average year. The capacity cost parameters imply that producing at capacity increases marginal cost by \$20.73 per metric tonne relative to producing at a utilization rate less than 29%.[11]

The price parameter (which we estimate) and the nesting parameter (which we pre-set at 0.90) together imply median bid elasticities of demand of -3.10 at the plant level but only -0.10 at the industry level. Thus, most buyer substitution is from one cement plant

[11] Appendix Figure G.3 plots marginal cost over the sample period, averaging across plants, along with a decomposition that separates the constant portion and the portion due to capacity constraints.

Table 1: Parameter Estimates and Derived Statistics

Parameter		Estimates	Std. Error
Gross Buyer Utility			
Constant	β_0	0.432	(0.043)
Overland Miles (000s)	β_1	-2.299	(0.090)
River Barge Used	β_2	-0.451	(0.007)
Time Trend	β_3	-0.001	(0.001)
Imported Cement	β_4	0.087	(0.017)
Imported Cement $\times$ Time Trend	β_5	0.004	(0.001)
Marginal Cost			
Constant	α_0	30.95	(2.27)
Fuel Cost	α_1	1.75	(0.05)
Time Trend	α_2	0.124	(0.028)
Capacity Cost	γ	41.12	(8.63)
Utilization Threshold	ν	0.289	(0.089)
Other Parameters			
Price Parameter	ϕ	0.005	(0.000)
Nesting Parameter	σ	0.9	—
Transportation Costs			
Overland Cost ($ per Tonne-Mile)	β_1/ϕ	0.42	
Barge Cost ($ per Tonne)	β_2/ϕ	82.46	
Bid Elasticity of Demand			
Plant-Level Demand		-3.10	
Demand for Cement		-0.10	

Notes: The results are based on nonlinear least squares estimation. Fuel Cost and the time trends are demeaned. Standard errors are shown in parentheses.

to another, rather than from cement plants to the outside good. This reflects the high nesting parameter, which we select based on our qualitative understanding that cement has significant advantages in most of the projects for which it is used because it is cheap, locally available, and has low maintenance costs (van Oss and Padovani, 2003). We have found it is difficult to identify the nesting parameter in practice. In Appendix E, we show that our results are robust to different values of the nesting parameter.

The mean markup in the sample is $22.32 per metric tonne, relative to a mean price of $94.82.[12] We find that the mean price-over-cost (p/c) margin and Lerner Index ($(p-c)/p$) are 1.32 and 0.24, respectively. Cement firms also profit from rents because marginal cost functions are upward-sloping. The average rent is $10.94 per metric tonne and, adding this to the markup, average variable profit is $33.26 per metric tonne. As mean buyer surplus is $116.17 per metric tonne, buyers capture most of the welfare benefits generated by the

[12]All means reported in this paragraph are quantity weighted.

industry.

We assess the model by evaluating its fit for the targeted endogenous outcomes and comparing its predictions to external sources. Appendix Figure G.4 plots the time series of total consumption, total production, and average price, along with the corresponding model predictions. Appendix Figures G.5 and G.6 show the fit of the model to the *California Letter* data on cross-region shipments, the panel data on consumption, production, and prices, and the time-series of production by wet kilns and the prevalence of barge shipments. Overall, our interpretation is that the model fits the data well.

For the external comparisons, a Census Bureau (1977) study reports that more than 80% of cement is transported within 200 miles, and the 1974 *Minerals Yearbook* reports average overland transportation costs of $0.43 per tonne-mile for trucking. Our analogous estimates are 84% and $0.42 per tonne-mile, respectively. Miller and Osborne (2014b) estimates a median firm-level price elasticity of -3.22 and Ganapati et al. (2020) estimates a plant-level demand elasticity of -2.90; our bid-elasticity is -3.10. Chicu (2012) and Fowlie et al. (2016) estimate more elastic demand elasticities of -6.55 and -7.35, respectively.[13]

5 The Evolution of Market Outcomes

5.1 Market Power

We now examine how market concentration and markups evolve over the sample period, relate those changes to each other and to prices, and explore mechanisms. We use county-level HHIs to measure concentration. In calculating the HHI, we exclude the outside good and treat imports as being provided by one distinct supplier of cement; alternative treatments of imports do not significantly affect our results. For our baseline markup measure, we use price minus marginal cost, which we obtain at the county-plant level. We also report price-over-cost (p/c) markups for comparability with De Loecker et al. (2020).

Figure 4 summarizes how concentration and markups have changed over time. The top panel shows that the quantity-weighted median HHI increased from 1876 to 2727 over the sample period, equivalent to a reduction in the number of symmetric competitors from roughly 5.3 to 3.7. Applying the 2023 *Merger Guidelines*, the proportion of consumption that occurs in "highly concentrated" counties (HHI$\geq$1800) rose from 55% to 84%. The proportion of consumption in counties with concentration levels that are at least triopoly-equivalent (HHI$\geq$3333) rose from 27.6% to 39.3%, and the proportion of consumption in counties with HHI under 1500 fell from 33.1% to 9.8%. From 1974 to 2019, the HHI

[13]Chicu (2012) estimates demand using older data that span 1949-1969. The market-level demand functions estimated in Fowlie et al. (2016) imply plant-level elasticities under their assumptions of Cournot competition.

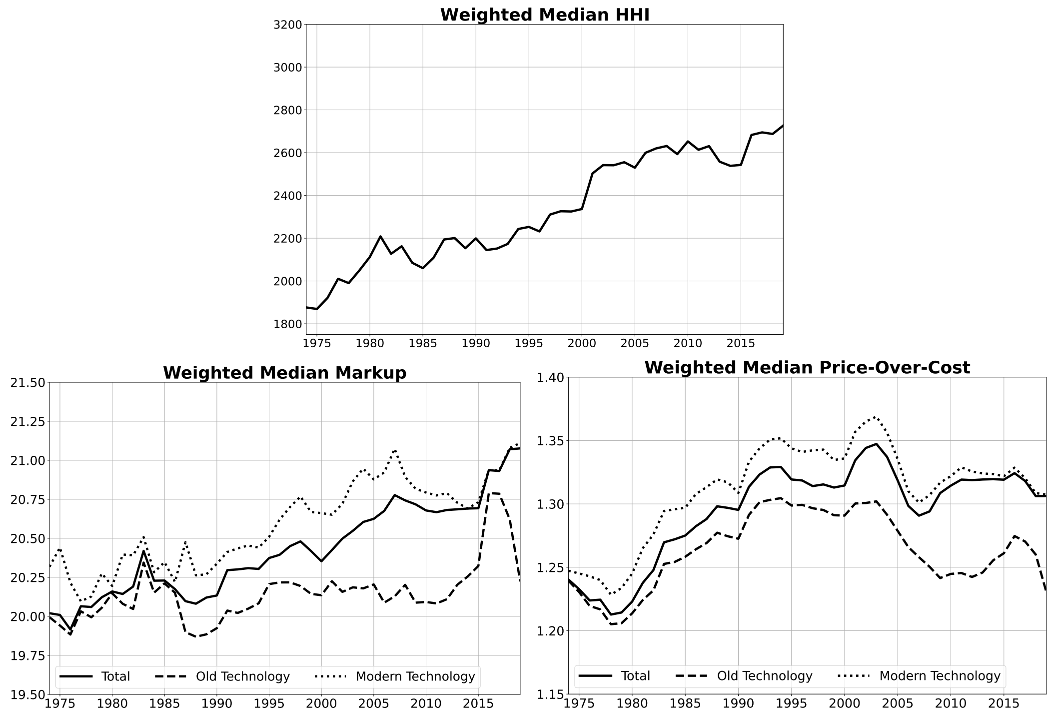

Figure 4: Changes in Local Market Concentration and Markups

Notes: The figure plots the quantity-weighted median county-level HHI (top panel), the quantity-weighted median markup in dollars per metric tonne (bottom left panel), and the quantity-weighted median price-over-cost markup (bottom right panel). The markup statistics are shown for all plants, plants with old technology, and plants with modern technology.

increased in 77.2% of counties. These statistics point to a significant, widespread increase in concentration contemporaneous with the transition to precalciner technology.[14]

Turning to markups, with our baseline measure, the quantity-weighted median markup steadily increased over the sample period, rising from \$20.02 in 1974 to \$21.08 in 2019, representing a 5.27% increase (bottom left panel, solid line). With price-over-cost markups, the quantity-weighed median increases more quickly in the 1980s, and then levels off (bottom right panel, solid line). The overall rise is from 1.24 to 1.31, representing a 5.31% increase.[15] The relative flatness of price-over-cost markups in more recent years is due to the combination of higher baseline markups and higher prices. Our results indicate significant spatial differences exist, with markups increasing in 78.8% of counties, and decreasing in the other 21.2%. That we find rising markups is consistent with the results of De Loecker

[14]In Appendix E, we show that even under a range of alternative estimation specifications, the increase in the county-level HHI is always substantial.

[15]Appendix Figure G.7 shows that changes in the Lerner Index resemble those of price-over-cost markups. In Appendix E, we show that the increase in markups remains modest across a range of alternative specifications, usually amounting to about a dollar or less.

et al. (2020) for the manufacturing sector in which cement is classified (NAICS Code 32), although the magnitude of change that we estimate is much smaller; De Loecker et al. (2020) find that price-over-cost markups increased from 1.35 in 1974 to 1.96 in 2016.

The figure also plots the change in markups separately for plants with modern technology (dotted lines) and other plants (dashed lines). The markups of plants with modern technology are higher than those of other plants and increase more over time. Thus, the overall markup trend reflects both compositional change in the sample, as more plants transition to modern technology, and increasing markups within the set of plants with modern technology. The latter effect could be due to the closure of some plants with old technology; we return to mechanisms later in this section.

While we consider the increase in concentration significant, the markup changes are reasonably characterized as modest. In support of this interpretation, we note that small changes in the model can eliminate the markup trend. For example, if we compute equilibrium in 2019 using a price coefficient that is 5% smaller than our estimate, then we obtain a quantity-weighted median markup that is virtually indistinguishable from what we report for 1974 using the baseline model. Analogously, in Appendix B, we extend the model to incorporate Nash bargaining between the buyer and the winning bidder, and derive that a 5% reduction in cement firms' bargaining power would eliminate the markup trend.

We now analyze the panel variation in the model predictions, and in particular, explore whether concentration changes correlate with changes in markups and prices.[16] Figure 5 shows scatter plots of the county-level HHI changes against county-level average markup changes (top panel) and county-level average price changes (bottom panel). Each circle represents one county, and the areas of the circles are proportional to county-level consumption. There is a clear positive correlation between the HHI and markup changes—those counties that experienced the greatest increase in concentration also experienced the largest increase in markups. The line of best fit has an R^2 of 0.448. In contrast, the relationship between the HHI and price changes is less obvious. Although there is a positive correlation, many counties experienced an HHI increase with a price decrease, or vice versa. This is reflected in the smaller R^2 of 0.065.

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

[16]The model provides a rich set of county-plant specific prices and a correspondingly rich set of shipment patterns. Fully exploring the spatial patterns is beyond the scope of this paper. To give some sense, however, in Appendix G we show that plants obtain both higher prices and greater market shares in nearby counties, with the degree of markup dispersion depending on the presence of competitors (Appendix Figure G.8). We also provide a map of plants and buyers that transport over the Mississippi River System (Appendix Figure G.9).

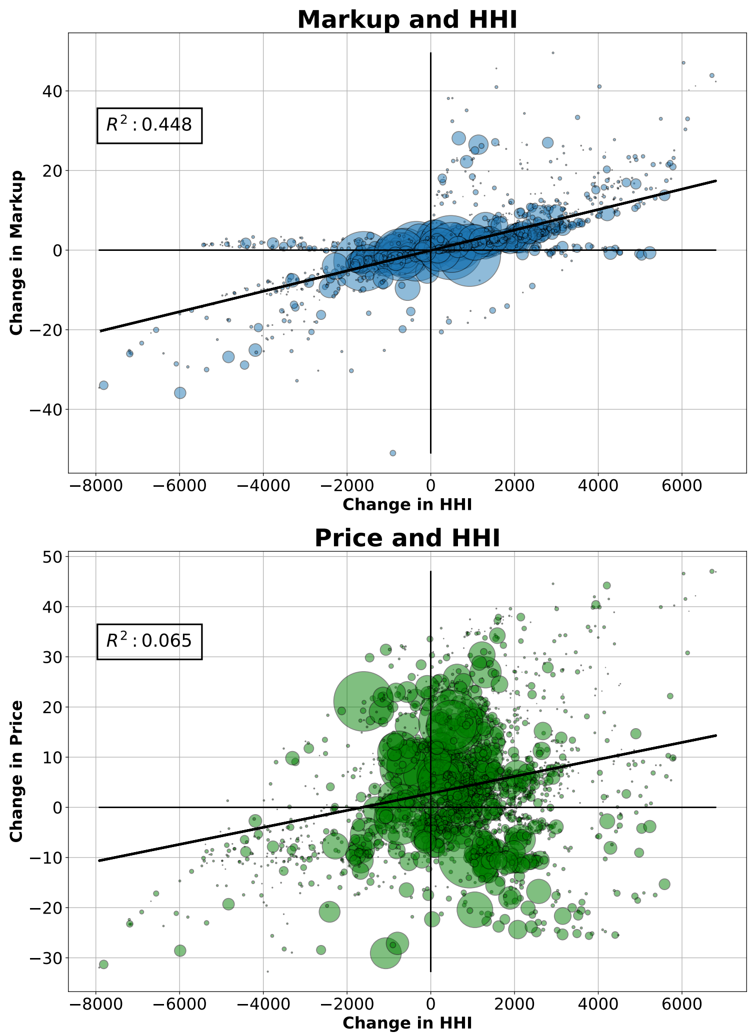

Figure 5: Markup and Price Changes Plotted Against HHI Changes, 1974 to 2019

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

extent that marginal cost reductions and the loss of competition have opposing effects.[17]

Still, a number of alternative mechanisms can generate similar relationships between concentration, markups, and prices, and we conduct decomposition exercises to extend the analysis. In the data, we observe changes in a wide range of market factors that bear on

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

equilibrium outcomes: plant closures, technology adoption, entry, mergers, fuel prices, and so on. To examine which of these matter most, we start with the 1974 data and introduce changes in sequence, computing equilibrium with each change, until we obtain the 2019 data. We then examine how concentration, markups, and prices shift as we move from 1974 to 2019 conditions.

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

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

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

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

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

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

With the final step, we reproduce the 2019 data. The interpretations we offer represent short run effects because the incentives for technology adoption, exit, entry, and mergers are intertwined in long run equilibrium. One relationship that is particularly relevant in our application is that the adoption of a cost-reducing, scale-increasing technology by some plants is likely to induce others to exit. Thus, what is isolated in step (ii) likely incorporates a long run effect of technology adoption, a matter that we revisit in the next section.[18]

Figure 6 summarizes the results of the decomposition exercise. Three waterfall graphs are provided, one each for the quantity-weighted median county-level HHI (top panel), the quantity-weighted median county-level additive markup (bottom left panel), and the quantity-weighted median county-level price (bottom right panel). The gray bars on the left and right provide the values in 1974 and 2019, respectively. The bars in the middle give the incremental effect of each sequenced change in the market, as enumerated above. We shade these bars blue for increases and red for decreases.

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

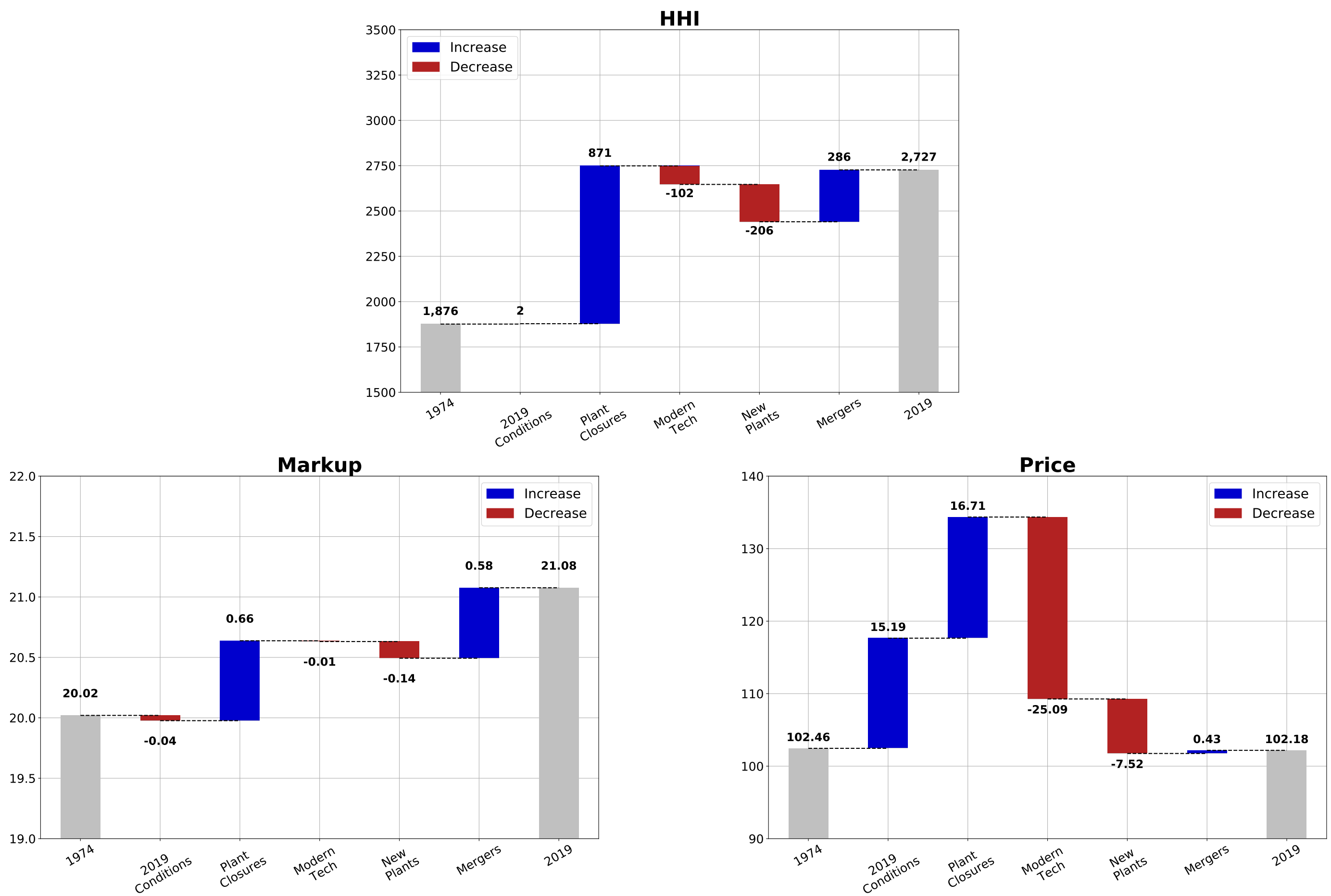

Figure 6: Short Run Determinants of HHI, Markup, and Price Changes

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

We find that plant closures contribute 871 points to the median HHI. Other meaningful factors include mergers, which contribute 286 points to the median HHI, and new technology adoption and plant entry, which reduce the median HHI by 102 and 206 points, respectively. For markups, the main contributing factors are plant closures ($0.66) and mergers ($0.58). Modern technology has almost no direct effect on markups (-$0.01). The changes in markups are small relative to average prices. Finally, we find that changes in demand and cost conditions contribute to higher prices ($15.19), as do plant closures ($16.71). Plant closures have a bigger effect on prices than markups because they increase the remaining plants' utilization (and thus their marginal costs). Offsetting these factors, we obtain price reductions from the adoption of modern technology ($25.09) and plant entry ($7.52). The effect of modern technology on prices is mainly due to better fuel efficiency and greater capacity, both of which reduce the marginal cost of production. Mergers increase prices by a much smaller amount ($0.43) that is commensurate with their effect on markups.

The decompositions are consistent with the main short run effects of technology adoption in the cement industry being marginal cost reductions that are passed through to cement buyers in the form of lower prices. To the extent that technology adoption contributes significantly to rising concentration and markups, our analysis indicates that it is through its effect on long run decisions, including on plant closures. We explore scale economies in greater quantitative detail in Section 5.3 to better understand long run effects.

Returning to the panel variation, we also note that the equilibrium model informs not only how and why concentration and markups changed over time, but also the location of changes. To illustrate these distributional effects, Appendix Figure G.10 provides maps with the HHI for each county in 1974, the HHI in 2019, and the change in the HHI from 1974 to 2019. Appendix Figures G.11 and G.12 do the same for average markups and prices, respectively. The level and change in the HHI, markups, and prices tend to be more modest in counties near the Mississippi River System. By contrast, counties with higher levels and greater changes—positive or negative—tend to be more isolated, such that the entry or closure of a single plant in the region, or changes in the accessibility of imports at nearby ports, can matter significantly. Thus, our results point to the Mississippi River System as a conduit that, by connecting a large number of buyers and suppliers, helps produce outcomes that are less extreme and more stable over time. More generally, our model helps explain the spatial distribution of equilibrium effects in industries such as cement.

5.2 Welfare Statistics

Another benefit of the equilibrium model is that it allows us to examine how variable profit, buyer surplus, and welfare—which we define as the sum of variable profit and buyer surplus—change over the sample period. Our approach is to compute equilibrium holding

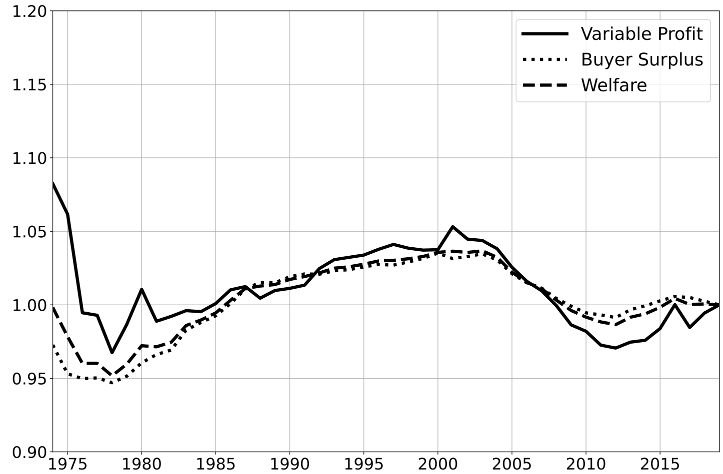

Figure 7: Changes in Variable Profit, Buyer Surplus, and Welfare

Notes: The figure plots indices for variable profit, buyer surplus, and welfare normalized to one in 2019. The welfare statistics are computed by holding demand-side conditions fixed as of 2019 and simulating outcomes given the supply-side conditions as they change over the sample period.

all demand-side considerations fixed at their 2019 values, and allowing supply-side considerations to adjust over the sample.[19] Thus, we assess how supply-side changes affect overall gains-from-trade, given the same set of buyers; an advantage is that this reduces the influence of market size assumptions on the results.

Figure 7 plots the welfare statistics as indices that equal one in 2019. We highlight two patterns. The first is that variable profit, buyer surplus, and welfare move together, increasing from 1980 to 2000, and falling afterward. This tracks changes in fossil fuel prices and cement plants' fuel costs (Appendix Table G.15). More gains-from-trade exist when fossil fuel prices are low, and these gains are split between buyers and sellers. The second pattern is that welfare is nearly identical in 1974 and 2019, reflecting that buyer surplus increased by three percentage points over the sample period and variable profit decreased by seven percentage points. Therefore, the trend toward greater concentration presented earlier does not correlate with reduced buyer surplus or reduced gains-from-trade, just as it does not correlate with rising prices over time or in the panel variation.

Appendix Figure G.13 shows the results of a waterfall decomposition similar to what we use for concentration, markups, and prices; the difference is that, in this exercise, demand conditions are held fixed at 2019 values throughout. We find that buyer surplus decreases

[19] The demand-side factors include the county-level market sizes and the demand time trend and its interaction with imports. The supply-side factors include the cement plants and their production technologies, the marginal cost time trend, fuel prices, and the active customs districts. We adjust plant capacities each year so that the ratio of industry capacity to market size does not change; this ensures that mechanical changes in capacity utilization do not drive results.

due to plant closures but increases due to new technology adoption and entry, reflecting anticipated impacts on competition, capacity, and fuel costs. The opposite patterns obtain for variable profit. Welfare resembles variable profit qualitatively, but is more muted, and the net effect moving from 1974 to 2019 is about zero, consistent with the index result.[20]

5.3 Economies of Scale

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

$$TFC = \begin{cases} F & \text{if keep old kiln} \\ (1-\delta)E + F' & \text{if adopt precalciner} \end{cases} \tag{22}$$

where δ is the discount factor, F and F' are the operational fixed costs of the old and new technologies, respectively, and E is the capital cost required for the new technology. To obtain this expression, we assume that both technologies are infinitely-lived, which is a reasonable approximation given that kilns tend to operate for many decades.

We assume a discount factor of $\delta = 0.90$. For the capital cost, we make assumptions based on the CEMBUREAU estimates of construction costs (discussed in Section 2.2). Specifically, we assume that the capital cost is €175 million, and we convert that to dollars using the average closing price of the exchange rate in 2010, which is 1.33. This implies a capital cost (E) of $233 million.[21] Finally, for the operational fixed cost, we apply the two-sided bounds approach of Eizenberg (2014). In doing so, we exploit 242 instances in which we observe that a kiln is not operated during a year. This is referred to as "idling" or "mothballing" a kiln and it is often done when demand conditions are unfavorable. In Appendix F, we develop the bounds formally and provide details on implementation.

Table 2 summarizes our numerical analysis of fixed costs. For the operational fixed costs, we obtain an estimated set that provides model-implied bounds, separately for old kilns and modern kilns. We report a 95% confidence interval around those estimated sets.

[20]We find it interesting that welfare decreases with technology adoption in this analysis. Mechanically, the effects on buyer surplus and markups roughly offset because industry demand is inelastic. The remaining effect on welfare is through infra-marginal rents, which decrease as capacity expands relative to demand.

[21]In the Appendix, we recreate the main figures of this section using capital costs of $116 million (50% lower) and $349 million (50% higher). See Appendix Figure G.14.

Table 2: Numerical Analysis of Fixed Costs

	Operational Fixed Cost Bounds	Capital Cost (Annualized)	Total Fixed Cost Bounds	Total Fixed Cost Midpoint
Wet and Long Dry Kilns	[0.44 , 4.16]	Sunk	[0.44 , 4.16]	2.30
Modern Preheater/Precalciner Kilns	[0.70 , 13.67]	23.27	[23.97 , 36.95]	30.46

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

For each old kiln the confidence interval is [0.44 , 4.16], and for each modern kiln it is [0.70 , 13.67], where units are in millions of real 2010 dollars. These confidence intervals overlap but we cannot rule out the operational costs are significantly higher for modern kilns. Putting these together with capital costs, we obtain an interval of [23.97 , 36.95] for the total fixed cost of modern kilns. Finally, for the analyses below, we assume that total fixed costs are at the midpoint of the bounds. This provides $2.30 million per kiln-year for old kilns and $30.46 million per kiln-year for modern kilns.

With this quantification of fixed costs, we recover an average cost function for each plant and year in the sample. Figure 8 provides an illustrative example using the Essroc plant in Nazareth, Pennsylvania. The left panel shows the plant's average cost and marginal cost functions in 1976, before adoption, and the right panel shows those functions in 1977, after adoption. The vertical dotted lines show equilibrium quantities (q^*). The efficient level of production increases from 0.71 million metric tonnes to 1.2 million metric tonnes due to the adoption of modern technology. Average cost at the efficient level of production decreases from $120 to $103 per metric tonne, relative to national average prices around $114 per metric tonne. Also of note, profitable adoption requires an expansion of output. If the plant had held its output fixed at its initial level of 0.49 million metric tonnes, adoption would have increased average cost from $125 to $132. Instead, the equilibrium output increases to 0.81 million metric tonnes, and average cost falls.

To generalize across plants, we use the ratio of average cost to marginal cost, which is a standard measure of scale economies (Syverson, 2019). If the ratio is greater than one then average costs are decreasing in output, meaning economies of scale exist. If it is less than one then diseconomies of scale exist, and if it equals one then output is at the efficient level. Furthermore, as the ratio of average cost to marginal cost equals the inverse of the elasticity of total cost with respect to quantity, its value can be interpreted as the percentage change in quantity that can be obtained from a one percent increase in cost, sometimes referred to as the *scale elasticity*. We calculate the ratio for every plant and year and examine how scale

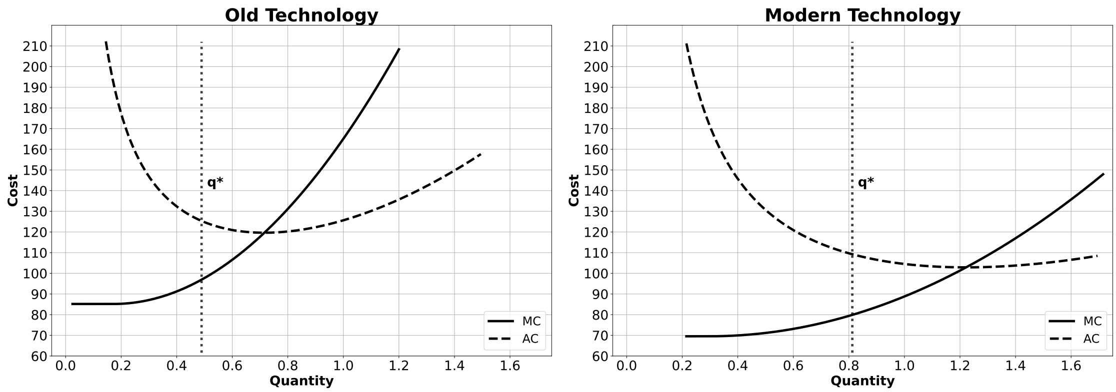

Figure 8: Plant-Level Cost Functions (Illustrative Example)

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

economies have evolved.

Figure 9 plots the quantity-weighted median scale elasticity evaluated at equilibrium quantities (left panel). The median scale elasticity increases from 1.05 in 1974 to 1.28 in 2019. The scale elasticity is greater for plants with modern technology than for plants with old technology, and the upward trend in the industry-wide number is mainly due to a compositional shift toward modern technology. These results incorporate output expansion, which partially exhausts scale economies created by modern technology. Therefore, we repeat the analysis holding output fixed (right panel). With this counterfactual, median scale elasticity increases from 1.12 in 1974 to 2.38 in 2019. Thus, the amount of additional output that can be generated by incurring an increase in costs nearly doubles.

This analysis of scale elasticities points to an advantage of our modeling approach. Namely, we are able to identify the impact of technological change separately from its implication for the equilibrium scale elasticity, which is an endogenous outcome. Our results indicate that modern kiln technology has significant scale-increasing effects.

As a final exercise, in Figure 10 we examine the ratio of price to average cost, a measure of economic profitability. The left panel plots this ratio evaluated at equilibrium quantities. We focus on plants with modern kilns because we have a measure of the capital costs for those kilns. The ratio is below one and then increases over time until it stabilizes around one for the back half of the sample, which we interpret as being consistent with plants' greater variable profit from adoption being just enough to recover the fixed costs associated with adoption. (Alternatively, if one has a prior that the cement industry is characterized by free entry and exit in the long run, the results are consistent with our fixed cost estimates

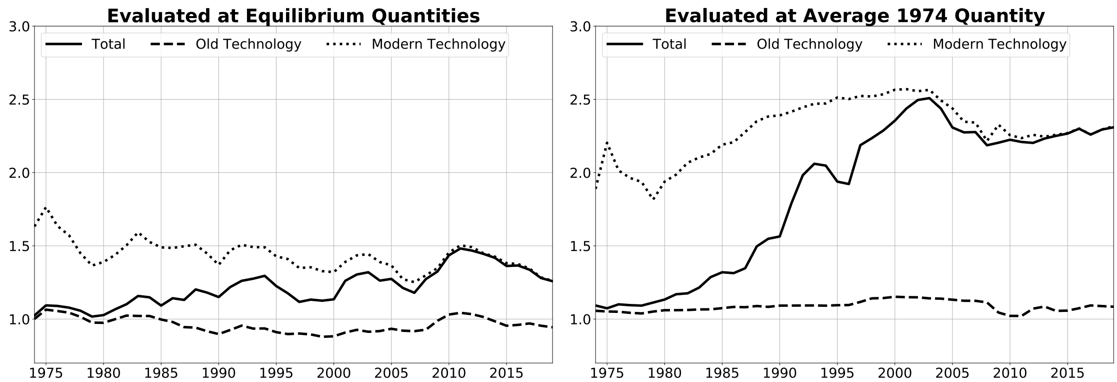

Figure 9: Changes in the Scale Elasticity

Notes: The panels plot the scale elasticity evaluated at equilibrium quantities (left) and at quantities that are fixed at the average 1974 level (right). Quantity-weighted medians are shown for all plants, plants with old technology, and plants with modern technology.

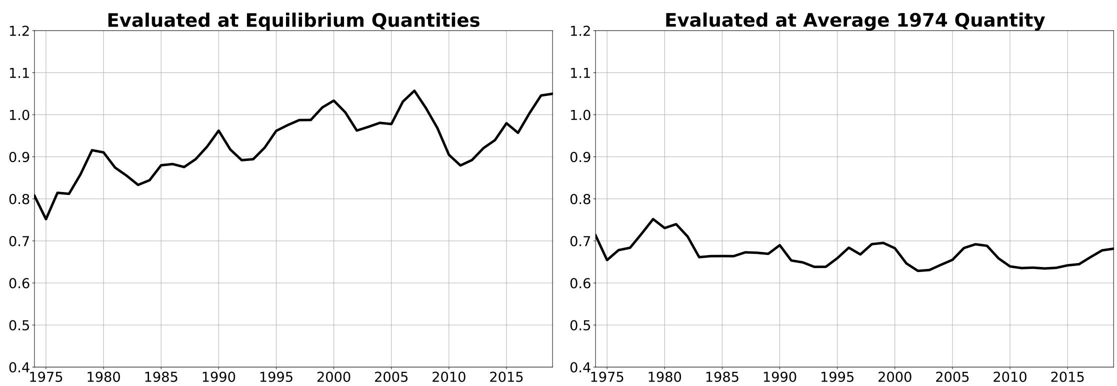

Figure 10: Changes in the Ratio of Price to Average Cost

Notes: The panels plot the quantity-weighted median ratio of price to average cost, at equilibrium quantities (left) and at quantities that are fixed at the average 1974 level (right). The median is among plants with modern technology.

being in a reasonable range.) However, if the ratio is evaluated at fixed quantities (right panel), it is well less than one throughout the sample period. Again, this is consistent with output expansion being necessary for profitable adoption, and supports that the adoption of modern kiln technology contributed to the many observed plant closures.

5.4 Comparison to the Production Approach

We now compare our markup results to those of De Loecker et al. (2020) ["DLEU"], which uses the so-called production approach to recover price-over-cost markups from accounting data on publicly-traded firms. The production approach involves first estimating the elastic-

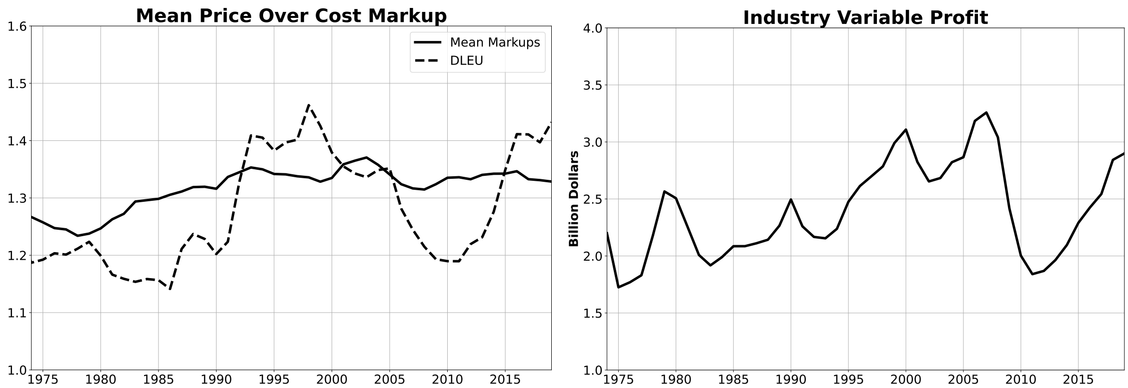

Figure 11: Comparison to the Production Function Approach

Notes: The left panel plots the sales-weighted average price-over-cost markup obtained from our model (solid line) and from an implementation of the production approach that tracks DLEU (dashed line). The right panel plots total industry variable profit over time, which we obtain from our model.

ity of output with respect to a freely adjustable variable input. Then, under an assumption of cost minimization, the price-over-cost markup is obtained as the output elasticity multiplied by the ratio of sales to expenditures on the variable input. DLEU uses the cost of goods sold (COGS) as the variable input. We implement by pairing the output elasticities provided in the DLEU replication files with accounting data from Compustat for firms classified under NAICS code 327310 ("cement manufacturing"). As the DLEU output elasticities run through 2016, we assume that the output elasticity is constant over 2016-2019.

We plot our sales-weighted mean price-over-cost markup alongside the production-approach estimate for cement firms in the left panel of Figure 11. Both measures are similar in magnitude. Averaging across years, we obtain 1.32, and the production approach obtains 1.28. However, markups from the production approach are significantly more pro-cyclical. To illustrate, the right panel provides a plot of industry-wide variable profit. A similar pattern arises in a recent study on automobiles (e.g. Grieco et al., 2024), with markups from the production approach being more pro-cyclical than those from a structural model. Mechanically, changes in the production approach markups are due to the ratio of sales to COGS because the DLEU output elasticity changes little over the sample period: the average is 0.860, and the standard deviation is 0.027.

A full exploration of this difference is beyond the scope of our study. Still, it is worth noting that our model incorporates capacity constraints, so favorable macroeconomic conditions can induce firms to produce more and shift to a higher point on their marginal cost function, thereby reducing the procyclicality of markups. We also posit that the use of sales and expenditure variables, rather than output and input variables, in production function estimation (e.g., as in DLEU) might lead the production approach to overstate the procyclicality of markups. However, there are other reasons that the two markup series are not immediately comparable. As one example, the largest cement firms operate internationally, and Compustat provides data on their global activity, not their US operations.

6 Conclusion

In this paper, we trace out the effects of a major technological advance in the cement industry—the precalciner kiln—and connect our results to the literature on *The Rise of Market Power*. We find significant increases in concentration, but markups increase only modestly, and real prices do not rise. These empirical patterns can be understood through the economics of precalciner technology, which lowered the marginal cost of production and significantly increased plant-level capacities, thereby contributing to an industry shakeout in which many plants closed. Our findings underscore the importance of accounting for technological change when assessing the implications of market concentration.

Our analysis is subject to limitations. We highlight three here. First, although we present evidence consistent with precalciner technology contributing to the shakeout that occurred during the sample period, we do not model that dynamic process formally because it would require sacrificing some of the modeling realism that lends credibility to our results. With our results in hand, however, there is an improved ability for future research to extend in that direction (e.g., as in Igami, 2017; Igami and Uetake, 2020). Second, there is an important role for research that synthesizes results obtained across various industries. In the context of *The Rise of Market Power*, this is increasingly likely to be fruitful, as studies have now been conducted in a number of different contexts; an early attempt is made in Miller (2025). Finally, our methodological approach uses modeling to infer objects of interest, such as local market concentration and markups. To the extent that more detailed data can be obtained—in the United States or elsewhere—a more data-driven analysis could provide useful insights that could corroborate (or contradict) our findings.

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

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Appendix Materials

A Additional Proofs

A.1 Proof of Theorem 1

We use "*" to denote realized values that result from firms bidding according to equation (9), as per the posited equilibrium. We first consider the case where all plant marginal cost functions are constant, following the discussion in Miller (2014).[22]

Lemma 1. *Assume that the plant marginal cost functions are such that* $c_j(q_j) = \bar{c}_j \; \forall j \in \mathcal{J}$*. Then, if all firms each own only one plant and submit bids according to equation* (9)*, no firm has an incentive to unilaterally change its strategy.*

Proof. First, note that no firm has an incentive to unilaterally change its strategy to any alternative that leaves unchanged the probability of the firm's plant winning and losing the same auctions. From equation (5), we see that b_{ij} does not appear when determining the price earned in an auction being won by plant j. Furthermore, each firm only owns one plant, which means the price for a winning firm is determined by bids from other firms. Therefore, any strategies, taking other firm bids as given, that result in identical probabilities for a plant winning and losing the same sets of customers give the same firm revenues. Furthermore, these strategies all result in the same costs, as expected plant quantities remain fixed. Thus, firm profits do not increase.

What remains is to establish whether the firm has an incentive to choose a strategy that changes which auctions the firm wins. There are two possibilities: (1) strategies that cause the firm to lose auctions it would otherwise win in the baseline strategy, and (2) strategies that cause the firm to win auctions it would otherwise lose in the baseline strategy.

Without loss of generality, we consider the incentives of some firm owning a plant we label x. We know from equation (5) that if plant x is the winning choice by buyer i and plant y is the second-best choice, the transaction price is such that

$$p^*_{ix} = \frac{1}{\phi}\left(u_{ix} - u_{iy}\right) + b^*_{iy}. \tag{A.1}$$

Furthermore, plant x must score the highest, which means that

$$u_{ix} - \phi \bar{c}_x \geq u_{iy} - \phi b^*_{iy}, \tag{A.2}$$

[22] The inequality in equation (9) rules out the case where the marginal cost of the winning firm is so high that it cannot provide positive surplus to the buyer even at a price equal to marginal cost.

where we have substituted in for the bid function of plant x. Rearranging this score inequality to solve for marginal cost gives

$$\bar{c}_x \leq \frac{1}{\phi}(u_{ix} - u_{iy}) + b^*_{iy}, \tag{A.3}$$

and combining this inequality with equation (A.1) implies that $\bar{c}_x \leq p^*_{ix}$. The price paid to the owner of plant x covers its marginal production costs for the auctions it wins. Thus, the owner of plant x would lower its profits if it instead raised its bids in these auctions such that it lost them.

Consider instead a case where, under the bidding strategies of equation (9), plant x loses an auction for buyer l to some plant z. Based on the scoring rule, we know that

$$u_{lz} - \phi b^*_{lz} \geq u_{lx} - \phi \bar{c}_x, \tag{A.4}$$

since plant z must score better than plant x. Rearranging gives

$$\bar{c}_x \geq \frac{1}{\phi}(u_{lx} - u_{lz}) + b^*_{lz}. \tag{A.5}$$

Suppose that the firm that owns plant x were to lower its bid to overtake plant z as the winner. Then, plant z would be the second-best option, determining the transaction price. That price would become

$$p'_{lx} = \frac{1}{\phi}(u_{lx} - u_{lz}) + b^*_{lz}, \tag{A.6}$$

by applying equation (5). We use "p'_{ix}" to denote the realized price under the alternative strategy. Combining these two equations implies that $\bar{c}_x \geq p'_{lx}$, meaning the potential price does not exceed the marginal cost of plant x. Therefore, the owner of plant x does not gain from outbidding rival plants in order to win auctions that it otherwise would have lost. □

Given that the above computations do not depend on the bids chosen by rival firms (note that equations (A.1) to (A.6) do not specify the exact bids that other firms make), we have found a weakly dominant strategy for firms with constant marginal costs.

Lemma 1 implies that, conditional on other firms bidding according to equation (9), for any realized level of marginal cost, there is an optimal set of customers for a plant to serve. This is restated in the following corollary.

Corollary 1. *Assume all firms each only own one plant and submit bids according to equation (9). Then no firm has an incentive to unilaterally switch to a strategy that gives the same plant marginal cost but changes the probabilities for which customers the firm will win.*

Proof. Again, consider some firm owning a plant we label x. From Lemma 1, if one substitutes $c_x(q_x^*)$ for $\bar{c}_x$ in equations (A.1) to (A.6), this establishes that, for a given level of plant marginal cost (denoted by "*"), using the proposed bidding strategy results in the firm winning auctions with prices that exceed this marginal cost and losing auctions where outbidding the winner would result in a price below this marginal cost. □

We are now ready to tackle the case with weakly increasing marginal cost functions.

Lemma 2. *Assume that all marginal cost functions adhere to Assumption 3. Then if all firms each only own one plant and submit bids according to equation* (9)*, no firm has an incentive to unilaterally change its strategy.*

Proof. Again, consider the incentives of some firm with a plant x. Corollary 1 rules out switching to a different strategy that gives the same plant quantity and therefore the same marginal cost. What remains is to consider strategies that result in a different marginal cost from $c_x(q_x^*)$. There are two possibilities: (1) alternative strategies where marginal costs are greater than $c_x(q_x^*)$, and (2) alternative strategies where marginal costs are less than $c_x(q_x^*)$. Given that firm marginal cost functions are non-decreasing, case (1) can occur only if a firm bids such that plant-level quantity increases, whereas case (2) can only occur only if a firm bids such that plant-level quantity decreases.

In order to increase total quantity, the firm that owns plant x would need to decrease its bids for some of the auctions it would lose under marginal cost bidding while continuing to prevail in the auctions it would win.[23] Consider one of these auctions, say for some buyer l, where plant x loses to plant z when bidding according to equation (9). Following the logic of Lemma 1, the price that would result if plant x instead lowered its bid to overtake plant z is given by p'_{lx} in equation (A.6). Furthermore, by substituting $c_x(q_x^*)$ for $\bar{c}_x$ in equation (A.5), we also find that $c_x(q_x^*) \geq p'_{lx}$. Given that the quantity increases under this alternative strategy, we have that $c_x(q'_x) \geq c_x(q_x^*)$, which implies in turn that $c_x(q'_x) \geq p'_{lx}$. Therefore, the price does not exceed plant costs in these additional auctions, meaning strategies that increase quantity do not raise profits.

In order to decrease total quantity, the firm that owns plant x would need to increase its bids for some of the auctions it would win under marginal cost bidding while continuing to lose in the other auctions.[24] Again referring to Lemma 1, equation (A.1) implies that the price earned by plant x in an auction it wins is p_{ix}^*. After substituting in $c_x(q_x^*)$ for $\bar{c}_x$ in equation (A.3), we see that $p_{ix}^* \geq c_x(q_x^*)$, which also means that $p_{ix}^* \geq c_x(q''_x)$, where q''_x

[23]Note that we can rule out a strategy that results in the firm losing some auctions it wins under marginal cost bidding, as this alternative is dominated by a strategy that produces the same quantity sold and hence the same costs but where those sales include all of customers that it would have won under marginal cost bidding. This is due to Corollary 1.

[24]Analogous to the above discussion in the case of increasing quantity, we can rule out a strategy where the firm wins some auctions it loses under marginal cost bidding, as those customers offer less lucrative price opportunities than the customers the firm wins with marginal cost bidding.

denotes the lower quantity that obtains when plant x wins fewer auctions. Therefore, the price in the auctions the firm wins under marginal cost bidding also covers the marginal cost realized in the alternative strategy. Forgoing winning these auctions would lower firm profits. □

We now extend to the case of multi-plant firms.

Lemma 3. *If all firms submit bids according to equation* (9)*, a firm that owns multiple plants does not have an incentive to switch to a strategy of bidding more than one plant for any customer.*

Proof. From Lemma 2, we see that a strategy giving the highest profit for a plant, conditional on submitting a bid for that plant, is to bid the marginal cost. This rules out an incentive to switch to other strategies besides marginal cost bidding.

The question remains whether the firm has an incentive to bid multiple plants. Assume instead of following equation (9), that some firm owning multiple plants deviated from the baseline strategy and instead submitted a bid for multiple plants for one or more buyers. Using equation (2), one can rank all the plants with submitted bids by decreasing score for each auction. Focus on one such auction for some buyer i. Given this ranking, there are three possible cases: (1) none of the plants owned by the firm have the highest score for this buyer, (2) the firm owns the plant with the highest score but not the plant with second highest, and (3) the firm owns both the plant with the highest score and the plant with the second highest. Given the auction format, in the first and second cases, the profits of the firm are the same under both the baseline and alternative bidding strategies, as in the first, the firm earns zero revenue, and in the second, the price is determined by a different firm's bid, as shown in equation (5).

Turning to the third case, without loss of generality, label the highest scoring plant x and the second highest scoring plant y, which are both owned by this firm. Label the next highest scoring plant that is owned by a separate firm plant z. Under the alternative strategy, applying equation (5), the firm earns a price of

$$p'_{ix} = \frac{1}{\phi}\left(u_{ix} - score_{iy}\right), \tag{A.7}$$

whereas under the baseline strategy, the firm earns a price of

$$p^*_{ix} = \frac{1}{\phi}\left(u_{ix} - score_{iz}\right). \tag{A.8}$$

Because, by assumption, $score_{iy} > score_{iz}$, the firm would earn a higher price if it chose the baseline strategy. □

That is, a firm does not bid against itself. This is the mechanism through which mergers can increase prices, as when plants are joined under the same owner, they cease offering bids against each other. The proof of Theorem 1 follows from Lemmas 1 through 3.

A.2 Proof of Theorem 3

The result for market shares in equation (13) follows by computing the expected probability, given equilibrium bids from equation (9), that a given plant j would have the highest score for a buyer in county n. This involves integrating over the nested logit shocks in the scores within the maximization problem,

$$\max_{k \in \mathcal{J}_i} \{\overline{u}_{kn} + \zeta_i + (1-\sigma)\epsilon_{ik} - \phi c_k^*\}. \tag{A.9}$$

Applying the usual nested logit market share formulas gives the result. Analogous computations for the probability of choosing the outside good give the result for s_{0n}^* in equation (16).

Turning to the proof for markups in equation (14), if we substitute the nested logit gross utility from equation (12) into the margin from equation (11), we have

$$m_{ij} = \frac{1}{\phi}\left(\overline{u}_{jn} + \zeta_i + (1-\sigma)\epsilon_{ij} - \phi c_j(q_j) - \max_{k \in \mathcal{J}_i \setminus \{j\}} \{\overline{u}_{kn} + \zeta_i + (1-\sigma)\epsilon_{ik} - \phi c_k(q_k)\}\right). \tag{A.10}$$

This margin assumes that plant j is the winner for buyer i.

Taking expectations of this equation involves calculating the value of the expected maximum of all bidders (conditional on plant j being the highest ranked) and the value of the expected maximum of all bidders, excluding the bid from the firm that owns plant j. Applying the nested logit inclusive value formulas gives

$$\overline{m}_{jn}^* = \frac{1}{\phi \sum_{k \in \mathcal{J}^{f(j)}} s_{kn}^*} \ln\left(\frac{1 + \left(\sum_{k \in \mathcal{J}} \exp\left(\frac{\overline{u}_{kn} - \phi c_k^*}{1-\sigma}\right)\right)^{1-\sigma}}{1 + \left(\sum_{k \in \mathcal{J} \setminus \mathcal{J}^{f(j)}} \exp\left(\frac{\overline{u}_{kn} - \phi c_k^*}{1-\sigma}\right)\right)^{1-\sigma}}\right) \tag{A.11}$$

for the expected margin of serving a buyer in county n, conditional on plant j winning the auction. Rearranging this expression gives equation (14). Solving for price in the definition of the margin, $m_{ij} = p_{ij} - c_j$, and taking expectations across logit shocks similar to the derivation in equation (A.11) gives equation (15).

Buyer surplus is calculated by finding the expected dollar value of utility in the maximization problem (A.9), substituting in for the outside good share using equation (16), and then subtracting off the additional increment over marginal costs that is paid to firms. This results in equation (17). □

B Incorporating Nash Bargaining

We introduce an alternative model that incorporates *ex post* Nash bargaining between the buyer and the supplier that wins the second score auction. We first derive expressions for markups and prices under the assumption that suppliers submit bids at cost, and discuss why it is difficult to separately identify the bargaining parameter and the price parameter without data on marginal cost. We then establish that suppliers submitting bids at cost is an equilibrium. Finally, we derive the change in the bargaining parameter that would exactly eliminate the rise in markups that we estimate.

B.1 Model

Consider an alternative model that incorporates *ex post* Nash bargaining. Buyers continue to score suppliers according to the rule in equation (2), and they continue to choose the plant with the best score as the winner. Therefore, the share equation (13) remains the same. However, in order to determine the price, the buyer and winning firm engage in Nash bargaining rather than using equation (5). We label the outcomes in this alternative model "B" for "bargaining" to distinguish them from those in the auction framework.

Suppose plant j is the best-scoring option for buyer i. The bargaining game between buyer i and plant j sets price according to

$$\max_{p_{ij}^B} \left\{ \left(\pi_{ij}^B - \pi_{ij}^{B^{NT}}\right)^{1-\lambda} \left(u_{ij}^B - u_{ij}^{B^{NT}}\right)^{\lambda} \right\}, \tag{B.1}$$

such that

$$\pi_{ij}^B - \pi_{ij}^{B^{NT}} \geq 0 \text{ and } u_{ij}^B - u_{ij}^{B^{NT}} \geq 0, \tag{B.2}$$

where $0 \leq \lambda \leq 1$ is a bargaining parameter that measures the relative bargaining power of buyers to firms. The objects with "NT" superscripts denote the outside options for the firm and buyer if the negotiation does not go through. The π_{ij}^B and $\pi_{ij}^{B^{NT}}$ are the profits that plant j earns if it trades with buyer i versus if it does not trade, respectively. Analogously, the u_{ij}^B and $u_{ij}^{B^{NT}}$ are the payoffs to buyer i if it trades with plant j versus if it does not. A firm and a buyer will only transact if neither receives negative gains from trade.

For buyers, we assume the disagreement payments are

$$u_{ij}^{B^{NT}} = \max_{k \in \mathcal{J}_i \setminus \{j\}} \left\{ u_{ik} - \phi b_{ik}^B \right\}, \tag{B.3}$$

meaning that if the buyer fails to trade with plant j, the disagreement payoff is the buyer's payoff from the second best scoring plant among those that bid. For the firm, we assume that the disagreement payoff is zero. Together, after substituting in for firm profit and buyer utility, these assumptions imply that the bargaining problem becomes

$$\max_{p_{ij}^B} \left\{ \left(p_{ij}^B - c_j(q_j^B)\right)^{1-\lambda} \left(u_{ij} - \phi p_{ij}^B - \max_{k \in \mathcal{J}_i \setminus \{j\}} \left\{ u_{ik} - \phi b_{ik}^B \right\} \right)^{\lambda} \right\}, \tag{B.4}$$

subject to

$$p_{ij}^B - c_j(q_j^B) \geq 0 \text{ and } u_{ij} - \phi p_{ij}^B - \max_{k \in \mathcal{J}_i \setminus \{j\}} \left\{ u_{ik} - \phi b_{ik}^B \right\} \geq 0, \tag{B.5}$$

which are the firm and buyer participation constraints, respectively.

If $\lambda = 0$, then the model collapses to our baseline. In that case, the firm has all the bargaining power and asks for as high a price as possible. The constraint for buyer participation binds, meaning the price is such that $u_{ij} - \phi p_{ij}^B = \max_{k \in \mathcal{J}_i \setminus \{j\}} \{u_{ik} - \phi b_k^B\}$, which is the same as the condition in equation (4). If $\lambda = 1$, then the buyer has all the bargaining power and wants to pay as low a price as possible. In this case, the firm participation constraint binds, meaning the price is given by $p_{ij}^B = c_j(q_j^B)$.

When $0 < \lambda < 1$, differentiating with respect to price after taking natural logs yields the first order condition of the bargaining problem,

$$\frac{1}{\phi} \frac{1-\lambda}{\lambda} = \frac{p_{ij}^B - c_j(q_j^B)}{u_{ij} - \phi p_{ij}^B - \max_{k \in \mathcal{J}_i \setminus \{j\}} \{u_{ik} - \phi b_{ik}^B\}}, \tag{B.6}$$

which implies that $1/\phi$ times the ratio of firm to buyer bargaining power equals the ratio of firm to buyer gains from trade. This calculation treats all marginal costs and other firms' bids as fixed. Rearranging this expression gives

$$m_{ij}^B \equiv p_{ij}^B - c_j(q_j^B) = \frac{1-\lambda}{\phi} \left(u_{ij} - \phi c_j(q_j^B) - \max_{k \in \mathcal{J}_i \setminus \{j\}} \{u_{ik} - \phi b_{ik}^B\} \right). \tag{B.7}$$

In the next subsection, we show that bidding at marginal cost remains an equilibrium of the bargaining model. If we impose that $b_{ik} = c_k$ for all $k \in \mathcal{J}_i \setminus \{j\}$, then equation (B.7) is identical to equation (11), except the right-hand side is multiplied by $1 - \lambda$. Solving for price gives

$$p_{ij}^B = \underbrace{\frac{1}{\phi} \left(u_{ij} - \max_{k \in \mathcal{J}_i \setminus \{j\}} \left\{ u_{ik} - \phi b_{ik}^B \right\} \right)}_{p_{ij} \text{ from second-score auction}} - \underbrace{\frac{\lambda}{\phi} \left(u_{ij} - \phi c_j(q_j^B) - \max_{k \in \mathcal{J}_i \setminus \{j\}} \left\{ u_{ik} - \phi b_{ik}^B \right\} \right)}_{\lambda\text{-fraction of incremental surplus provided by } i\text{-}j \text{ trade}}. \tag{B.8}$$

The first half of the right hand side is the same result for price in the second-score auction model from equation (5). The second half subtracts off a fraction λ of the surplus provided by plant j to buyer i, which is the portion of gains from trade that the buyer is able to retain under bargaining.

Applying the nested logit inclusive value formulas we arrive at an expression for expected markups similar to equation (14),

$$\overline{m}_{jn}^{B*} = -\frac{1-\lambda}{\phi}\frac{1}{\sum_{k\in\mathcal{J}^{f(j)}} s_{kn}^{B*}} \log\left[1-\left(1-s_{0n}^{B*}\right)\left(1-\left(1-\sum_{k\in\mathcal{J}^{f(j)}}\frac{s_{kn}^{B*}}{1-s_{0n}^{B*}}\right)^{1-\sigma}\right)\right]. \tag{B.9}$$

The bargaining version of the model only adds the parameter λ as a multiplier to the markup equation. An implication is that it may be difficult to separately identify the bargaining power and the price parameter in practice. As discussed in Appendix D, the parameters of marginal cost and ϕ are not separately identified by the market share equations in (13), meaning that the markup relationship is needed to isolate ϕ. Therefore, absent additional information about markups or costs, we have only the markup equation to identify both λ and ϕ, and separating the two is not possible. If the true model features *ex post* Nash bargaining, then our results for the baseline model can be interpreted as providing an estimate of ϕ relative to $1-\lambda$.

B.2 Equilibrium

The marginal cost bidding strategy in equation (9) is also an equilibrium of this alternative model with bargaining. Note that the first part of Lemma 1 continues to hold, because the price, conditional on a plant winning, does not depend on that plant's bid, per equation (B.8).

With constant marginal cost functions, again consider a case where, for buyer i, plant x is the highest ranked bidder and plant y is the second highest when bids equal marginal cost. The markup earned by plant x is then

$$m_{ix}^{B*} = \frac{1-\lambda}{\phi}\left(u_{ix} - \phi\overline{c}_x - \left(u_{iy} - \phi b_{iy}^{B*}\right)\right). \tag{B.10}$$

The scoring inequality remains as in (A.2), meaning $u_{ix} - \phi\overline{c}_x - (u_{iy} - \phi b_{iy}^{B*}) \geq 0$. As $(1-\lambda)/\phi$ is positive, this inequality implies that the margin is non-negative. Therefore, the price covers marginal costs for the auctions won.

For the auctions where a firm would lose, again consider the case where, for buyer l, plant z is the winner and plant x is ranked worse under marginal cost bidding. If the owner of plant x were instead to decrease its bid to beat plant z, it would earn a margin given by

$$m_{lx}^{B'} = \frac{1-\lambda}{\phi}\left(u_{lx} - \phi\overline{c}_x - \left(u_{lz} - \phi b_{lz}^{B*}\right)\right). \tag{B.11}$$

However, we know from the initial scoring inequality that $u_{lz} - \phi b_{lz}^{B*} \geq u_{lx} - \phi \bar{c}_x$, which means this additional margin from outbidding plant z is not positive and hence does not increase the profits for plant x. Therefore, Lemma 1 continues to hold. By the same token, Corollary 1 also continues to hold, as equations (B.10) and (B.11) imply that, for a given level of marginal cost, the equilibrium strategy causes each plant to win those auctions where prices cover this marginal cost, and lose those auctions where prices do not.

As for Lemma 2, which deals with increasing marginal cost, consider the case where plant x is contemplating an alternative strategy with a higher marginal cost than occurs in the baseline equilibrium, meaning $c_x(q_x^{B'}) > c(q^{B*})$. Given that quantity must increase to give higher costs, the owner of plant x would need to change its bids to win some auctions that it lost under the baseline strategy. However, we know from Corollary 1 that the price that would be earned in those auctions already gives a negative margin for a cost of $c(q^{B*})$, by applying equation (B.11). Therefore, the margin would also be negative for a higher marginal cost, $c(q^{B'})$. If we instead consider the case where plant x is contemplating an alternative strategy with a lower marginal cost than occurs in the baseline equilibrium, meaning $c_x(q_x^{B''}) < c(q^{B*})$, this situation would involve the plant losing some auctions it would have otherwise won. According to Corollary 1, through an application of equation (B.10), we know that the margin for these auctions plant x would have won are positive for a cost of $c(q^{B*})$, meaning they would also be positive for a lower marginal cost like $c_x(q_x^{B''})$. As a result, the firm that owns plant x would lower its profits if it were to change its bids to lose these auctions. Thus, Lemma 2 continues to hold.

Finally, Lemma 3 for multi-plant firms continues to apply. As can be seen from equation (B.7), a firm owning multiple plants has no incentive to bid any plants other than its best scoring one, as bidding additional either lowers the margin (if the firm owns both the first and second most-preferred plants) or results in no change to the margin (in all other cases). Therefore, Lemmas 1 to 3 continue to hold, meaning marginal cost bidding according to equation (9) is also an equilibrium of the model with bargaining.

B.3 Offsetting Changes in Bargaining Power

Our results from our baseline auction model imply that the quantity-weighted median markup increased by 5.3% over the period we study. We can calculate the offsetting change in bargaining power that would be needed for markups in 2019 to be equal to those in 1974, under an alternative assumption that markups are determined according to the model of *ex post* bargaining. That the offsetting change is identified is evident from equation (B.7), where the markups decrease as firms' bargaining power, $1 - \lambda$, falls, all else equal.

Our baseline result is

$$\frac{m^{2019}}{m^{1974}} = \frac{f(s^{2019}; \phi, \sigma)}{f(s^{1974}; \phi, \sigma)} = 1.053, \tag{B.12}$$

where the markups for each year are functions $f(\cdot)$ of the market shares and model parameters, as given in equation (14). Under *ex post* bargaining, the markups would have an additional term from the bargaining power parameters,

$$\frac{m^{2019}}{m^{1974}} = \frac{1-\lambda^{2019}}{1-\lambda^{1974}} \frac{f(s^{2019}; \phi, \sigma)}{f(s^{1974}; \phi, \sigma)}, \tag{B.13}$$

as can be seen from equation (B.9). Therefore, the offsetting change in firms' bargaining power that keeps markups the same ($m^{2019} = m^{1974}$) can be obtained as follows, exploiting that changes in the bargaining parameter do not affect market shares:

$$1 = \frac{1-\lambda^{2019}}{1-\lambda^{1974}} \times 1.053 \quad \Rightarrow \quad \frac{1-\lambda^{2019}}{1-\lambda^{1974}} = 0.95. \tag{B.14}$$

Therefore, our model indicates that firms' bargaining power would have to fall by 5% in order to generate markups in 2019 that equal those in 1974.

C Incorporating Vertical Integration

Past research in Syverson and Hortaçsu (2007) has documented the presence of vertical integration between cement producers and ready-mix concrete producers. In this Appendix, we demonstrate how one can incorporate vertical integration into our framework. We show that under certain assumptions the parameters of the baseline model (without vertical integration) can absorb the economic effects of vertical integration under a change-of-variables: the baseline marginal costs would represent the marginal costs of cement production plus any transaction costs related to vertical interaction.

We modify the baseline models as follows. In the vertical structure, concrete firms are downstream and cement firms are upstream. The concrete firms, in effect, act like distributors for cement (in its final form, concrete), where production and distribution can be vertically integrated. Let there be a number of symmetric concrete firms, each with a fixed marginal cost $\tilde{c}$ for transforming cement into concrete. Furthermore, cement firms incur a transaction cost of ψ when dealing with a concrete plant. This cost can be impacted by vertical integration; for example, an increase in vertical integration might reduce transaction costs, which can be captured by a smaller ψ. Assume that there is perfect competition between concrete firms in the provision of their services. This assumption seems reasonable, as Syverson and Hortaçsu (2007) show that, according to their geographic market delineations, there tend to be a large number of competitors in concrete. The authors report that concrete markets on average contain about 12 firms. Prices to final customers (construction firms) are set according to the second-score auction presented in our baseline model.

Given perfect competition between concrete firms, the fee they charge to cement plants is equal to the downstream marginal cost. Thus, the relevant marginal cost of cement plant j in the modified model is

$$\hat{c}_j(q_j) = c_j(q_j) + \tilde{c} + \psi \tag{C.1}$$

where $c_j(q_j)$ is as defined in the baseline model. We assume that all sellers—including the outside good—must flow through an intermediary (a concrete plant or equivalent). If Assumption 3 holds for $c_j(q_j)$ then it also holds for $\hat{c}_j(q_j)$. Furthermore, Theorems 1, 2, and 3 extend trivially, replacing $c_j(q_j)$ in most instances with $\hat{c}_j(q_j)$.[25] Then, equilibrium choice probabilities and cement firm markups do not change, and the price to final customers is

$$\hat{p}_{ij} = m_{ij} + c_j(q_j) + \tilde{c} + \psi \tag{C.2}$$

where the cement markup term, m_{ij}, is as defined in the baseline model. Of this price, the concrete plant receives $\tilde{c}$ and the cement plant receives $p_{ij} = m_{ij} + c_j(q_j) + \psi$.[26]

Suppose that this modified model is the data-generating process, and that we estimate the baseline model nonetheless. We select the marginal cost function to rationalize the prices p_{ij} that accrue to the cement plant, taking into account the markup m_{ij}. Therefore, we would overstate the pure cement marginal cost by ψ; given our specification, this additional cost would be absorbed by the constant. Restated, the marginal costs that we estimate would represent the marginal cost of cement production plus the transaction cost. Similarly, linear changes in ψ over time would be absorbed by the time trend.

This model could be further modified to allow for concrete firms to earn a positive markup $\tilde{m}$, such as the fixed markup that results from some models of monopolistic competition. In this case, the marginal cost that a cement plant would bid at would include this markup, giving $\hat{c}_j(q_j) = c_j(q_j) + \tilde{c} + \tilde{m} + \psi$. The important assumption is that the behavior of downstream firms does not cause upstream concrete firms to alter their bidding behavior in a way that causes a strategic interaction between upstream and downstream markups. The estimation of the baseline model can accommodate changes in vertical integration (in ψ) that manifest as a shift upwards (or downwards) in bids and/or a linear trend over time.

[25] When doing the calculations for Theorem 3, we treat the outside good as having a marginal cost of $\tilde{c} + \psi$. The buyer surplus in equation (17) also needs to be modified to subtract off these additional costs.

[26] The average price in equation (15) is the price received by cement plants, meaning the modified model adds ψ alongside c_j^* to the markup.

D Data and Estimation

D.1 Fuel Costs

We measure the fuel costs of each kiln based on fossil fuel prices and the kiln's energy requirements, following Miller et al. (2017). The calculation is

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

where the primary fuel price is in dollars per mBtu and the energy requirements are in mBtu per metric tonne of clinker. We use the state-level average prices of coal, natural gas, and distillate fuel oil paid by the industrial sector, which we obtain from the State Energy Database System (SEDS). In the *Plant Information Summary*, some kilns list multiple primary fuels. As the mix of primary fuels is unknown, we treat such kilns as follows: We calculate fuel costs with the price of coal if coal is 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. Throughout our analysis, we treat petroleum coke as coal.

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 1990-2019. 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. 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.

Figure G.15 plots the fraction of industry capacity that uses each fossil fuel as its primary energy source (top panel). Early in the sample, natural gas, coal, and fuel oil are primary fuels. Coal is the only primary fuel in the middle years. Some kilns switch back to natural gas late in the sample. The figure also shows the prices of these fuels (bottom panel). Comparing across panels, the usage of the coal and natural gas tracks relative prices.

D.2 Customs Districts

We assume that buyers can purchase imported cement from customs districts. In the data, we observe the volume of cement that flows through every customs district in each year. These volumes reflect nearby domestic supply and demand conditions, as captured in the model. They also reflect forces outside the model, including foreign supply conditions and the capacity of the customs district to process imports (e.g., many customs districts include ports, so the maritime infrastructure matters). We observe that some customs districts process a small or negligible amount of cement early in the sample and become a significant source of cement imports only later in the sample.

To accommodate this pattern, we designate selected ports as "active" and assume buyers can purchase cement from any active customs district. For our baseline specification, we assume an active customs district meets the following criteria: (1) it is one of the largest 20 customs districts as measured by the maximum volume of cement imported in any year during the sample period, and (2) the port has reached 30% of its maximum volume of imports. These specific thresholds do not appear to be consequential, and our main results are robust to alternatives (Appendix E and columns (ix) and (x) of Table G.1). The model predictions match well the volume of imports over time (Figure G.6). At the district-year level, the bivariate correlation statistic between the model predictions and the data is 0.62. We provide a scatter plot in Figure G.16.

The top 20 customs districts, in descending order of the maximum quantity of imported cement received in a year, are: New Orleans LA, Tampa FL, Los Angeles CA, Houston TX, San Francisco CA, Detroit MI, Miami FL, Seattle WA, New York City NY, Charleston SC, Columbia-Snake/Portland OR, Nogales AZ, Cleveland OH, Buffalo NY, Norfolk VA, Mobile AL, Ogdensburg NY, Providence RI, San Diego CA, and El Paso TX.[27] The customs districts outside the top 20, listed 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. Throughout the sample, these fifteen small customs districts account for about ten percent of imports.

D.3 Market Size

We model the market size of each county with data on an exogenous demand factor (e.g., as in Berry et al., 1995; Nevo, 2001). We use the number of construction employees, a measure of construction activity highly predictive of cement consumption. Data are available at the

[27] Import quantities fall precipitously in Duluth MN and Milwaukee WI after 2005, and in Nogales AZ after 2009; we code those port as inactive accordingly.

county level throughout our sample period. First, to convert "units of employment" to "units of consumption," we regress cement consumption on construction employment and a time trend interacted with construction employment. We aggregate the data to the state level because we do not observe county-level consumption data. We let the coefficients be state-specific. The regression equation is:

$$Consumption_{rt} = \beta_{1r} Employment_{rt} + \beta_{2r} Employment_{rt} \times Trend_t + \epsilon_{rt} \tag{D.1}$$

where r indexes states and t indexes years. Second, we use the relationship implied by the regression coefficients to obtain predicted values for each county. Third, we double the predicted values to obtain the county market sizes we use in estimation. This last step ensures that the market size exceeds consumption in every region-year observation. A similar approach is used in Miller and Osborne (2014b).

We assume cement prices do not affect construction employment, motivated by the empirical fact that cement accounts for a small fraction of total construction expenditures (Syverson, 2004). We also assume construction activity (with employment as a proxy) affects demand only through market size. Restated, it does not enter gross utility (equation (1)) and market shares (equation (6)). As a result, changes in market size rotate demand, proportionally increasing or decreasing the number of buyers that exist throughout the gross utility distribution. Market size affects price if it shifts firms along increasing regions of their marginal cost functions, thereby inducing changes in equilibrium bids.

We summarize the regression results in Figure G.17. The top panel is a scatter plot of the data and predicted values. Construction employment is highly predictive of cement consumption; the R^2 of the regression is 0.9862. This is consistent with inelastic market-level demand or, equivalently, a sizeable nesting parameter. At the same time, little residual variation remains to pin down the nesting parameter. Together, these observations help motivate the $\sigma = 0.90$ assumption we impose in estimation. The bottom panels provide histograms for the estimated β_{1r} and β_{2r} coefficients, respectively. Construction employment has a positive relationship with cement consumption in every state (bottom left), and the relationship attenuates somewhat over time in most states (bottom right).

D.4 Identification

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

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

$$s_{jnt} = \frac{\exp(\boldsymbol{x}_{jnt}\boldsymbol{\beta} - \phi \boldsymbol{w}_{jt}\boldsymbol{\alpha})}{1 + \sum_k \exp(\boldsymbol{x}_{knt}\boldsymbol{\beta} - \phi \boldsymbol{w}_{kt}\boldsymbol{\alpha})} \tag{D.2}$$

and

$$\overline{p}_{jnt} = \boldsymbol{w}_{jt}\boldsymbol{\alpha} + \frac{1}{\phi}\frac{1}{s_{jnt}}\log\left(\frac{1}{1-s_{jnt}}\right). \tag{D.3}$$

Consider first the cost and price parameters. It is possible to solve equation (D.3) for both $\boldsymbol{\alpha}$ and ϕ under mild conditions because both market shares and average prices are data. To see why, stack the prices into a vector $\overline{\boldsymbol{p}}$ and let the matrix $\boldsymbol{W}$ combine the cost shifters and the markup terms, such that the row corresponding to plant j, county n, and period t is given by

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

With this notation in place, we can write

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

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

For the demand parameters, once $\boldsymbol{\alpha}$ and ϕ have been recovered, they can be plugged into equation (D.2), and this allows a solution for $\boldsymbol{\beta}$ to be obtained under mild conditions. In particular, note that the usual share inversion holds:

$$\log(s_{jnt}) - \log(s_{0nt}) = \boldsymbol{x}_{jnt}\boldsymbol{\beta} - \phi \boldsymbol{w}_{jt}\boldsymbol{\alpha}, \tag{D.4}$$

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

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

and let $\boldsymbol{X}$ be a matrix with the same row given by $\boldsymbol{x}_{jnt}$. Identification is obtained if $\boldsymbol{Y} = \boldsymbol{X}\boldsymbol{\beta}$ can be solved for $\boldsymbol{\beta}$. A sufficient condition is that there are at least L equations and that $\boldsymbol{X}$

has full column rank, with intuition again identical to the case of regression.

These identification arguments reveal an important property of the second-score auction model: estimation based on the market share inversion of equation (D.4) alone does not separate the price parameter from the cost parameters, as these enter only through their multiplicative products. Furthermore, each demand parameter is identified only to the extent that the corresponding demand shifter is not also a cost shifter. Thus, price variation is necessary to separately identify all of the parameters of the model.

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

D.5 Fixed Effects

Building upon the identification discussion above, we now explain why it can be difficult to separately estimate cost and demand fixed effects in the second-score auction framework; our discussion extends to any variable that enters both gross utility and marginal cost. This has implications for the additional specifications we can present for robustness purposes in Appendix E. For concreteness, consider a modified version of our model. Let the indirect gross utility that buyer i in county n and period t receives from plant j be

$$\overline{u}_{ijnt} = \boldsymbol{x}_{jnt}\beta + \xi^d_{r(n)} + \epsilon_{ijnt} \tag{D.5}$$

where $\xi^d_{r(n)}$ is demand-side fixed effect for region, r, in which county n is located. Let the marginal cost of plant j be

$$c_{jt} = \boldsymbol{w}_{jt}\alpha + \xi^c_{r(n)} \tag{D.6}$$

where $\xi^c_{r(n)}$ is a cost-side fixed effect. Finally, let $\zeta_{r(n)} \equiv \xi^d_{r(n)} - \phi\xi^c_{r(n)}$ be the difference between the demand-side and cost-side fixed effects (in equivalent units) and, for mathematical tractability, let $\sigma = 0$, so the model collapses to a flat logit.

Applying these modifications to (13)-(15) obtains the following expressions for equilibrium market shares and prices:

$$s^*_{jnt} = \frac{\exp\left(\boldsymbol{x}_{jnt}\beta - \phi \boldsymbol{w}_{jt}\alpha\right)}{\exp\left(-\zeta_{r(n)}\right) + \sum_{k\in\mathcal{J}} \exp\left(\boldsymbol{x}_{knt}\beta - \phi \boldsymbol{w}_{kt}\alpha\right)} \tag{D.7}$$

$$\overline{p}^*_{jnt} = \boldsymbol{w}_{jt}\alpha + \xi^c_{r(n)} - \frac{1}{\phi}\frac{1}{\sum_{l\in\mathcal{J}^{f(j)}} s^*_{lnt}} \log\left(\sum_{l\in\mathcal{J}^{f(j)}} s^*_{lnt}\right) \tag{D.8}$$

By inspection, share-based and quantity-based moments that build on equation (D.7) can identify the net of the demand and cost fixed effects (i.e., ζ), but they cannot separately identify the two. Furthermore, they identify the net only if they involve substitution between the inside and outside goods, as the relative shares of any two inside goods are unaffected by the fixed effects:

$$\frac{s^*_{jnt}}{s^*_{knt}} = \frac{\exp\left(\boldsymbol{x}_{jnt}\beta - \phi \boldsymbol{w}_{jt}\alpha\right)}{\exp\left(\boldsymbol{x}_{knt}\beta - \phi \boldsymbol{w}_{kt}\alpha\right)} \tag{D.9}$$

Among the moments we use, only those that exploit variation in regional production and consumption build on equation (D.7) in a way that could inform the net of demand-side and cost-side fixed effects.

The ability to separately identify demand-side and cost-side fixed effects in practice then rests on the price-based moments that build on equation (D.8). In that equation, the cost-side fixed effect has a direct effect, and the net of the fixed effects has an indirect effect through market share. In practice, the variation we incorporate with our price moments does not allow us to disentangle the cost and demand-side fixed effects, as they ultimately have similar impacts on equilibrium prices.

D.6 Computational Burden

The main computational challenge is that equilibrium must be computed for every candidate parameter vector. In most years of our sample there are more than 300,000 prices and shares at the plant-county level. We exploit the properties of the second-score auction model to make computation tractable. The key insight is that equilibrium can be characterized by plant-level shares (equation (10)). 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.[28] To implement, we use the large-scale

[28]Two of us applied a brute-force approach to estimate a Bertrand/logit model of the cement industry (Miller and Osborne, 2014b). We focused exclusively on Arizona, California, and Nevada in order make the problem

nonlinear equation solver of La Cruz et al. (2006) and parallelize by assigning each of the 46 years in the estimation sample to a different processor.

A second challenge is that equilibrium outcomes are nonlinear in the demand and cost parameters; we cannot "concentrate out" some parameters from the objective function (e.g., as in Berry et al., 1995; Nevo, 2001). This limits the number of parameters. Our baseline specification features twelve estimated parameters, and estimation can take multiple days, depending on the starting values. Our robustness specifications typically feature more parameters and require longer convergence times. With region fixed effects, there are an additional seven estimated parameters, and the total estimation time can be multiple weeks. We benefit from the empirical setting because it is possible to capture the salient industry features with a sparsely parameterized model.

D.7 Asymptotic Consistency

Our estimates are consistent under the identifying assumption, $\mathbb{E}[\omega_{mt}|\boldsymbol{X}_t] = 0$, where ω_{mt} is prediction error for endogenous outcome m in year t and $\boldsymbol{X}_t$ is data. The primary threat to consistency is misspecification due to unobserved plant characteristics.[29] If one region has higher prices and greater output because its plants provide higher unobserved quality, then this could lead us to understate the price sensitivity of buyers. Alternatively, if plants in one region have higher marginal costs than plants in other regions due to unobservables, then the region may exhibit relatively higher prices and lower output, and this could lead us to overstate price sensitivity.

However, we believe that the model accounts for the bulk of the heterogeneity. On the demand side, the cement itself is produced in accordance with ASTM standards. Some plants may have a reputation for good customer service, or for being reliable, 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) are subsumed by the preference shocks and thus unproblematic, conditional on the distributional assumption. On the supply side, we use data on the technologies, capacities, and fuel costs of the kilns in our sample to incorporate heterogeneity. Corroborating our interpretation is that we find elasticities within the range reported in the literature, and our transportation cost estimates align with those reported by the USGS (Section 4.2).

Our approach involves modeling the relevant demand-side and supply-side factors and selecting parameters under which the model best predicts the prices and quantities in the data. As both prices and quantities are dependent variables, our approach is conceptually

manageable. The typical year featured around 1,000 prices and market shares at the plant-county level.

[29] Strictly interpreted, price endogeneity bias does not arise in our application because price data are not used to construct the right-hand-side of equation (20).

distinct from the alternative of seeking to isolate exogenous variation in prices (e.g., with an instrument) and then selecting parameters based on the relationship between quantities and the exogenous portion of prices. Empirical correlations between price and quantity are not problematic in our framework, so long as what generates the correlations is modeled. For example, an increase in construction activity could increase price, as plants move up their cost curve and gain market power, but this would not bias our results because the model embeds capacity constraints and flexible, location-specific markups.

D.8 Details on Implementation

We estimate the model using Nelder-Mead. We then apply Levenberg-Marquardt to confirm that convergence occurs at a local minimum. The estimates are stable in the sense that when we re-estimate using starting values perturbed from their estimated values, we obtain the same results. In the initial application of the Nelder-Mead algorithm, we constrain some parameters to ensure that the equilibria we compute are economically sensible; these constraints include $\phi > 0$, $\alpha_1 > 0$, $\nu \in [0, 1]$, and $\gamma > 0$. These constraints restrict the price parameter, fuel cost parameter, utilization threshold, and capacity cost, respectively. When applying the Levenberg-Marquardt algorithm, we do not apply the constraints.

For the moment weights, we calculate the variance among each of the six types of endogenous outcomes enumerated in Section 4.1, and weight all the moments of the same type by the corresponding inverse variance. Additionally, we reduce the weight on the consumption and production moments by 50%; they are highly correlated and together they account for 75% of the endogenous outcomes used in estimation. Absent this downweighting, the estimator drifts into areas of the parameter space for which we could not solve the fixed point problem.

E Robustness Analyses

Table G.1 summarizes the results of eight robustness analyses. Across the columns of the table, the specifications that we use are as follows:

(i) We interact Overland Miles with the gasoline price. We obtain the gasoline price from the same SEDS database that we use for fossil fuel prices. There is panel variation at the state-year level, and we assign a price based on the state of the cement plant.

(ii) We include fixed effects for each of the eight BEA regions: New England, Mideast, Great Lakes, Plains, Southeast, Southwest, Rocky Mountain, and Far West. We implement this by putting the fixed effects in the marginal cost specification, so the constant in the marginal cost function is absorbed. It is difficult to separately identify cost and demand fixed effects in practice, as discussed in Appendix D.5.

(iii) We include fixed effects for five-year windows of time: 1980-1984, 1985-1989, 1990-1994, and so on. The first period has six years (1974-1979). We again place these fixed effects in the marginal cost function.

(iv) We incorporate kiln age and the price of electricity into the marginal cost function. We obtain the price of electricity from the SEDS database; there is panel variation at the state-year level.

(v) We treat customs districts as active once they hit 20% of their maximum observed volume, rather than 30%. See Appendix D.2.

(vi) We use the top 25 customs districts, rather than the top 20. See Appendix D.2.

(vii) We use a nesting parameter of 0.85.

(viii) We use a nesting parameter of 0.95.

We set the utilization parameter at the baseline estimate of 0.289 in columns (ii)-(iv), rather than estimate it, because the parameter can be difficult to identify separately. The changes in the nesting parameter used in columns (vii)-(viii), relative to the baseline of 0.90, represent meaningful changes because demand derivatives scale multiplicatively with the ratio $\phi/(1-\sigma)$, for price parameter ϕ and nesting parameter σ.

In the bottom rows, Table G.1 shows the implied changes in the quantity-weighted median HHI and markup from 1974 to 2019. Across columns, the changes in the HHI range from 512 to 1086, and the changes in the markup range of \$0.65 to \$1.43. Thus, the results are consistent with those that we obtain with the baseline specification—they point to significant increases in concentration and modest increases in markups.

Looking at specific parameters, we find that the demand parameters are quite stable across columns, but some of the supply-side parameters shift. Relative to the baseline specification, the price parameter is somewhat larger with region fixed effects, and somewhat smaller with time fixed effects. This leads to median plant-level elasticities of -6.92 and -2.04, respectively, relative to the baseline elasticity of -3.10. With region fixed effects, we also find that the Fuel Cost parameter is substantially higher (and less economically reasonable) than the baseline result, and we obtain a negative trend in marginal costs. With time fixed effects, the Fuel Cost parameter is smaller than the baseline result. Therefore, some of our results can be sensitive to the variation that is used in estimation. Finally, we note that the signs of the estimated electricity price and kiln age parameters are negative, which runs counter to our expectations. Still, our main results are unaffected.

F Two-Sided Bounds on Operational Fixed Costs

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

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

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

Let firms simultaneously determine which kilns to operate each year, with payoffs then being determined by the second-score auction model of Section 3. We assume that observed outcomes satisfy the equilibrium condition that no firm can improve its profit by idling a kiln observed to be active, or by operating a kiln observed to be idle, taking as given the status of all other kilns. In support, we observe that idling often occurs when demand conditions are unfavorable. For instance, in the average year we observe that 2% of kilns idle, but in 2010—just after the Great Recession—19 of 155 kilns (12%) idle.[30]

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

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

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

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

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

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

One-sided bounds are possible to compute without additional assumptions.[31] To inform the two-sided bounds of equation (F.1), Eizenberg assumes that the variation in incremental gain across observations is likely to exceed the variation in fixed costs, and describes why assumption is reasonable in many settings. We adopt that assumption here. Letting A_d^0 and A_d^1 be the sets of kilns that idle and operate, respectively, and separately by kiln technology, the bounds then can be expressed:

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

and

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

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

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

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

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

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

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

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

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

We implement using 10,011 kiln-year observations. Of these, we observe 242 in which a kiln is idled in a given year—194 involving old technology kilns and 48 involving modern

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

kilns. Our counterfactual simulations indicate that Δ_r equals zero for 550 observations (5.5%), and we exclude those from our subsequent calculations. One limitation of our analysis is that, among the 48 instances in which a modern kiln idles, 47 involve preheater kilns that do not have the supplementary combustion chamber of a precalciner kiln. Thus, our bounds estimates may reflect the operational fixed cost of preheater kilns more than the broader set of modern preheater and precalciner kilns.

G Additional Figures and Tables

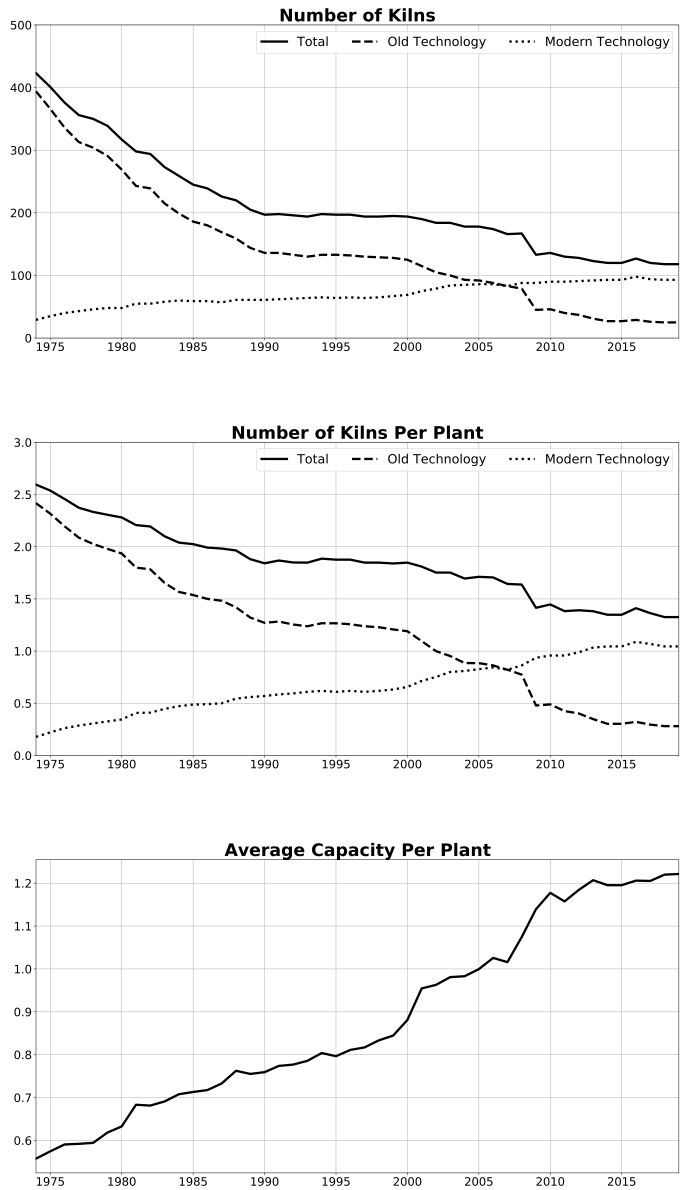

Figure G.1: Additional Kiln-Level and Plant-Level Statistics, 1974-2019

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

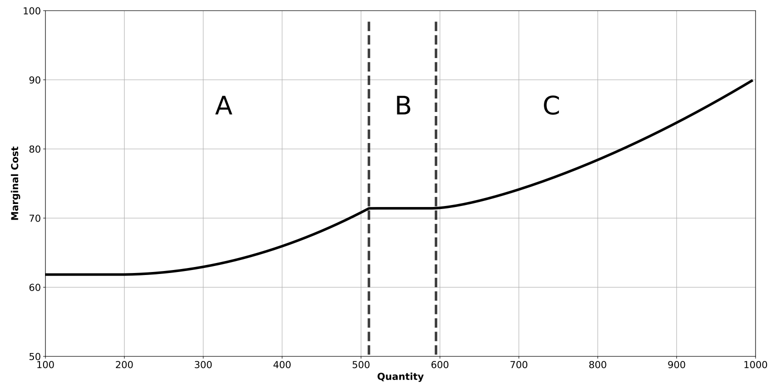

Figure G.2: Plant-Level Marginal Cost per Metric Tonne (Illustrative Example)

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

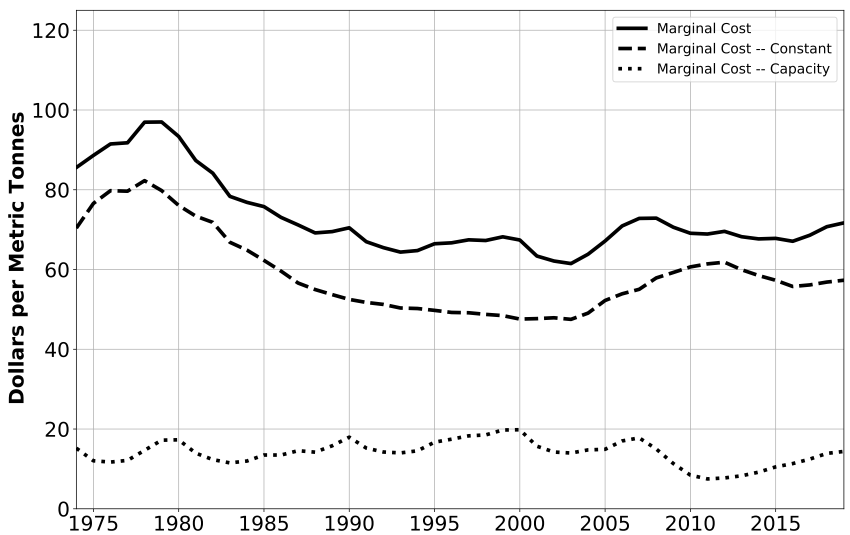

Figure G.3: Marginal Cost and Marginal Cost Components

Notes: The figure plots the average plant-level marginal cost over the sample period, as well as a decomposition that separates marginal cost into a constant portion and a portion that is due to capacity constraints. Variation in the constant portion of marginal cost is predominately due to changes in fossil fuel prices (e.g., Figure G.15) and changes in kiln technology that improve fuel efficiency. Variation in the portion due to capacity constraints is predominately attributable to macroeconomic demand-side fluctuations that affect the utilization rates of domestic kilns.

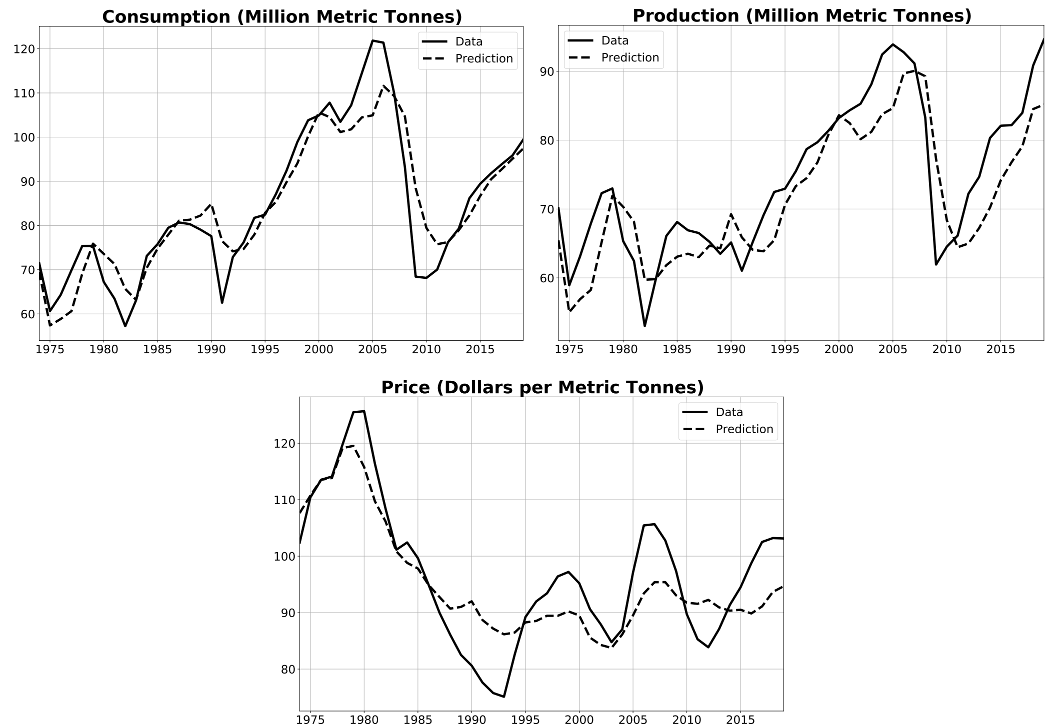

Figure G.4: Model Fits for Consumption, Production, and Prices

Notes: The panels show the time series fits of the model to total consumption, total production, and average prices among the states of the contiguous US.

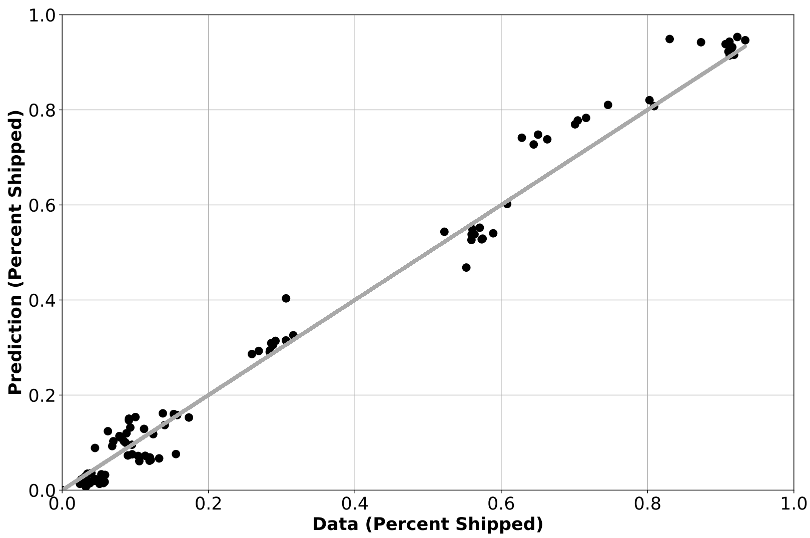

Figure G.5: Model Fit for Observed Cross-Region Shipments

Notes: The dots represent the fraction of shipments from Northern California, Southern California, or California that go to the same regions, Arizona, and Nevada. The horizontal location of each dot provides the value in the data and the vertical location provides the value in the model. Section 2.3 describes the *California Letter* data in greater detail.

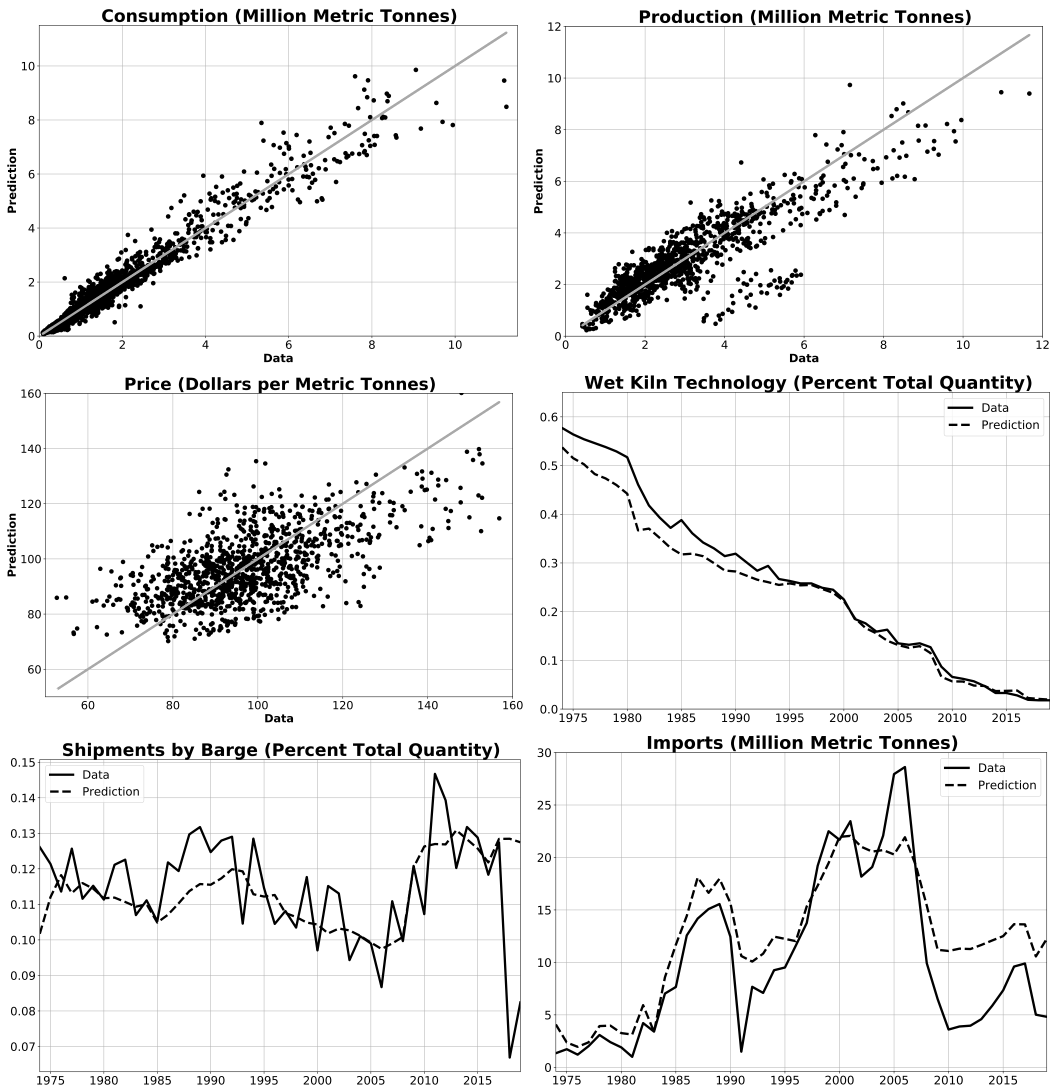

Figure G.6: Additional Model Fits

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

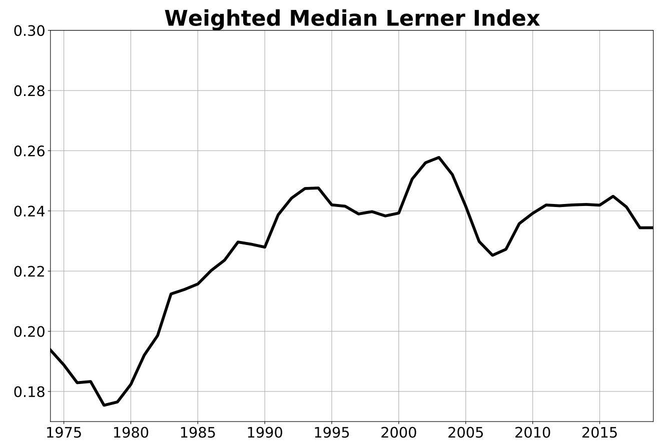

Figure G.7: Changes in the Lerner Index

Notes: The figure plots the the quantity-weighted median county-level markup Lerner index ($(p-c)/c$).

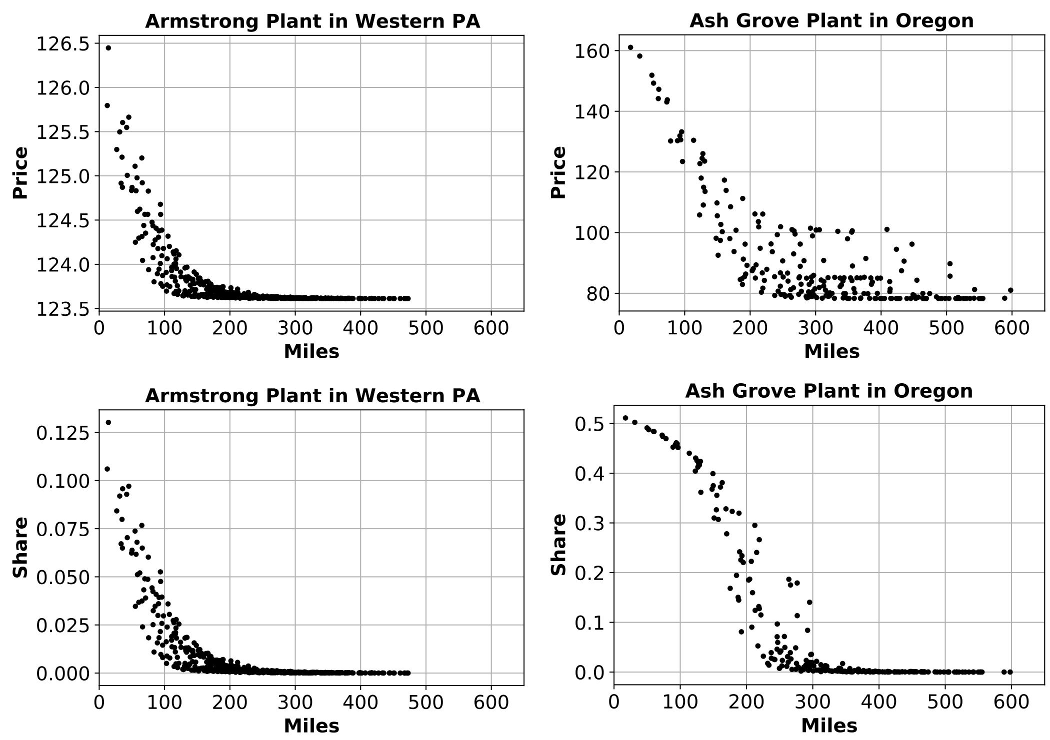

Figure G.8: Illustration of Spatial Differentiation and Price Discrimination

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

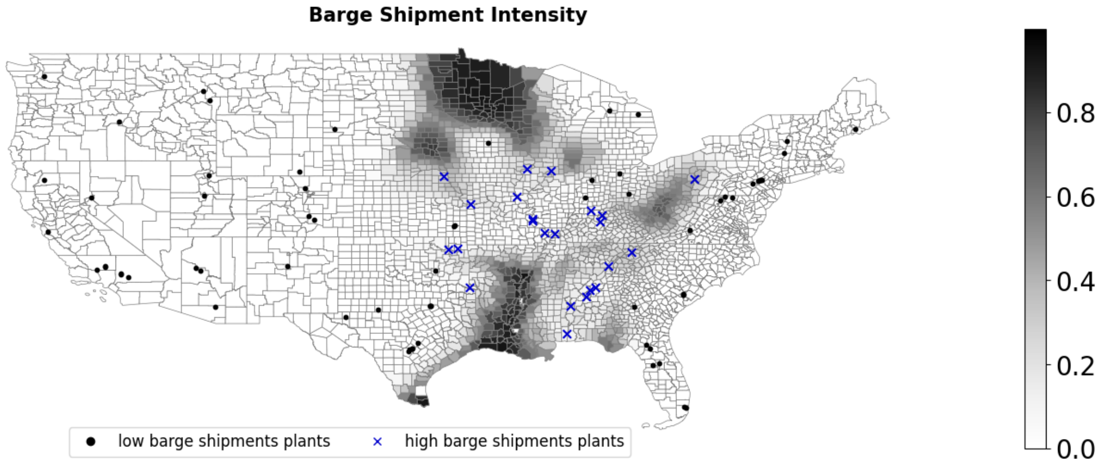

Figure G.9: Barge Shipment Sources and Destinations

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

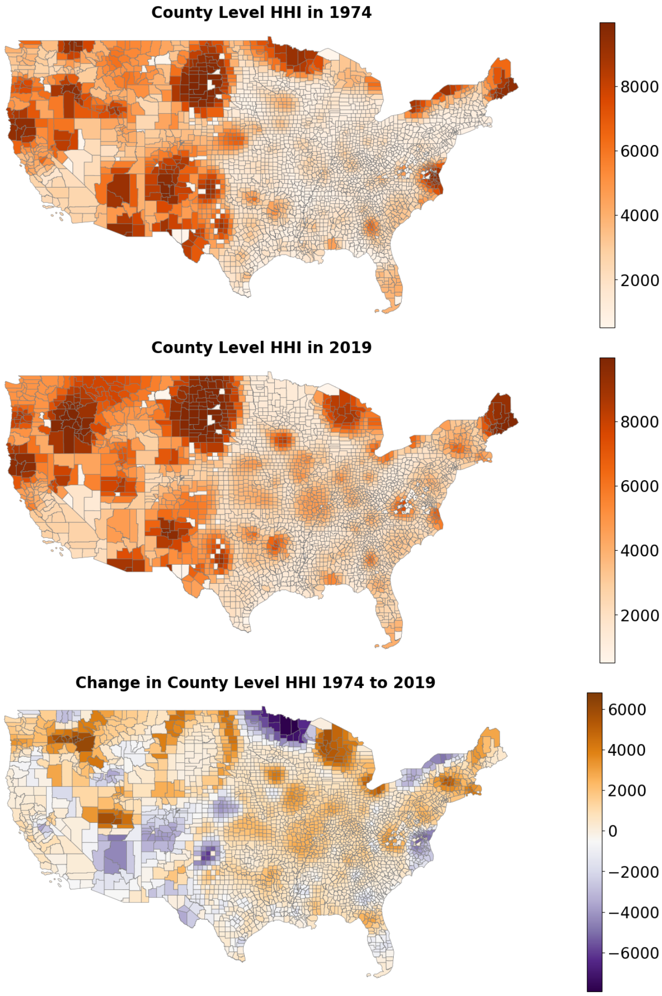

Figure G.10: County-Level HHIs in 1974 and 2019, and the Change from 1974 to 2019

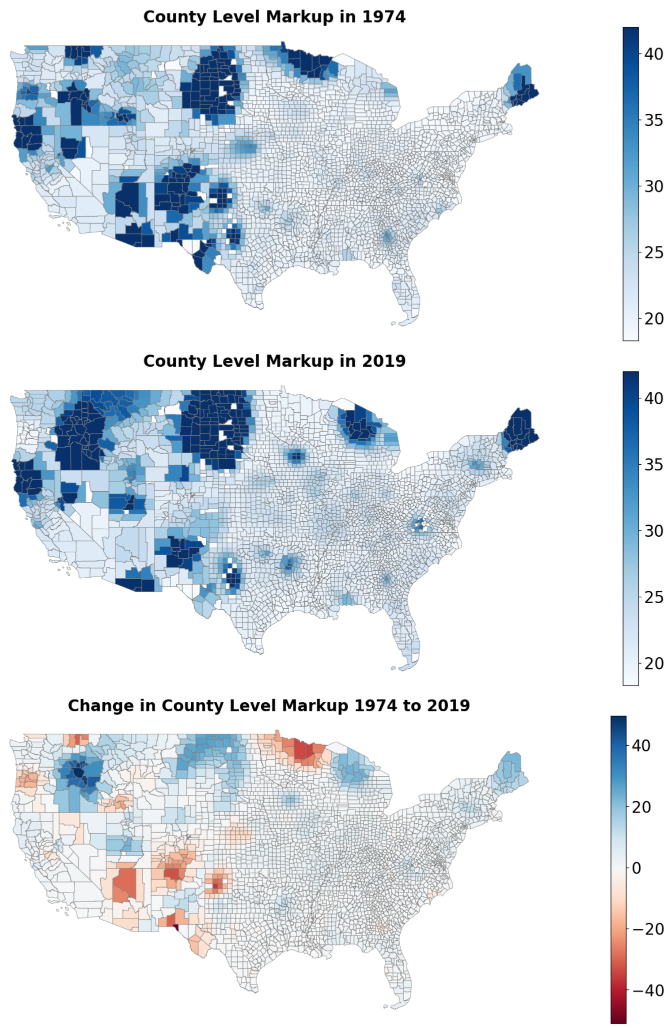

Figure G.11: County-Level Markups in 1974 and 2019, and the Change from 1974 to 2019

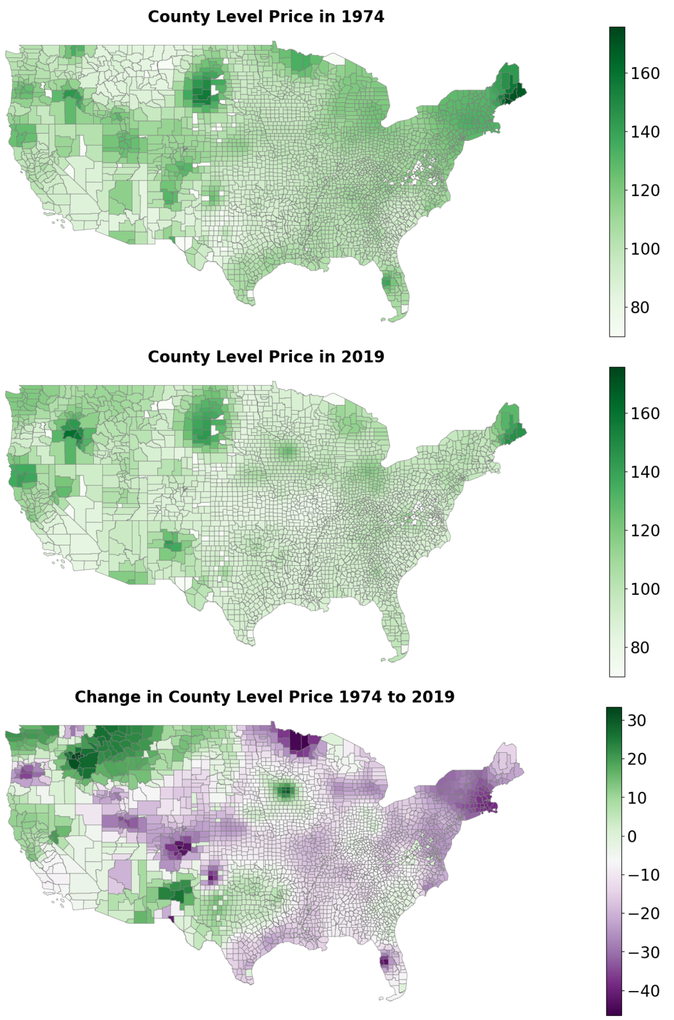

Figure G.12: County-Level Prices in 1974 and 2019, and the Change from 1974 to 2019

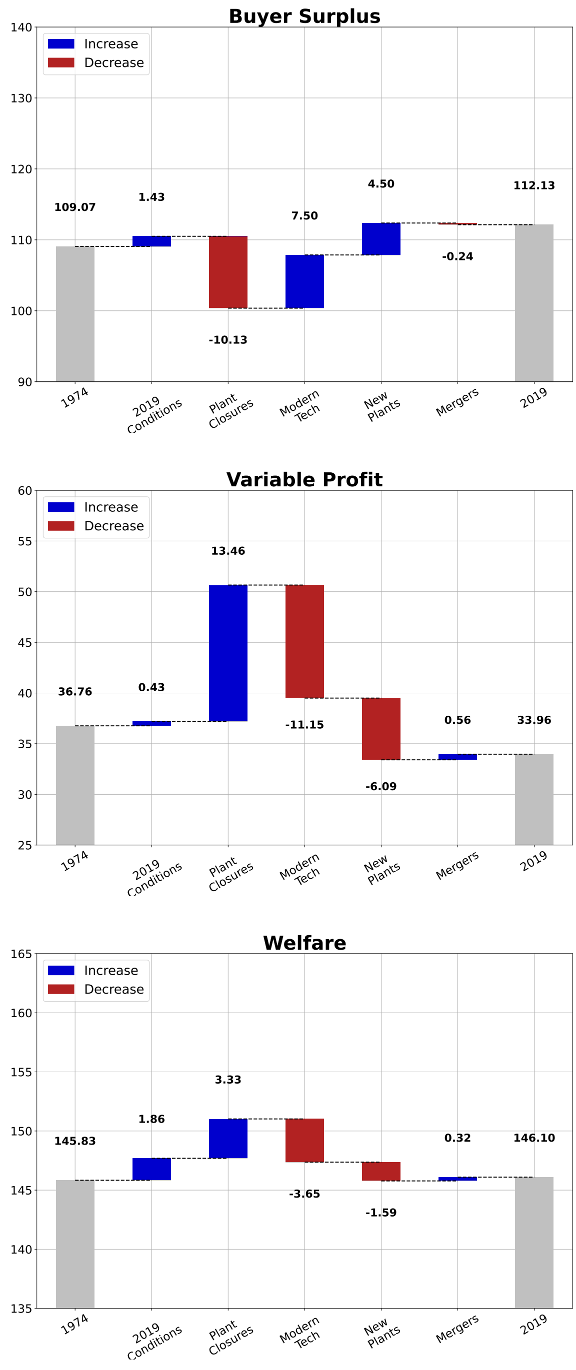

Figure G.13: Short Run Determinants of Welfare Changes

Notes: The figure provides waterfall graphs for the quantity-weighted mean buyer surplus (top panel), variable profit (middle panel), and welfare (bottom panel). The units are in dollars per metric tonne. The welfare statistics are obtained by holding demand-side factors at their 2019 values, and iteratively allowing supply-side factors to change from their 1974 values to their 2019 values.

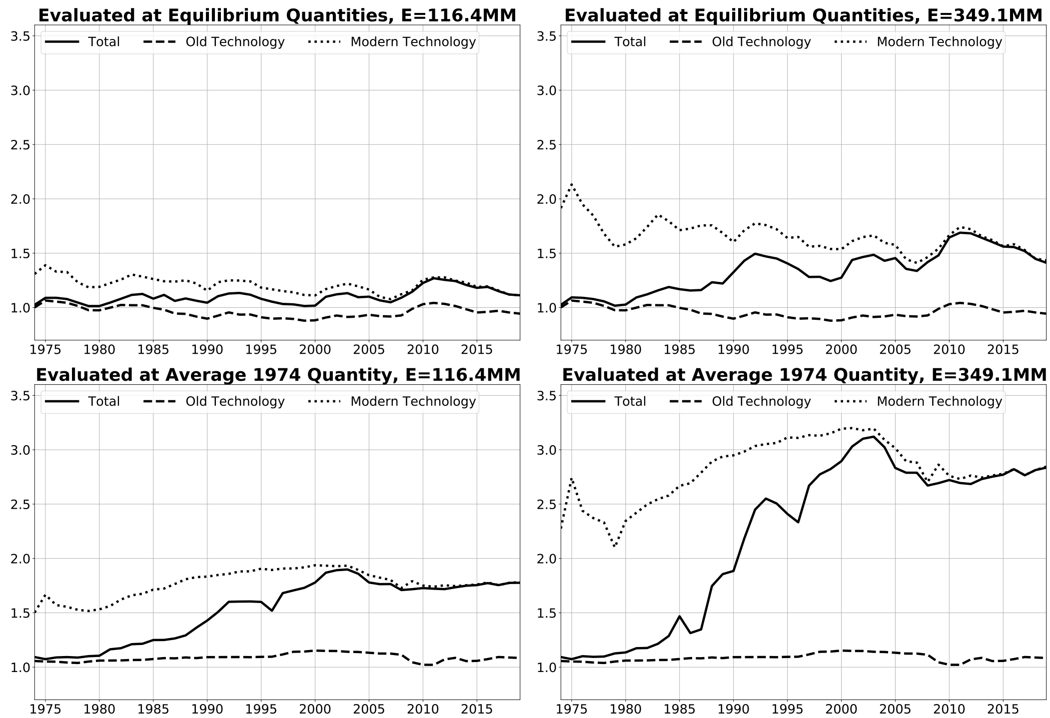

Figure G.14: Robustness Analysis for the Scale Elasticities

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

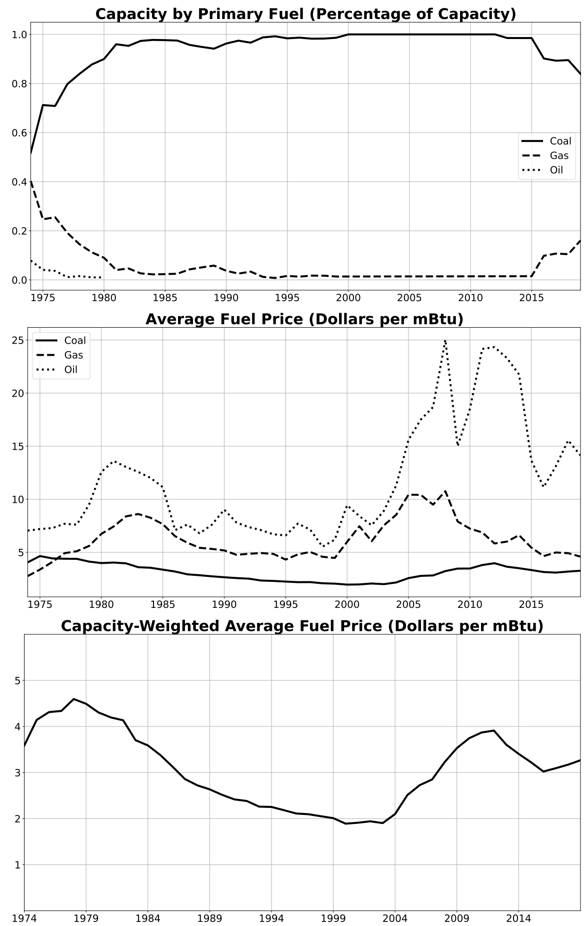

Figure G.15: Primary Fuels, Fossil Fuel Prices, and Fuel Costs

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 middle panel plots the average national prices paid for these fuels by the industrial sector in real 2010 dollars per mBtu. The bottom panel provides the capacity-weighted average fuel cost per metric tonne.

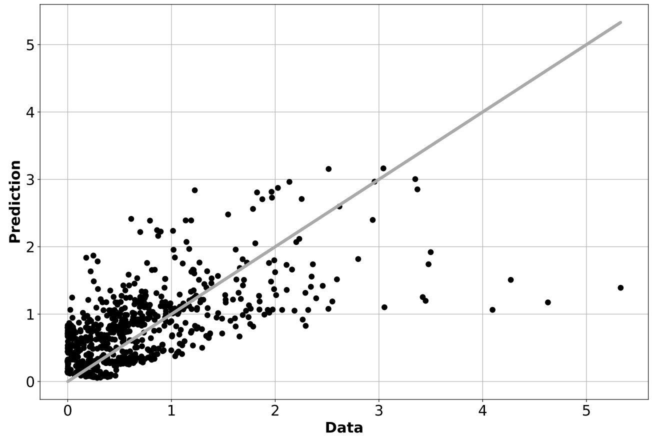

Figure G.16: Model Fit for Import Volumes

Notes: The dots represent the volume of imported cement that enters each active customs district each year. The horizontal location provides the value in the data and the vertical location provides the model prediction. Units are in thousands of metric tonnes. The four dots on the lower right of the scatter plot represent New Orleans, including data from two years after Hurricane Katrina. The model may understate the demand associated with rebuilding and the extent to which imports into New Orleans can access the Mississippi River System.

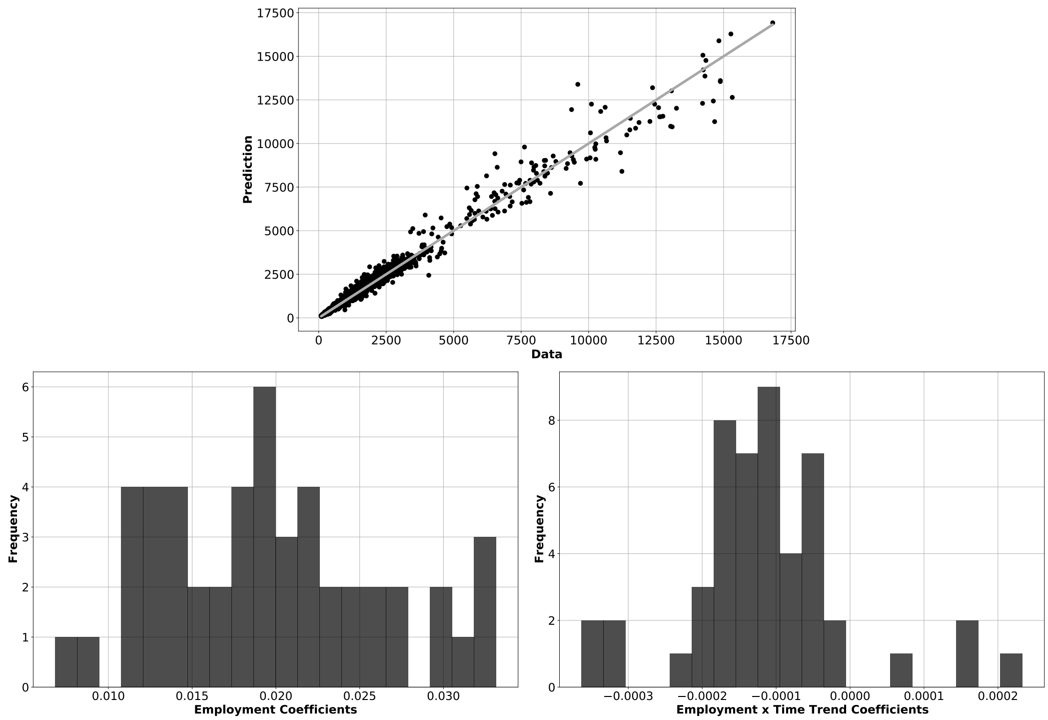

Figure G.17: Regressions of Cement Consumption on Construction Employment

Notes: We regress cement consumption on construction employment and construction employment interacted with a time trend to help construct market size. The units of observation are at the state-year level. We allow the coefficients to be state-specific. The top panel plots the predicted values (vertical axis) against the (data). Construction employment is highly predictive of cement consumption; the dots are along the 45-degree line. The bottom left and bottom right panels are histograms of the estimated state-specific employment coefficients and estimated interaction coefficients, respectively. Construction employment is positively correlated with cement consumption in every state, and the relationship attenuates somewhat over time in most states.

Table G.1: Results with Alternative Specifications

Specification	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Gross Buyer Utility								
Constant	0.456	0.737	0.219	0.474	0.546	0.411	0.530	0.309
	(0.044)	(0.047)	(0.033)	(0.048)	(0.045)	(0.040)	(0.055)	(0.030)
Overland Miles		-1.389	-1.924	-2.266	-2.139	-2.161	-3.516	-1.070
		(0.056)	(0.066)	(0.094)	(0.082)	(0.080)	(0.140)	(0.043)
Overland Miles	-1.083							
× Gasoline Price	(0.044)							
River Barge Used	-0.445	-0.377	-0.414	-0.448	-0.439	-0.441	-0.673	-0.223
	(0.007)	(0.004)	(0.005)	(0.007)	(0.006)	(0.006)	(0.010)	(0.003)
Time Trend	0.001	-0.001	0.001	-0.002	-0.002	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Imported Cement	0.078	0.347	0.069	0.116	0.088	0.089	0.101	0.060
	(0.016)	(0.021)	(0.014)	(0.019)	(0.017)	(0.015)	(0.024)	(0.010)
Imported Cement	0.005	0.006	0.000	0.005	0.005	0.005	0.005	0.004
× Time Trend	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Marginal Cost								
Constant	34.40			44.199	26.347	31.231	26.81	35.47
	(2.34)			(2.188)	(2.671)	(2.152)	(2.93)	(1.95)
Fuel Cost	1.58	4.280	0.522	1.839	1.891	1.719	1.71	1.79
	(0.05)	(0.145)	(0.052)	(0.047)	(0.052)	(0.046)	(0.05)	(0.05)
Kiln Age				-0.315				
				(0.046)				
Electricity Price				-0.355				
				(0.031)				
Time Trend	-0.006	-0.831	0.121	-0.002	-0.002	-0.001	-0.001	-0.001
	(0.029)	(0.067)	(0.134)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Capacity Cost	36.73	169.77	25.39	45.69	45.29	52.12	24.18	88.29
	(8.81)	(8.88)	(1.61)	(2.63)	(8.60)	(10.70)	(5.97)	(16.95)
Utilization Threshold	0.260	0.289	0.289	0.289	0.170	0.354	0.110	0.426
	(0.107)	—	—	—	(0.092)	(0.073)	(0.152)	(0.052)
Fixed Effects	none	region	time	none	none	none	none	none
Other Parameters								
Price Parameter	0.006	0.010	0.004	0.006	0.006	0.005	0.007	0.004
	(0.000)	(0.0004)	(0.0002)	(0.0004)	(0.0004)	(0.0003)	(0.000)	(0.000)
Nesting Parameter	0.90	0.90	0.90	0.90	0.90	0.90	0.85	0.95
	—	—	—	—	—	—	—	—
Transportation Costs								
Overland Cost	0.20	0.14	0.50	0.38	0.36	0.41	0.51	0.29
Barge Cost	79.98	38.18	107.14	74.35	70.90	83.84	96.65	61.32
Bid Elasticity of Demand								
Plant-Level Demand	-3.20	-6.92	-2.04	-3.52	-3.70	-3.00	-2.49	-4.50
Demand for Cement	-0.10	-0.20	-0.06	-0.11	-0.23	-0.20	-0.11	-0.07
Change 1974-2019								
Median County HHI	1022	1086	888	818	512	821	777	805
Median Markup	1.13	0.65	1.43	0.91	0.92	1.08	1.08	0.90

Notes: Column (i) allows motor gasoline prices to affect the disutility of overland miles. Columns (ii) and (iii) add region and time fixed effects to the marginal cost specification, respectively. The time fixed effects identify 5-year windows. Column (iv) adds kiln age and the electricity price to marginal cost. Column (v) treats customs districts as active once they hit 20% of their maximum volume, rather than 30%, and Column (vi) uses the top 25 customs districts, rather than the top 20. Columns (vii) and (viii) use nesting parameters of 0.85 and 0.95, respectively. Fuel Cost, Kiln Age, Electricity Price, and Time Trend are demeaned. Overland Cost is in dollars per tonne-mile, and Barge Cost is in dollars per tonne. We use quantity-weighted median county HHIs and markups. Standard errors are shown in parentheses; we use "—" to indicate a parameter that is not estimated.