

The Evolution of Concentration and Markups in the United States Cement Industry*

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Abstract

We examine local market concentration and markups in the United States cement industry over 1974-2016. We estimate a model in which buyers use a second-score auction to procure cement from spatially differentiated plants. The model matches aggregated outcomes in the data, and the implied transportation costs and shipping distances are consistent with external sources. We infer local market concentration and markups from the model. At the county-level, the average HHI rises from 1,890 to 2,800 during the sample period. Average markups increase modestly, but prices do not rise. We attribute these changes to a technological innovation—the precalciner kiln—that lowered marginal costs, increased plant-level capacities, and also contributed to an industry shakeout in which many plants closed.

JEL Codes: L11, L13, L41, L61

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1 Introduction

Does the American economy suffer from a market power problem? A substantial literature points to a decades-long increase in industrial concentration in the United States,¹ and recent research from a macroeconomics perspective suggests a coincident increase in price-cost markups (De Loecker et al., 2020; Autor et al., 2020). To this literature, we contribute a detailed study of competition in the portland cement industry based on data that spans much of the previous five decades. During this period, technological innovation lowered the average variable cost of production and increased plant-level capacity; it also caused a shakeout that nearly halved the number of plants available to buyers. We characterize the implications of this technological change for local market concentration, markups, and prices. We also analyze the extent to which consolidation in plant ownership has affected market outcomes.

Our inferences are based on a structural model of procurement in which buyers purchase from spatially differentiated cement plants. Each plant submits bids to buyers in each county; prices and identities of the winning supplier are determined according to second-score auctions. The model includes a number of features that allow it to match the data, including capacity constraints on domestic plants, variable costs that depend on input prices and the efficiency of the plant, and the ability to reduce long-haul trucking distances by using barges on the Mississippi River System.

We use a variant of the simulated nonlinear least squares estimator developed in Miller and Osborne (2014). For each candidate parameter vector, we compute equilibrium and then evaluate the distance between the implied equilibrium outcomes and a rich set of aggregate-level data, including regional average prices, regional consumption and production, and the flow of shipments from some regions to others. As the underlying bids are unobserved, we rely on parametric assumptions analyzed in Miller (2014) to compute equilibrium. We validate our estimates by comparing the implied transportation costs and shipping distances to industry and academic sources. The model fits observed trends in the time-series as well as the cross-section.

We find that local market concentration increased substantially over 1974 to 2016, with the average county-level Herfindahl-Hirschmann Index (HHI) rising from 1,890 to 2,800. At the end of the sample, 61% of counties are highly concentrated according to the thresholds of the U.S. Department of Justice/Federal Trade Commission *Horizontal*

¹See, for example, Peltzman (2014); Barkai (2016); CEA (2016); Gutierrez and Philippon (2017); Grullon et al. (2019); Ganapati (2021); Autor et al. (2020); and Covarrubias et al. (2020).

Merger Guidelines. We conduct a decomposition exercise and determine that nearly two-thirds of the change is due to plant closures (itself a product of increasing scale economies), with the remainder attributable to mergers and other changes in plant ownership. Competition from newly constructed plants somewhat offsets the effects of plant closures and consolidation.

We also find that average markups increase modestly. The Lerner Index rises from 0.15 in 1974 to 0.19 in 2016. As with concentration, the main driver is first plant closures and then consolidation, with competition from new plants providing a partial offset. At the county-level, increases in markups correlate highly with increases in concentration. By contrast, we find that cement prices fall during the sample period, primarily due to the (observable) adoption of modern kiln technology. Thus, we conclude that technological innovation gradually lowered the costs of cement production and that, despite the ensuing shakeout and a trend towards consolidation, these cost savings mostly were passed through to consumers in the form of lower prices.

In our final analyses, we compare the markups that arise in the observed equilibrium to those obtained in a counterfactual in which each plant is independently owned. We find that multi-plant ownership increases markups only modestly, and this effect does not materially change over time. This reinforces our finding that the increases in markups that we estimate are not primarily due to industry consolidation but rather exit spurred by technological change. The Federal Trade Commission investigated a number of proposed mergers during the sample period. With some, it obtained a consent decree in which the merging firms divested one or more plants; in others it successfully challenged the merger. These enforcement actions appear to have been effective in preserving competition.

Our research contributes to a growing literature that uses structural models to explore market power in specific industries over long time horizons. Ganapati (2021) examines wholesalers and determines that greater scale economies and improved service quality has both increased markups and benefited consumers. Grieco et al. (2021) examines automobile manufacturers and finds that markups have decreased over time due to competitive pressures, despite substantial declines in marginal cost and increases in product quality. Brand (2021) and Döpper et al. (2021) examine consumer products manufacturers and determine that markups have increased due to lower marginal costs that are not passed-through to consumers. Each of these contributions—consistent with our own—points to technological innovation as a primary driver of long term equilibrium outcomes. They also suggest that the extent to which technological

innovation benefits consumers, and the speed with which it does so, may depend on the competitive environment and market dynamism, among other considerations.

The portland cement industry is a commonly-studied industry because it is amenable to modeling and there is a wealth of publicly-available data. Steven Berry has referred to it as one of a handful of “model industries” in industrial organization.² Recent contributions explore the consequences of environmental regulation (Ryan, 2012; Fowlie et al., 2016; Miller et al., 2017), the patterns of spatial price discrimination (Miller and Osborne, 2014), how firms approach strategic entry decisions (Perez-Saiz, 2015), and the determinants of technology adoption (Macher et al., 2021). In the broader context of understanding economy-wide trends in market power, our contribution is best understood as complementing both the macroeconomic literature and other empirical applications to specific industries.

We structure the paper as follows. We first describe the cement industry and our data sources (Section 2). We then present the model and the estimator (Section 3). Next, we provide the estimation results, evaluate the fit to the data, and validate our estimates to the extent possible (Section 4). Finally, we consider the implications of the model for the evolution of market concentration and markup (Section 5) and conclude (Section 6).

2 The Portland Cement Industry

2.1 Background

Portland cement is a finely ground dust that forms concrete when mixed with water and coarse aggregates such as sand and stone. Concrete, in turn, is an essential input to many construction and transportation projects. The production of cement involves feeding limestone and other raw materials into large rotary kilns. The output of the kilns, “clinker,” is cooled, mixed with a small amount of gypsum, and ground to form portland cement. The product can be shipped to ready-mix concrete plants or directly to construction sites. For decades, the production of cement has conformed to standards published by the American Society for Testing and Materials (ASTM), which helps assure reliability and consistency across plants.

²Berry, Steve [@steventberry]: “. . . I was reading about “model organisms” in biology research. Maybe RTE cereal, airlines and cement are IO’s model industries—our versions of mice, fruit flies and tapeworms . . .” (Twitter, January 26, 2021).

There have been substantial improvements in productive efficiency due to the adoption of modern precalciner technologies. Most plants now preheat the raw materials using the exhaust gases of the kiln and heat from a supplementary combustion chamber. Modern precalciner kilns are 25-35% more fuel efficient than older kilns, and also tend to have much greater productive capacity. Adoption is uneven, both spatially and over time, but nonetheless the pace is sufficient that the industry nearly fully turns over during the four decades of our sample.³

Figure 1 plots industry capacity (top panel), the number of plants (middle panel), and the average plant capacity (bottom panel) over 1974-2016. Total industry capacity increases over this period from 91 million metric tonnes to 109 million metric tonnes, yet the number of plants decreases from 163 to 90. This reflects the adoption of higher-capacity precalciner kilns. As shown, plants with modern kiln technology account for an increasing fraction of industry capacity and the number of plants over time. These plants tend to have larger capacities than those that rely on older technology.⁴ Furthermore, this gap grows over time because the more recently installed precalciner kilns tend to have larger capacities than earlier precalciner kilns.

[Figure 1 about here.]

Figure 2 plots the location of cement plants in 1974 (top panel) and in 2016 (bottom panel). The reductions in the number of plants and the changes in kiln technology are apparent. Also notable is that plants cluster around river systems, urban areas, and interstate highways (not shown).⁵ The geographic configuration of the industry reflects the importance of transportation costs. Most commonly, cement is driven from the plant directly to the ready-mix concrete plant or construction site. In some parts of the country, river barges can be used to reduce driving distances; the per-mile cost of barge transport is perhaps 1-2% of the per-mile cost of truck transport. Still, transportation can account for a substantial portion of buyers' total acquisition costs.

The variable costs of production are mainly attributable to the procurement of fossil fuels to heat the kiln, the cost of the raw materials, electricity costs, and kiln maintenance (EPA (2009)). For the fossil fuels, most plants rely primarily on coal or natural

³Prior empirical research shows that precalciner adoption is most likely if fuel prices are high, there are few nearby competitors, and local demand conditions are favorable (Macher et al., 2021).

⁴In making these comparisons, we designate plants as using old technology if they have a long dry kiln or a wet kiln, neither of which utilizes preheating. We designate plants as using new technology if they use a precalciner kiln or a preheater kiln (which uses exhaust gases but not the additional supplementary combustion chamber). We make finer distinctions when measuring the fuel costs of production.

⁵For comparison, Appendix Figure C.2 maps the construction employment—a proxy for cement demand—across the counties of the contiguous United States.

gas, but some plants use petroleum coke, oil, or waste, either as the primary fuel or as a supplement. The most important raw material is limestone, which typically is obtained from a quarry adjacent to the plant. Maintenance typically occurs over a 4-6 week period each year, with the plant running at full capacity all other times. Thus, output is adjusted by shortening or lengthening the maintenance period. However, plants incur a shadow cost if they defer maintenance because future costs can escalate.

[Figure 2 about here.]

Cement producers typically sign short-term contracts with buyers.⁶ The contracts specify a mill price (or a “free-on-board” price) and can include discounts that reflect the ability of buyers to substitute to other producers. Thus, transportation costs affect trade patterns and the contract terms that are negotiated. Buyers are responsible for the cost of transportation. Miller and Osborne (2014) discuss the history of spatial price discrimination in the industry, and provide some results on pricing patterns.

Figure 3 plots domestic consumption and production in the contiguous United States over 1974-2016. Both are pro-cyclical because demand is tied to construction activity. When macroeconomic conditions are favorable, consumption tends to outstrip production due to domestic capacity constraints. The gap between production and consumption aligns with import quantities (Appendix Figure C.1). Imports are processed at designated customs districts and most arrive via transoceanic freighter. The enabling technology was invented in the late 1970s, which explains the tighter connection between consumption and production in the early years of the sample. Exports are negligible. Cement cannot be stored for any meaningful period of time because it gradually absorbs moisture, rendering it unusable.

[Figure 3 about here.]

Figure 4 plots the average inflation-adjusted price and fuel cost per metric tonne (top panel) and a national capacity-based HHI (bottom panel) over 1974-2016. Prices fluctuate over time but take similar values at the beginning and end of the sample. Some of the variation in the time-series appears to correlate with changes in fuel costs, which exist due to changes in fuel prices and the gradual adoption of precalciner kilns.⁷

⁶There is a limited amount of vertical integration in the industry. Syverson and Hortaçsu (2007) report that 30% of cement plants and 11% of ready-mix concrete plants were vertically integrated in 1997, but determine that vertical integration has little impact on economic outcomes.

⁷Miller et al. (2017) examine the pass-through of fuel costs to prices and find evidence of over-shifting. This could be due to convexity in the demand schedule or because fuel costs correlate with other variable cost determinants, such as electricity costs.

The national capacity-based HHI increases from about 400 to more than 900 over the sample period—this does not however appear to be associated with higher prices (the bivariate correlation coefficient is -0.27). The extent to which local markets are more concentrated cannot be determined based on these data alone.⁸

[Figure 4 about here.]

2.2 Data

We draw data from numerous sources. Chief among these is the *Minerals Yearbook*, an annual publication of the United States Geological Survey (USGS) that summarizes a census of portland cement plants. Most reported information is aggregated to the level of regions or the nation. We make use of region-level data on (i) the average free-on-board price obtained by plants in the region, (ii) the total production of plants in the region, and (iii) total consumption of cement by buyers in the region. Importantly, regions are delineated to protect data confidentiality, and do not approximate local markets in any economic sense. The regions used for price and production are most typically combinations of states (e.g., “Wisconsin and Michigan”) and usually align with each other. In many years, these regions are redefined so that each includes at least three independently-owned plants; this prevents any one firm from obtaining the business data of its competitors. Consumption regions are most typically states.

Also from the *Minerals Yearbook*, we use national-level data on the total production by plants with wet kilns, the total production by plants with dry kilns (including old dry kilns and modern preheater/precalciner kilns), and national-level data on the fraction of shipments that utilize barge transportation. Finally, the *Minerals Yearbook* provides the location of customs districts through which foreign imports enter the contiguous United States. It also provides the quantity and customs value of the imported cement, the latter of which represents the cost of bringing the cement to the United States, and includes the freight, insurance, and delivery charges associated with shipping to the port of entry. All of these data span the full sample period of 1974-2016.

We also make use of the *California Letter*, another publication of the USGS, which tracks trade flows from Northern California (NCA) and Southern California (SCA) to NCA, SCA, Arizona, and New Mexico. Data are available over 1990-2010, though some

⁸Appendix Table C.1 lists the largest eight producers (by national capacity share) in 1974 and 2019. The observed change in the national capacity-based HHI is equivalent to what would arise due to a shift from 25 to 11 symmetric firms.

information is withheld or aggregated in some years. To our knowledge, no other publicly-available data directly links the locations of cement producers to the locations of their customers, though some indirect inferences can be made based on the spatial mismatches in the production and consumption data from the *Minerals Yearbook*.

Our plant- and kiln-level data are from the *Plant Information Summary*, a publication of the Portland Cement Association that is published annually over 1973-2003, semi-annually over 2004-2010, and then again in 2013 and 2016.⁹ The data provide an end-of-year snapshot on the location, owner, and primary fuel of each cement plant in the U.S. and Canada, as well as the age, capacity, and technology class of each kiln. Also from the Portland Cement Association, we make use of 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 have data for 1974-1979, 1990, 2000, and 2010.

With these data in hand, we calculate the fuel costs of production at the plant-year level using the methodology of Miller et al. (2017). As this requires data on fossil fuel prices, we obtain the average prices of coal, natural gas, and distillate fuel oil for the industrial sector from the State Energy Database System (SEDS) of the Energy Information Administration (EIA). Details on the calculation are in Appendix A.2.

In order to help model demand, we obtain county-level data on construction employment from the County Business Patterns of the Census Bureau (NAICS Code 23 and SIC Code 15). We obtain the data for 1986-2016 from the Census Bureau website,¹⁰ and the data for 1974-1985 from the University of Michigan Data Warehouse.

We obtain the latitude and longitude of the cement plants and the centroid of every county using Google Maps. From the Army Corps of Engineers, we also obtain the latitude and longitude of the mile markers along four navigable river systems. These river systems include the Columbia-Snake, the Chesapeake, the Savannah, and the Mississippi (Appendix Figure C.3). The Mississippi River System includes some canal-type waterways, most notably the Gulf Intercoastal Waterway, which has a depth of 12 feet and was designed for barges. We calculate the straight-line distance between every plant and county to approximate the trucking distance between them. We also calculate the straight-line distances between plants/counties and the river systems. This allows

⁹See Appendix A.1 for some details about how we process these data. At present, we have the *Plant Information Summary* for all available years except 1973, 1978, 1981, and 1996. We exclude the missing years from the estimation sample.

¹⁰See <https://www.census.gov/programs-surveys/cbp/data.html>, last accessed February 16, 2022.

us to incorporate that some cement is trucked to and from a river system in order to reduce the costs associated with long-haul transportation.

3 Model and Estimation Strategy

3.1 Demand

We examine a model in which construction firms (“buyers”) use scoring auctions to purchase cement from one of many domestic producers or an importer. Each domestic producer f operates one or more plants that we collect in the set \mathbb{J}_f . Buyers can forego a purchase of cement by selecting the outside good; this could require the use of wood or asphalt as an alternative input in the construction project, for example. We apply a nested logit structure under which the cement options are closer substitutes for one another than they are for the outside good.

The indirect gross utility that buyer i in county n and year t receives from plant $j = 1, 2 \dots, J_t$ is given by:

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

where $\bar{u}_{jnt}(\cdot)$ is function of data and parameters that is common to all buyers in the same county, ζ_{int} and ϵ_{ijnt} are buyer-specific preference shocks for cement and plant j , respectively, and $\sigma \in [0, 1]$ is a nesting parameter that determines the extent to which preference shocks for different cement plants are correlated. Higher values of σ imply less buyer substitution between cement and the outside good. The gross indirect utility that buyer i receives from the outside good is $u_{i0nt} = \epsilon_{i0nt}$. We assume that each ϵ_{ijnt} is distributed iid Type 1 extreme value, and that ζ_{int} has the unique distribution such that $\epsilon_{ijnt}^* \equiv \zeta_{int} + (1 - \sigma)\epsilon_{ijnt}$ also is Type 1 extreme value (Berry, 1994; Cardell, 1997).

We specify demand such that (i) buyers can value geographic proximity to the plant, taking into account the option to utilize barge transportation along river systems, and (ii) buyers can value domestic cement differently from imported cement. On the latter, we assume that if imported cement is selected (“plant J ”) then it is sourced from the nearest customs office. The common component of indirect gross utility is:

$$\begin{aligned} \bar{u}_{jnt}(\mathbf{X}_t, \boldsymbol{\theta}) = & \beta_0 + \min\{\beta_1 d_{j \rightarrow n}, \beta_1 (d_{j \rightarrow R} + d_{R \rightarrow n}) + \beta_2\} \\ & + \beta_3 IMPORT_j + \beta_4 IMPORT_j \times TREND_t \end{aligned} \quad (2)$$

where $d_{j \rightarrow n}$ is the distance between the plant and the county, $d_{j \rightarrow R}$ is the distance between the plant and the (best-suited) river system, $d_{R \rightarrow j}$ is the distance between the same river system and the county, $IMPORT_j$ is an indicator for imported cement, and $TREND_t$ is a demeaned time trend. The parameters (β_1, β_2) capture, respectively, the per-mile disutility associated with truck transport and a fixed disutility associated with using barge transport (e.g., due to loading charges).

Each buyer conducts a second-score auction in which plants submit bids, b_{ijnt} , and receive scores of $u_{ijnt} - \phi b_{ijnt}$, with $\phi > 0$. We assume that all producers participate in the auction and that, when submitting bids, they know the common components of gross utility, $\bar{u}_{jnt}(\cdot)$ for all j , but not the buyer-specific preference shocks. As, in addition, the marginal costs of production will not vary across buyers, plants submit the same bid to all buyers in the same county and year: $b_{ijnt} = b_{jnt}$. Finally, we assume that the bid of the outside good is zero and that the option with the highest score is selected. Integrating over the buyer-specific preference shocks, the probability that plant j wins an auction in county n and year t is given by:

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

where \mathbf{b}_{nt} contains all the bids submitted for county n in year t . The share of plant j within the inside goods is given by \bar{s}_{jnt} . Letting M_{nt} denote market size, the total quantity of cement sold by plant j in year t , summing across all buyers, is $Q_{jt}(\mathbf{b}_t; \mathbf{X}_t, \boldsymbol{\theta}) = \sum_n s_{jnt}(\mathbf{b}_{nt}; \mathbf{X}_t, \boldsymbol{\theta}) M_{nt}$.

In a second-score auction, the transaction price is determined by the score of the second-best bidder. Without loss of generality, assume that plant j is the winning plant for an auction in county n . Then the transaction price is given by:

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

where $f(j)$ is the producer that operates plant j . This embeds the notion that plants

operated by the same producer do not bid against each other.¹¹ Even though each plant submits the same bid to all auctions in the same county, the transaction prices are heterogeneous and depend on the realized values of the buyers' preference shocks. This does not give rise to endogeneity bias in estimation; the moments we use are based on the expected prices that arise within counties (i.e., integrating over buyers) and these expected prices are unaffected by preference shocks.

A final consideration relates to the county-level market sizes. We assume that overall construction activity is unaffected by cement prices because cement accounts for a small fraction of total construction expenditures (e.g., Syverson, 2004). Under that assumption, an appropriate market size would scale with construction activity, and we use construction employment as a proxy because it is available at the county-level for every year in our sample period. Specifically, we allocate cement consumption—which is observed at the region level—to individual counties in proportion to construction employment, and then double the allocated consumption to construct market size. With this approach, the outside good share is always 50%, so there is no empirical variation to identify the nesting parameter. Thus, we assume $\sigma = 0.90$, which implies relatively little substitution between cement and substitutes such as wood or asphalt.

3.2 Supply

Turning to the supply-side, the variable profit function of producer f is given by

$$\pi_{ft}(\mathbf{b}_t; \mathbf{X}_t, \boldsymbol{\theta}) = \sum_{j \in \mathbb{J}_f} \sum_n \bar{p}_{jnt}(\mathbf{b}_{nt}; \mathbf{X}_t, \boldsymbol{\theta}) s_{jnt}(\mathbf{b}_{nt}; \mathbf{X}_t, \boldsymbol{\theta}) M_{nt} - \sum_{j \in \mathbb{J}_f} \int_0^{Q_{jt}(\mathbf{b}_t; \mathbf{X}_t, \boldsymbol{\theta})} c_{jt}(Q; \mathbf{X}_t, \boldsymbol{\theta}) dQ \quad (5)$$

where $\bar{p}_{jnt}(\cdot)$ is the expected price obtained by plant j conditional on winning an auction in county n and year t , and $c_{jt}(\cdot)$ is a marginal cost function. Implicit in our notation is that marginal costs do not depend on the identity of the buyer.

We specify the marginal cost function for domestic plants following Ryan (2012)

¹¹Different micro-foundations are possible. If the second-score auction is recast as a descending-price auction, then the winning producer would not continue to lower its bids after the last remaining competitor drops out. Or, given the assumptions we maintain, a profit-maximizing producer need only bid in its “best” plant, defined as having the greatest gap between value and marginal cost.

and Miller and Osborne (2014):

$$c_{jt}(Q_{jt}; \mathbf{X}_t, \boldsymbol{\theta}) = \mathbf{w}'_{jt} \boldsymbol{\alpha} + \gamma \mathbb{1} \left\{ \frac{Q_{jt}(\cdot)}{CAP_{jt}} > \nu \right\} \left(\frac{Q_{jt}(\cdot)}{CAP_{jt}} - \nu \right)^2 \quad (6)$$

where \mathbf{w}_{jt} includes a constant and the fuel costs of production, CAP_{jt} is plant capacity, and the parameters include $(\boldsymbol{\alpha}, \gamma, \nu)$. Marginal costs start to increase in production once utilization exceeds the threshold ν , capturing that production near capacity creates shadow costs due to foregone kiln maintenance. Production at capacity increases marginal costs by $\gamma(1 - \nu)^2$ relative to production below the utilization threshold. For imports, we assume that marginal costs are constant and equal to the customs value, inclusive of insurance, freight, and other delivery charges to the port of entry.

We assume that plants submit bids that equal their marginal costs. This is a dominant strategy in some special cases of the model, such as if marginal costs are constant ($\gamma = 0$) or if buyers are homogeneous (i.e., $\bar{u}_{jn}(\cdot) = \bar{u}_{jm}(\cdot)$ for all counties n and m). Furthermore, in the general case, if bids equal marginal cost then no producer can increase its profit by changing only one of its bids. Still, our assumption rules out some more complicated bidding strategies that can be profitable (see Appendix B.1).

The vector of plant-level quantities, $\mathbf{Q}_t^* = (Q_{1t}^*, Q_{2t}^*, \dots, Q_{Jt}^*)$, clears the market in year t if and only if

$$Q_{jt}(\mathbf{c}_t(\mathbf{Q}_t^*; \mathbf{X}_t, \boldsymbol{\theta}); \mathbf{X}_t, \boldsymbol{\theta}) = Q_{jt}^* \quad (7)$$

for every plant j , where $\mathbf{c}_t = (c_{1t}, c_{2t}, \dots, c_{Jt})$ contains the implied marginal costs of each plant (and thus also the bids). A solution to this system of equations is guaranteed to exist under the parametric restrictions that we place on demand and marginal costs (Appendix B.2). Numerical checks support uniqueness at our parameter estimates.

With the strategies we examine, the expected price that plant j receives conditional on winning an auction is given by:

$$\begin{aligned} \bar{p}_{jnt}^*(\mathbf{X}_t, \boldsymbol{\theta}) &= c_{jt}(Q_{jt}^*; \mathbf{X}_t, \boldsymbol{\theta}) \\ &- \frac{1}{\phi} \frac{1}{\sum_{k \in \mathbb{J}_{f(j)}} s_{knt}^*} \log \left[1 - (1 - s_{0nt}^*) \left(1 - \left(1 - \sum_{k \in \mathbb{J}_{f(j)}} \frac{s_{knt}^*}{1 - s_{0nt}^*} \right)^{1-\sigma} \right) \right] \end{aligned} \quad (8)$$

The second term on the right side is the expected markup; we drop function arguments for brevity. See Appendix B.3 for a derivation. The second-score auction is efficient,

in the sense that the winning plant is the one that creates the greatest total surplus, defined as $u_{ijnt} - \phi c_{jt}(\cdot)$. Multi-plant ownership does not affect the probabilities with which specific plants are selected by the buyer; it does however affect the expected prices and markups that are obtained conditional on winning.

3.3 Estimation

We estimate the model with simulated non-linear least squares. The loss function is based on the distance between the endogenous data and the outcomes implied by the model. Formally, we observe a set \mathcal{L} of endogenous outcomes. We assume these outcomes arise from the data generating process:

$$y_{lt} = h_l(\mathbf{X}_t; \boldsymbol{\theta}_0) + \epsilon_{lt}$$

where y_{lt} is the observed value of outcome $l \in \mathcal{L}$ during year t , ϵ_{lt} is a zero-mean random shock that we interpret as measurement error, and $h_l(\cdot)$ is a known function defined by the model that returns the expected value of outcome l conditional on the exogenous data in \mathbf{X}_t : $\mathbb{E}[y_l | \mathbf{X}_t] = h_l(\mathbf{X}_t; \boldsymbol{\theta}_0)$.

The parameters to be estimated are $\boldsymbol{\theta}_0 = (\beta_1, \beta_2, \beta_3, \beta_4, \phi, \boldsymbol{\alpha}, \gamma, \nu)$. Stacking outcomes and predictions into vectors, $\mathbf{y} = \{y_{lt} : l \in \mathcal{L}, t = 1, \dots, T\}$ and $\mathbf{h}(\mathbf{X}, \boldsymbol{\theta}) = \{h_l(\Psi_t, \boldsymbol{\theta})\} : l \in \mathcal{L}, t = 1, \dots, T\}$, we define our estimate of $\boldsymbol{\theta}_0$ as:

$$\hat{\boldsymbol{\theta}}(\Sigma) = \underset{\boldsymbol{\theta} \in \Theta}{\operatorname{argmin}} \quad (\mathbf{y} - \mathbf{h}(\mathbf{X}, \boldsymbol{\theta}))' \Sigma^{-1} (\mathbf{y} - \mathbf{h}(\mathbf{X}, \boldsymbol{\theta})) \quad (9)$$

where Σ is a positive definite weighting matrix. In estimation, we use a diagonal weighting matrix in which each element is the sample variance of the relevant endogenous series; we reduce the weight placed on consumption and production moments by half because they are highly correlated.

The exogenous data in \mathbf{X} include the market sizes, the customs value of imported cement, and the locations, fuel costs, and capacities of the domestic cement plants. The endogenous outcomes in \mathbf{y} include: average prices, total production, and total consumption within regions over 1974-2016 (824, 827, and 1,801 observations, respectively); the proportion of national production that is accounted for by plants with a wet kiln over 1974-2016 (32 observations) and the proportion of cement that is shipped using river barges over 1974-2016 (33 observations); the proportion of cement produced in Northern California that is shipped to buyers in Northern California

over 1990-2000 (10 observations), the proportion of cement produced in Southern California that is shipped to buyers in Northern California over 1990-2000 (10 observations), and the proportion of cement produced in California that is shipped to buyers in Northern California over 2001-2010 (7 observations).

3.4 Computation

We estimate the model using an adaptive Nelder-Mead method. For each candidate parameter vector, we compute the solution to equation (7) using “dfsane,” a large-scale nonlinear equation solver developed in La Cruz et al. (2006). We parallelize this inner step, using different processors for different years. With the market-clearing quantities in hand, we aggregate the implied modeling results to the level of the endogenous data, evaluate the loss function, and iterate to convergence. We then use the Levenberg-Marquardt algorithm to confirm the that convergence occurs at a local minimum.

For a typical year, the inner step involves obtaining well more than 300,000 quantities and average markups at the plant-county level. This is computationally feasible because equilibrium is characterized by a system of equations with one equation per plant, rather than with one equation for each plant-county combination. Indeed, although the second-score auction accords well with our understanding of how prices are set in the industry, its main benefit is computational. The alternatives of Nash-Bertrand competition (e.g., as in Miller and Osborne, 2014) or a first-score auction would be unworkable in our setting because the computation of equilibrium would involve searching over hundreds of thousands of prices. All of these models obtain similar economic outcomes under similar parametric assumptions (e.g., Miller and Sheu, 2021), so our use of the second-score auction should not affect inferences much.

Other assumptions that we make impact computational feasibility. The logit preference shocks allow us to obtain analytical expressions for market shares and expected markups, and furthermore allow markets shares to be continuous and convex functions of bids. The logit shocks also have economic implications. For example, because they have unbounded support, competition is global, in the sense that every plant ships at least some cement to every county. Thus, we find it comforting that the model predicts shipping patterns well, and that very few shipments involve great distances. Another assumption that we maintain for computational reasons is that all plant-level heterogeneity in quality or marginal costs can be characterized based on observables. Overall, we view our assumptions as reasonable for the cement industry. Furthermore, as we

develop shortly, our estimates fit the endogenous data well and are corroborated by various other industry sources and academic publications.

4 Estimation Results

In this section, we summarize the estimation results, validate the parameter estimates to the extent possible, and show that the model fits the endogenous data well. To start, Table 1 presents parameters estimates, standard errors, and some derived statistics. The parameters take the expected signs and are precisely estimated. On the demand-side, buyers prefer nearby cement plants, prefer domestic cement over imported cement, and prefer to pay lower prices, all else equal. On the supply-side, the marginal costs increase with fuel costs and as production approaches capacity.

[Table 1 about here.]

For our purposes, the two most important parameters are the price parameter and the trucking parameter, as the first directly affects markups and the second affects the magnitude of spatial differentiation. To corroborate our estimates, we note that the ratio of the two (β_1/ϕ) is a measure of the trucking cost per tonne-mile. Outside sources suggest that our estimate of \$0.30 is reasonable. First, the 1974 *Minerals Yearbook* notes that transportation costs are about \$0.43 per tonne-mile on average. Second, *Transportation in America* (2007, 20th Edition) reports that the revenues per tonne-mile of Class I general freight common carriers (i.e., basic truck transport) range from \$0.36-\$0.43 over 1983-2003. Finally, Miller and Osborne (2014) estimate a transportation cost of \$0.46 per tonne-mile using an approach that is similar to ours, but with data covering one region of the United States over 1983-2003.

The barge parameter also affects spatial differentiation. Buyers that use barge transport incur a fixed economic cost of \$58.33 (β_2/ϕ) that can be interpreted as including the loading/unloading costs for the barge and any frictions associated with barges that we have not modeled (e.g., due to limited river entry points). Using barges to lower the per-mile shipping cost is only economical for long distance shipments.

Figure 5 provides histograms of the straight-line distances between the cement plants and their customers, both for the 89% of shipments that are done only with trucks (in red) and the 11% of shipments that make use of barges (in turquoise). In the former category, the median shipment travels 78 miles and 84% travel less than 200 miles. This aligns with a Census Bureau study (1977) that reports that more than 80%

of cement is transported within 200 miles. Similarly, Miller and Osborne (2014) find that 90% of cement travels less than 200 miles. By contrast, the median distance between a plant and the buyer is 536 miles if a barge is used. Nearly all barge shipments utilize the Mississippi River System (Appendix Figure C.5).

[Figure 5 about here.]

These transportation costs give rise to spatial price discrimination. As buyers bear the cost of transportation, plants obtain higher prices from nearby buyers; they also obtain higher prices from buyers with less attractive alternatives. Price discrimination tends to be more pronounced for plants that face less competitive pressure. Figure 6 illustrates by plotting the county-specific prices in 2016 for the Oldcastle plant in Western Montana and the Cemex plant in Southern Texas. Both obtain higher prices from nearby buyers. The scale of discrimination is much greater for the Oldcastle plant, however, which reflects that it is more spatially differentiated.

[Figure 6 about here.]

Another check on the price parameter is whether it generates reasonable demand elasticities. We define the *bid elasticity of demand* for plant j , county n , and period t as follows:

$$e_{jnt}^b \equiv \frac{\partial s_{jnt}}{\partial b_{jnt}} \frac{b_{jnt}}{s_{jnt}} = \frac{\phi}{1 - \sigma} mc_{jt}(1 - \sigma \bar{s}_{jnt} - (1 - \sigma)s_{jnt}) \quad (10)$$

where the equality obtains after taking the derivative of equation (3) with respect to the plant's bid, and applying the assumption that plants bid their marginal cost. Weighting by quantities, we find that the average bid elasticity of demand is -4.65. For comparison, Miller and Osborne (2014) report price elasticities of demand (in a model of Bertrand pricing) that range between between -2.84 and -3.75.

Turning to the other parameters, the willingness-to-pay for domestic cement rather than imported cement (β_3/ϕ) is \$23.50 during the median year. Even in years with substantial imports, most counties rely nearly exclusively on domestic cement (Appendix Figure C.6). On the supply-side, the constant of \$41.62 provides the marginal cost of production if fuel costs and implicit capacity costs are zero. The coefficient on fuel costs somewhat exceeds one, which could obtain if fuel costs are correlated with electricity or other inputs. Marginal costs are constant in output until utilization reaches a threshold of 58.9%. Production at capacity increases marginal costs by \$18.81.

Figure 7 summarizes the model’s ability to fit the data. The panels on the left show the time series of total consumption, total production, average prices, the proportion of national production that is accounted for plants with a wet kiln, and total imports. The panels on the right show the fits for the region-year observations on consumption, production, and prices, the time series on the proportion of shipments that utilize river barges, and the fits of the cross-region shipments. For the cross-region shipments, the purple dots are for shipments that we use in estimation. The green dots are for shipments that we *do not* use in estimation: shipments from Southern California to each of Southern California, Arizona, and Nevada (1990-2000), and from California to each of the same regions (2001-2010).

[Figure 7 about here.]

Evaluating the fits together, we conclude that the model fits the outcomes observed the data reasonably well despite the parsimonious specification that we use. This is especially the case for data related to production, consumption, and shipments. We rely on the model to make inferences about the industry in our next analyses.

5 The Evolution of Concentration and Markups

5.1 Concentration in Local Markets

To support our analysis of market concentration, we first define a set of relevant markets as the supply of cement to each county in the United States. This follows principles laid out in the *Horizontal Merger Guidelines* for settings in which suppliers can exercise spatial price discrimination:

“When the hypothetical monopolist could discriminate based on customer location, the Agencies may define geographic markets based on the locations of targeted customers.”¹²

We then calculate county-level HHI statistics based on the market shares of every supplier of cement to the county:

$$HHI_{nt} = 10,000 \times \sum_f \left(\sum_{j \in \mathbb{J}_f} \frac{s_{jnt}}{1 - s_{0nt}} \right)^2 \quad (11)$$

¹²*Horizontal Merger Guidelines* §4.2.2. Counterfactual simulations verify that a hypothetical monopolist of cement would raise price by more than five percent to each county.

where $s_{jnt}/(1 - s_{0nt})$ is the probability that plant j wins an auction in county n and year t , conditional on cement being purchased. For the purposes of the calculation, we treat imports as being provided by one distinct supplier of cement. The *Horizontal Merger Guidelines* classify markets with an HHI less than 1,500 as “unconcentrated,” markets with an HHI between 1,500 and 2,500 as “moderately concentrated,” and markets with an HHI above 2,500 as “highly concentrated.”

Figure 8 shows that the median HHI among counties, weighted by market size, increased steadily from 1,890 in 1974 to 2,800 in 2016.

[Figure 8 about here.]

Table 2 shows that, between 1974 and 2016, the number of unconcentrated counties fell from 1,008 (34.1% of consumption) to 303 (8.3% of consumption). The number of moderately concentrated counties increased somewhat. The larger change, however, is the number of highly concentrated counties, which increased from 1,178 (40% of consumption) to 1,860 (57.8% of consumption). Given this shift towards greater concentration, an interesting feature of the modeling results is that the number of exceptionally concentrated markets has not increased much. For instance, the number of counties with an HHI above 5,000 increases, but only slightly, and the number of counties with an HHI above 6,000 decreases.¹³

[Table 2 about here.]

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

- (i) Using the 2016 market sizes, fossil fuel prices, and value of the import trend.
- (ii) Also removing all plants that are not present in the 2016 data.
- (iii) Also applying the 2016 capacities and primary fuels.
- (iv) Also adding plants that are present in 2016 but not 1974.
- (v) Also using the 2016 mapping from plants to firms.

¹³Appendix Figure C.7 provides histograms for 1974 in 2016. Appendix Figure C.8 maps the HHIs in 1974 and 2016, as well as the changes in HHI that occur between these years.

The final step reproduces the 2016 data. In each of these steps, we scale the plant capacities so that total capacity aligns with that of 2016, which avoids mismatches in supply and demand that could mask more interesting mechanisms. Of particular interest are steps (ii), (iv), and (v), which isolate the competitive effects of exit, entry, and mergers, respectively.

Figure 9 summarizes how the weighted-average median HHI changes with each of these steps. Plant closures increase the median HHI by 805, and consolidation increases the median HHI by 476; these effects are partially offset by competition from new plants, which reduces the median HHI by 325. We interpret this as evidence that most of the increase in local market concentration is due to changes in technology—specifically, the precalciner kiln—that increase the minimum efficient scale of production and thereby reduce the number of plants over time. Nonetheless, mergers and acquisitions also have a substantial impact on local market concentration.

[Figure 9 about here.]

5.2 Markups

We now turn to the markups and prices implied by the model. To start, Figure 10 plots the weighted average markup of domestic plants over 1974-2016. The top panel uses an additive markup (i.e., $p - mc$), the middle panel uses the Lerner Index (i.e., $(p - c)/p$), and the bottom panel uses the multiplicative markup (i.e., p/c). Each of these measures rises modestly over the sample period: the additive markup increases from 15.919 to 16.584, the Lerner Index increases from 0.149 to 0.190, and the multiplicative markup increases from 1.179 to 1.238. Most of the increase in the additive markup occurs since 2000, whereas most of the increases in the Lerner Index and the multiplicative markup occur in the 1970s and 1980s. As there is no commensurate increase in average prices (Figure 4), the increase in markups is due to marginal cost reductions.

[Figure 10 about here.]

We repeat the decomposition exercise to examine why additive markups and prices change between 1974 and 2016 as they do. Figure 11 summarizes the results. The top panel shows that plant closures and consolidation increase the markup by \$1.15 and \$0.50, respectively, and that competition from new plants decreases the markup by \$0.85. Also notable is that the adoption of modern precalciner technology by incumbents increases markups by \$0.24. All of these effects, however, are modest relative

to the magnitude of markups. The bottom panel shows that reductions in the average price are due almost exclusively to the adoption of precalciners by incumbents. Putting these results together, our model suggests that the marginal cost reductions associated with precalciner adoption are mostly passed through to consumers.

[Figure 11 about here.]

Next, we compare the changes in average county-level markups and prices to the changes in the county-level HHI, again focusing on 1974 and 2016. The top panel shows that there is a strong positive correlation between markup changes and HHI changes.¹⁴ This makes sense given that plant closures and consolidation tend to increase both markups and the HHI, just as competition from new plants tends to reduce both markups and the HHI. The bottom panel shows that the relationship between price changes and HHI changes is more complicated. We believe this reflects that modern kiln technology lowers the cost of production but also increases the minimum efficient scale of production, and so reduces competition in the long run. Whereas the former effect benefits buyers in the form of lower prices, the latter does the opposite. The net of the two effects depends on local supply and demand conditions.¹⁵

[Figure 12 about here.]

The decomposition exercise suggests that changes in plant ownership between 1974 and 2016 contribute modestly to changes in prices and markups. We explore this in greater detail by simulating equilibrium in every year of our sample under the counterfactual that each plant is independently owned. In Figure 13, we plot the weighted average additive markup ($p - c$) that obtains, along with what we obtain from the model for the observed equilibrium. The gap between these metrics is small, with markups in the observed equilibrium being about 2.25% higher than markups in the counterfactual equilibrium. This reinforces that the increases in markups that we estimate are not primarily due to industry consolidation. Notably, the Federal Trade Commission investigated a number of proposed mergers during the sample period. With some, it obtained a consent decree in which the merging firms divested one or more plants; in

¹⁴There are a cluster of counties that experience large HHI decreases but not substantial changes in markups. These are counties that have high import volumes in 2016. Examples include Citrus County and Seminole County (Florida), Chautauqua County (New York), Dare County and Warren County (North Carolina), and Lancaster County and Middlesex County (Virginia).

¹⁵Appendix Figure C.9 maps the average markups in 1974 and 2016, as well as the changes in average markups that occur between these years. Appendix Figure C.10 does the same for average prices.

others it successfully challenged the merger. One interpretation of our results is that these enforcement actions have been effective in preserving competition.

[Figure 13 about here.]

6 Conclusion

In this paper, we have used structural modeling techniques to interpret publicly-available data on the United States cement industry over 1974-2016 and, specifically, to estimate the extent of local market concentration and the magnitude of price-cost markups. The model, though parsimonious, contains a number of elements appropriate to the cement industry, including spatially differentiated preferences, multi-modal transportation options, and supply that allows for capacity constraints and technological change. We estimate this model using aggregated data and are able to replicate patterns of production and consumption over time and across regions.

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

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

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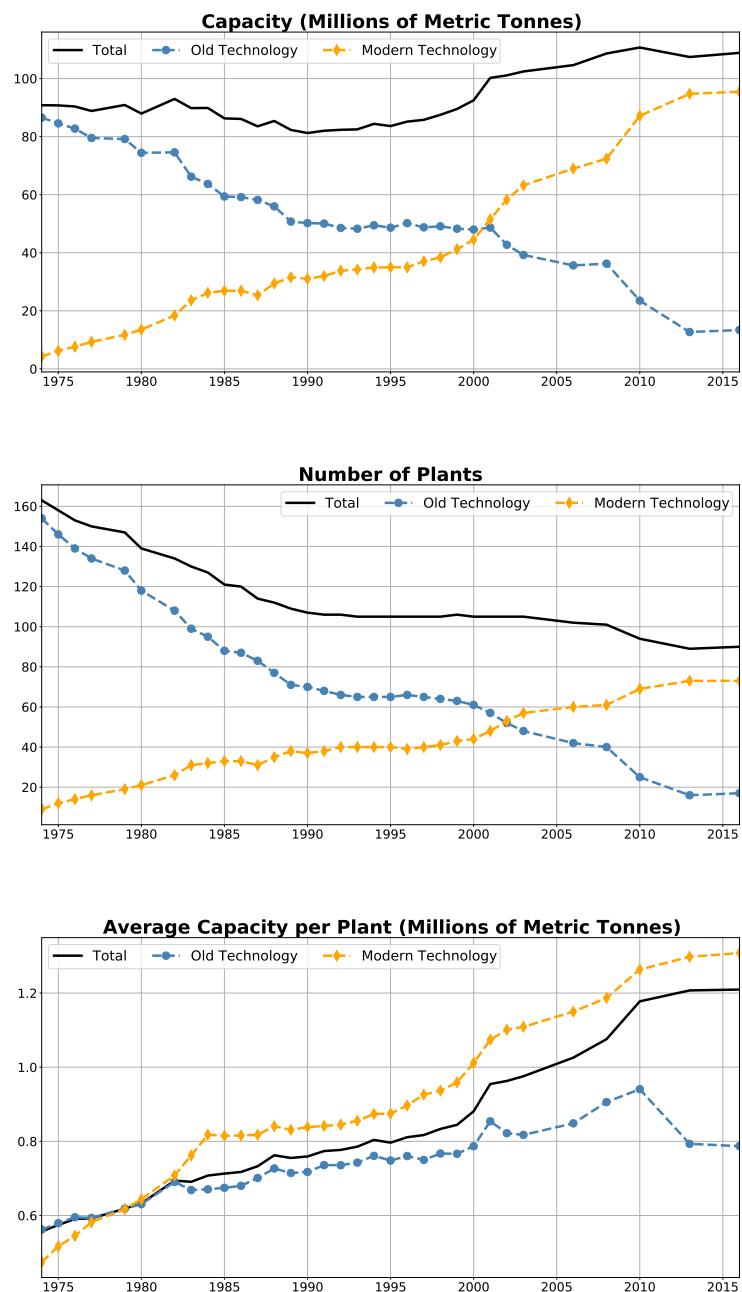
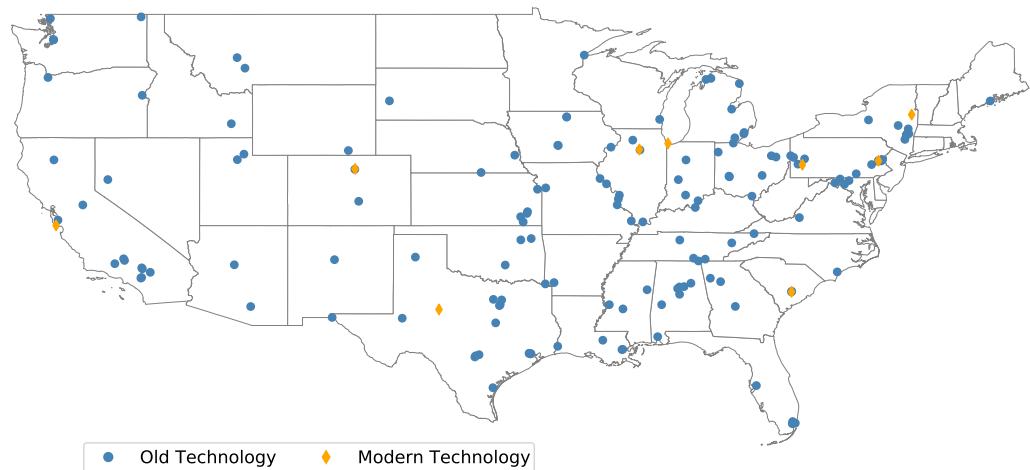


Figure 1: Capacity and Number of Cement Plants over 1974-2016

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

Cement Plants in 1974



Cement Plants in 2016

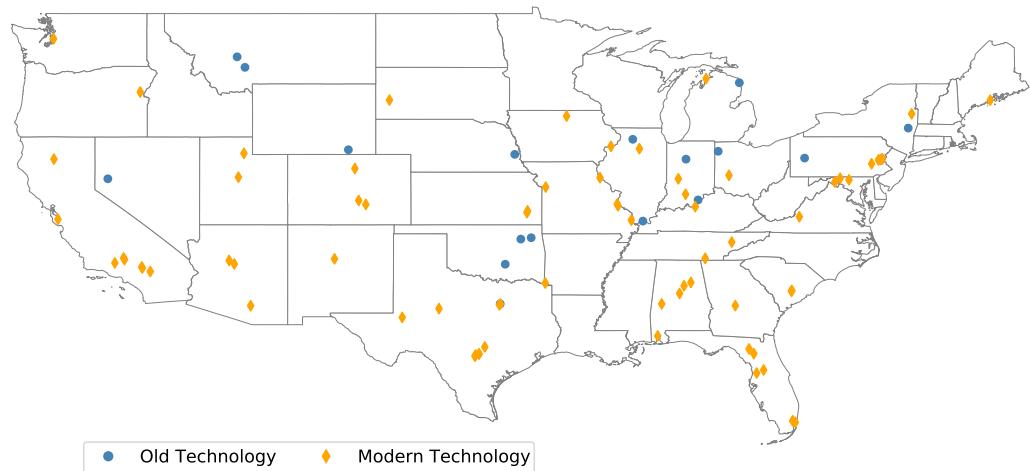


Figure 2: Cement Plant Locations in 1974 and 2016

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

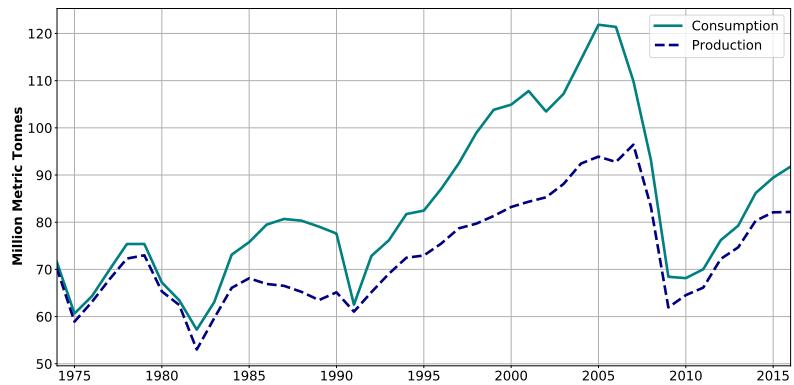


Figure 3: Cement Production and Consumption 1974-2016

Notes: Data are from the *Minerals Yearbook* of the United States Geological Survey.

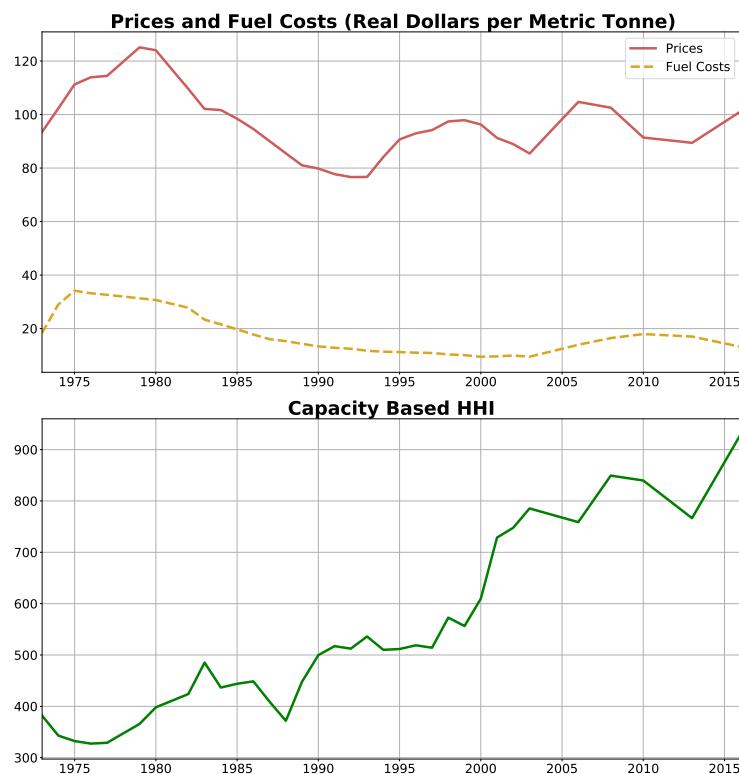


Figure 4: Prices, Fuel Costs, and National Capacity-Based HHI, 1974-2016

Notes: The price data are from the *Minerals Yearbook*. Fuel costs are based on the authors' calculations and use multiple data sources. The HHI is calculated with data from the *Plant Information Summary* of the Portland Cement Association. Imports are excluded from the HHI calculation.

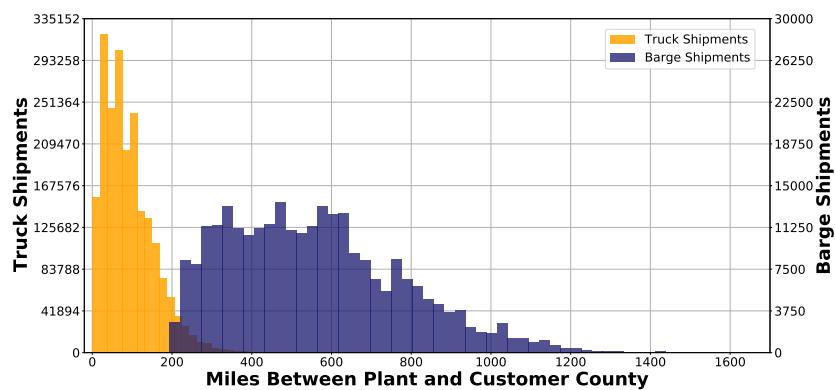


Figure 5: Distributions of Shipping Distances

Notes: The figure provides histograms for the miles between the plant and the county for all shipments that exclusively use truck transportation (red) and all shipments that use barge transportation (blue). Shipping distances are obtained from the model.

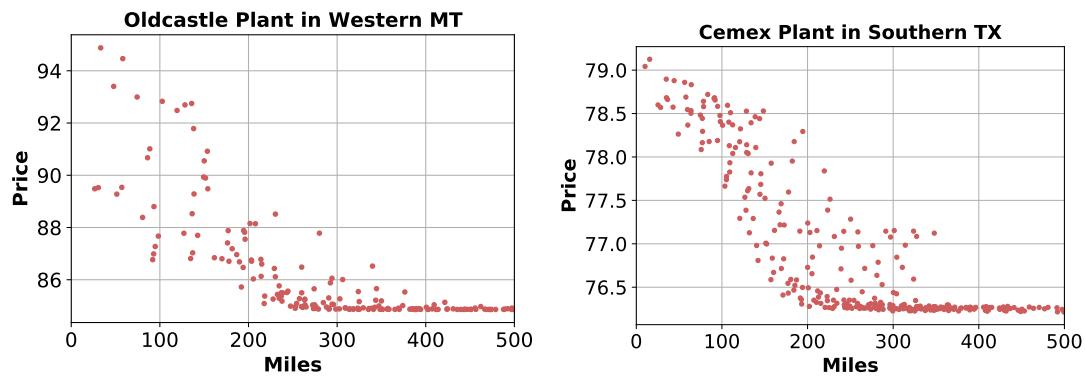


Figure 6: Spatial Price Discrimination in 2016

Notes: The average prices that each plant earns from each county are obtained from the model. The horizontal axis is the miles between the county and the Oldcastle Plant in Montana (left panel) and the Cemex plant in Texas (right panel).

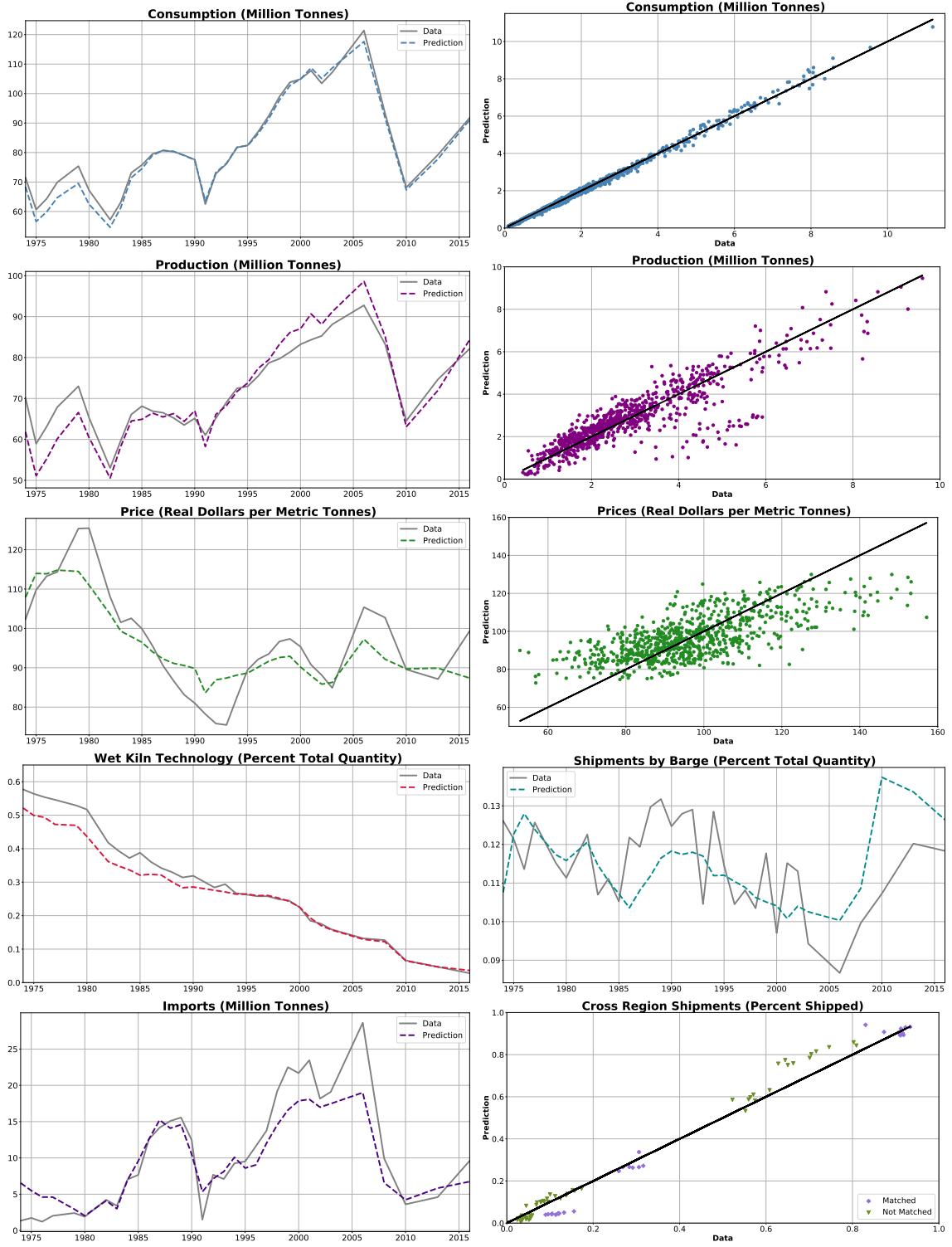


Figure 7: The Fit of the Model at the Estimated Parameters

Notes: The left panels show the time series of consumption, production, prices, production by plants with a wet kiln, and total imports. The right panels show region-year fits for consumption, production, and prices, the time series on shipments that use river barges, and the cross-region shipments. A 45-degree line is plotted in all scatter plots. For cross-region shipments, data used in estimation are in purple; withheld data are in green.



Figure 8: Median HHI Among Counties, Weighted by Market Size, 1974-2016

Notes: County-level HHIs are calculated from the county-level market shares that are obtained from the model.

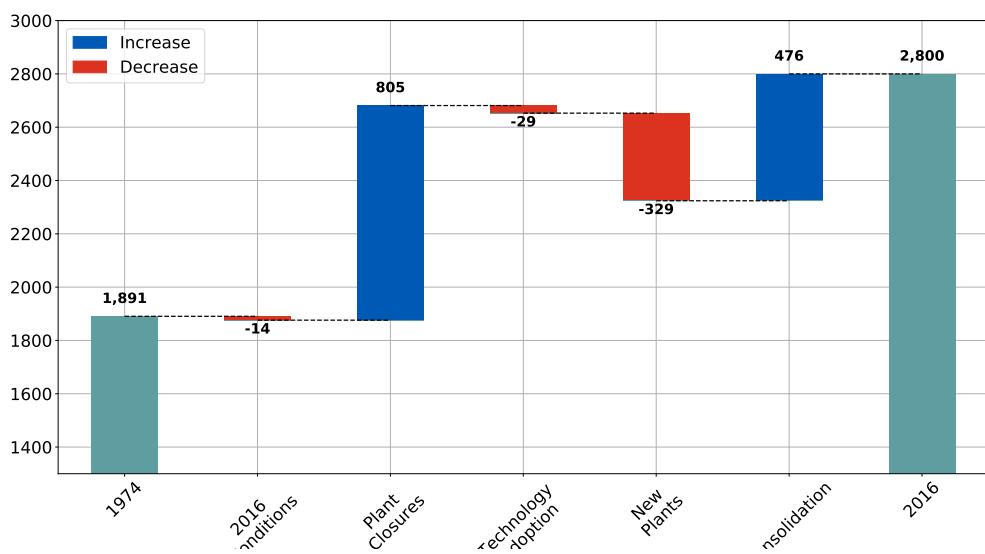


Figure 9: Decomposition of Changes in the Median County-Level HHI

Notes: The bars on the left and right show the 1974 and 2016 median county-level HHI, weighted by county-level quantities. The middle bars show changes that occur in counterfactual simulations that, cumulatively, move from the 1974 equilibrium to the 2016 equilibrium.

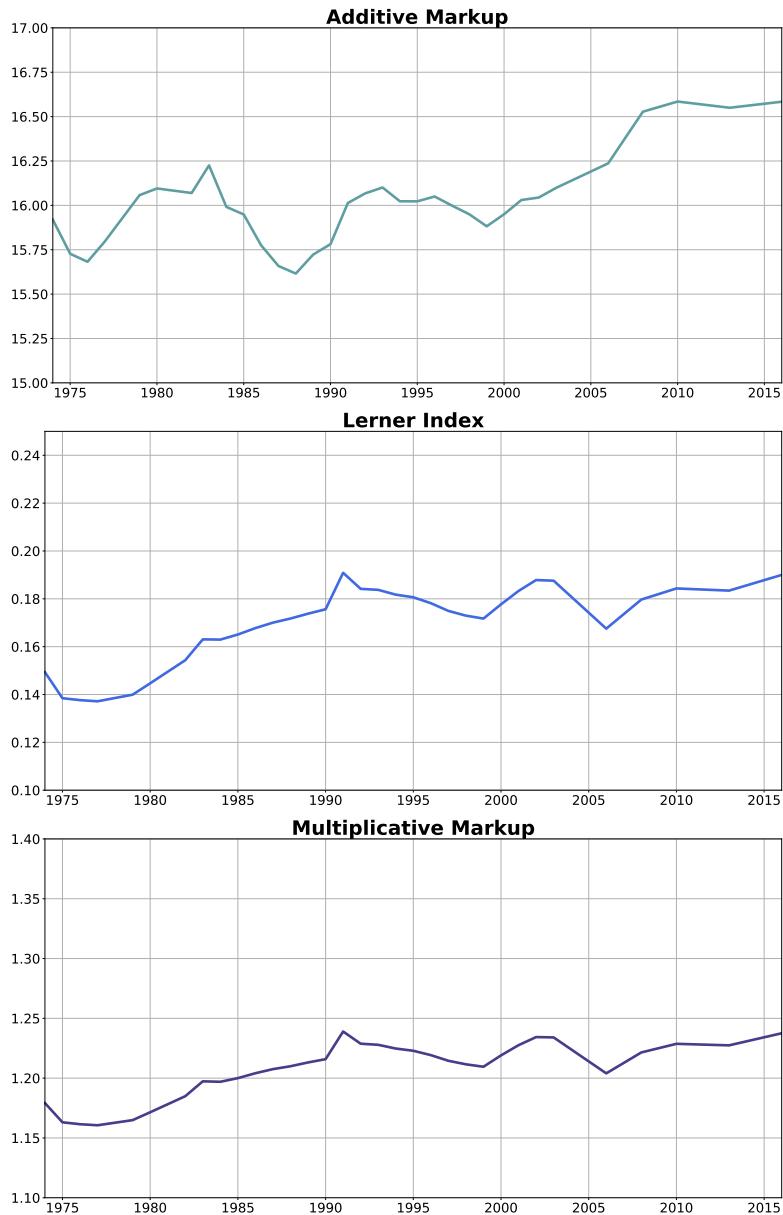


Figure 10: Weighted Average Markups over 1974-2016

Notes: The additive markup is price less cost (i.e., $p - c$), the Lerner Index is the additive markup divided by price (i.e., $(p - c)/p$), and the multiplicative markup is price over cost (i.e., p/c).

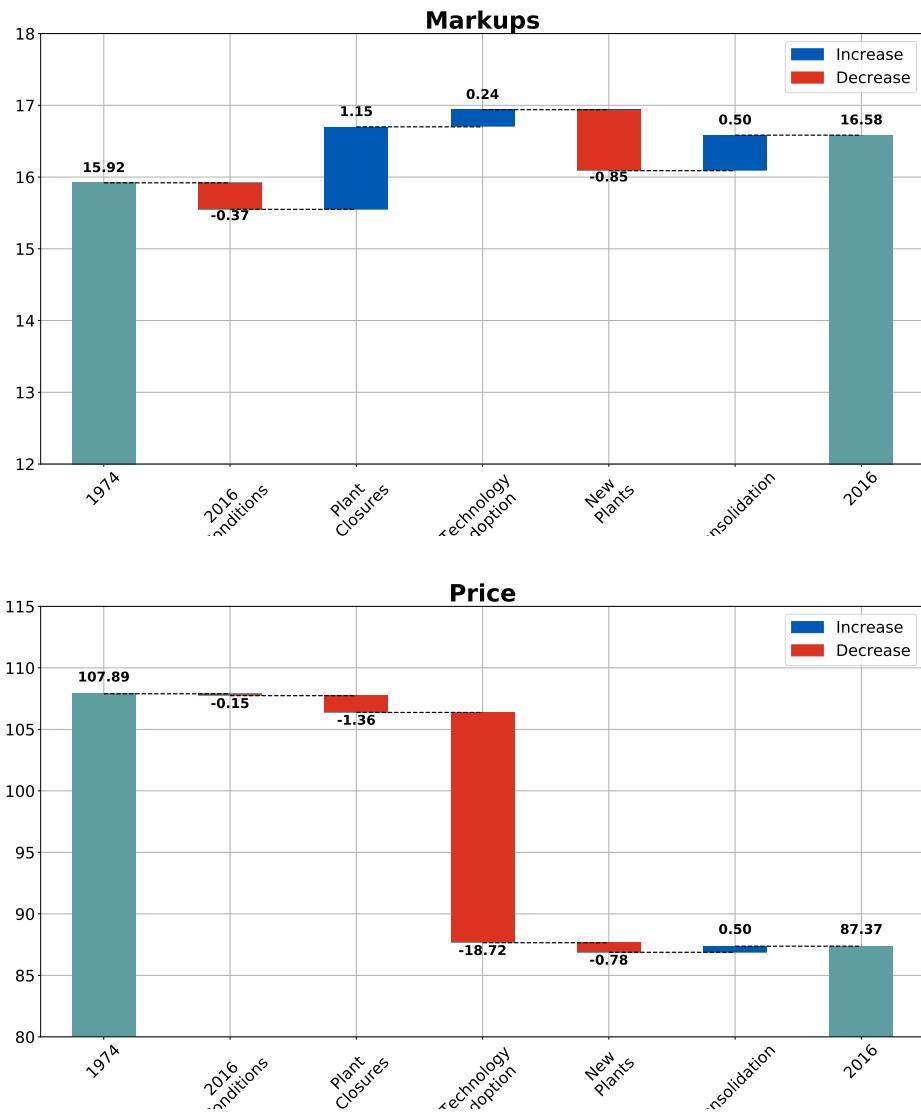


Figure 11: Decomposition of Markup and Price Changes

Notes: The bars on the left and right show the 1974 and 2016 average additive markup (top panel) and price (bottom panel). The middle bars show changes that occur in counterfactual simulations that, cumulatively, move from the 1974 equilibrium to the 2016 equilibrium.

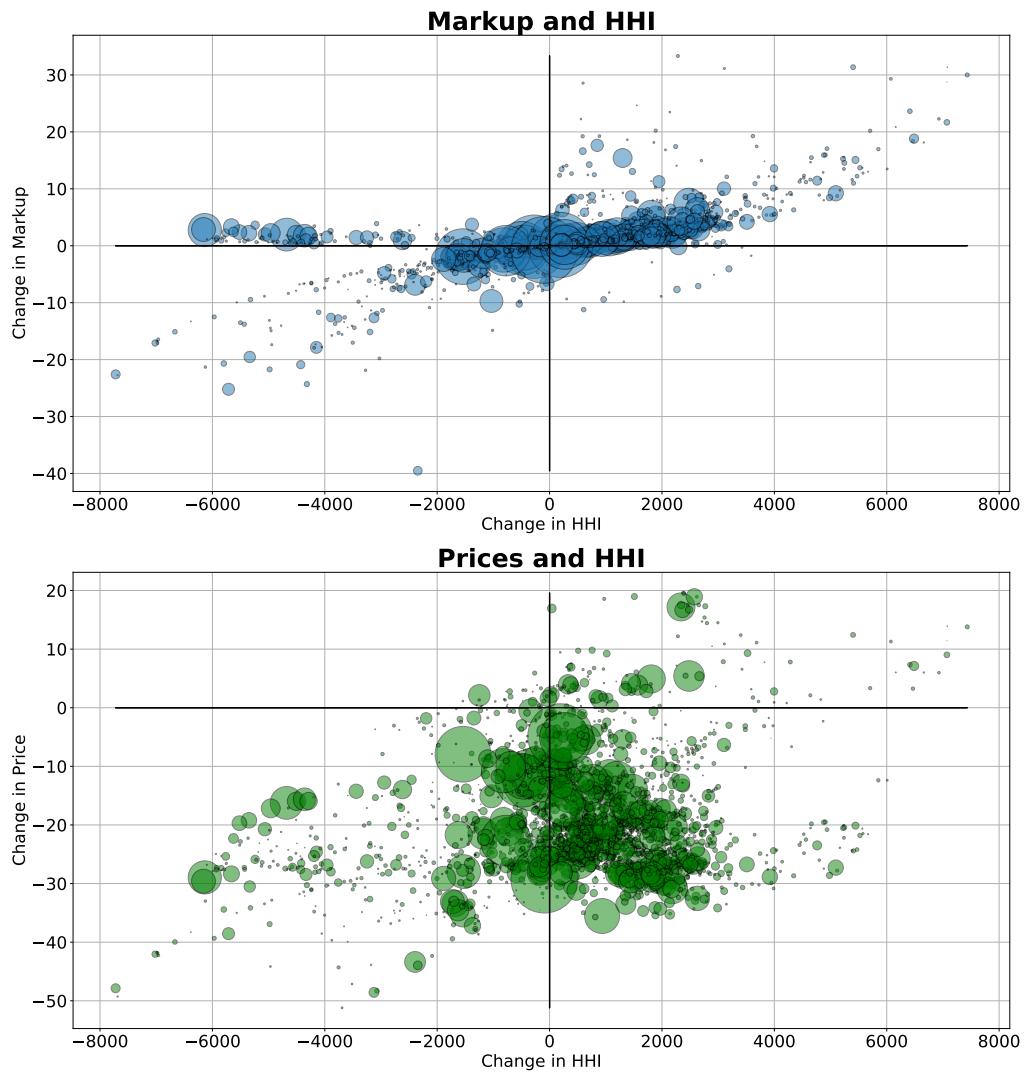


Figure 12: Markup and Price Changes Plotted Against HHI Changes, 1974 to 2016

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 circles are proportional to consumption.

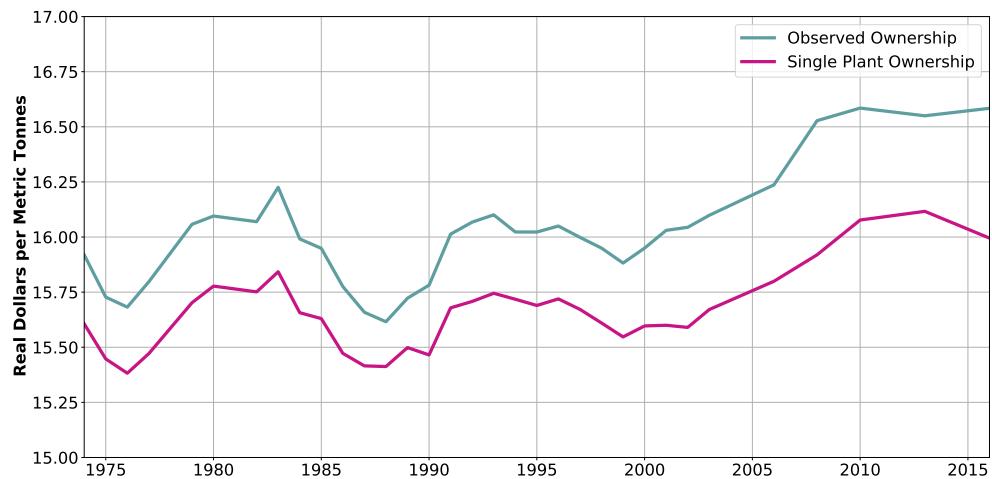


Figure 13: Impact of Multi-Plant Ownership on Markups

Notes: The blue line plots the weighted average additive markup ($p - c$) that we obtain from estimation, taking into account the observed ownership of plants. The red line plots the same statistic obtained under a counterfactual with single-plant firms.

Table 1: Parameter Estimates and Derived Statistics

Parameter		Point Estimate	Standard Error
<i>Demand</i>			
Constant	β_0	0.611	(0.058)
Trucking Miles (000s)	β_1	-2.306	(0.108)
River Barge Used	β_2	-0.433	(0.007)
Imported Cement	β_3	-0.188	(0.025)
Imported Cement \times Trend	β_4	-0.006	(0.001)
Price Parameter	ϕ	-0.008	(0.001)
Nesting Parameter	σ	0.9	.
<i>Marginal Cost</i>			
Constant	α_0	41.62	(1.77)
Fuel Cost	α_1	1.58	(0.04)
Capacity Cost	γ	111.34	(26.01)
Utilization Threshold	ν	0.59	(0.05)
<i>Derived Statistics</i>			
Trucking Cost (\$ per Tonne-Mile)	β_1/ϕ	0.30	
Fixed Cost of Barge (\$ per Tonne)	β_2/ϕ	58.33	
Bid Elasticity of Demand		-4.66	

Notes: Estimates are based on simulated non-linear least squares.

Table 2: Market Concentration in 1974 and 2016

	1974		2016	
	Number of Counties	Proportion of Consumption	Number of Counties	Proportion of Consumption
$\text{HHI} < 1500$	1,008	34.1%	303	8.3%
$1500 \leq \text{HHI} < 2500$	843	25.9%	866	34.2%
$\text{HHI} \geq 2500$	1,178	40.0%	1,860	57.6%
$\text{HHI} \geq 5000$	496	7.1%	516	10.1%
$\text{HHI} \geq 6000$	359	5.0%	346	6.3%

Notes: County-level HHIs are obtained from the model.

Appendix Materials

A Data and Estimation Details

A.1 Plant and Kiln Data

Our plant- and kiln-level data are from the *Plant Information Summary*, which is published annually over 1973-2003, semi-annually over 2004-2010, and then again in 2013 and 2016. We make use of all available years, except for 1973, 1978, 1981, and 1996. Our analysis focuses on the plants in the United States. If a kiln is identified as idle then we do not take it into account when measuring its plant's capacity or fuel costs. A handful of kilns drop out of the *Plant Information Summary* and then reappear in later years. We treat those observations on a case-by-case basis using information in the *Minerals Yearbook*, as we detail in our annotated code. We remove from our analysis a small number of kilns that produce white cement, which takes the color of dyes and is used for decorative purposes. The production of white cement requires higher kiln temperatures and iron-free raw materials, and the resulting cost differential makes it a poor substitute for gray cement (i.e., standard portland cement).

The data provide an end-of-year snapshot on the location, owner, and primary fuel of each cement plant, as well as the kiln's age, capacity and technology (i.e., wet, long dry, modern preheater, modern precalciner). Both daily and annual capacities are reported. We interpret the daily capacity as the boilerplate rating. Multiplied by 365, the daily capacities are larger than the annual capacity. We believe this reflects that the annual capacity builds in maintenance time; this also is the interpretation of ?. As the time spent in maintenance is an endogenous choice, we use the boilerplate rating to construct our measure of capacity.

A.2 Measuring Fuel Costs

We describe first the fuel cost variable, which we calculate based on the energy requirements of the plant's least efficient kiln* and the price of the primary fuel:

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

*We view the least efficient kiln as most likely to produce the marginal output.

where the fuel price is in dollars per mBtu and the energy requirements are in mBtu per metric tonne of clinker. For fuel prices, we use the national 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). The SEDS data are in dollars per mBtu.

Some plants list multiple primary fuels in the *Plant Information Summary*. As the mix of primary fuels is unknown, we treat such plants as follows: We calculate fuel costs with the price of coal if coal or petroleum coke are among the primary fuels. If not, we use petroleum coke prices if coke is among primary fuels. Otherwise 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. [?] explore more sophisticated measures that use data published in the *Minerals Yearbook* on the total amounts of each fossil fuel burned by cement plants nationally, and find that they generate similar estimates.

Appendix Figure C.4 plots the fraction of industry capacity that uses each fossil fuel as its primary source of energy, based on this methodology (Top Panel). In the early years of the sample, natural gas and fuel oil are used as the primary fuel by some plants. In the middle years, coal and petroleum coke are the only primary fuels used. In the final year, some plants switch back to natural gas. The figure provides the prices of these fuels (Bottom Panel). Usage tends to track the relative prices.

We calculate energy requirements of each kiln technology based on the *U.S. and Canadian Portland Cement Labor-Energy Input Survey*. There is no discernible change in the energy requirements of production, conditional on the kiln type, over 1990-2010. We calculate the average mBtu per metric tonne of clinker required in 1990, 2000, and 2010, separately for each kiln type, and apply these averages over 1990-2016. These requirements are 3.94, 4.11, 5.28, and 6.07 mBtu per metric tonne of clinker for dry precalciner kilns, dry preheater kiln, long dry kilns, and wet kilns, respectively. A recent survey of the USGS accords with our calculations (?). By contrast, 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 over the early years of the sample period accordingly. Lastly, we scale down by our calculated energy requirements by five percent to reflect that a small amount of gypsum is ground together with the kiln output to form cement.

A.3 Customs Districts

In the model we assume that buyer can purchase cement from the nearest active customs district. Implementing this assumption in an empirically-grounded way is challenging for a number of reasons. First, there is a great deal of heterogeneity in the size of the customs districts. Second, the amount of cement that flows through specific customs districts is often small or negligible through the early years of the sample, then grows later in the sample. Third, in some years with low demand, the quantity of imports can fall to near zero even in the largest customs districts.

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

1. For each customs district, we calculate the maximum quantity of imported cement that arrives within a year over 1974-2016.
2. We rank the customs districts according to this maximum, and select the top 20.
3. We designate these top 20 ports as “active” once import quantities reach 30% of the port’s maximum level, and in every subsequent year.
4. We assume that imported cement is available only at the top 20 customs districts, and only in years in which they are active.

We find that this approach allows the model to match the quantity of imports over time (Figure 7). The top 20 customs districts, in descending order of the maximum quantity of imported cement received in a year, are: Tampa FL, Los Angeles CA, Houston TX, San Francisco CA, Detroit MI, Miami FL, Seattle WA, New York City NY, Charleston SC, Columbia-Snake / Portland OR, Nogales AZ, Cleveland AZ, Buffalo NY, Mobile AL, Providence RI, San Diego CA, and El Paso TX.

Collectively, the top 20 customs districts account for 89.6% of the cement imported into the contiguous United States over 1974-2016. The customs districts that we exclude, again in descending order of the maximum quantity of imported cement received in a year, are: Philadelphia PA, Milwaukee WI, Savannah GA, St. Albans VT, Baltimore MD, Wilmington NC, Boston MA, Duluth MN, Pembina ND, Chicago IL, Great Falls MT, Laredo TX, Minneapolis MN, Portland ME, and Bridgeport CT.

B Model Details

B.1 Strategic Bidding

Our supply model assumes that plants submit bids equal to their marginal costs. Given the second-score nature of the auction, where price is determined by the second-best bidder rather than by the winner’s own bid, this behavior is clearly a dominant strategy when marginal costs are constant. In such a situation, any bid above marginal cost results in the plant forgoing some margin-positive sales with positive probability, while any bid below marginal cost results in the plant making some margin-negative sales with positive probability. Thus bids are driven to marginal costs. This strategy is also dominant with increasing marginal costs when expected demand is homogeneous across consumers. In this case, a plant can lower its realized marginal cost by raising its bid, but doing so again causes it to forgo some margin-positive sales without creating any new profit opportunities from high demand customers, since consumers are *ex ante* identical.

The situation can be more complicated in cases where plants have increasing marginal costs and preferences vary between customers in an observable, deterministic manner. Suppose, for example, there are two counties, l and h , and if all plants set their bids equal to their marginal costs, the expected prices for plant j are such that $p_{jlt}^* < p_{jht}^*$. If plant j were to slightly raise its bid in county l and slightly drop its bid in county h , it could shift sales from a lower priced market to a higher priced market without increasing its total quantity produced (and thus without increasing its marginal cost). The presence of increasing marginal costs creates an opportunity cost for plants when making low value sales, which encourages plants to reallocate their sales to higher value customers, so long as those consumers can be identified and targeted. This incentive is most obvious when plants face constant marginal costs up to a vertical capacity constraint, as then plans would want to bid down to their marginal cost in high priced markets until their production capacities are exhausted, and then bid above the reservation price, effectively withdrawing their participation, in all lower valued markets.

We rule out these complex bidding strategies by assumption. Given our marginal cost specification, in cases where plants are not approaching their utilization thresholds, marginal costs are constant and such strategies are not relevant. In cases where plants are nearing or past their utilization thresholds, these strategies require plants to adjust bids across multiple markets at once, which may not be feasible. These strategies

may also be risky in the presence of demand uncertainty.

B.2 Existence of Equilibrium

The market clearing condition in equation (7) can be restated in terms of market shares as

$$s_{jnt}(\mathbf{b}_{nt}(\mathbf{c}_t(\mathbf{s}_t^*; \mathbf{M}_t, \mathbf{X}_t, \boldsymbol{\theta}))) = s_{jnt}^* \quad \forall j, n. \quad (\text{B.1})$$

The left-hand side of this expression is a vector-valued function that takes a set of shares, translates them into quantities using the county market sizes, calculates the marginal costs that result from these quantities, sets bids equal to these costs, and then outputs the shares implied by these bids. An equilibrium is a fixed point of this function.

This function adheres to three properties: (1) it is continuous, given nested logit demand, (2) its domain is nonempty, closed, bounded, and convex, since each market share must be in the unit interval, and (3) it maps this domain into itself, as each output market share must also be in the unit interval. More specifically, the domain and range of the function is the space defined by $[0, 1]^{J_t N_t}$, up to and including the plane defined by $\sum_j s_{jnt} = 1$ for each county, where $J_t N_t$ is the number of plants times the number of markets in this period. For the two-plant, single-market case (with an outside good share set at zero), this space is a triangle with its vertices at $(0, 0)$, $(0, 1)$, and $(1, 0)$. Given that these conditions are satisfied, according to the Brouwer Fixed-Point Theorem, a fixed point of this function exists. In turn, an equilibrium for our problem exists.

Whether there is a unique equilibrium depends on the shape of the market share function. Simple examples can be verified by hand. For instance, in the single-plant, one county logit case where there is only one plant j and the outside good, the share equation simplifies to

$$s_{jt} = \frac{\exp(\bar{u}_{jt}(\mathbf{X}_t, \boldsymbol{\theta}) - \phi c_{jt}(s_{jt}; M_t, \mathbf{X}_t, \boldsymbol{\theta}))}{1 + \exp(\bar{u}_{jt}(\mathbf{X}_t, \boldsymbol{\theta}) - \phi c_{jt}(s_{jt}; M_t, \mathbf{X}_t, \boldsymbol{\theta}))}. \quad (\text{B.2})$$

We already know a crossing between the right hand side and the left hand side of this expression exists, according to Brouwers. Furthermore, if we assume that the marginal cost function is monotonic in s_{jt} (in our specification it is non-decreasing), then the right hand side of this expression is monotonic in s_{jt} . Therefore, the right hand side

must cross the left hand side (given by the 45-degree line within the $[0, 1]$ domain) at most once. Thus, the crossing is unique.

Issues can arise if there are more firms than just one, insofar as including shares for additional plants in the share function can reverse the monotonicity argument. However, uniqueness can be verified numerically in some instances.

B.3 Derivation of Expected Markups

In deriving equation (8), we start from a plant's margin, defined as price less marginal cost. From equation (4), we see that the expected margin for plant j in county n (conditional on a sale being made) can be constructed from

$$\mathbb{E}[m_{jnt} | j \text{ wins}] = \frac{1}{\phi} \mathbb{E}[u_{ijnt} - \phi c_{jt} - \max_{k \notin \mathbb{J}_{f(j)}} \{u_{iknt} - \phi c_{kt}\} | j \text{ wins}], \quad (\text{B.3})$$

where the expectation is taken over the distribution of buyer-specific preference shocks for a randomly drawn consumer i located in county n . This expression incorporates the assumption that bids equal marginal costs in equilibrium. We omit the function arguments from marginal cost to save on notation.

In taking expectations, we substitute in the nested logit inclusive values, giving

$$\begin{aligned} \mathbb{E}[m_{jnt} | j \text{ wins}] &= \frac{1}{\phi \sum_{k \in \mathbb{J}_{f(j)}} s_{knt}^*} \left\{ \log \left[1 + \left(\sum_{k \neq 0} \exp \left(\frac{\bar{u}_{knt} - \phi c_{kt}}{1 - \sigma} \right) \right)^{1-\sigma} \right] \right. \\ &\quad \left. - \log \left[1 + \left(\sum_{k \notin \mathbb{J}_{f(j)}} \exp \left(\frac{\bar{u}_{knt} - \phi c_{kt}}{1 - \sigma} \right) \right)^{1-\sigma} \right] \right\}. \end{aligned} \quad (\text{B.4})$$

Then algebraic manipulation and substituting in for market shares gives

$$\begin{aligned} \mathbb{E}[m_{jnt} | j \text{ wins}] &= \\ &- \frac{1}{\phi \sum_{k \in \mathbb{J}_{f(j)}} s_{knt}^*} \log \left[1 - (1 - s_{0nt}^*) \left(1 - \left(1 - \sum_{k \in \mathbb{J}_{f(j)}} \frac{s_{knt}^*}{1 - s_{0nt}^*} \right)^{1-\sigma} \right) \right]. \end{aligned} \quad (\text{B.5})$$

Equation (8) follows by adding the marginal cost to the expected margin in order to recover price.

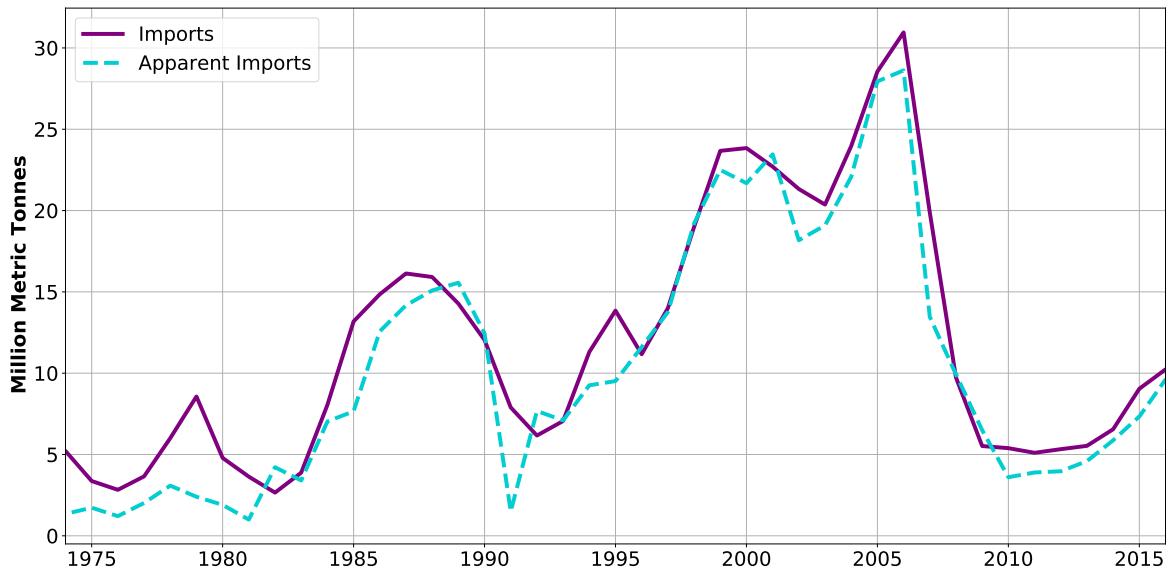


Figure C.1: Imports and Apparent Imports, 1974-2016

Notes: Imports are data from the *Minerals Yearbook*. Apparent imports are calculated as the difference between domestic consumption and domestic production, both of which are data from the same source.

C Additional Figures and Tables

Table C.1: Eight Largest Cement Producers in 1974 and 2016

Producer	1974		
	Number of Plants	Capacity Share	Cumulative Capacity Share
Ideal Basic	14	0.075	0.075
General	9	0.055	0.130
Martin Marietta	9	0.052	0.182
Universal Atlas	10	0.047	0.230
Marquette	12	0.045	0.275
Lonestar	8	0.044	0.319
Amcord	5	0.043	0.362
Medusa	6	0.040	0.402
Producer	2016		
	Number of Plants	Capacity Share	Cumulative Capacity Share
LafargeHolcim	13	0.189	0.189
Lehigh	13	0.128	0.317
Cemex	9	0.115	0.432
Buzzi Unicem	8	0.097	0.529
Ash Grove	8	0.078	0.607
Argos	4	0.053	0.659
Cal	3	0.044	0.703
Eagle	6	0.041	0.744

Notes: Data are from the *Plant Information Summary*.

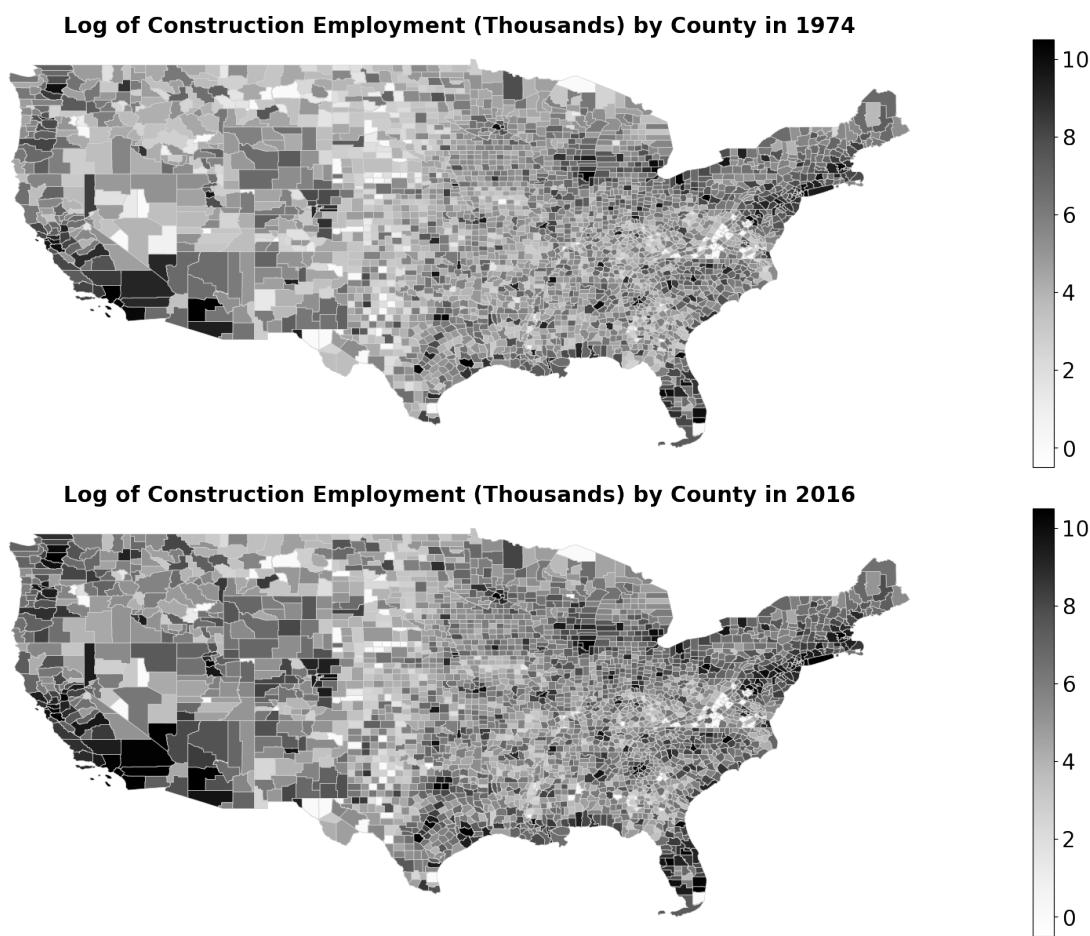


Figure C.2: The Location of Construction Employment in 1974 and 2016

Notes: County-level construction employment (SIC code 15 and NAICS code 23) is from the County Business Patterns data of the Census Bureau.

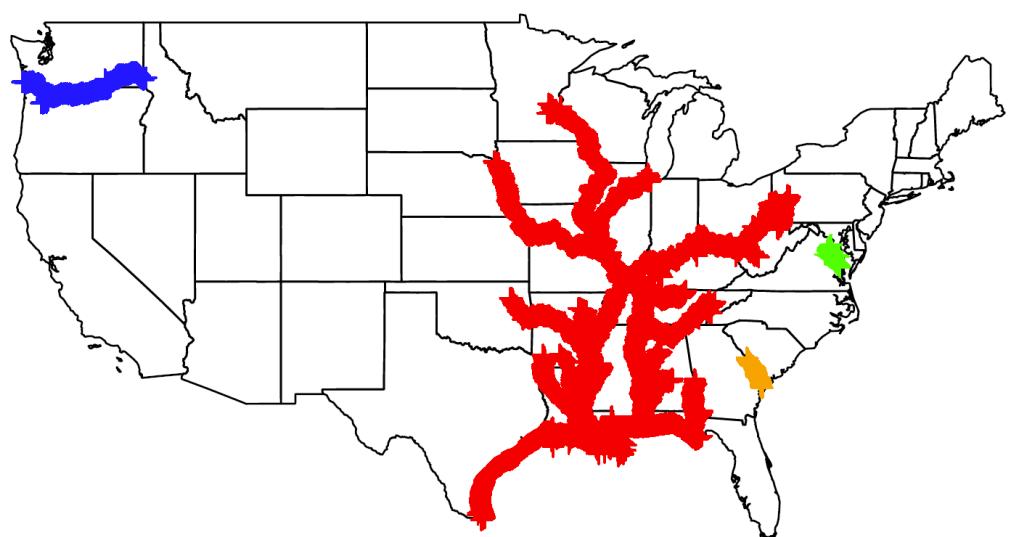


Figure C.3: The Four Navigable River Systems in the United States

Notes: The river systems include the Columbia-Snake (blue), the Chesapeake (green), the Savannah (orange), and the Mississippi (red). The Mississippi River System includes canal-type waterways, most notably the Gulf Intercoastal Waterway, which has a depth of 12 feet and was designed for barges. We plot the rivers systems using the mile-markers provided by the Army Corps of Engineers.

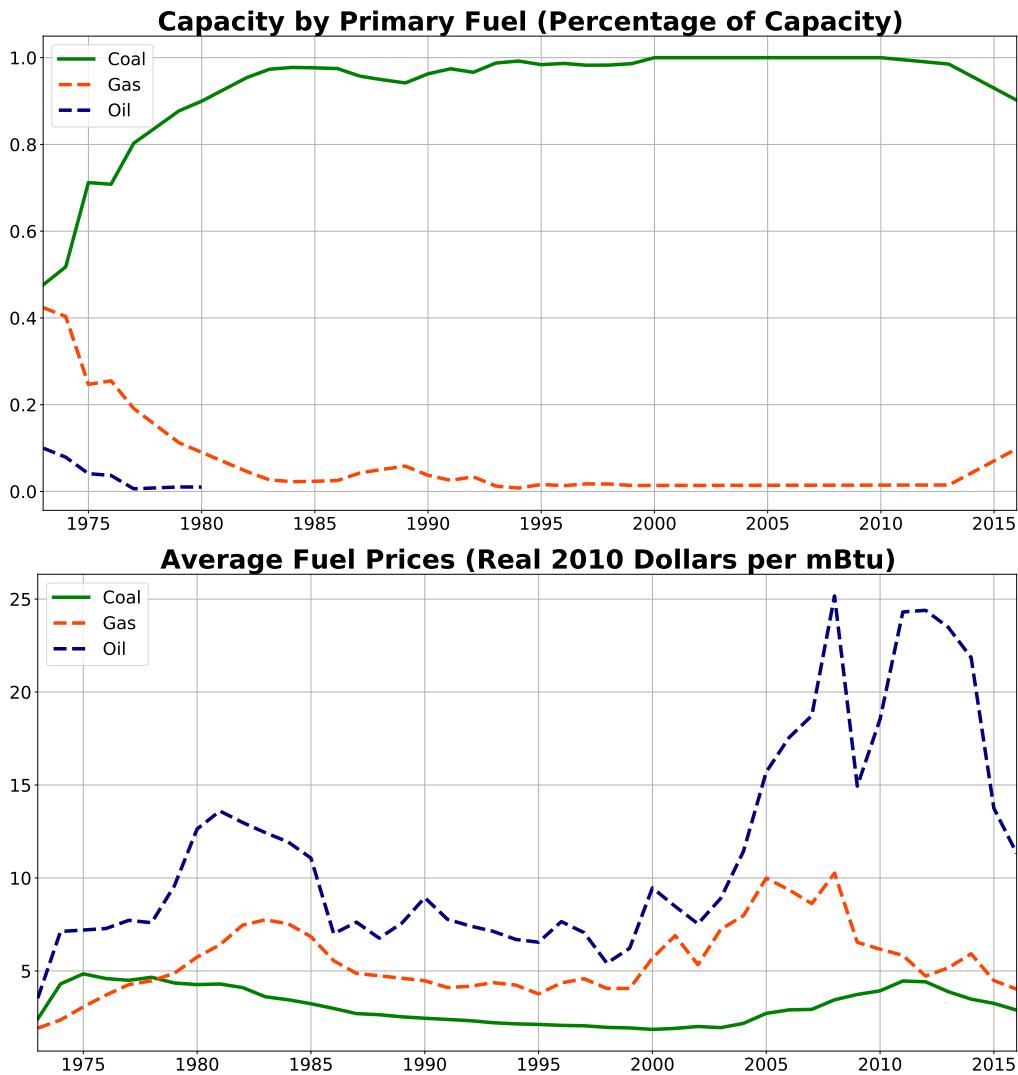


Figure C.4: Primary Fuels and Fuel Prices

Notes: The top panel plots the fraction of kiln capacity that burns as its primary fuel (i) coal or petroleum coke, (ii) natural gas, and (iii) fuel oil. Data are from *Plant Information Summary*. The bottom panel plots the average national prices paid for these fuels by the industrial sector in real 2010 dollars per mBtu. Data are from the State Energy Data System (SEDS).

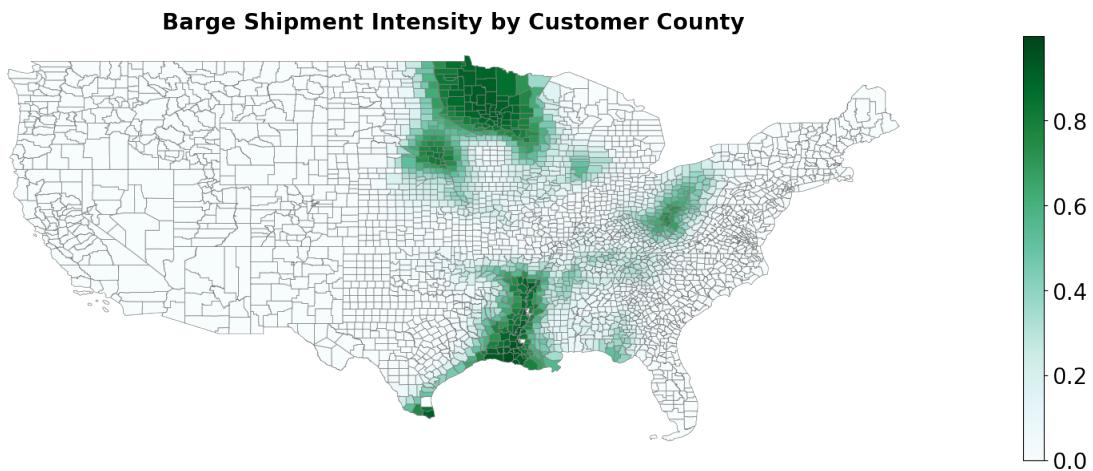


Figure C.5: Barge Shipment Destinations in 2016

Notes: The figure depicts the proportion of county-level cement consumption in 2016 for which barge transportation is utilized.

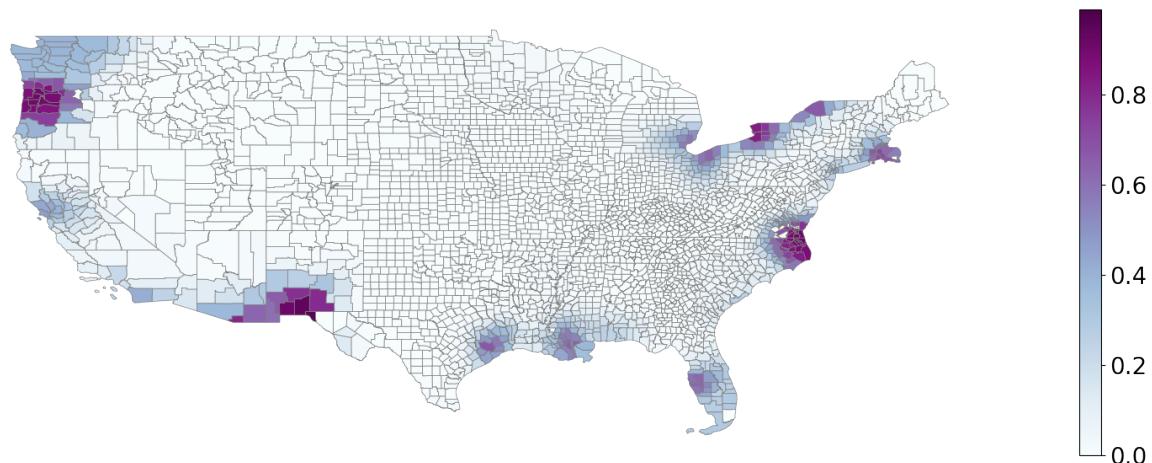


Figure C.6: Import Market Shares in 2006 by Customer County

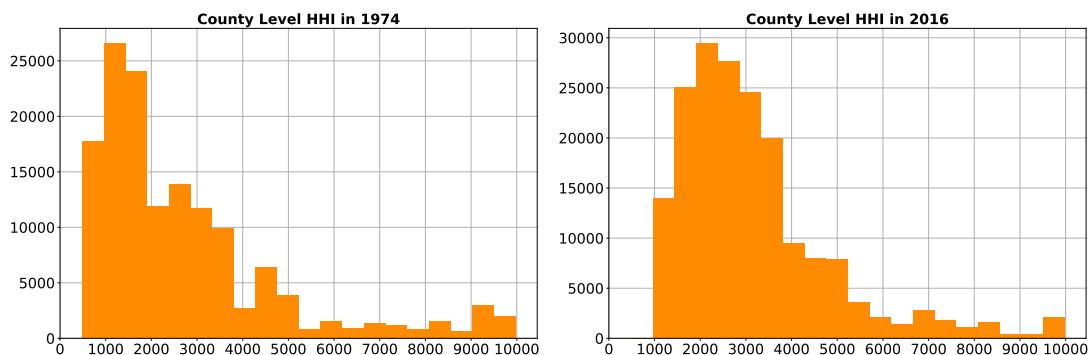


Figure C.7: Histogram of County-Level HHIs in 1974 and 2016

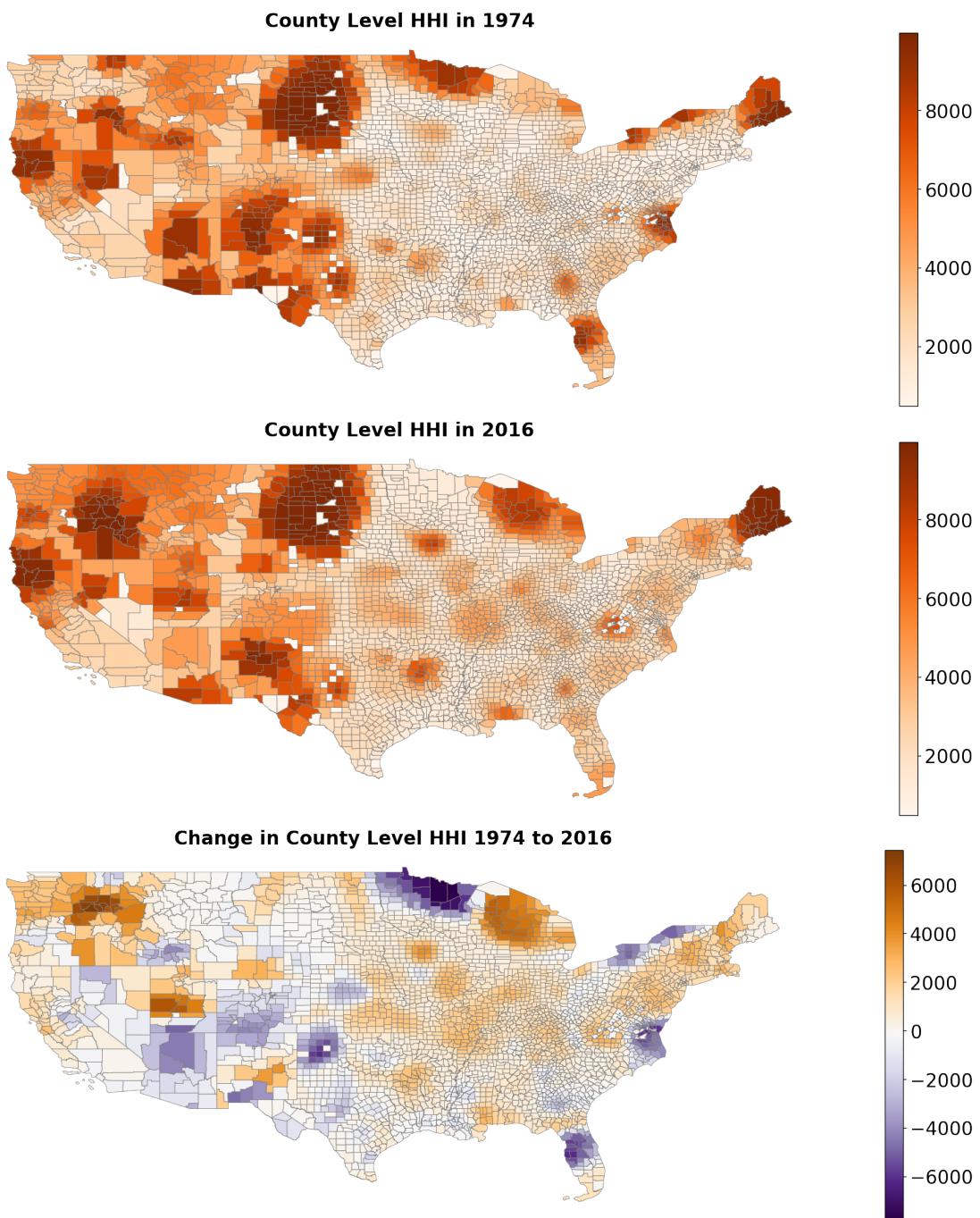
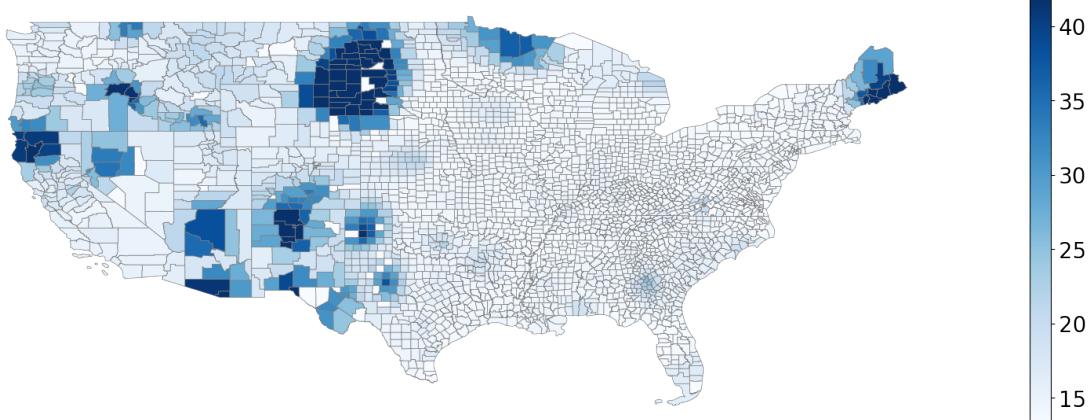
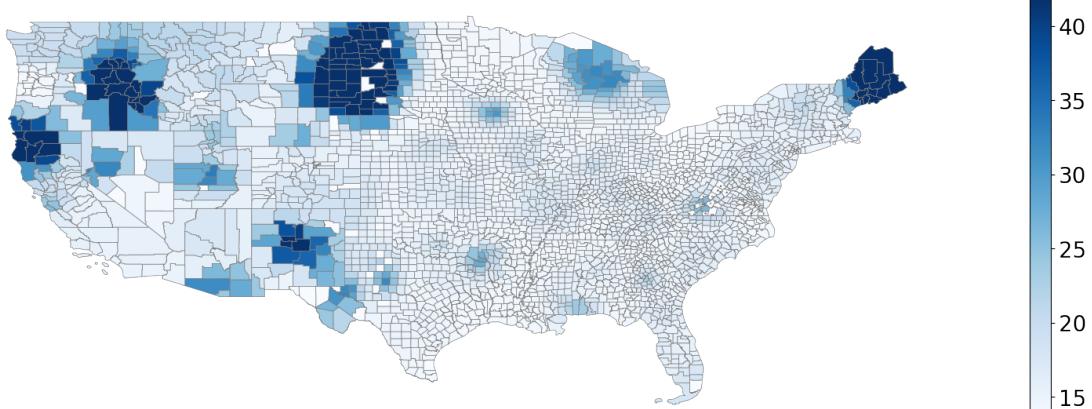


Figure C.8: Map of County-Level HHIs

County Level Markup in 1974



County Level Markup in 2016



Change in County Level Markup 1974 to 2016

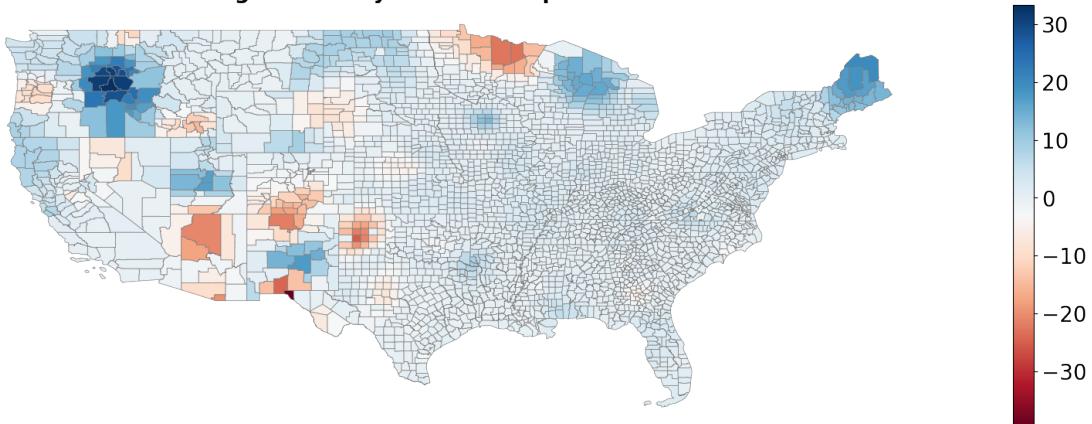


Figure C.9: Map of County-Level Markups

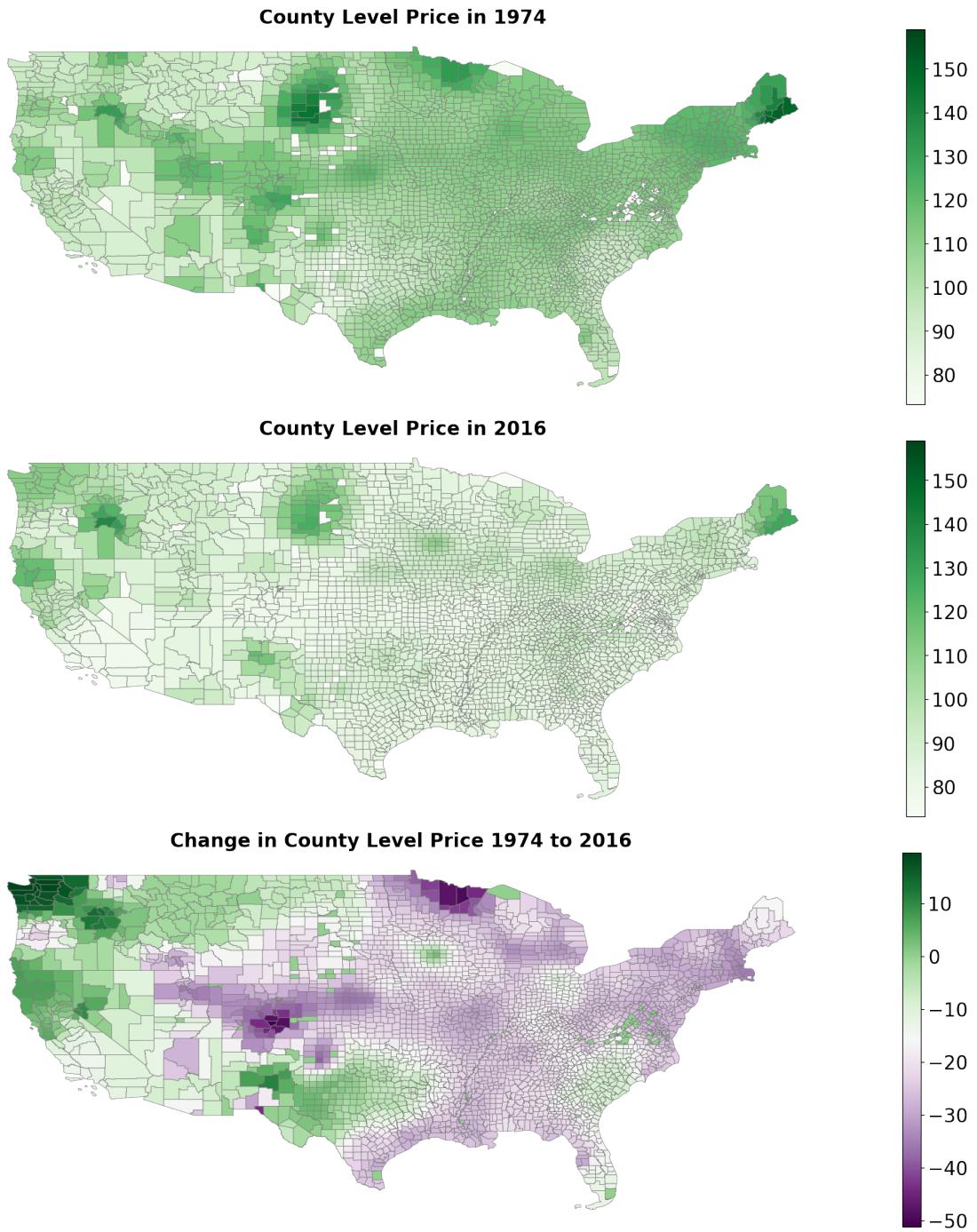


Figure C.10: Map of County-Level Prices