Process Repositioning*

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Abstract

Firms seeking to maintain competitive advantage through cost leadership may, on occasion, alter their production processes in response to market forces. We provide a formal definition of process repositioning and highlight that it can entail investment or disinvestment. We then develop a conceptual framework for understanding when one repositioning choice likely dominates others. Firm-specific adjustment costs create heterogeneous responses to similar market forces. An empirical application to the portland cement industry demonstrates the real-world applicability of the framework. Our research addresses an important gap in the repositioning literature, which heretofore has focused on how firms adjust the attributes of differentiated products.

Keywords: process repositioning, cost leadership, technology adoption, cement

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1 Introduction

Firms that seek competitive advantage attempt to occupy market positions characterized by some amount of product differentiation or cost leadership (Porter (1985, 1996); Rumelt et al. (1994); Brandenburger and Nalebuff (1996)). The sustainability of competitive advantage often depends on the commitment a firm makes to its market position, because commitment discourages imitation by competitors and potential competitors (Ghemawat (1995)). Such commitment, however, creates inflexibility. This gives rise to what we refer to as the repositioning question: How should an established firm respond to changes in demand and supply that shift the relative desirability of different market positions?

A substantial literature in strategy analyzes *product repositioning*, which addresses how firms modify product characteristics or enter new consumer markets, drawing on economics research that dates to Hotelling (1929). A number of articles explore responses to changes in consumer preferences or the competitive landscape. For instance, Greve (1998) studies the decision of radio stations to adopt newly popular programming formats, and Wang and Shaver (2014) examine how firms in the Chinese satellite television industry alter programming content in response to encroachment by the dominant government-owned station. Other articles invoke internal adjustment costs as a mechanism that generates heterogeneous firm responses (e.g., Argyres et al. (2019)).

This literature develops useful insights about the conditions under which firms reposition to create or preserve product differentiation. However, it offers a partial answer to the repositioning question because it considers only some of the strategic commitments available to firms. In this paper, we develop and analyze the concept of *process repositioning*, which involves strategic commitments in the production process. Many firms may consider such strategic commitments as an appropriate response to changes in market conditions. However, the framework we introduce is particularly relevant for producers of homogeneous products, for which cost leadership provides the most plausible source of competitive advantage.

We define process repositioning as a substantial investment or disinvestment in a factor of production that is fixed in the short run. For many firms, the fixed production factor is capital, and process repositioning can be achieved through the adoption of new technology that economizes on the variable factors of production. Examples of such technology include some of the best-known inventions in United States history, such as the cotton gin, the sewing machine, and the combine harvester, each of which allowed firms willing to incur adoption costs to reduce the labor-intensity of production (Habakkuk (1962)). Modern-day equivalents are automation and robotics. However, it is also possible that labor is the fixed factor for some firms, especially in the presence of unions, in which case process repositioning is achieved with substantial changes in the amount or type of labor employed.

Firms that consider process repositioning balance sunk adjustment costs with the benefit of using one or more variable factor of production more efficiently. The tradeoff is inherently strategic because it entails a commitment (in the short run) to a particular production process. Many insights of the product repositioning literature do not extend cleanly. As a simple hypothetical, consider a homogeneous-products market where one firm uses a low-cost production technology. Should a competitor use a high-cost technology so as to distinguish itself from the first firm? Intuition suggests not, and this is confirmed by the canonical model of homogeneous-product markets (Cournot (1838)).

We take initial steps to address this gap in the strategy literature. Our conceptual framework considers how process repositioning decisions are affected by three important market conditions: factor prices, demand, and competition. Firm-specific adjustment costs help generate heterogeneous responses to similar market forces. An interesting aspect of process repositioning is that it can involve investment *or* disinvestment. Indeed, often waves of repositioning occur in the wake of technical inventions that increase the minimum efficient scale of production. Because not every firm can profitably invest there is no strategy that prevails in all settings. The conceptual framework identifies the market conditions under which one process repositioning choice is likely to be preferable to another.

We emphasize that process repositioning should be conducted with an appropriate understanding of the relevant institutional details. This conditional approach is necessary because the literature indicates that the relationship between technology adoption and market forces is fundamentally situational. For example, in a comprehensive analysis of competition and innovation, Gilbert (2006) notes:

> "Economic theory does not offer a prediction about the effects of competition on innovation that is robust to all of these different market and technological conditions. Instead, there are many predictions...." (p. 162.)

We therefore apply the framework to generate hypotheses that are specific to our empirical setting—portland cement—based on our understanding of that industry. We also discuss how these hypotheses might differ in settings with different institutional details.

The portland cement industry is a nearly ideal empirical setting. We observe the universe of decisions by cement plants in the United States to install a precalciner kiln—a technical invention of the late 1960s that improves fuel efficiency but requires large sunk capital expenditures. Over more than four decades, plants which install precalciner kilns gradually come to dominate production; other plants retire their older kilns and exit the market. Because this technological transition occurs over such a long time and amidst heterogeneous local market conditions, there is sufficient empirical variation in factor prices, demand, and competition to bring the conceptual framework to the data. This combination of features is unique among the existing econometric studies of process technology adoption.

We develop three core sets of predictions.[1] The first—Hypothesis 1—is that precalciner kiln adoption and incumbent kiln retirement should increase with fuel prices. The variable factors of production in cement (fuel, limestone, labor) must be used in roughly fixed proportions. In such a setting, high factor prices create the kinetic market environment in which process repositioning in some fashion—via investment or disinvestment—is most likely to outperform the status quo. However, the economics literature proves that the relationship between a factor price and the adoption of efficiency-enhancing technology depends on the substitutability of the variable factors (Acemoglu (2002, 2007)). Thus, different predictions would obtain for industries in which other variable inputs could readily substitute for fuel in the production process, because simple changes to the variable input mix would eliminate the need for firms to incur sunk repositioning costs.

The second set of predictions—Hypothesis 2—is that process repositioning via investment is more likely, and repositioning via disinvestment is less likely, if variable cost savings can be scaled across greater output. Empirically, we test whether precalciner kiln adoption increases with stronger demand and fewer competitors—conditions that increase the equilibrium output of firms (Dasgupta and Stiglitz (1980)). We also test whether incumbent kiln retirement decreases with stronger demand and fewer competitors. The relationship between process repositioning and competition can become more nuanced in the presence of dynamics (Fudenberg and Tirole (1985, 1986)). Thus, in arriving at our predictions, we consider certain institutional details which lead us to believe that dynamic incentives are unlikely to dominate scale effects in the cement industry.

Considering the first two hypotheses together yields an additional insight into the timing of repositioning. Hypothesis 1 suggests that empirical variation in factor prices of variable inputs should generate synchronous investment and disinvestment. For instance, with higher factor prices firms might find it profitable to reposition, one way or the other, whereas repositioning might be unnecessary with low factor prices because the status quo is relatively desirable. By contrast, Hypothesis 2 suggests that empirical variation in demand generates asynchronous repositioning decisions—either investment (with high demand) or

[1] We take two approaches to hypothesis development. Section 2 supports the hypotheses based on the existing literatures on repositioning and technology adoption. Appendix A derives the hypotheses formally using an oligopoly model of Cournot competition. We view the approaches as complements.

disinvestment (with low demand). Thus, the conceptual framework posits conditions under which similar firms may pursue diametrically different strategies, as well as conditions under which firms may appear to mimic each other.

Our third set of predictions—Hypothesis 3—is that firms with larger adjustment costs are less likely to engage in process repositioning, all else equal. Relevant adjustment costs can be explicit or implicit. With process repositioning, explicit costs incorporate monetary investments in the fixed factor net of scrap value. Implicit costs include the stream of profit that the firm would have earned without repositioning. In the cement industry, plants with older and lower-capacity kilns may tend to have lower implicit adjustment costs and thus may be more likely to reposition. Empirically, we test whether plants with older and lower-capacity kilns are both more likely to install a precalciner kiln and more likely to retire their incumbent kilns without replacement.

The empirical application demonstrates the usefulness of the conceptual framework in a real-world setting and serves to confront the hypotheses with empirical evidence. In developing an appropriate regression model, endogeneity concerns arise regarding the causal effect of competition. Because unobserved market shocks affect both repositioning and the competitive environment, there is a risk that their impact on repositioning could wrongly be attributed to competition. We discuss how instruments can be constructed with panel data, and incorporate them in our estimation approach. With these in hand, causal relationships can be estimated under reasonable assumptions. Our approach may allow other research to proceed even in the absence of the natural experiments that have been exploited elsewhere in the strategy repositioning literature (e.g., George and Waldfogel (2006); de Figueiredo and Silverman (2007)).

Our results fully support the conceptual framework for process repositioning. With regard to market forces, we find that firms are more likely to install precalciner kilns if fuel costs are high, demand conditions are favorable, and competitors are few; and more likely to retire their existing kilns with high fuel costs, unfavorable demand, and many competitors. We also find that plants with older and smaller kilns are both more likely to install precalciner kilns and more likely to exit, consistent with heterogeneous adjustment costs creating firm-level differences in repositioning decisions. These effects are precisely estimated and robust to alternative identifying assumptions and specifications.

The rest of this paper is organized as follows. Section 2 reviews the strategy repositioning literature and develops the hypotheses. Section 3 provides institutional details on the portland cement industry. Section 4 describes the empirical approach and identification strategy, defines the variables used in the empirical analysis, and provides descriptive statistics. Section 5 presents the estimation results. Section 6 elaborates on the managerial implications. Section 7 concludes by outlining some of the limitations, summarizing the main contributions, and offering direction on future research.

2 Theory and Hypotheses

2.1 The Strategy of Repositioning

The extant strategy literature examines product repositioning in response to new market opportunities or changes in the competitive environment. New market opportunities can arise as consumer preferences change (e.g., Greve (1995, 1998); Adner and Levinthal (2001); Makadok and Ross (2013)) or new products are commercialized (e.g., Semadeni and Anderson (2010); Asaba and Lieberman (2012); Bigelow et al. (2019)). The competitive environment can change due to firm entry or exit (Olivares and Cachon (2009)) or due to the actions of a dominant competitor (George and Waldfogel (2006); de Figueiredo and Silverman (2007); Wang and Shaver (2014)). In general, the emphasis of the literature is on the conditions under which firms adjust the characteristics of their output in order to maintain competitive advantage via product differentiation.

This literature is less relevant for firms with homogeneous products, for which cost leadership provides the most plausible source of competitive advantage. To help guide managerial effort, we therefore develop the analog concept of process repositioning. In our context, the positioning of the firm is determined by the inputs to production that are fixed in the short run. To better ground these ideas, we term the fixed factor capital and contrast it with variable inputs such as labor and materials. Capital is strategically important because its adjustment is costly and slow, providing a mechanism for commitment. However, the capital stock that is optimal in one market environment may be suboptimal in another. Thus the question of repositioning arises: under which circumstances should a firm incur costs to adjust its capital stock in response to changing market conditions?

In defining process repositioning as involving a substantial investment or disinvestment in a factor of production that is fixed in the short run, we attempt to cast a reasonably wide net. Real-world examples might include a power plant which considers installing a scrubber to reduce emissions in response to environmental regulation; a chemicals plant which contemplates shutting down after a more efficient and proximate competitor enters; or a steel plant which considers adopting a technology that lowers marginal cost in response to demand growth. We seek to provide a unifying framework to help understand the conditions under which one repositioning choice is likely to dominate another.

Some process adjustments are nonetheless excluded from our definition. First, firms may adjust the mix of variable inputs they use in production in response to changes in relative factor prices. Because such a change does not entail commitment and thus is strategically unimportant, we do not consider it repositioning. Second, we assume that process repositioning does not affect how consumers perceive the product; changes that affect both production processes and product attributes would require a richer framework. Finally, we do not seek to explain architectural innovation, in which firms change how inputs are combined but not the inputs themselves (Henderson and Clark (1990)). Thus, for example, our framework does not apply to the early twentieth century innovation by the Ford Motor Company of moving automobiles rather than workers along the assembly line.

Our organizing premise is that firms reposition if doing so maximizes the present value of profit, net of adjustment costs. As the specific characteristics of firms and markets affect causal relationships, we tailor our hypotheses to the empirical setting. We highlight throughout the institutional details that lead us to our hypotheses, so as to illuminate how different relationships may arise in other settings. In the following sections, we examine how firms reposition in response to external market forces—factor prices, competition, and demand—and then return to adjustment costs as a source of firm-level heterogeneity.

In developing our hypotheses, we invoke the literatures on repositioning and technology adoption. However, few existing articles consider more than one or two of the determinants that we examine. We therefore also derive the hypotheses formally using an oligopoly model of Cournot competition (see Appendix A), which serves to connect hypotheses and provides a mathematical foundation for the regression model (see Section 4).

2.2 Factor Prices

Process repositioning via investment allows firms to more efficiently convert the variable factors of production into output. Thus, it stands to reason that the factor prices of variable inputs should affect repositioning decisions. To flesh out this relationship, we draw on the economics literature on "induced innovation," which addresses the question of whether higher factor prices spur the adoption of efficiency-improving technology (e.g., Hicks (1932); Kennedy (1964); Salter (1966); Nordhaus (1973); Acemoglu (2002, 2007)).

We focus on the equilibrium analysis of Acemoglu (2002, 2007). For intuition, consider a firm which uses two variable factors in production: labor and materials. If the wage paid to labor increases then so too does the benefit of improving labor efficiency.[2] Holding fixed the amount of labor employed, an increase in the wage unambiguously increases the incentives of firms to invest in technology that improves labor efficiency. Some firms that face higher wages, however, may substitute materials for labor. In that case, fewer workers are employed and the benefits realized from labor-saving technology diminish.

The simple comparison illustrates that the relationship between the factor price of a variable input and process repositioning (via investment) depends on the substitutability of the variable factors. In our application, we are interested in fuel prices and a fuel-efficient technology in the cement industry. The main variable inputs (e.g., fuel, limestone, labor) must be used in fixed proportions, so firms cannot substitute from fuel to other variable inputs in response to higher fuel prices. Economic theory therefore indicates that the adoption incentives for efficiency-improving technology should increase with fuel prices.[3] Bolstering this prediction is empirical evidence from other settings that firms adopt more fuel-efficient technologies and processes when fuel prices are high (Newell et al. (1999); Popp (2002); Linn (2008); Hassler et al. (2011); Aghion et al. (2016)).

Of course, higher factor prices also reduce profit, all else equal. If a firm can no longer recover its fixed costs then process repositioning via disinvestment may maximize present value. The induced innovation literature does not typically consider the possibility that higher factor prices could induce firms to cease production, though Acemoglu (2007) allows for it in one variant of the model. There is some empirical evidence, however, of synchronous technology adoption and retirement: In a study of the 1860s British textile industry and its response to the blockade of the U.S. South during the Civil War, Hanlon (2015) notes that higher cotton prices led both to technological innovation and "a sharp depression in the industry." We therefore expect that high fuel prices could induce incumbent technology retirement in the cement industry as well.

Collecting these arguments, we predict that firms consider the factor prices of variable inputs in process repositioning decisions. In particular, higher factor prices increase the relative desirability of both repositioning via investment and repositioning via disinvestment, relative to the status quo. The empirical analog for the cement industry considers fuel prices with respect to precalciner kiln adoption and incumbent kiln retirement. We examine the following hypothesis:

Hypothesis 1: Firms are more likely to adopt precalciner kilns and more likely

[2] As a familiar analogy, the benefit of automobiles with high miles-per-gallon is greatest when gasoline prices are high, and consumers respond accordingly (e.g., Langer and Miller (2013); Busse et al. (2013)).

[3] We show this formally in the context of our oligopoly model in Appendix A.4, Proposition 1.

to retire incumbent kilns (without replacement) if fuel prices are high.

2.3 Competition and Demand

We first consider process repositioning via investment, in which case the firm incurs upfront adjustment costs in exchange for the more efficient use of the variable factors of production. We start with the observation that the profit effect of a variable cost reduction increases with the amount of output (Gilbert (2006)). Indeed, this connection features in a number of theoretical articles (e.g., Dasgupta and Stiglitz (1980); Flaherty (1980); Shaked and Sutton (1987); Klepper (1996)).

It follows that—holding demand fixed for the moment—firms with fewer competitors benefit more from cost reductions because they produce more in equilibrium. Indeed, Dasgupta and Stiglitz (1980) examine one-shot games of Cournot competition and show that firms invest more to obtain marginal cost reductions as the number competitors decreases. An analogous argument can be made with respect to demand: holding the number of competitors fixed, firms benefit more from variable cost reductions if demand is high because the equilibrium output of each firm is greater.[4] The underlying mechanism—which we refer to as a scale effect—suggests that process repositioning via investment increases with demand and decreases with the number of competitors.

A somewhat richer set of possibilities obtains if firms consider the effect of their repositioning choice on the subsequent repositioning choices of competitors. In so-called "preemption games," the adoption of cost-reducing technology by one firm may temporarily forestall adoption on the part of its competitors (e.g., Fudenberg and Tirole (1985)). The relationship between competition and adoption in these models is highly nuanced: Duopoly produces an earlier first adoption than monopoly; with more firms the first adoption occurs sometime between that of duopoly and monopoly (Bouis et al. (2009); Argenziano and Schmidt-Dengler (2013)). There are many possibilities for the timing of adoptions after the first (Argenziano and Schmidt-Dengler (2014)). Thus, if dynamic incentives are sufficiently strong, it is possible that competition could spur repositioning via investment.[5]

An older empirical literature on technology adoption examines market concentration

[4]In Appendix A.4, Propositions 2 and 3, we show that (i) under a mild normalcy condition increased competition increases the benefit of technology adoption, and increases the likelihood of disinvestment, and (ii) stronger demand increases both the benefit of adoption as well as profit, reducing the likelihood of disinvestment.

[5]A number of other articles consider "patent races" in which one firm gains exclusive rights to the technology (e.g., Gilbert and Newbery (1982); Reinganum (1983); Harris and Vicker (1985); Doraszelski (2003)). In such a setting, there is an even stronger incentive for early adoption.

and firm size as determinants. Among the settings considered are the basic oxygen furnace in the steel industry (Oster (1982)), automated teller machines in banking (Hannan and McDowell (1984)), coal-fired steam-electric generating technologies among electric utilities (Rose and Joskow (1990)), machine tools in engineering (Karshenas and Stoneman (1993)), and automation technologies in metalworking (Colombo and Mosconi (1995)). The results on concentration are mixed; perhaps because modern econometric techniques often are not employed to establish causality or because the actual causal relationships differ across markets and technologies.[6] More robust support is found for larger firms being more likely to adopt new technology, which supports the argument that scale represents the dominating mechanism in process technology adoption.[7]

We next consider process repositioning via disinvestment. In the canonical Cournot model, profit decreases if demand weakens or more competitors enter the market. If such market condition changes prevent a firm from recovering its fixed costs then process repositioning via disinvestment may maximize present value. Dynamics also can be important: Fudenberg and Tirole (1986) examine a "war of attrition" in which firms strategically delay exit in a declining market in an attempt to outlast their competitors; Takahashi (2015) provides an empirical application to the movie theater industry. Competition therefore has the potential to delay disinvestment if dynamic incentives are sufficiently strong.

The institutional details of the cement industry suggest, however, that dynamic incentives may be weak. The legal environment does not allow an early adopter of precalciner kiln technology to foreclose subsequent adoption (e.g., via patent). Further, the economic effect of precalciner technology adoption by any single cement plant on its competitors may be small because most plants face many nearby competitors and because the ability to profitably steal market share is limited by transportation costs.[8] We therefore predict that cement plants are more likely to reposition via investment and less likely to reposition via disinvestment if there are fewer competitors and if demand is strong. The empirical analog considers precalciner kiln adoption and incumbent kiln retirement. We examine the following

[6] Gilbert (2006) conjectures that "one reason why empirical studies have not generated clear conclusions about the relationship between competition and innovation is a failure of many of these studies to account for different market and technological conditions."

[7] A much larger literature examines how market concentration and firm size affects R&D spending, patenting, and productivity, often exploiting cross-industry variation in the data. We refer interested readers to the reviews of Gilbert (2006), Cohen (2010), and Shapiro (2012). We consider the study of technology adoption in a specific industry as a somewhat cleaner setting for empirical work. For example, a broader focus on R&D and patenting does not restrict the empirical setting to process technologies.

[8] Chicu (2012) finds some evidence of preemption in the cement industry over 1949-1964. However, to ease the computational burden of simulating a fully-specified preemption game, the result is developed using data from Arizona, a duopoly market. Whether the results extend more broadly is not established.

hypothesis:

> **Hypothesis 2:** Firms are more likely to adopt precalciner kilns and less likely to retire incumbent kilns (without replacement) if there are fewer competitors and demand is strong.

2.4 Adjustment Costs

The existing research on product repositioning invokes adjustment costs as a source of heterogeneity in firms' proclivities to reposition. Adjustment costs have been shown to derive from a number of sources, including contractual arrangements (Argyres and Liebeskind (1999); Nickerson and Silverman (2003)), frictions associated with reallocating capital and labor inputs (Hamermesh and Pfann (1996); Sakhartov and Folta (2014); Madhok et al. (2015)), and various organizational rigidities (e.g., Hannan and McDowell (1984); Leonard-Barton (1992); Sorensen and Stuart (2000)). Further, if firms are to account for competitors' decisions, comparative adjustment costs matter (Argyres et al. (2015, 2019)).

Importantly, adjustment costs can be explicit or implicit. With process repositioning, the explicit cost includes the monetary investments necessary to change the factor of production that is fixed in the short run net of any scrap value. The implicit adjustment costs—or opportunity cost—is the present value of the profit stream the firm would have earned without repositioning. Heterogeneity in adjustment costs exists if firms differ in the explicit or implicit costs (or both) that they must incur when repositioning. The role of opportunity costs in our framework creates a strategic irony: the firm best positioned in one market environment may find itself disadvantaged if the market environment changes, as its competitors more successfully reposition. Theoretical antecedents exist in the economics literature: Tirole (1988) refers to the reluctance of incumbents to cannibalized existing profit streams as the "replacement effect," with the basic intuition dating to at least Arrow (1962).

We therefore expect firms are more likely to engage in process repositioning if their adjustment costs are lower. In our empirical setting industry, cement plants with older and lower-capacity kilns may tend to have lower implicit adjustment costs.[9] Using precalciner kiln adoption and incumbent kiln retirement as the empirical manifestation of process repositioning, we therefore examine the following hypothesis:

> **Hypothesis 3:** Firms are more likely to adopt precalciner kilns and more likely

[9] The *Minerals Yearbook* of the USGS indicates that production does not approach capacity constraints in most years. Still, kilns with greater capacity can benefit more from periods of unusually strong demand.

to retire incumbent kilns (without replacement) if the incumbent kilns are older and lower-capacity.

3 Empirical Setting

3.1 Portland Cement Industry

Portland cement is a finely ground dust that forms concrete when mixed with water and coarse aggregates such as sand and stone. Our empirical focus is on the large rotary kilns used in production, and in particular the adoption of precalciner kilns, which reduce the energy requirement of production by 25-35 percent. Precalciner technology allows plants to preheat raw materials—predominantly limestone—using the exhaust gases of the kiln and heat from a supplementary combustion chamber. As this speeds chemical reactions, the rotary kiln must be shorter in length. Cement producers outsource kiln design to one of several industrial architecture firms with expertise in cement. Installation is not demanding, and many industrial construction firms can manage the steel plates, refractory linings, and duct work. Nonetheless, total design and installation costs are large: publicly-available estimates place the total cost of building a modern cement plant around \$800 million.[10]

Table 1 tracks the kiln technologies used by cement plants in five-year increments over the sample period. In 1973, the first year of the sample, nearly all plants use inefficient wet and long dry kilns.[11] A few plants utilize preheater technology, which recycles exhaust gases without a supplementary combustion chamber, but no plant uses precalciners. The adoption of precalciner kilns plays out gradually over the ensuing years and, by 2013, precalciner kilns account for 74 percent of industry capacity. The number of wet kilns decreases from 249 to 19 and the number of long dry kilns decreases from 157 to 26.[12]

Table 2 provides the average fuel cost among kilns in each technology class. Statistics are again reported at five-year increments over the sample period. The fuel cost depends on

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

[11]Wet kilns process raw materials that are wet-ground into a slurry, while dry kilns process raw materials that are dry-ground into a powder. The wet process is somewhat more energy intensive because the added moisture must evaporate. Preheater and precalciner kilns use the dry process.

[12]Shuttered kilns typically remain on plant site because they are costly to relocate, but the supporting equipment can be repurposed profitably.

Table 1: Kiln Technology over 1973-2013

Year	Wet Kilns	Long Dry Kilns	Dry with Preheater	Dry with Precalciner	Total Kilns	Total Plants	Total Capacity
1973	249	157	23	0	429	159	76.67
1978	201	111	42	2	356	151	79.85
1983	121	90	36	24	271	132	79.79
1988	96	70	35	26	227	116	75.47
1993	72	65	38	27	202	107	74.50
1998	67	63	34	31	195	106	76.79
2003	53	49	38	45	185	106	90.88
2008	45	31	32	56	164	103	96.00
2013	19	26	29	66	140	95	98.45

Notes: The table shows data at five-year snapshots spanning 1973-2013. Kiln counts are provided separately for each of the four production technologies: wet kiln, long dry kilns, dry kilns with preheaters, and dry kilns with precalciners. Total capacity is in millions of metric tonnes. The data are for the contiguous U.S. and are obtained from the *PCA Plant Information Survey*.

the price of the primary fossil fuel (typically coal or natural gas) and the efficiency of the kiln; we provide details on measurement in Appendix B.2. Comparing across columns, the fuel costs of precalciner kilns are low relative to those of wet kilns and long dry kilns. Within each column, fuel costs are somewhat lower in the 1990s due to favorable fossil fuel prices. The final column provides the national average price of portland cement: depending on the year and kiln technology, fuel costs account for between 8 and 33 percent of revenues.

Transportation costs play an important role in the industry. Cement is typically transported by truck to ready-mix concrete plants and large construction sites, and these associated costs generally account for a sizable portion of purchasers' total expenditures. Recently published structural models either incorporate these costs explicitly (Miller and Osborne (2014)) or divide plants and consumers into distinct local markets (e.g., Ryan (2012); Fowlie et al. (2016)). To gain a sense of the geographic dispersion in the industry, Figure 1 provides a map of the cement plants in operation in 2010. Some geographic areas (e.g., southern California) have many plants, while others areas (e.g., South Dakota) have only a single nearby plant. These differences provide useful cross-sectional variation. Other patterns in the map (e.g., the string of plants through Texas, Oklahoma, and Nebraska) can be explained by the location of interstate highways, cities, and rivers.

Finally, as cement is used in construction projects, demand is highly procyclical. Figure 2 illustrates this stylized fact by plotting total production and consumption over 1973-2013. When macroeconomic conditions are favorable, consumption tends to outstrip production

Table 2: Fuel Costs per Metric Tonne of Cement

Year	Wet Kilns	Long Dry Kilns	Dry with Preheater	Dry with Precalciner	Average Price
1973	18.99	16.41	13.30	·	85.59
1978	36.42	31.13	24.56	23.35	110.25
1983	28.84	23.63	18.06	16.78	94.41
1988	19.81	15.91	13.28	12.41	79.78
1993	15.35	12.66	9.86	9.77	77.97
1998	13.50	11.24	8.75	8.39	98.13
2003	12.94	11.26	8.76	8.40	87.53
2008	22.81	19.85	15.45	14.81	105.55
2013	25.70	22.36	17.40	16.83	89.93

Notes: The table provides average fuel costs by kiln technology and the national average price of portland cement. Fuel costs are based on authors' calculations as detailed in Appendix B.2. Prices are obtained from the USGS *Minerals Yearbook*. All statistics are in real 2010 dollars per metric tonne of cement output.

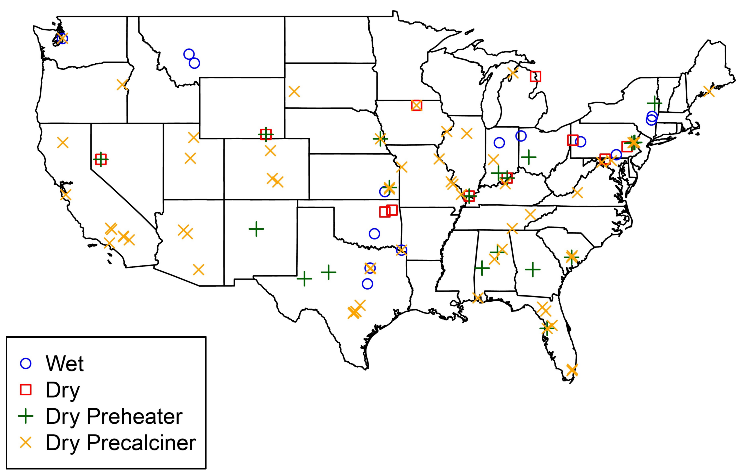

Figure 1: Portland Cement Plants in the Contiguous United States, in 2010

due to domestic capacity constraints; imports make up the differential. 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. Finally, we note that cement cannot be stored for any meaningful period of time, because the product gradually absorbs moisture which renders it unusable. We describe our data sources in detail in Appendix B.1.

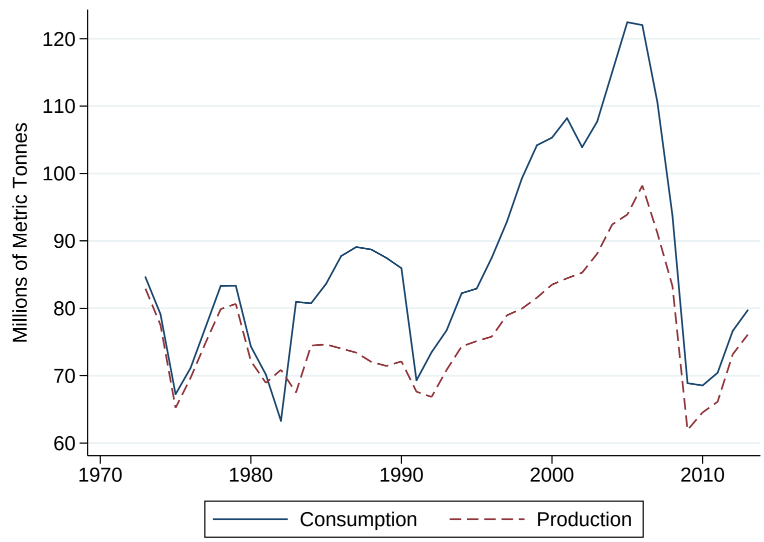

Figure 2: Consumption and Production in the United States, 1973-2013

4 Empirical Model

4.1 Specification and Hypothesis Tests

The empirical model is based on a two-stage game. In the first stage, producers determine whether to adopt precalciner technology, maintain their incumbent kiln, or retire their incumbent kiln (without replacement). In the second stage, producers compete in prices or quantities, taking the outcomes of the first stage as given. We conceptualize producers as playing this two-stage game each year, which exploits the annual observations in our panel data. This framing is analogous to the static games of perfect information estimated in the industrial organization literature (e.g., Bresnahan and Reiss (1991); Berry (1992); Gowrisankaran and Stavins (2004); Toivanen and Waterson (2005); Perez-Saiz (2015)).[13]

The first-stage decisions are made to maximize profit in the second-stage. We assume the change in profit due to precalciner technology adoption for plant j in year t is given by $b(x_{jt};\theta) - \zeta_t + \epsilon^A_{jt}$, where $b(\cdot)$ captures the benefit of adoption as a function of data $x_{jt} = \left[x^{(1)}_{jt}, x^{(2)}_{jt}, \ldots, x^{(K)}_{jt}\right]$ and parameters θ, ζ_t is an installation cost that may vary over time, and ϵ^A_{it} summarizes unobserved factors. If the producer shutters its incumbent kiln then it forgoes some amount of profit, $\pi(x_{jt};\theta) + \epsilon^0_{jt}$, in the second-stage but obtains the

[13]If we are correct that preemption incentives tend to be weak in the cement industry then a coherency problem due to multiple equilibria (e.g., Ciliberto and Tamer (2009)) is unlikely to be meaningful.

scrap value $\chi_t + \epsilon^S_{jt}$. This leads to the maximand:

$$\Pi_{it} = \begin{cases} b(x_{jt};\theta) - \zeta_t + \epsilon^A_{jt} & \text{if adopt} \\ \epsilon^0_{jt} & \text{if maintain} \\ -\pi(x_{jt};\theta) + \chi_t + \epsilon^R_{jt} & \text{if retire} \end{cases} \tag{1}$$

Any fixed costs can be conceptualized as being absorbed by (ζ_t, χ_t).

The functional forms of $b(\cdot)$ and $\pi(\cdot)$ depend on the competitive game played in the second stage. Different structural assumptions have been made in the literature—recent articles have modeled competition in the cement industry as Cournot in local markets (e.g., Ryan (2012); Fowlie et al. (2016)) and Bertrand with spatial differentiation (e.g., Miller and Osborne (2014)). We employ a reduced-form approach that allows us to characterize empirical relationships without imposing much additional structure. Taking first-order Taylor series expansions of $b(x_{jt};\theta)$ and $\pi(x_{jt};\theta)$ obtains linearized regression equations:

$$b^*(x_{jt};\theta) \equiv \sum_k \left.\frac{\partial b(x;\theta)}{\partial x^{(k)}}\right|_{x=\bar{x}} (x^{(k)}_{jt} - \bar{x}^{(k)}) \tag{2}$$

$$\pi^*(x_{jt};\theta) \equiv \sum_k \left.\frac{\partial \pi(x;\theta)}{\partial x^{(k)}}\right|_{x=\bar{x}} (x^{(k)}_{jt} - \bar{x}^{(k)}) \tag{3}$$

in which the derivatives can be interpreted as reduced-form coefficients to be estimated. The explanatory variables include fuel costs, the number of nearby competitors, local demand conditions, kiln age and capacity, and control variables. The coefficients we obtain for these variables provide tests for Hypotheses 1–3. As Corollary 1 is a reinterpretation of the core hypotheses, we use the estimated regression coefficients to illustrate the effect.

We assume that $(\epsilon^A, \epsilon^0, \epsilon^R)$ have a multivariate normal distribution, in which case the model can be estimated with a multinomial probit regression. We use the two-stage approach of Rivers and Vuong (1988) to account for potential endogeneity in the number of nearby competitors. In the first stage, the number of competitors is regressed on the exogenous variables and at least one excluded instrument. The residuals from the first stage regression are then included in the second stage Probit model, and act as a control function that absorbs confounding variation and allows for causal inference. We provide a more formal treatment of the econometric details in Appendix C.

4.2 Identification

The main econometric challenge is that the number of nearby competitors may be correlated with the unobserved determinants of process repositioning. We rely on instruments to isolate exogenous variation in competition, which allows the reduced-form coefficients in equations (2) and (3) to be estimated consistently. The stochastic properties of the unobserved terms affect the appropriate identification strategy. In this section, we examine three stylized variance structures and discuss implications for identification. The result is a suite of estimation strategies that can be taken to the data.

The variance structures we consider incorporate an element of spatial correlation, without which there would be no obvious connection between the unobserved shocks of one plant and the adoption/retirement decisions of its competitors. Spatial correlation could arise in practice if regions experience common demand or cost shocks. Focusing on the adoption equation, consider the following decomposition:

$$\epsilon^A_{jt} - \epsilon^0_{jt} = \xi_{rt} + \eta_{jt}$$

where η_{jt} is an iid shock and ξ_{rt} is a region-specific term that affects all cement plants in the same geographic region and may exhibit autocorrelation. The precise form of autocorrelation affects how valid instruments can be constructed. Three leading candidates include:

1. Suppose $\xi_{rt} = \xi_r$, so that the region-specific effect is constant over time. This process could arise in practice due to state-level differences in unionization policies or tax rates. Regions with a larger ξ_r are more profitable and would feature more producers in equilibrium. Consistent estimates can be obtained with a specification that employs region fixed effects to absorb the confounding variation.

2. Suppose instead that the region-specific term evolves according to a finite moving-average process: $\xi_{rt} = u_{rt} + \sum_{s=1}^{S} \beta_s u_{r,t-s}$, where $\beta_1, \ldots, \beta_S > 0$ and u_{rt} is an iid shock. This process could arise in practice if construction projects take multiple periods to complete, but there are no spillovers from one construction project to future projects. In such a setting, regions with positive (negative) shocks attract adoption (retirement), and region fixed effects do not eliminate the confounding variation. Lags of the exogenous regressors (i.e., past realizations of demand) are valid instruments. A $T-$period lag of the endogenous regressor (i.e., the number of competitors in period $t - T$) also is a valid instrument if $T > S$.

3. Suppose instead that the region-specific term evolves according to the autoregressive process: $\xi_{rt} = \rho\xi_{r,t-1} + u_{it}$, where $\rho > 0$ captures first-order autocorrelation and u_{it} is a iid shock. This process could arise in practice if construction projects have positive spillovers on future projects, so that the effect of a positive region shock diminishes over time but never fully dies out. Lagged regressors taken from the period $t - T$ are valid instruments if they are orthogonal to $\xi_{r,t-T}$ and the entire series of shocks $u_{r,t-T}, u_{r,t-T+1}, \ldots, u_{r,t}$. Thus, lags of the exogenous regressors are valid instruments but lags of the endogenous regressor are not. However, under the reasonable assumption that the current shock is more highly correlated with the endogenous regressor than its lag, i.e.,

$$|Cor(N_{rt}, \xi_{rt})| > |Cor(N_{r,t-T}, \xi_{rt})|$$

where N is the endogenous regressor, the lagged endogenous regressor is an *imperfect instrument* that bounds the parameters (Nevo and Rosen (2012)).

We explore each of these identification strategies in estimation, with a focus especially on the use of lagged exogenous and lagged endogenous regressors as instruments. Lagged exogenous regressors allow for consistent estimation under weaker conditions, but lagged endogenous regressors may nonetheless be theoretically preferable to the extent that (i) they are highly relevant and (ii) any imperfection is small (DiTraglia (2016)). The former property seems likely to hold in our application because lagged competition embeds the net impact of all historical determinants of entry/exit, rather than only the ones observed in our data. The latter property also is plausible because our dataset allows incorporation of long (i.e., 20-year) lags without discarding observations. However, it is unnecessary to form strong theoretical priors because similar results are obtained.

4.3 Regressors

Factor Prices: Cement plants differ in their choice of primary fuels, with the most popular being bituminous coal and natural gas. To construct a single regressor that is comparable across kilns, we focus on the fuel cost per metric tonne of cement, which depends on the price of the primary fuel and kiln efficiency. The specific formula is:

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

where the fuel price is in dollars per mBtu and the energy requirements are in mBtu per metric tonne of cement. Details on this calculation are provided in Appendix B.2. We treat fuel prices as exogenous because the cement industry accounts for only a small fraction of the fossil fuels consumed in the United States. Consistent with this interpretation, fuel prices do not track the strongly pro-cyclical pattern of cement consumption.

Number of Competitors: We exploit time series and cross-sectional variation in the number of competitors that cement plants face. In particular, for each plant, we calculate the number of competing plants within a distance radius of 400 to obtain an empirical measure. The distance metric is the multiplicative product of miles and a gasoline price index that equals one in the year 2000. This radius is motivated by prior findings that 80-90 percent of portland cement is trucked less than 200 miles (Census Bureau (1977); Miller and Osborne (2014)). Thus, plants separated by a distance of more than 400 are unlikely to compete for many customers (by contrast, plants at a distance of 300 have more customer overlap). We exclude plants owned by the same firm from the competition measure, though few such plants exist within the radius. In robustness checks, we obtain similar results with alternative distance radii of 200, 300, and 500.[14]

Demand: We proxy for demand size using a variable that measures construction activity. Specifically, we use county-level data on building permits and construction employment, which together explain nearly 90 percent of the variation in USGS-reported state-level consumption. To obtain a single regressor, we create a county-specific construction variable as a linear combination of building permits and construction employment. The specific formula, which we estimate based on the state-level regressions, is $0.0154 \times PER + 0.0122 \times EMP$, where PER and EMP are building permits and construction employment, respectively. We then sum among counties within the distance radii of 400 from each cement plant to obtain the regressor. We treat construction activity as exogenous because cement accounts for a small fraction of total construction expenditures (Syverson (2004)). The units can be interpreted as being in millions of metric tonnes.

Adjustment Costs: We proxy for the (implicit) adjustment cost using the age and capacity of the incumbent kiln.

Other Variables: We account for imports using the distance between each plant and the nearest customs district in which foreign cement is processed. Many customs districts process only small amounts of imports and so are unlikely to have a strong effect on domestic

[14]Our treatment of distance reflects the predominant role of trucking in cement distribution. A fraction of cement is shipped to terminals by train (6 percent in 2010) or barge (11 percent in 2010), and only then is trucked to customers. Some cement plants may therefore be closer than our metric indicates if, for example, both are located on the same river system. Straight-line miles are highly correlated with both driving miles and driving time and, consistent with this, previously published empirical results on the industry are not sensitive to which of these measures is employed (e.g., Miller and Osborne (2014)).

Table 3: Number of Observations per Kiln

	Count	Mean Obs.	Order Statistics: Observations				
			10%	25%	50%	75%	90%
All Kilns	460	17.81	2	6	12	34	41
Replaced Kilns	144	15.39	2	5	8	28	34
Retired Kilns	244	12.82	2	4	10	16	36
Maintained Kilns	72	37.57	37	41	41	41	41

Notes: The table provides the count of unique non-precalciner kilns in the 1973-2013 data, both together and separately for (i) kilns replaced with a precalciner kiln, (ii) kilns closed without replacement, and (iii) kilns in operation as the end of sample period. The table also summarizes the distribution of (annual) observations per kiln.

cement plants. We thus rank the customs districts according to the maximum observed inflow of foreign cement, and construct regressors based on: (i) the distance to the nearest active customs district among of the largest five; and (ii) the distance to the nearest active customs district among the largest ten. A complication is that foreign imports increase over time and differentially across customs districts. We apply the rule-of-thumb that each customs district becomes active once its inflow reaches 30 percent of its observed maximum.[15]

4.4 Summary Statistics

Table 3 describes the sample composition. The data include observations on 460 distinct non-precalciner kilns: 144 are replaced with precalciner technology, 244 are retired without replacement, and 72 survive to the end of the sample. The median kiln is observed for 12 years. At the median, kilns that are replaced with precalciner technology are observed for eight years, kilns that are retired (without replacement) are observed for ten years, and kilns that maintain to the end of the sample are observed for 41 years. There is some variation in the number of observations for surviving kilns due to infrequent greenfield entry. There are 8,192 kiln-year observations in the regression sample.

Table 4 provides summary statistics for the dependent variables (indicators for adoption and retirement) and the main explanatory variables. The unconditional probabilities of adoption and retirement, in a single given year, are 1.8% and 3.0%, respectively. The explanatory variables exhibit a fair amount of variation and the bivariate correlation coef-

[15]The purpose of the import control variables is to distinguish those plants that are relatively proximate to large and active import points. The particular selection criteria are not special and results do not change with alternative choices. The top five customs districts are: New Orleans, Tampa, Los Angeles, Houston, and San Francisco. The top ten also include: Detroit, Miami, Seattle, New York City, and Charleston.

Table 4: Summary Statistics

Variable		Mean	St. Dev	Correlation Coefficients (1)	(2)	(3)	(4)	(5)	(6)
(1)	Adoption	0.018	0.13						
(2)	Retirement	0.030	0.17	-0.023					
(3)	Fuel Costs	22.15	9.63	0.067	0.057				
(4)	Number of Competitors	20.56	12.34	-0.004	-0.002	0.029			
(5)	Construction Activity	12.85	8.85	0.003	-0.043	-0.370	0.710		
(6)	Kiln Age	30.87	16.12	0.077	0.095	-0.171	-0.130	0.021	
(7)	Kiln Capacity	0.26	0.18	-0.052	-0.096	-0.203	-0.012	0.122	-0.381

Notes: The table provides means, standard deviations, and correlation coefficients for the dependent variables (indicators for precalciner kiln adoption and incumbent kiln retirement) and the main regressors. The regression sample is comprised of 8,192 kiln-year observations over the period 1973-2013.

ficients are relatively low.[16] Figure 3 provides decadal histograms for the count of nearby competitors. Cross-sectional variation is due to dispersion in plant locations, while intertemporal variation arises due to gasoline price fluctuations and cement plant exit. We observe only sixteen instances of entry over the 41-year sample period. Mergers occur with some frequency but plausibly do not affect local competition much due to antitrust oversight.

4.5 Instruments

We construct instruments using lags on demand and competition, for which we have data well before the first precalciner kiln adoption. It is therefore possible to construct long lags without losing observations in the regression dataset, which is important for two reasons: first, regarding the lagged demand instruments, longer lags provide greater explanatory power in the first stage because demand itself exhibits autocorrelation;[17] and second, assuming the error term follows an S^{th}-order MA process, the number of competitors lagged by T years is a valid instrument if $T > S$. The success of this identification strategy hinges on the ability of long lags to predict current cement plant activity. We benefit from the specific institutional detail that kilns operate for decades—the average kiln is 40 years old at retirement—so that

[16] We assess more formally whether collinearity could be problematic by calculating the variance inflation factors (VIFs) of the regressors. This is done by regressing each regressor k on the other regressors, and calculating $VIF(k) = \frac{1}{1-R^2}$. A rule of thumb is that collinearity is a threat to asymptotic consistency if the VIF exceeds ten (Mela and Kopalle (2002)). None of our regressors has a VIF that exceeds two.

[17] For example, the building permits instrument we define below has a first-stage F-statistic of 29.88 if constructed using a 13-year lag, but only 3.98 if constructed using a 5-year lag.

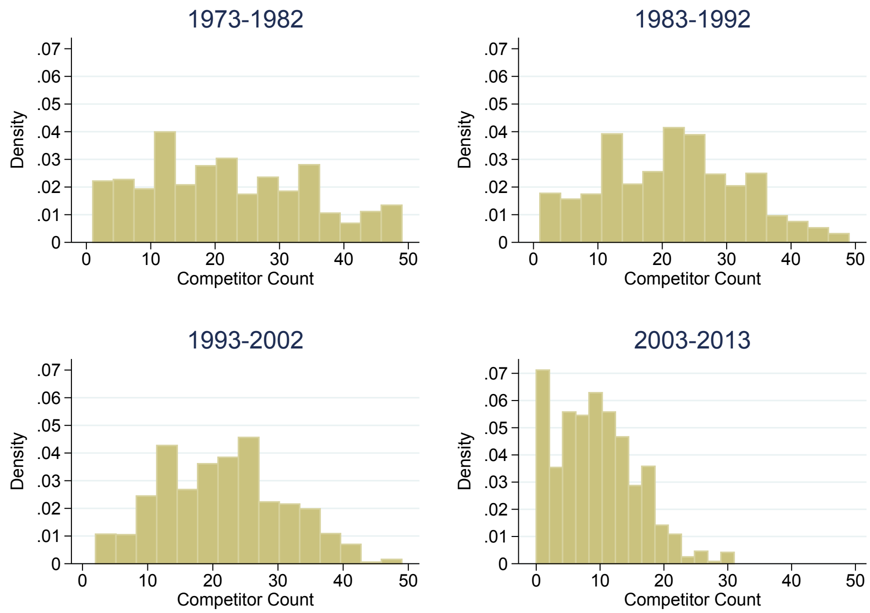

Figure 3: Count of Competitors within a Distance of 400 by Decade

even long lags have explanatory power. The construction of the lagged regressors that we use as excluded instruments are thus as follows:

- For construction, we rely on the number of building permits issued in each cement plant's state, which is available starting in 1960. We use the maximal 13-year lag.[18]

- For import availability, we exploit that the relevant USGS data back to 1958, allowing for 15-year lags on the regressors. Because we use a simple cut-off rule to define when ports become active, we supplement with 10-year and 5-year lags.

- For the number of nearby competitors, we use the locations of cement plants 20 years prior to the observation in question. Because gasoline prices are plausibly exogenous, we use the same distance (miles $\times$gasoline index) radii to calculate both the competition and lagged competition measures. Consider a kiln observation in the year 2000, when the gasoline index equals one: instruments are constructed based on the plants in 1980 within 400 miles of the location of this kiln, even though gasoline prices differ.

For robustness, we also consider the number of commercial limestone quarries located

[18]Data on construction employment and building permits are not available at the county-level for enough years before 1973 to be useful as an instrument.

within a 400 distance (miles ×gasoline index) radius.[19] The variable summarizes the suitability of the local geology for limestone extraction: areas with many commercial limestone quarries are likely to be attractive to cement plants as well. There are situations in which the exclusion restriction will not hold; the most likely being a correlation in local demand for limestone and cement. However, our controls for cement demand are highly predictive of consumption (see Section 4.3) and likely soak up any confounding variation.

5 Regression Results

5.1 Baseline Analysis

Table 5 summarizes the results obtained from a multinomial probit model in which all instruments are included in the first stage regression. To start, we note that a test for whether the instruments are jointly significant in the first stage generates an $F-$Statistic of 569.07, far exceeding the rule-of-thumb level of 10 for strong instruments. The residuals from the first stage are included as a regressor in the multinomial probit model, serving as a control for the endogenous response of competition to the error term (Rivers and Vuong (1988)). As shown, the first stage residuals produce a positive and significant coefficient in the precalciner technology adoption equation, consistent with unobserved regional shocks affecting both adoption and the number of competitors. By contrast, there is little support for endogeneity in the incumbent technology retirement equation. We further explore issues related to endogeneity bias and instrument choice in the next section, after developing a set of baseline results.

Consistent with Hypothesis 1, the coefficient on fuel costs is positive and statistically significant in both the adoption and shutdown equations. Increases in factor prices appear to induce some firms to invest in efficiency-improving technology (repositioning via investment) and others to shutter production (repositioning via disinvestment). To provide a sense of magnitudes, we calculate the elasticity of the adoption and retirement probabilities with respect to fuel costs, holding all other regressors at their means. The regression coefficients imply that a one percent increase in fuel costs increases the probabilities of adoption and retirement by 1.90 and 0.28 percent, respectively. As factor prices vary substantially in our sample, these elasticities represent large effects.

[19] To any approximation, the geological suitability of an area for limestone extraction is fixed over time, so the useful variation is in the cross-section. This comports with what is available in the MRDS data, which does not provide the dates of operation for the commercial limestone quarries.

Table 5: Baseline Multinomial Probit Analysis

	Adoption	Retirement
Coefficients and Standard Errors		
Fuel Costs	0.047***	0.011**
	(0.006)	(0.005)
Number of Competitors	-0.043***	0.019**
	(0.008)	(0.007)
Construction Activity	0.061***	-0.032***
	(0.011)	(0.010)
Kiln Age	0.018***	0.016***
	(0.004)	(0.003)
Kiln Capacity	-0.962**	-2.039***
	(0.407)	(0.518)
First Stage Residual	0.074***	-0.010
	(0.013)	(0.012)
First-Stage F-Statistic	569.07***	
Mean Elasticities with Respect to		
Fuel Costs	1.90	0.28
Number of Competitors	-1.77	0.77
Construction Activity	1.56	-0.83
Kiln Age	0.90	0.75
Kiln Capacity	-0.41	-0.97

Notes: The table summarizes results obtained from multinomial probit regressions. The sample is comprised of 8,192 kiln-year observations over 1973-2013. All regressions include controls for the distance to active Top 5 and Top 10 customs districts. Excluded instruments include lagged construction, lagged port distance, lagged competition, and commercial quarries. Standard errors are clustered at the kiln level and shown in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted with *, **, and ***, respectively.

We also find econometric support for Hypothesis 2. The coefficient on the number of competitors is negative in the adoption equation and positive in the shutdown equation; the coefficient on construction activity takes the opposite signs. All four coefficients are statistically significant. The theory suggests a single mechanism: firms are more likely to adopt efficient technology (repositioning via investment) and less likely to retire inefficient technology (repositioning via disinvestment) if equilibrium output is greater. In terms of magnitudes, the regression coefficients imply that a one percent increase in the number of competitors decreases the probability of adoption by 1.77 percent and increases the probability of retirement by 0.77 percent. A one percent increase in construction activity increases the probability of retirement by 1.56 percent and decreases the probability of retirement by 0.83 percent.

The results developed thus far suggest conditions exist under which similar firms might reasonable pursue diametrically different strategies, just as conditions exist under which firms might appear to mimic each other. To illustrate, we obtain the predicted adoption and retirement probabilities over a range of fuel costs holding all other regressors at their mean value. We then do the same for construction activity. Figure 4 graphs the results. Panel A shows that both precalciner kiln adoption and incumbent kiln retirement are more likely with higher fuel costs; Panel B shows adoption is more likely and retirement is less likely with higher construction activity. Thus, pronounced variation in fuel prices tend to make adoption and retirement synchronous, whereas pronounced variation in demand tends to make adoption and retirement asynchronous.[20]

Finally, consistent with Hypothesis 3, the coefficients on kiln age are positive in the adoption and retirement equations, whereas the coefficients on kiln capacity are negative in both equations. The results support that cement plants with older and smaller incumbent kilns have lower (implicit) adjustment costs and thus are more likely to reposition. Heterogeneity in adjustment costs generates differences in repositioning decisions across firms.

5.2 Robustness

5.2.1 Alternative Instrument Sets

Table 6 presents multinomial probit results for the technology adoption equation under alternative identifying assumptions. We focus discussion on the effect of the endogenous regressor—the number of competitors. As shown, the relevant coefficient is negative in

[20] The number of competitors, similar to construction, leads to adoption and retirement under different conditions. However, it incorporates an endogenous response by firms so we do not focus on it here.

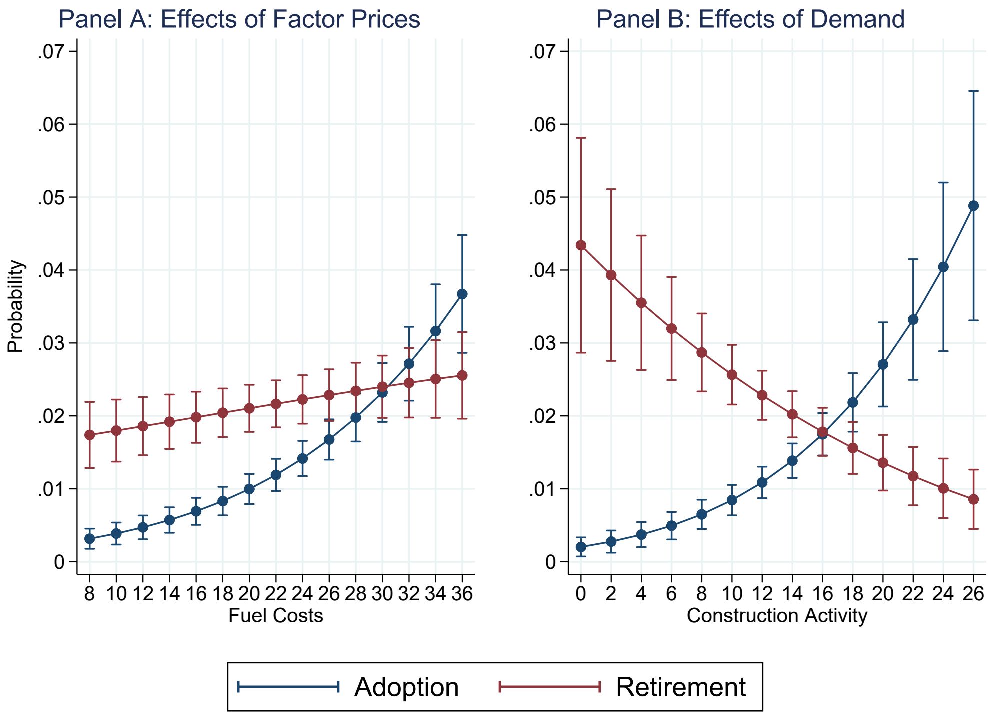

Figure 4: The Timing of Adoption and Retirement

Notes: Panel A plots the probabilities of adoption and retirement over a range of fuel costs, holding the other the regressors at their means. Panel B plots these probabilities over a range of construction activity, again holding other regressors at their mean. The bars provide 90% confidence intervals.

each specification and its magnitude at least doubles if instruments are used. The direction of bias adjustment implies a positive relationship between the number of competitors and unobserved determinants of adoption, consistent with our priors. The coefficients on the first stage residuals, which are positive and often statistically significant, also are consistent with this interpretation. Across columns (iii)-(vi), the mean elasticity of the adoption probability with respect to competition ranges from -1.40 to -3.19. This degree of consistency helps bolster the validity arguments for the different instruments (Hausman (1978)). Of particular interest is that the competition coefficient of column (v) falls in the middle of the estimated range, suggesting that any imperfection in the lagged competition instrument does not affect results much.[21]

[21] As Section 4.2 discusses, there is a theoretical basis for the 20-year competition lag being an imperfect instrument, in the sense that it may only be *less* correlated with the error term than unlagged competition. Such a relationship would exist, for example, if unobserved determinants follow an AR process. In that case, the theoretical results of Nevo and Rosen (2012) suggest that the estimated coefficient provides an upper bound on the population parameter.

Table 6: Precalciner Technology Adoption under Alternative Instrument Sets

Regressor	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
			Coefficients and Standard Errors				
Fuel Costs	0.035***	0.037***	0.056***	0.043***	0.050***	0.063***	0.047***
	(0.006)	(0.006)	(0.012)	(0.018)	(0.006)	(0.020)	(0.006)
Competitors	-0.013**	-0.009	-0.069**	-0.034*	-0.048***	-0.090*	-0.043***
	(0.007)	(0.007)	(0.030)	(0.018)	(0.009)	(0.052)	(0.008)
Construction	0.030***	0.034***	0.094***	0.055**	0.066***	0.112**	0.061***
	(0.010)	(0.011)	(0.034)	(0.022)	(0.011)	(0.060)	(0.011)
Kiln Age	0.021***	0.024***	0.014***	0.018***	0.017***	0.012*	0.018***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.007)	(0.004)
Kiln Capacity	-0.707*	-0.518	-1.137***	-0.896**	-0.942**	-1.294**	-0.962**
	(0.406)	(0.400)	(0.034)	(0.432)	(0.388)	(0.574)	(0.407)
First Stage Residual			0.058*	0.024	0.076***	0.078	0.074***
			(0.030)	(0.019)	(0.013)	(0.053)	(0.013)
			Mean Elasticities of Pr(Adoption) with Respect to				
Fuel Costs	1.40	1.54	2.17	1.70	2.02	2.41	1.90
Competitors	-0.56	-0.43	-2.58	-1.40	-1.98	-3.19	-1.77
Construction	0.78	0.96	2.23	1.38	1.70	2.69	1.56
Kiln Age	1.05	1.28	0.74	0.92	0.88	0.65	0.90
Kiln Capacity	-0.28	-0.18	-0.48	-0.38	-0.40	-0.55	-0.41
			Identification Strategy				
Region Fixed Effects	no	yes	no	no	no	no	no
Lagged Construction IV	no	no	yes	no	no	no	yes
Lagged Port Distance IV	no	no	no	yes	no	no	yes
Lagged Competitors IV	no	no	no	no	yes	no	yes
Commerical Quarries IV	no	no	no	no	no	yes	yes
First-Stage F-statistic	·	·	31.22	10.99	2671.50	20.56	569.07

Notes: The table summarizes results obtained from multinomial probit regressions. The sample is comprised of 8,192 kiln-year observations over 1973-2013. All regressions include controls for the distance to active Top 5 and Top 10 customs districts. We implement region fixed effects using Bureau of Economic Analysis economic regions. Columns (i) and (ii) do not use instruments and therefore we do not provide a first-stage F-statistic. Standard errors are clustered at the kiln level and shown in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted with *, **, and ***, respectively.

5.2.2 Alternative Specifications

Table 7 presents multinomial probit results for the technology adoption equation obtained under selected alternative specifications. Column (i) redefines the number of nearby competitors using a distance threshold of 200 (not 400) and finds directionally similar results. The results also are robust to distance thresholds of 300 and 500. Column (ii) uses two variables for the number of nearby competitors, with distance thresholds of 400 and 200.[22] As shown, both competition regressors are found to have negative and statistically significant effects. Note that the total effect of a competitor within a radius of 200 combines the coefficients: $-0.051 - 0.026 = -0.077$. Closer competitors thus appear to matter more, consistent with the role of transportation costs in creating spatial differentiation in the industry.

Column (iii) shows that effects are robust if the competition and demand regressors and instruments are in logs, suggesting that results are not overly driven by repositioning in very large markets. Column (iv) adds two alternative cost savings measures to the specification, based on fossil fuel prices five years ahead and behind the year of the observation. The coefficient on the baseline measure (based on current prices) retains its magnitude and statistical significance. The lead measure has little impact, but the lag measure is statistically significant. There are limits on our ability to pin down precisely the timing of the adoption decision, however, as short leads and lags become highly correlated.

Finally, columns (v) and (vi) add a linear time trend and a fifth-order polynomial in time, respectively. These specifications control for learning-by-doing in precalciner installation or any other changes that are experienced uniformly across the industry. Again the main results are robust. Finally, our results are robust to other empirical approaches: we obtain similar results both in terms of magnitude and statistical significance using binomial logit, the linear probability model, and a competing risks hazard rate model (Fine and Gray (1999)) in which kiln retirement is incorporated as an exogenous event.

5.2.3 Robustness of the Retirement Results

We have thus far focused the robustness analysis on the determinants of repositioning via investment. Appendix Tables D.1 and D.2 provide the corresponding robustness results for repositioning via disinvestment. Considered together, summarized regressions support the baseline findings that kiln retirement (without replacement) increases with the number of nearby competitors, increases with fuel costs, and decreases with construction activity.

[22]This entails two first-stage regressions, and we add to the instrument set a lagged competition variable constructed with the distance threshold of 200.

Table 7: Precalciner Technology Adoption with Alternative Specifications

Regressor	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Fuel Costs	0.043***	0.049***	0.044***	0.062***	0.041***	0.044***
	(0.005)	(0.006)	(0.006)	(0.009)	(0.006)	(0.007)
Fuel Costs ($t+5$)				-0.005		
				(0.005)		
Fuel Costs ($t-5$)				-0.031***		
				(0.008)		
Competitors		-0.051***		-0.048***	-0.043***	-0.039***
		(0.017)		(0.008)	(0.009)	(0.009)
Competitors ($d < 200$)	-0.070***	-0.026***				
	(0.016)	(0.008)				
log(Competitors)			-0.708***			
			(0.141)			
Construction	0.047***	0.067***		0.052***	0.060***	0.052***
	(0.010)	(0.011)		(0.011)	(0.011)	(0.012)
log(Construction)			0.832***			
			(0.166)			
Kiln Age	0.021***	0.019***	0.019***	0.019***	0.022***	0.021***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Kiln Capacity	-0.744*	-0.982**	-1.014**	-0.449	-0.723	-0.752**
	(0.370)	(0.394)	(0.422)	(0.423)	(0.471)	(0.467)
Time Trend Polynomial	none	none	none	none	1st Order	5th Order

Notes: The table summarizes results obtained from multinomial probit regressions for the adoption decision. The sample is comprised of 8,192 kiln-year observations over 1973-2013. All regressions include controls for the distance to active Top 5 and Top 10 customs districts and the residual(s) from the first stage regression(s). The first stage regressions include as excluded instruments variables for lagged construction, lagged port distance, lagged competitors, and commercial limestone quarries. The lagged competition and lagged construction instruments are in logs in column (ii). Standard errors clustered at the kiln level and shown in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted with *, **, and ***, respectively.

However, the precision with which some of the coefficients are estimated varies with the identification strategy and specification. We suspect this reflects that incumbent technology retirement is more difficult to predict than precalciner technology adoption given the available data. For example, kilns often are retired because the adjacent limestone quarry is exhausted. We do not observe the stock of available limestone, so this injects noise in the retirement equation and may make precise estimates more difficult to obtain.

6 Managerial Implications

Firms which face changing market conditions may seek to determine whether their production processes remain strategically appropriate. This is fundamentally a question of process repositioning: Should the firm incur sunk adjustment costs to realign its production processes with new market conditions? In this section, we provide an overview of our framework, with the goal of providing guidance to managers. For expositional convenience, we consider a situation in which the repositioning options available to firms includes (i) the adoption of a capital technology that economizes on the variable factors of production ("investment"), and (ii) the retirement of production facilities ("disinvestment"). The repositioning decision should be made to maximize the present value of profit net of adjustment costs. The framework considers how market forces affect the present value calculations.

Our first set of predictions (Hypothesis 1) is that higher factor prices on the variable inputs to production should induce both incumbent technology retirement and new technology adoption. The retirement prediction arises because higher factor prices increase costs and reduce profitability, all else equal. If the firm can no longer recover its fixed costs then process repositioning via disinvestment may maximize present value. The adoption prediction is somewhat more nuanced and is conditional on the details of the production process. Indeed, if the firm can easily substitute away from the costly variable input then there is no need to incur the sunk adjustment costs of technology adoption. It is in the opposite situation—when the costly input is integral to production, as is fuel in cement manufacture—that higher factor prices spur technology adoption. Considering the core prediction in its entirety, it is natural to inquire whether, in response to higher factor prices for an essential input, repositioning via investment or disinvestment is more appropriate; we return to that question shortly.

Our second set of predictions (Hypothesis 2) includes that technology adoption is more profitable if demand conditions are favorable and competitors are few. In such settings, the value of the technology adoption is greater because unit cost savings can be scaled over more output. Further, incumbent technology retirement is less likely if demand conditions are favorable and competitors are few because the status quo is relatively attractive. One caveat to these predictions is that dynamic incentives can also be important. For example, small markets may not support adoption by all firms, placing firms in an adoption race. Such dynamics tend to induce earlier adoption and delayed retirement. Whether dynamic incentives are strong can be evaluated given the particulars of the market; for an example see Section 2.3 for our evaluation of the cement industry.

We now return to the question of how a firm should choose between technology adoption and retirement, if faced with higher prices on an essential input. Our second hypothesis provides a partial answer: technology adoption is the preferred solution so long as market conditions allow for production at a scale sufficient to recoup adjustment costs. This is most likely if demand conditions are favorable and competitors are few.

Finally, repositioning analysis involves comparisons of net present value under adoption, retirement, and the status quo. Our third prediction (Hypothesis 3) states that firms with lower adjustment costs are more likely to reposition, all else equal. A corollary is that firms that earn relatively high profits with the status quo are less likely to reposition. That is, firms best positioned initially may be least inclined to reposition in response to changes in the market environment. This creates opportunities for (initially) disadvantaged firms to achieve competitive advantage via timely investment.

7 Conclusion

7.1 Limitations and Future Research

We highlight a number of limitations in our study, with an eye toward guiding future research on process repositioning. The present study focuses on a single industry with a particular set of institutional details. The theoretical literature in economics suggests that the course of process repositioning is highly dependent on market characteristics, and we have attempted to construct hypotheses reflecting that richness of possibility. Additional studies in settings similar to cement would help confirm our results. Studies in settings with distinguishing characteristics would help enrich our understanding of process repositioning.

We have focused on market conditions—factor prices, demand conditions, competition—that contribute to process repositioning. In the literature on product repositioning, adjustment costs within the firm also have been found to be important (Argyres et al. (2015, 2019)), arising from contractual arrangements, frictions associated with reallocating capital and labor, or other various organizational rigidities. We find empirical support for the role of adjustment costs in process repositioning as well, but our analysis on that front is relatively nascent. We have neither sought to flesh out the many possible sources of adjustment costs nor addressed the possibility that comparative adjustment costs are important. A more comprehensive examination would be helpful in understanding why some firms facing similar market conditions make different process repositioning choices.

Our empirical application focuses on a setting in which (we believe) dynamic incentives related to repositioning are relatively weak. However, our conceptual framework highlights that dynamics could be important in other settings. The methodologies necessary to explore dynamic incentives are being developed in the economics literature. Studies that examine repositioning using those methodologies would have value.

We view these limitations as providing opportunities for future research on process repositioning in real-world markets. The scope of possibilities supports the theoretical and empirical contributions of the present study.

7.2 Contributions

We make three main contributions to the extant literature. The first is a conceptual framework that can be used to guide process repositioning decisions. We distill research in induced innovation and technology adoption into a set of hypotheses that can be taken to the data. One point of emphasis is that process repositioning must be understood within the context of the relevant market. Thus, we formulate hypotheses that are specific to the cement industry, while describing how predictions could change under an alternative set of institutional details. The framework should be helpful both to future researchers and to managers seeking to learn about the tradeoffs associated with process repositioning.

Our second contribution is the empirical study of repositioning in the cement industry. By amassing data that span the contiguous United States over more than four decades, we are able to explore the determinants of technology adoption and retirement to a greater extent than most previous studies. Our analysis indicates that firms are more likely to adopt fuel-efficient technology if fuel costs are high, demand is favorable, and competitors are few. Interpreting the results using the conceptual framework, the first of these results obtains because fuel is an integral part of the production process. The latter two results arise because firms that operate under favorable demand conditions and with few competitors are able scale the cost reductions associated with efficient technology adoption over more units of output. Our analysis also indicates that firms are more likely to retire less-efficient technology if fuel costs are high, demand is unfavorable, and competitors are many.

Our final contribution is methodological. Identification in static models of competition, such as the one we estimate, is difficult because competition measures (such as the number of competitors) should be correlated with unobserved demand and cost conditions. If unaddressed, endogeneity bias results. One solution that has been used in the strategy literature is to exploit so-called natural experiments to establish causality (e.g., George and Waldfogel (2006); Wang and Shaver (2014); Argyres et al. (2015)). However, natural experiments are unavailable in many settings, including ours. We therefore take an alternative approach: using instruments to construct control functions that absorb the confounding variation (Rivers and Vuong (1988)). We discuss how valid instruments can be constructed in panel datasets such as ours, and show that correcting for endogeneity bias strengthens our main empirical results regarding competition and repositioning.

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Appendices for Online Publication

A Formal Model of Process Repositioning

A.1 Overview

In this appendix, we develop a simple oligopoly model in order to (i) derive the hypotheses of Section 2 analytically, and (ii) more explicitly connect the regression equations of Section 4 to the underlying economics. This formal approach to hypothesis development complements our previous approach (Section 2), which invokes the substantial literatures on repositioning and technology adoption. Most existing articles focus on one or two of the the predictions we consider; as a result, a synthesis of this literature does not make apparent the connections between the factors driving these predictions.[23] Our analysis in this appendix demonstrates that there is a single, conceptually straightforward model which underlies our conceptual framework for repositioning.

The oligopoly model plays out in two stages: a process repositioning stage and a competition stage. In the first stage, a single "focal" firm select between an efficient technology, an inefficient technology, or no technology at all (in which case it does not compete in the second stage). We conceptualize the focal firm as entering the game with the inefficient technology and being able to choose to adopt the efficient technology, maintain its existing technology, or retire its technology and exit. In the second stage of the game, all firms select factors of production and payoffs are obtained as the outcome of Cournot competition.

A key simplifying assumption we make is that a single firm makes the technology choice. Thus, we hold fixed the firm's beliefs about competitors' adoption or exit decisions when deriving comparative statics. This sidesteps complications from preemption and signaling behavior that arise in dynamic strategic games (e.g. Fudenberg and Tirole (1985); Fudenberg and Tirole (1986)). The model is nonetheless illustrative for markets in which dynamic strategic incentives are relatively weak. The body of the paper provides an informal discussion of the additional considerations that come into play more generally (Section 2). We proceed by way of backwards induction, examining the competition stage first then the process repositioning stage. All proofs are provided in Appendix A.5.

[23] For example, competition and technology adoption in Dasgupta and Stiglitz (1980) and the role of heterogeneous adoption costs in Argyres et al. (2019).

A.2 The Competition Stage

We assume that each firm has a constant elasticity of substitution (CES) production function in two inputs, M (materials) and Z (fuel), according to:

$$y = [\gamma(A_M M)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(A_Z Z)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}$$

where Y is output, A_M and A_Z are two technology terms, $\gamma \in (0,1)$ determines the relative importance of the factors, and $\sigma \in (0,\infty)$ is the elasticity of substitution between the factors. This production function nests three important special cases: (i) as $\sigma \to 0$ it becomes Leontieff and the factors are not substitutes, (ii) as $\sigma \to \infty$ it becomes linear and the factors are perfect substitutes, and (iii) if $\sigma = 1$ then it is Cobb-Douglas.

Firms differ in the productivity with which they employ fuel. Firms that use efficient technology have $A_Z^i = A_Z^1$ and firm that use inefficient technology have $A_Z^i = A_Z^0$, with $A_Z^1 > A_Z^0$. Firms are homogeneous in all other respects. For a given level of output, each firm selects the combination of materials and fuel that minimizes costs, given factor costs w_M for materials and w_Z for fuel. With the CES production function, this provides a marginal cost function, $c_i = G(w_M, w_z, A_M, A_Z^i)$, that is constant in output:

Lemma 1. *The marginal cost function of firm i is given by:*

$$G(w_M, w_z, A_M, A_Z^i) = \left[w_M^{1-\sigma}\gamma^\sigma A_M^{\sigma-1} + w_Z^{1-\sigma}(1-\gamma)^\sigma \left(A_Z^i\right)^{\sigma-1}\right]^{\frac{1}{1-\sigma}}$$

In the limit case of a Leontieff production function ($\sigma = 0$), marginal cost simplifies to $G(w_M, w_z, A_M, A_Z^i) = w_M/A_M + w_Z/A_Z^i$.

Let $c_1 = G(w_M, w_z, A_M, A_Z^1)$ and $c_0 = G(w_M, w_z, A_M, A_Z^0)$ be the marginal cost of firms with efficient and inefficient technology, respectively. Define $\Delta c \equiv c_0 - c_1$ as the marginal cost difference between the technologies. It is easy to verify that marginal cost is decreasing in A_Z (Lemma 1, noting that $\sigma - 1 < 0$), and it follows that $\Delta c > 0$.

Each firm i selects the quantity of output that maximizes its profit, taking as given the quantity of other firms. The variable profit function of firm i is given by:

$$\pi_i(q_i, Q) = (P(Q) - c_i)q_i$$

where q_i and q_i are the respective quantities of firm i and its competitors; $P(Q)$ is a market inverse demand curve; $Q = \sum_k q_k$ is total quantity; and k_i is the technology-specific fixed cost. The first order conditions that characterize profit maximization are:

$$\frac{\partial \pi}{\partial q_i} = P(Q) - c_i + P'(Q) q_i = 0$$

For tractability, we assume a linear market demand curve with a unit slope, yielding $P(Q) = a - Q$ with $a > c_0$ such that gains to trade exist between consumers and firms.

Let there be N firms, E of which use the efficient technology and $N - E$ of which use the inefficient technology. Define the average of firms' marginal cost as $\overline{c} = \frac{1}{N}(Ec_1 + (N-E)c_0)$. Stacking the first order conditions and solving obtains the Nash equilibrium prices and quantities of the second stage Cournot game:

Lemma 2. *The Nash equilibrium is characterized by the following equations:*

$$\begin{aligned}
P^*(\overline{c}, N) &= \frac{a + N\overline{c}}{N+1} \\
Q^*(\overline{c}, N) &= \frac{N(a - \overline{c})}{N+1} \\
q^*(c_i, c_{-i}, N) &= \frac{a - c_i + N(\overline{c} - c_i)}{N+1} \\
P^* - c_i &= q^*(c_i, c_{-i}, N)
\end{aligned}$$

It is important to keep in mind that the marginal costs c_1 and c_0 are implicit functions of factor prices and the parameters in the production function. We suppress their arguments for convenience. Because the Cournot model implies that the firm's output and markup are equal to each other in equilibrium, variable profit can be denoted by $\pi^*(c_i, c_{-i}, N) = (q^*(c_i, c_{-i}, N))^2$.

A.3 The Process Repositioning Stage

We now consider the process positioning choice of the focal firm, which can choose between using the efficient technology at fixed cost $\zeta + \epsilon^A$, using the inefficient technology at fixed cost ϵ^0, or not competing and receiving scrap payment $\chi + \epsilon^R$. We assume the $(\epsilon^A, \epsilon^0, \epsilon^R)$ terms are stochastic private shocks that are known to the focal firm (but not competitors) at the time of the positioning choice. These shocks are i.i.d. across firms. The firm makes the process positioning choice that maximizes its profit net of fixed costs and scrap payments, conditional on its beliefs about industry costs and taking as given equilibrium play in the subsequent competition stage.

Under these assumptions, one can derive the maximand of the empirical model (see equation (1)). A useful function that we use both in the empirical model and the present analysis is the *benefit of adoption*, which we define as the variable profit the focal firm would obtain with the efficient technology less the variable profit it would obtain with the inefficient technology.

Lemma 3. *The benefit of adoption is given by:*

$$\pi_i^*(c_1, \tilde{c}_{-i}, N) - \pi_i^*(c_0, \tilde{c}_{-i}, N) \equiv b^*(\tilde{c}_{-i}, N) = \frac{2N}{N+1} q^*(\hat{c}, \tilde{c}_{-i}, N)\Delta c$$

where $\hat{c} = (c_0 + c_1)/2$ *is the average of* c_0 *and* c_1*,* $\Delta c = c_1 - c_0 > 0$ *is the marginal cost reduction associated with the efficient technology, and* $\tilde{c}_{-i}$ *is the firm's perceived marginal costs of its competitors.*

A.4 Derivation of Hypotheses

Provided the distribution of the error terms $(\epsilon^A, \epsilon^0, \epsilon^R)$ has broad enough support, predictions about the *ex ante* likelihood of particular outcomes can be obtained by analyzing the comparative statics of the model.[24] Thus,

- An increase in factor x increases (decreases) the likelihood of efficient technology being selected, relative to that of the inefficient technology, if $\frac{\partial b^*(\tilde{c}_{-i}, N)}{\partial x} > (<)\ 0$.
- An increase in factor x increases (decreases) the likelihood of retirement being selected, relative to that of the inefficient technology, if $\frac{\partial \pi^*(c_0, \tilde{c}_{-i}, N)}{\partial x} > (<)\ 0$.

Marginal cost is an implicit function of factor prices so comparative statics can be developed for both factor prices (Hypothesis 1) and the number of competitors or demand (Hypothesis 2). Hypothesis 3 is straight-forward given the way fixed costs and scrap values affect decisions so we do not discuss it further here.

Factor Prices

Hypothesis 1 states that if factors of production are substitutable, both precalciner adoption and the retirement of existing kilns (without precalciner adoption) are more likely if fuel

[24] This holds, for example, with the multivariate normal distribution used in the empirical model because support of the multivariate normal is not bounded.

prices are high. The prediction regarding adoption is conditional, in the sense that it depends on the empirical fact that in cement production the main variable inputs (e.g., fuel, limestone, labor) must be used in fixed proportions, so firms cannot substitute from fuel to other variable inputs in response to higher fuel prices. Thus, we first formalize the prediction for the special case of a Leontieff production function ($\sigma = 0$) and then consider alternative production functions.

Lemma 4. *The derivative of the benefit of adoption with respect to the fuel price, given any arbitrary σ, is given by:*

$$\frac{\partial b^*(\tilde{c}_{-i}, N)}{\partial w_Z} = \frac{2N}{(N+1)^2}\left(a + \sum_{k \neq i} \tilde{c}_k + N\left(\frac{\partial c_0}{\partial w_Z} c_1 - \frac{\partial c_1}{\partial w_Z} c_0\right)\right)$$

Proposition 1. *An increase in the fuel price increases the benefits of adoption and decreases the profit obtained with the inefficient technology:*

$$\frac{\partial b^*(\tilde{c}_{-i}, N)}{\partial w_Z} > 0 \quad \textit{and} \quad \frac{\partial \pi^*(c_0, \tilde{c}_{-i}, N)}{\partial w_Z} < 0$$

where the first inequality holds assuming a Leontieff production function ($\sigma = 0$).

If materials and fuel are readily interchangeable then it is possible that an increase in fuel prices can decrease the benefit of adopting the efficient technology. The reason is that the firm can substitute toward away from fuel toward materials, such that it no longer gains as much from improving fuel efficiency. This effect is well illustrated with the extreme case of perfect substitutability ($\sigma = \infty$). Let a firm be initially indifferent between materials and fuel. Holding technology fixed for the moment, if fuel prices go up by some amount, say Δw_Z, then the firm utilizes only materials. Now consider the technology choice. If the efficient technology does not more than offset Δw_Z then there is zero benefit of adoption. In this case, the increase in fuel prices reduces the incentive to adopt the efficient technology. The mathematics of intermediate cases ($\sigma \in (0, \infty)$) are complicated, but in our case the continuity of marginal costs with respect to σ will imply that there is a $\hat{\sigma}$ in the neighborhood of $\sigma = 0$ such that the benefit of adopting efficient technology increases in the factor price if and only if $\sigma < \hat{\sigma}$. The results obtained by Acemoglu (2002) for a similar model also suggest that there will be some range of σ values where the benefit of adopting increases in the factor price.

It is straightforward to show that the likelihood of retirement is increasing in the factor price of fuel. Holding beliefs about competitor costs fixed, increases in fuel prices will decrease output, and decrease second stage profits.

Competition and Demand

Hypothesis 2 states that having more competitors reduces the likelihood of efficient technology adoption and increases the likelihood of retirement. To establish the prediction formally, we differentiate $b^*(\tilde{c}_{-i}, N)$ and $\pi^*(c_0, \tilde{c}_{-i}, N)$ with respect to N. This requires one to specify the marginal costs of the firms being added or removed. We assume that the marginal costs of these firms is $\bar{\bar{c}} = \frac{1}{N}(\sum_{j\neq i} \tilde{c}_j + \widehat{c})$ so that they do not affect average marginal costs.

Proposition 2. *An increase in the number of competitors decreases the benefits of adoption and decreases the profit obtained with the inefficient technology:*

$$\frac{\partial b^*(\tilde{c}_{-i}, N)}{\partial N} < 0 \quad \textit{and} \quad \frac{\partial \pi^*(c_0, \tilde{c}_{-i}, N)}{\partial N} < 0$$

where the first inequality holds under the normalcy condition:

$$\left(\bar{\bar{c}} - \widehat{c}_i\right) < (a - \widehat{c}_i)\left[\frac{N-1}{2N}\right]$$

For intuition regarding competition and adoption, note that the number of competitors affects the quantity of equilibrium output over which the cost reduction (Δc) can be applied (Lemma 3). Thus, the result supports the theoretical argument presented in Section 2 that the incentives for cost-reducing technology adoption increase with firm size (e.g., Dasgupta and Stiglitz (1980)). The normalcy condition is guaranteed to hold if half of firms employ the efficient technology because then $\bar{\bar{c}} - \widehat{c}_i \leq 0$. Otherwise, it holds if the gap between the maximum consumer willingness-to-pay (a) and marginal cost ($\widehat{c}$) is large relative to cost dispersion in the market, which can be reasonably expected to hold in most settings.

Proposition 3. *Stronger demand increases the benefits of adoption and increases the profit obtained with the inefficient technology. Formally,*

$$\frac{\partial b^*(\tilde{c}_{-i}, N)}{\partial a} > 0 \quad \textit{and} \quad \frac{\partial \pi^*(c_0, \tilde{c}_{-i}, N)}{\partial a} > 0$$

The intuition is similar: stronger demand increases the equilibrium quantity of units over which the cost reduction Δc can be applied (Lemma 3). It also increases the output and markups in equilibrium (Lemma 2) and thus increases profit.

Propositions 2 and 3 combine to provide Hypothesis 2.

A.5 Proofs

Proof of Lemma 1. The equation can be derived analytically; we sketch the steps here. To simplify the mathematics, redefine the production function to be:

$$q_i = (\alpha_L L^\rho + \alpha_Z Z^\rho)^{\frac{1}{\rho}},$$

where

$$\rho = \frac{\sigma - 1}{\sigma} \tag{A.1}$$

$$\alpha_L = \gamma A_L^{\frac{\sigma-1}{\sigma}} \tag{A.2}$$

$$\alpha_Z = (1-\gamma) A_Z^{\frac{\sigma-1}{\sigma}} \tag{A.3}$$

From the first order conditions it can be shown that:

$$\frac{w_L}{w_Z} = \frac{\alpha_L L^{\rho-1}}{\alpha_Z Z^{\rho-1}}$$

and the factor demands are:

$$L = q_i \frac{\left[\frac{w_L}{\alpha_L}\right]^{\frac{1}{\rho-1}}}{\left(\alpha_L \left[\frac{w_L}{\alpha_L}\right]^{\frac{\rho}{\rho-1}} + \alpha_Z \left[\frac{w_Z}{\alpha_Z}\right]^{\frac{\rho}{\rho-1}}\right)^{\frac{1}{\rho}}}$$

$$Z = q_i \frac{\left[\frac{w_Z}{\alpha_Z}\right]^{\frac{1}{\rho-1}}}{\left(\alpha_L \left[\frac{w_L}{\alpha_L}\right]^{\frac{\rho}{\rho-1}} + \alpha_Z \left[\frac{w_Z}{\alpha_Z}\right]^{\frac{\rho}{\rho-1}}\right)^{\frac{1}{\rho}}}$$

As a result the marginal cost function is:

$$c = \frac{w_L \left[\frac{w_L}{\alpha_L}\right]^{\frac{1}{\rho-1}} + w_Z \left[\frac{w_Z}{\alpha_Z}\right]^{\frac{1}{\rho-1}}}{\left(\alpha_L \left[\frac{w_L}{\alpha_L}\right]^{\frac{\rho}{\rho-1}} + \alpha_Z \left[\frac{w_Z}{\alpha_Z}\right]^{\frac{\rho}{\rho-1}}\right)^{\frac{1}{\rho}}}$$

Converting this back to the original notation using equations (A.1)-(A.3) obtains the equation provided in the lemma.

□

Proof of Lemma 2. The profit function can be expressed:

$$\begin{aligned}\pi_i(q_i, Q) &= (P(Q) - c_i)q_i \\ &= (a - Q - c_i)q_i\end{aligned}$$

Leading to the first order conditions:

$$\begin{aligned}\frac{\partial \pi_i(q_i, Q)}{\partial q_i} = (a - Q - c_i)q_i &= 0 \\ a - Q - c_i - q_i &= 0 \end{aligned} \tag{A.4}$$

Summing over firms $i = 1, \ldots, N$ yields:

$$\begin{aligned}Na - NQ - \sum_k c_k - Q &= 0 \\ Q = \frac{N}{N+1}(a - \overline{c}) & \end{aligned} \tag{A.5}$$

Substituting equation (A.5) into equation (A.4) yields:

$$\begin{aligned}0 &= a - \frac{N}{N+1}(a - \overline{c}) - c_i - q_i \\ q_i &= \frac{a - c_i + N(\overline{c} - c_i)}{N+1}\end{aligned}$$

which provides the expression for equilibrium quantities provided in the lemma. With this in hand, the derivation of equilibrium prices and markups require only a few lines of algebra. □

Proof of Lemma 3. The result can be derived with a few lines of algebra. Starting with the result (Lemma 2) that $\pi^* = (q_i^*)^2$, we have:

$$\begin{aligned}q^*(c_i, q_{-i}; N)^2 - q^*(c_0, q_{-i}; N)^2 &= \left(\frac{a - Nc_1 + \sum_{j\neq i}\tilde{c}_j}{N+1}\right)^2 - \left(\frac{a - Nc_0 + \sum_{j\neq i}\tilde{c}_j}{N+1}\right)^2 \\ &= \frac{(2a - N(c_1 + c_0) + 2\sum_{j\neq i}\tilde{c}_j(N(c_0 - c_1))}{(N+1)^2} \\ &= \frac{2N}{N+1}q^*(\hat{c}, \tilde{c}_{-i}, N)(c_0 - c_1) \\ &= \frac{2N}{N+1}q^*(\hat{c}, \tilde{c}_{-i}, N)\Delta c\end{aligned}$$

where $\hat{c} = (c_0 + c_1)/2$ and the first and third lines uses the equation for equilibrium quantity

(Lemman 2).

$\square$

Proof of Lemma 4. Start with the result from Lemma 1 that:

$$b^*(\tilde{c}_{-i}, N) \quad = \quad \frac{2N}{N+1} q^*(\hat{c}, \tilde{c}_{-i}, N)(c_0 - c_1)$$

and recall the c_0 and c_1 are implicit functions that depend on factor prices. Differentiating $b^*(c_{-i}, N)$ with respect to the fuel price w_Z yields:

$$\begin{aligned}
\frac{\partial b^*(\tilde{c}_{-i}, N)}{\partial w_Z} &= \frac{2N}{N+1}\left[\frac{1}{2}\frac{\partial q^*}{\partial c_0}\frac{\partial c_0}{\partial w_Z} + \frac{1}{2}\frac{\partial q^*}{\partial c_1}\frac{\partial c_1}{\partial w_Z}\right](c_0 - c_1) + \frac{2N}{N+1}q^*(\hat{c})\left(\frac{\partial c_0}{\partial w_Z} - \frac{\partial c_1}{\partial w_Z}\right) \\
&= \frac{2N}{N+1}\frac{\partial q^*}{\partial c}\left[\frac{1}{2}\frac{\partial c_0}{\partial w_Z} + \frac{1}{2}\frac{\partial c_1}{\partial w_Z}\right](c_0 - c_1) + \frac{2N}{N+1}q^*(\hat{c})\left(\frac{\partial c_0}{\partial w_Z} - \frac{\partial c_1}{\partial w_Z}\right) \\
&= -\frac{2N}{N+1}\frac{N}{N+1}\left[\frac{1}{2}\frac{\partial c_0}{\partial w_Z} + \frac{1}{2}\frac{\partial c_1}{\partial w_Z}\right](c_0 - c_1) \\
&\quad + \frac{2N}{N+1}\frac{a + N(\frac{1}{2}c_0 + \frac{1}{2}c_1) + \sum_{k\neq j} c_k}{N+1}\left(\frac{\partial c_0}{\partial w_Z} - \frac{\partial c_1}{\partial w_Z}\right) \\
&= \frac{2N}{N+1}\frac{a + \sum_{k\neq j} c_k}{N+1} \\
&\quad + \frac{N}{N+1}\frac{N}{N+1}\left\{-\left[\frac{\partial c_0}{\partial w_Z} + \frac{\partial c_1}{\partial w_Z}\right](c_0 - c_1) + (c_0 + c_1)\left(\frac{\partial c_0}{\partial w_Z} - \frac{\partial c_1}{\partial w_Z}\right)\right\} \\
&= \frac{2N}{N+1}\frac{a + \sum_{k\neq j} c_k}{N+1} + \frac{N}{N+1}\frac{N}{N+1}2\left\{\frac{\partial c_0}{\partial w_Z}c_1 - \frac{\partial c_1}{\partial w_Z}c_0\right\} \\
&= \frac{2N}{(N+1)^2}\left(a + \sum_{k\neq j} c_k + N\left(\frac{\partial c_0}{\partial w_Z}c_1 - \frac{\partial c_1}{\partial w_Z}c_0\right)\right)
\end{aligned}$$

$\square$

Proof of Proposition 1. For the first part of the proposition, we assume the limit case of a Leontieff production function ($\sigma = 0$), which produces a marginal cost function of:

$$G(w_M, w_z, A_M, A_Z^i) = w_M/A_M + w_Z/A_Z^i \tag{A.6}$$

From (Lemma 4) we have:

$$\frac{\partial b^*(\tilde{c}_{-i}, N)}{\partial w_Z} = \frac{2N}{(N+1)^2}\left(a + \sum_{k\neq j} c_k + N\left(\frac{\partial c_0}{\partial w_Z}c_1 - \frac{\partial c_1}{\partial w_Z}c_0\right)\right)$$

which is guaranteed to be positive if:

$$\frac{\partial c_0}{\partial w_Z}c_1 - \frac{\partial c_1}{\partial w_Z}c_0 > 0$$

Substituting based on equation (A.6) obtains:

$$\begin{aligned}
\frac{\partial c_0}{\partial w_Z}c_1 - \frac{\partial c_1}{\partial w_Z}c_0 &= \frac{1}{A_Z^0}\left(\frac{w_M}{A_M} + \frac{w_Z}{A_Z^1}\right) - \frac{1}{A_Z^1}\left(\frac{w_M}{A_M} + \frac{w_Z}{A_Z^0}\right) \\
&= \frac{w_M}{A_Z^0 A_M} + \frac{w_Z}{A_Z^0 A_Z^1} - \frac{w_M}{A_Z^1 A_M} - \frac{w_Z}{A_Z^0 A_Z^1} \\
&= \frac{w_M}{A_M}\left(\frac{1}{A_Z^0} - \frac{1}{A_Z^1}\right) > 0
\end{aligned}$$

The final inequality holds because $A_Z^1 > A_Z^0$, confirming the first part of the proposition.

For the second part, by inspection marginal costs increase with the fuel price for any positive and finite σ (Lemma 1) and, similarly by inspection, profit decreases as marginal costs increase (Lemma 2). Thus it follows that an increase in fuel costs decreases the profit obtained with the inefficient technology.

□

Proof of Proposition 2. For the first inequality, we have:

$$\begin{aligned}
0 &< \frac{\partial b^*(\tilde{c}_{-i}, N)}{\partial N} \\
0 &< \frac{\partial}{\partial N}\left(\frac{2N}{N+1}\frac{a - \widehat{c} + N(\overline{\overline{c}} - \widehat{c})}{N+1}\Delta c\right) \\
0 &< 2\Delta c\left(\frac{2(N+1)[N(a-\widehat{c}) + N^2(\overline{\overline{c}} - \widehat{c})] - (N+1)^2[a - \widehat{c} + 2N(\overline{\overline{c}} - \widehat{c})]}{(N+1)^4}\right)
\end{aligned}$$

which with a few lines of algebra this inequality can be shown to be true if and only if:

$$\left(\overline{\overline{c}} - \widehat{c}_i\right) < (a - \widehat{c}_i)\left[\frac{N-1}{2N}\right]$$

The second inequality is easily verified from Lemma 2 because: $\pi^*(c_0, \tilde{c}_{-i}, N) = (q^*(c_0, \tilde{c}_{-i}, N))^2$ and $q^*(c_0, \tilde{c}_{-i}, N)$ decreases in N. To confirm latter statement, $q^*(c_0, \tilde{c}_{-i}, N)$ decreases in N, it is sufficient to inspect the formula for equilibrium output:

$$q^*(c_0, \tilde{c}_{-i}, N) = \frac{a - c_0 + N(\overline{c} - c_0)}{N+1}$$

keeping in mind that $\bar{c} - c_0 \leq 0$ by construction.

$\square$

Proof of Proposition 3. The proposition is confirmed by inspection. Because equilibrium quantities increase with the demand parameter, a, so does the benefit of adoption (Lemma 3) and the profit obtained with the inefficient technology (Lemma 2). $\square$

B Data

B.1 Sources

We draw on several data sources to construct a panel of kiln-year observations that span the contiguous United States over 1973-2013. This sample period is determined by the Portland Cement Association's (PCA) *Plant Information Survey* (PIS), which is published annually over 1973-2003, semi-annually over 2004-2010, and then again in 2013. The PIS provides an end-of-year snapshot of the industry that includes 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. We impute values in missing years by using data from preceding and following years, as well as by using information in the *Minerals Yearbook* of the United States Geological Survey (USGS), which summarizes an annual cement plant census.

We combine the PIS kiln data with supplementary data that contain kiln locations over 1949-1973. These data were constructed by backcasting the 1973 PIS using information culled from the trade publication *Pit and Quarry*, occasionally printed *Pit and Quarry* maps of the industry, and the *American Cement Directory*.[25] The supplementary dataset is useful because it allows construction of lagged competition measures without discarding the earlier years of the PIS sample.

We calculate the fuel costs of production based on kiln efficiency and fossil fuel prices, using the PCA's *U.S. and Canadian Portland Cement Labor-Energy Input Survey* to measure production energy requirements. This survey is published intermittently, and we use the 1974-1979, 1990, 2000, and 2010 versions. 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). We use fossil fuel prices at the national level because they are more predictive of cement prices (Miller et al. (2017)), perhaps due to

[25] We refer interested readers to Chicu (2012) for details, and thank Mark Chicu for making these data available.

the measurement error associated with imputing withheld state-level data. We obtain retail gasoline prices from the EIA's *Monthly Energy Review*.[26]

We use county-level data on construction employment and building permits from the Census Bureau to account for demand-side fluctuations.[27] Construction employment is part of the County Business Patterns data. We use NAICS Code 23 and (for earlier years) SIC Code 15. The data for 1986-2010 are available online.[28] The data for 1973-1985 are obtained from the University of Michigan Data Warehouse. The building permits data are maintained online by the U.S. Department of Housing and Urban Development.[29] We obtain information on the location of commercial limestone quarries from the Mineral Resources Data System (MRDS) of the USGS. Finally, data on cement prices, consumption, and production reported in the previous subsection are obtained from the USGS *Minerals Yearbook*. USGS does not provide firm-level or plant-level data.

B.2 Measuring Fuel Costs

We calculate the energy requirements of production based on the labor-energy input surveys of the PCA. There is no discernible change in the requirements over 1990-2010, conditional on the kiln type. We calculate the average mBtu per metric tonne of clinker required in 1990, 2000, and 2010, and apply these averages over 1990-2013. Clinker is the immediate output of the kiln; it combined with a small amount of gysum after cooling and then ground into cement. These 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 recent USGS survey accords with our calculations (Van Oss (2005)). Technological improvements are evident over 1973-1990 within kiln type: 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 improvements are realized linearly over 1973-1990. We scale down by our calculated energy requirements by five percent to reflect that gypsum is ground together with the kiln output (i.e., clinker) to form cement.

Plants sometimes list multiple primary fuels in the PIS. In those instances, we calculate

[26]The gasoline prices include federal and sales taxes, and are for regular leaded gasoline until 1990 and regular unleaded gasoline thereafter. See `http://energy.gov/eere/vehicles/fact-915-march-7-2016-average-historical-annual-gasoline-pump-price-1929-2015`, last accessed April 25, 2016.

[27]For both the construction employment and building permits, it is necessary to impute a small number of missing values. We calculate the average percentage difference between the observed data of each county and the corresponding state data, and use that together with the state data to fill in the missing values.

[28]See `http://www.census.gov/econ/cbp/download/`, last accessed April 16, 2014.

[29]See `http://socds.huduser.org/permits/`, last accessed April 16, 2014.

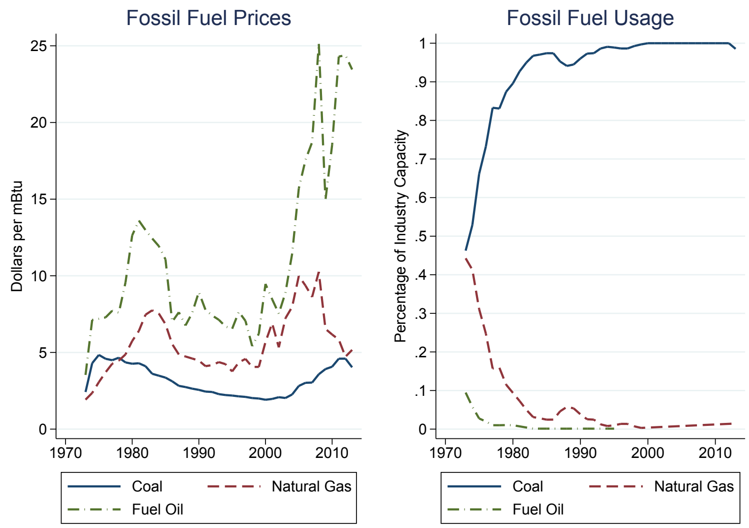

Figure B.1: Fossil Fuel Prices and Usage 1973-2013

fuel costs with the coal price if coal is among the 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. In the 1980s, petroleum coke supplements or replaces coal at many kilns. The price of coal and petroleum coke are highly correlated, and we simply use the coal price for those observations. Figure B.1 plots fossil fuel prices and usage over the sample period. In the mid-1970s, coal and natural gas wer the most popular fuel choices, while only a small subset of plants used oil. Coal quickly came to dominate the industry due to a change in relative prices, and fuel costs thereafter track the coal price.

Our methodology does not incorporate secondary fuels, the most popular of which are waste fuels such as solvents and used tires. The labor-energy input surveys of the PCA indicate that waste fuels account for around 25% of the energy used in wet kilns and 5% of the energy used in dry kilns. We do not have data on the prices of waste fuels but understand them to be lower on a per-mBtu basis than those of fossil fuels. Accordingly, we construct an alternative fuel cost measure in which we scale down the fossil fuel requirements of wet and dry kilns in accordance with the survey data. Whether this adjustment better reflects the fuel costs of marginal output depends in part on (i) the relative prices of waste and fossil fuels and (ii) whether the average fuel mix reported in the survey data reflect the marginal fuel mix. On the latter point, if marginal cement output is fired with fossil fuels then our baseline measurement should reflect marginal fuel costs more closely than the alternative measurement. Regardless, our regression results are not very sensitive to the adjustment.

C Econometric Details

We provide a more formal description of the Rivers and Vuong (1988) estimator in this appendix section. For notational simplicity we consider the case of a binomial choice model. The method extends naturally to the multinomial context. Suppose the maximand for firm i in period t is as follows:

$$\Pi_{it} = \begin{cases} \beta_1 x_{it}^{(1)} + \beta_2 x_{it}^{(2)} + \epsilon_{jt}^A \\ \epsilon_{jt}^0 \end{cases} \tag{C.1}$$

where $x_{it}^{(1)}$ is a potentially endogenous regressor in the sense that it might be correlated with ϵ_{it}^A. Further suppose that $x_{it}^{(1)}$ can be modeled with the following reduced-form equation:

$$x_{it}^{(1)} = \gamma_1 z_{it} + \gamma_2 x_{it}^{(2)} + v_{it} \tag{C.2}$$

where z_{it} is a vector of one or more instruments that are excluded from the maximization problem and v_{it} is a reduced-form error term. Collect the exogenous variables in the vector X_{it}. Let $(X_{it}, \epsilon_{it}^A, v_{it})$ be i.i.d. and let $(\epsilon_{it}^A, v_{it})$ have a mean-zero joint normal distribution, conditional on X_{it}, with the finite positive definite covariance matrix:

$$\Omega \equiv \begin{bmatrix} \sigma_{\epsilon\epsilon} & \sigma_{\epsilon v} \\ \sigma_{\epsilon v} & \sigma_{vv} \end{bmatrix} \tag{C.3}$$

Endogeneity is present if $\sigma_{\epsilon v} \neq 0$. Under joint normality, the stochastic shocks can be rewritten as $\epsilon_{it}^A = v_{it}\lambda + \eta_{it}$, where $\lambda = \sigma_{\epsilon u}/\sigma_{vv}$ and $\eta_{it} = \epsilon_{it}^A - v_{it}\lambda$. Thus, if a control function is used as a proxy for the reduced-form error, v_{it}, then the endogenous variable is orthogonal to the remaining error terms. Estimation proceeds in two stages:

1. OLS estimation of $x_{it}^{(1)}$ on the exogenous regressors and the excluded instrument(s). This obtains an estimate of the reduced-form error term that we denote $\widehat{v}_{it}$.

2. Maximum likelihood estimation of the multinomial probit equations using $\widehat{v}_{it}$ as a control function. Differences between v_{it} and $\widehat{v}_{it}$ are normally distributed and thus compatible with the distributional assumptions of the probit model.

D Additional Figures and Tables

Table D.1: Kiln Retirement under Alternative Instrument Sets

Regressor	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
			Coefficients and Standard Errors				
Fuel Costs	0.012**	0.002	0.027**	0.011*	0.009*	0.047***	0.011**
	(0.006)	(0.005)	(0.012)	(0.007)	(0.005)	(0.018)	(0.005)
Competitors	0.015***	0.018***	-0.027	0.018	0.022***	-0.081*	0.019**
	(0.005)	(0.006)	(0.030)	(0.015)	(0.008)	(0.047)	(0.007)
Construction	-0.027***	-0.059***	0.020	-0.031*	-0.036***	0.084	-0.032***
	(0.009)	(0.011)	(0.034)	(0.018)	(0.011)	(0.054)	(0.010)
Kiln Age	0.016***	0.017***	0.011**	0.016***	0.016***	0.005	0.016***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.006)	(0.003)
Kiln Capacity	-2.091***	-2.237	-2.421***	-2.045***	-2.049***	-2.834***	-2.039***
	(0.406)	(0.517)	(0.600)	(0.549)	(0.527)	(0.625)	(0.518)
First Stage Residual			0.043	0.004	-0.016	0.098**	-0.010
			(0.030)	(0.015)	(0.012)	(0.047)	(0.012)
			Identification Strategy				
Region Fixed Effects	no	yes	no	no	no	no	no
Lagged Construction IV	no	no	yes	no	no	no	yes
Lagged Port Distance IV	no	no	no	yes	no	no	yes
Lagged Competitors IV	no	no	no	no	yes	no	yes
Commerical Quarries IV	no	no	no	no	no	yes	yes

Notes: The table summarizes results obtained from multinomial probit regressions. The sample is comprised of 8,192 kiln-year observations over 1973-2013. All regressions include controls for the distance to active Top 5 and Top 10 customs districts. Standard errors are clustered at the kiln level and shown in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted with *, **, and ***, respectively.

Table D.2: Kiln Retirement with Alternative Specifications

Regressor	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Fuel Costs	0.013***	0.011*	0.018***	0.0004	0.017**	0.001
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.006)
Fuel Costs ($t+5$)				0.004		
				(0.005)		
Fuel Costs ($t-5$)				0.027***		
				(0.007)		
Competitors		0.013*		0.018**	0.017**	0.026***
		(0.007)		(0.008)	(0.008)	(0.009)
Competitors ($d < 200$)	0.025**	0.016				
	(0.012)	(0.013)				
log(Competitors)			0.090			
			(0.152)			
Construction	-0.024***	-0.034***		-0.027**	-0.030***	-0.033***
	(0.009)	(0.011)		(0.011)	(0.011)	(0.011)
log(Construction)			-0.075			
			(0.146)			
Kiln Age	0.015***	0.016***	0.015***	0.016***	0.016***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Kiln Capacity	-2.118***	-1.994***	-2.243**	-2.114***	-1.949***	-2.106***
	(0.525)	(0.516)	(0.544)	(0.649)	(0.555)	(0.467)
Time Trend Polynomial	none	none	none	none	1st Order	5th Order

Notes: The table summarizes results obtained from multinomial probit regressions for the shutdown decision. The sample is comprised of 8,192 kiln-year observations over 1973-2013. All regressions include controls for the distance to active Top 5 and Top 10 customs districts and the residual(s) from the first stage regression(s). The first stage regressions include as excluded instruments variables for lagged construction, lagged port distance, lagged competitors, and commercial limestone quarries. The lagged competition and lagged construction instruments are in logs in column (ii). Standard errors clustered at the kiln level and shown in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted with *, **, and ***, respectively.