Finding Mr. Schumpeter: Concrete Evidence on Competition and Technology Adoption*

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Abstract

We examine the adoption of precalciner technology in the portland cement industry over 1974-2010. Our estimation results indicate that adoption is positively affected by the "fuel cost gap" between incumbent kilns and precalciner kilns, but that this relationship dissipates with both domestic and import competition. We motive this interactive effect of competition using a theoretical model adapted from Dasgupta and Stigliz (1980). Interpreted through the model, our results indicate that competition limits the ability of firms to appropriate the benefits of new technology adoption. Our research contributes to the literature on competition and innovation, and has practical implications for policy-makers.

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1 Introduction

Does competition spur innovation and new technology adoption? This question has occupied economic researchers since Schumpeter (1942) posited that the stability of large firms in concentrated markets gives rise to greater R&D investment.[1] An early empirical literature shows some propensity of firms in moderately concentrated industries to invest more in R&D, but these effects largely dissipate in econometric studies that control for industry-specific effects (e.g., Scott (1984); Levin et al (1985)). This development accords with the theoretical literature: while market power can induce investment (e.g., Dasgupta and Stiglitz (1980)), the opposite effect can arise, for example, if innovation cannibalizes monopoly profit (e.g., Arrow (1962)), if preemptive investments deter entry (e.g., Gilbert and Newbery (1982)), or if firms innovate to escape competitive pressure (e.g., Aghion et al (2005)). Thus, industry details matter because there is no single theory. The more recent empirical literature accordingly explores more well-defined settings (e.g., Cockburn and Henderson (1994); Nickell (1996); Lerner (1997); Blundell et al (1999); Aghion et al (2004); Aghion et al (2009); Goettler and Gordon (2011)).

We examine a wave of new technology adoption in the portland cement industry that plays out over roughly forty years. Portland cement is a finely ground dust that forms concrete when mixed with water and coarse aggregates such as sand and stone. Production involves feeding limestone and other raw materials into large rotary kilns that reach peak temperatures of 1400-1450° Celsius. Our focus is on the adoption of precalciner technology. Precalciners attach to one end of a rotary kiln and preheat raw materials using exhaust gases from the kiln and a supplementary combustion chamber, and can reduce fuel costs by 25 to 35 percent relative to the dominant incumbent kiln technologies. Installation is not simply a matter of appending to an existing rotary kiln, however, as precalciners completely alter the manufacturing process. The adoption of precalciner technology thus requires the construction of a new kiln system, entailing substantial capital outlays (e.g., Ryan (2012)).

To inform the empirical inquiry, we first adapt the Dasgupta and Stiglitz (1980) model of Schumpeterian competition. With our modification, a focal firm can invest in cost-reducing technology by paying a pre-determined investment cost. This firm then competes *à la* Cournot against a set of rivals. Investment incentives increase with the cost reduction available and, as in Dasgupta and Stiglitz (1980), decrease with the number of competitors.

[1] Aghion and Tirole (1994) refer to the Schumpeterian hypotheses regarding the impact of firm size and market structure on innovation as the second most tested relationships in industrial organization. Even the number of literature reviews is daunting (see e.g., Kamien and Schwartz (1982); Baldwin and Scott (1987); Cohen and Levin (1989); Cohen (1995); Gilbert (2006); Cohen (2010)).

The model clarifies, however, that the number of competitors affects investment decisions *only through its interaction with the available cost reduction.* The intuition is straightforward: if the benefits of technology adoption are small then there is little remaining scope for deterrents such as competition to have addition impact. By contrast, if the benefits of adoption are meaningful then the degree of competition helps determine whether sufficient returns on investment can be earned. The immediate implication is that empirical estimates of the impact of competition on innovation are likely to suffer from misspecification bias unless the analysis accounts for this interaction. This can be done either by (i) identifying well-defined empirical settings in which the benefits of adoption are invariant, or (ii) exploiting independent variation in competition and the benefits of innovation.[2]

We take the second approach. The portland cement industry provides an advantageous laboratory for two reasons. First, we are able to observe new technology adoption directly, as well as the economic circumstances of cement firms. This feature allows us to sidestep the use of R&D expenditures or patent counts as proxies for innovation – a common practice in the empirical literature (Gilbert (2006); Cohen (2010)). Second, the cost advantage of precalciner technology is measurable via the "fuel cost gap," or the difference between the fuel costs of incumbent kilns and those at the technological frontier. Changes in fossil fuel prices create substantial variation in the fuel cost gap over the 1974-2010 sample period. Because transportation costs create localized cement markets (Miller and Osborne (2014)), the fuel cost fluctuations experienced by firms occur in heterogeneous competitive settings. These complementary sources of variation allow us to capture empirically the interactive effects of opportunity and competition on technology adoption. To our knowledge, we are the first to examine explicitly the interaction of the intensity of competition with the magnitude of new technology opportunity on firms' innovation approaches.

We use reduced-form logit regressions to model firms' technology adoption decisions. The regression sample includes 7,450 kiln-year observations, including data from 445 unique kilns that could be replaced with precalciner technology. The baseline specification includes as regressors the fuel cost gap and its interactions with two variables that measure the amount of domestic and import competition, respectively. The results are entirely consistent with the predictions of the theoretical model: the probability of precalciner adoption increases with the fuel cost gap, and this relationship dissipates as domestic and import competition

[2]Substantial empirical research examine how *opportunity* and *appropriability* affect innovation and new technology adoption (Cohen (2010)). The analogs to these concepts in our model are the reductions available in marginal cost and the number of competitors, respectively. Generalizing somewhat, our theoretical results identify an interaction between opportunity and appropriability that is relevant for empirical research.

intensify. Overall, we estimate that the median effect of a one standard deviation increase in the fuel cost gap raises the probability of precalciner adoption by 28 percent. However, among kilns in the lowest quartile of our domestic competition variable the median effect is 41 percent, while among kilns in the highest quartile the median effect is 15 percent. The results are statistically significant and robust across a range of specification and modeling choices.

Further, when we impose that domestic and import competition affect precalciner adoption directly – rather than through their interactions with the fuel cost gap – statistical significance diminishes greatly and is sensitive to specification choices. This finding underscores the importance of accounting for the "confounding factors" that Gilbert (2006) and Cohen (2010) characterize as plaguing the early empirical literature. It also reinforces the connection between the adapted Dasgupta and Stiglitz (1980) model and the empirical setting. Interpreted through the lens of the theoretical model, our results indicate that competition limits the ability of firms to appropriate the benefits of new technology opportunity and adoption. This result appears to dominate impacts documented in other market settings that arise due to strategically-motivated investments (e.g., Grabowski and Baxter (1973); Cockburn and Henderson (1994); Lerner (1997)) and investments to "escape competition" (e.g., Aghion et al (2004, 2009)). Interestingly, our results are closer to the finding of Goettler and Gordon (2011) that the presence of AMD as a competitor in the computer microprocessor industry diminishes Intel's R&D spend, despite the stark differences between the two empirical settings.

Our results have practical implications for policy-makers. The production of portland cement accounts for around 5 percent of global anthropogenic CO_2 emissions (Van Oss (2005)). Because demand is inelastic at prevailing prices (Miller and Osborne (2014)), whether market-based regulation would produce abatement from the industry depends, in large part, on whether it would spur plants to adopt less carbon-intensive production technologies. The existing empirical studies on the market-based regulation of the cement industry do not address this margin (e.g., Fowlie et al (2015); Miller et al (2015)).[3] Our results indicate that competitive considerations are likely to slow the pace of technology adoption, and raise the possibility that direct subsidies could amplify the efficacy of market-based regulation.[4]

[3] The analogous question has been researched in the context of the automobile sector (e.g., Knittel (2011); Linn and Klier (2012)).

[4] The practical implications extend to a number of other public policy interventions. For instance, the antitrust agencies often cite innovation as a consideration in their merger challenges (Gilbert (2006)). Our results indicate that such judgments are appropriate only on a case-by-case basis, as increases in market

The rest of this paper is organized as follows. Section 2 highlights the empirical context, by describing the changes in kiln technology in the portland cement industry over the sample period. Section 3 presents the adapted Dasgupta and Stiglitz (1980) model of Schumpeterian competition, and discusses the implications for empirical research. Section 4 describes the data sources and defines the dependent, independent and control variables. Section 5 presents the empirical model and discusses identification. Section 6 presents the econometric results, and Section 7 concludes.

2 The Portland Cement Industry

We examine the portland cement industry in the United States (U.S.) over 1974-2010. Table 1 tracks the progress of technology adoption over the sample period. At the outset, nearly all kilns are relatively inefficient wet kilns or long dry kilns.[5] Only a single precalciner kiln is operational in 1974, and a handful of "preheater" kilns account for the remainder of industry capacity.[6] Yet precalciner kilns become the dominant production technology by the end of the sample period. In 2010, the last year of our data, precalciner kilns account for fully 70 percent of industry capacity. By contrast, fewer than 60 wet and long dry kilns remain operational, and those older kilns account for only 17 percent of industry capacity. As new technology replaces old, total capacity increases even as the number of kilns falls because precalciner kilns have greater capacities.

The wave of precalciner adoption coincides with variation in underlying economic conditions. Time-series fluctuations in different fossil fuel prices creates variation in the fuel cost advantage of precalciners. Table 2 shows the average fuel costs for each of the kiln technologies, using snapshots across the sample period. We calculate fuel costs based on the kiln efficiency and the price of the kiln's primary fossil fuel (see Appendix A for details). Within each technology class, average fuel costs decrease and then increase through the sample period. The table also provides the fuel costs of the technological frontier, which we define as the combination of precalciner efficiency and the cheapest fossil fuel available in that year. The "fuel cost gap" between older kilns and the frontier plays an important role in the empirical analysis. The fuel cost gap tends to be larger when fossil fuel prices (and

power can in some instance result in more innovation and technological adoption.

[5]The distinction between "wet" and "dry" processes arises from how raw materials are processed: with wet kilns, the raw materials are wet-ground to form a slurry; with dry kilns, raw materials are dry-ground to form a powder. Modern precalciner kilns use the dry process.

[6]In preheater kilns, the raw materials are preheated using only exhaust gases; a supplementary combustion chamber is not employed.

Table 1: Plants, Kiln Technologies, and Capacity Shares

Year	Wet Kilns		Long Dry Kilns		Dry with Preheater		Dry with Precalciner		Total Kilns	Total Capacity
1974	230	58%	157	33%	25	8%	1	1%	413	79.28
1975	218	56%	145	32%	31	11%	1	1%	395	79.48
1980	167	49%	102	27%	38	16%	10	8%	317	76.47
1985	107	36%	81	24%	36	16%	24	24%	248	76.51
1990	79	32%	67	23%	38	19%	24	27%	208	73.07
1995	71	28%	67	22%	38	19%	27	30%	203	75.66
2000	65	24%	62	20%	35	18%	35	39%	197	83.62
2005	46	15%	48	14%	38	17%	49	54%	181	93.97
2010	28	8%	29	9%	32	14%	64	70%	153	103.48

Notes: The table shows kiln counts, capacity shares, and total capacity in five-year snapshots spanning 1974-2010. Tabulations 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*.

thus fuel costs) are high.[7] The final column of the table provides the national average price of portland cement, in order to establish that fuel costs absorb a substantial portion of plant revenues, especially during periods of high fossil fuel prices.

These fuel cost changes are experienced by plants in an array of heterogeneous competitive conditions. Cement plants sell to ready-mix concrete producers and large construction firms. Most cement is trucked directly from the plant to the customer, though some cement is first transported by barge or rail to distribution terminals and then trucked to customers. The costs of transportation are large relative to the overall price, which creates localized market power. Figure 1 provides a map of the operational cement plants circa 2010. Some geographic areas have many plants (e.g., southern California) while others areas have only a single nearby plant (e.g., South Dakota). For perspective, the distance between plants and customers often is less than 100 miles, and only rarely more than 200 miles (Miller and Osborne (2014)). Thus, plants differ substantially in the number of relevant competitors that they face. They also differ in their proximity to the customs districts through which foreign imports can enter the U.S. market, and our empirical analysis analyzes the effects of both domestic and import competition.

[7] There is a well known analogy in the automobile industry: the driving cost of vehicles with low miles-per-gallon (MPG) is more sensitive to the gasoline price than that of high MPG vehicles, and automobile prices adjust accordingly (e.g., Busse, Knittel and Zettelmeyer (2013); Langer and Miller (2013)).

Table 2: Fuel Costs per Metric Tonne of Cement

	Wet	Long Dry	Preheater	Precalciner	Frontier	Price
1974	26.66	23.81	19.38	20.33	12.02	98.98
1975	31.23	28.25	21.70	22.41	15.36	106.49
1980	32.42	25.76	23.21	18.67	18.67	122.16
1985	23.08	18.65	14.57	13.53	13.53	95.87
1990	15.73	13.13	10.90	10.23	9.59	86.87
1995	12.75	10.11	8.61	8.00	6.06	95.43
2000	11.13	9.59	7.49	7.27	6.75	101.74
2005	14.32	12.28	9.88	9.50	7.44	104.26
2010	17.91	15.67	12.19	11.72	11.58	92.00

Notes: The table provide average fuel costs across four different kiln technologies (wet, long dry, preheater, and precalciner), along with the average price of portland cement. Fuel costs are based on authors' calculations. See Appendix A for details. The "frontier" is calculated based on the fuel efficiency of precalciner kilns and the most affordable fossil fuel. National average prices are obtained from the USGS *Minerals Yearbook*. All numbers are in real 2010 dollars per metric tonne of cement output.

3 Theoretical Rationale

Our core methodological insight that the impact of competition on new technology adoption depends on the magnitude of the technological opportunity. We develop this interaction in our empirical results, exploiting variation in the fuel cost gap and local competitive conditions. We also show that competition does not robustly predict precalciner adoption, *except* through its interaction with the fuel cost gap. Here we develop a theoretical rationale for the interactive effects of competition and opportunity.

We adapt an oligopoly model initially studied in Dasgupta and Stiglitz (1980) that generates Schumpeterian predictions.[8] The model features N firms engaged in Cournot competition. A single focal firm can pay an investment cost to lower its marginal costs. Both the investment cost and the marginal cost reduction are fixed – the focal firm can pay the investment cost or not. This represents a key departure from the original model, in which investment is treated as a continuous variable.[9] With the modification, the interactive effects

[8]See also chapter five of Stiglitz and Greenwald (2014). The model is featured in the Gilbert (2006) discussion of innovation incentives with non-exclusive property rights.

[9]In the original Dasgupta and Stiglitz (1980) model, each firm can invest to lower marginal costs. The amount invested determines the magnitude of marginal cost reductions. The equilibrium level of investment diminishes as the number of firms increases, which derives from two intuitions: First, the benefit of cost-reducing technology is proportional to the amount of production such that, for example, a monopolist benefits more than a (single) duopolist. This follows the basic insight of Arrow (1962). Second, competition hampers the ability of firms to appropriate the benefits of cost-reducing technology, amplifying the discrep-

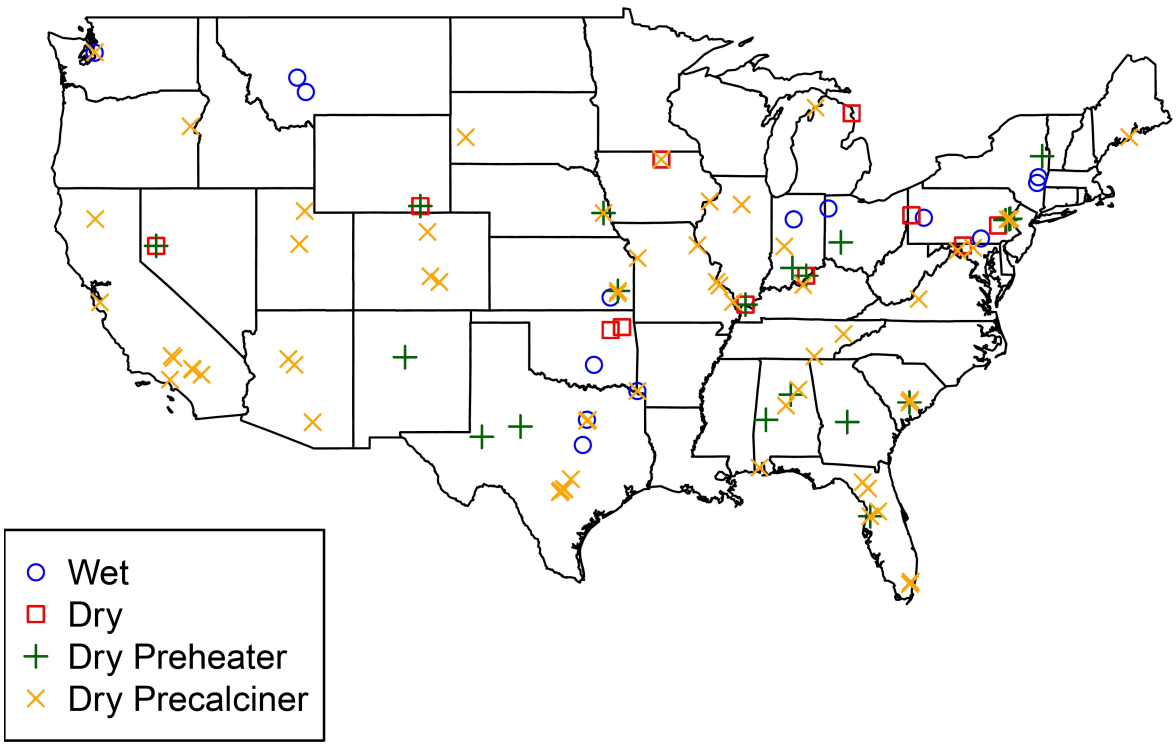

Figure 1: Cement Plants in 2010

of competition and technological opportunity become readily transparent. The modification also accords with our empirical application, in which cement plants consider whether to install a technology that lowers production costs by a known amount.

The model has two stages: First, the focal firm chooses whether to reduce its marginal costs by investing in the new technology. Second, payoffs are determined according to Cournot principles. We solve the model with backward induction. We then develop comparative statics that show how competition affects new technology adoption.

3.1 Cournot equilibrium

In the second stage of the model, $i = 1, 2, \ldots, N$ firms compete in a Cournot output game. Marginal costs are given by the vector $c = (c_1, c_2, \ldots, c_N)$. The unweighted average of the firms' marginal costs is given by $\bar{c} = \frac{1}{N}\sum_{i=1}^{N} c_i$. Each firm i selects output q_i to maximize profit, taking as given the output of other firms. Price is determined by an inverse demand curve $P(Q) = a - Q$, where $Q = \sum_i q_i$. Profit is given by $\pi_i = (P(Q) - c_i)q_i$. The model

ancy between the social and private returns to investment. The end result are predictions that accord with Schumpeterian hypotheses regarding competition and innovation.

is standard and solutions can be derived with the usual steps. Under normalcy conditions that guarantee positive output for each firm, equilibrium is characterized by the quantities

$$q_i^* = \frac{(a - c_i + N(\bar{c} - c_i))}{(N+1)}, \tag{1}$$

and this corresponds to the following market prices and total output:

$$P^* = \frac{1}{N+1}a + \frac{N}{N+1}\bar{c} \qquad Q^* = \frac{N}{N+1}(a - \bar{c}). \tag{2}$$

A number of initial comparative statics are useful in solving the first stage of the model. We start with three equilibrium pass-through relationships:

$$\frac{\partial P^*}{\partial c_i} = \frac{1}{N+1} \qquad \frac{\partial Q^*}{\partial c_i} = \frac{-1}{N+1} \qquad \frac{\partial q_i^*}{\partial c_i} = -\frac{N}{N+1} \tag{3}$$

The pass-through of a firm-specific cost change to the market price is thus determined by the number of firms, equaling 1/2 in the special case of monopoly and converging to zero as N grows large. Using an application of the envelope theorem, tractable expressions can then be obtained that relate marginal costs and the number of firms to profit:

$$\frac{\partial \pi_i}{\partial c_i} = -\frac{2N}{N+1}q_i^* \qquad \frac{\partial \pi_i}{\partial N} = -\frac{2a}{(N+1)^2}q_i^* \qquad \frac{\partial^2 \pi_i}{\partial c_i \partial N} = \frac{2Na}{(N+1)^3} \tag{4}$$

The profit of each firm decreases with its marginal costs and N. The negative effect of a firm's marginal costs on its profit attenuates as N grows large, consistent with the benefit of cost-reducing technology being proportional to the amount of production. Analogously, the negative effect of competition also attenuates as c_i grows large because high-cost firms have small levels of output and profit.

3.2 Technology adoption

We now turn to the first stage of the model. Suppose that firm i can purchase a cost-reducing technology by paying the investment cost I. The technology, if adopted, lowers the marginal costs of firm i by Δc. Let the marginal costs with and without adoption be c_i^1 and c_i^0, respectively, such that $c_i^1 = c_i^0 - \Delta c$. The corresponding levels of profit (excluding the investment cost) are $\pi_i(c_i^1, c_{-i})$ and $\pi_i(c_i^0, c_{-i})$, where c_{-i} is a vector of competitor costs. Technology adoption occurs if and only if $I < \pi_i(c_i^1, c_{-i}) - \pi_i(c_i^0, c_{-i})$.

We use the following equality to develop the comparative statics of interest to the empirical application:

$$\pi_i(c_i^1, c_{-i}) - \pi_i(c_i^0, c_{-i}) = -\left.\frac{\pi_i(c_i, c_{-i})}{\partial c_i}\right|_{c_i = c_i^0} \Delta c \tag{5}$$

The equality holds because equilibrium profit is a quadratic function of marginal costs, given Cournot competition, linear demand, and constant marginal costs.[10] The expression greatly simplifies the analysis, and allows the implications of the model for technology adoption to flow easily from the Cournot comparative statics in equations (3) and (4).

Result 1: The incentive to adopt the cost-reducing technology increases with Δc, and the magnitude of this effect decreases with N.

Proof: Differentiating the RHS of equation (5) with respect to Δc yields $-\partial \pi_i / \partial c_i$, which is positive by equation (4). Next, differentiating the RHS of equation (5) with respect to Δc and N yields $-\partial^2 \pi_i / (\partial c_i \partial N)$ which equals $-2Na/(N+1)^3$ by equation (4).

Result 2: The incentive to adopt the cost-reducing technology decreases with N, and the magnitude of this effect is proportional to Δc.

Proof: Differentiating the RHS of equation (5) with respect to N yields $-\frac{\partial^2 \pi_i}{\partial c_i \partial N} \Delta c$, which equals $-\frac{2Na}{(N+1)^3} \Delta c$ by equation (4). This is negative and proportional to Δc.

These results indicate an interactive effect of the echnological opportunity (Δc) and the degree of competition (N). The intuition is straight-forward: if the benefits of new technology adoption are small then there is little remaining scope for deterrents such as competition to have any incremental impact. This rationale is why competition affects adoption incentives only through its interaction with the technological opportunity. By contrast, if the benefits of adoption are large then competition affects whether an adequate return is possible.

3.3 Discussion

The theoretical analysis provides direction for empirical research. To identify the effects of competition on new technology adoption, a suitable experiment should seek to either hold the technological opportunity fixed, or to incorporate the opportunity into the analysis by

[10] The right-hand-side of equation (5) represents a single step of Newton's method. This is sufficient for a first order approximation under general conditions, and is exact in the quadratic case. See Jaffe and Weyl (2013) and Miller, Remer, Ryan and Sheu (2015) for other economic applications of this technique.

modeling its interactions. The difficulties associated with implementing such an experiment are widely recognized in the academic literature (e.g., Gilbert (2006)). More fundamentally, it is exceedingly rare to find empirical settings that feature variation in competitive conditions with variation in technological opportunity that is either fixed or measurable.[11]

Our empirical application fortunately overcomes these difficulties using the institutional details of the portland cement industry outlined in Section 2. In particular, we exploit that fossil fuel price fluctuations create measurable variation in the fuel cost gap between older kilns and the technological frontier, and that these changing technological opportunities are experienced by firms in quite different competitive situations. This variation identifies the interactive effects of competition in a manner that, to our knowledge, is unique in the substantial empirical literature on competition and new technology adoption.

4 Data and Variables

4.1 Data sources

We draw on data from numerous sources to construct a panel of kiln-year observations that span the contiguous U.S. over 1974-2010. The kiln data are from the *Plant Information Survey* (PIS), an annual publication of the Portland Cement Association (PCA). This publication provides the location, owner, and primary fuel of each cement plant, as well as the age, annual capacity and technology of each kiln. The PIS is published annually over 1974-2003 and semi-annually in 2004, 2006, 2008 and 2010. We impute values in the missing years based on the data from the preceding and following years.[12] There are 4,416 plant-year observations and 8,775 kiln-year observations in the sample.

We calculate the fuel costs of production based on kiln efficiency and fossil fuel prices. The details of the calculation are deferred to Appendix A. We use the PCA's *U.S. and Cana-*

[11] This may help explain why the positive relationship between market concentration and R&D spending identified in the early empirical literature, based on cross-industry comparisons, tend to disappear once industry-level control variables are added to the specification (e.g., Scott (1984); Levin, Cohen and Mowery (1985)). Baldwin and Scott (1987) conclude that "[t]he most common feature of the few R&D and innovation analyses that have sought to control for the underlying technological environment is a dramatic reduction in the observed impact of the Schumpeterian size and market power variables."

[12] In most instances, imputation is trivial because capacity, process technology and fuel are persistent across years. When the data from the preceding and following years differ, we use the data from the preceding year. We are able to identify kilns that are built in the missing years because the PIS provides the year of construction for each kiln. A handful of kilns in the PIS drop out and then reappear in latter years. We treat these observations on a case-by-case basis leveraging detailed qualitative and quantitative information provided in the *Minerals Yearbook* of the United States Geological Survey (USGS), an annual publication that summarizes a census of portland cement plants.

dian Portland Cement Labor-Energy Input Survey to measure kiln efficiency. The survey is published intermittently, and we use 1974-1979, 1990, 2000, and 2010. We use three sources to obtain fossil fuel prices. We obtain the national average delivered bituminous coal price in the industrial sector over 1985-2010 from the annual *Coal Reports* of the Energy Information Agency (EIA). We backcast these prices to the period 1974-1984 using historical data on national average free-on-board prices of bituminous coal published in the 2008 *Annual Energy Review* of the EIA.[13] We obtain the national prices of petroleum coke, natural gas, and distillate fuel oil – again for the industrial sector – from the State Energy Database System (SEDS) of the EIA. The SEDS also includes data on coal prices, but no distinction is made between bituminous coal, sub-bituminous coal, lignite, and anthracite, despite the wide price differences that arise between those fuels.

The demand for portland cement derives from construction activity. We use county-level data from the Census Bureau on construction employment and building permits to account for demand-side fluctuations.[14] Construction employment is part of the County Business Patterns data. We identify construction as NAICS Code 23 and (for earlier years) as SIC Code 15. The data for 1986-2010 are available online.[15] The data for 1980-1985 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.[16]

Lastly, we use the *Minerals Yearbook*, an annual publication of the USGS, to account for the presence of foreign imports. The availability of imported cement itself is due primarily to transoceanic freighter technology adopted around 1980. In subsequent years, imports are common especially when demand outstrips domestic capacity. The *Minerals Yearbook* identifies the customs districts through which foreign importers enter the domestic market. The number of customs districts grows during the sample period. We focus on active customs districts, defining each district as active in the first year in which imports exceed five thousand metric tonnes, and continuing through all subsequent years.[17] The *Minerals Yearbook* also is the source of the national price data provided in Table 2.

[13]The coal price data are in dollars per metric tonne, and we use the conversion factor of 23 mBtu per metric tonne to convert the data to dollars per mBtu. This conversion factor reflects the average energy content of bituminous coal obtained by cement plants based on the labor-energy input surveys.

[14]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.

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

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

[17]The two exceptions are Duluth, Minnesota and Milwaukee, Wisconsin, which we code as inactive starting in 2005 due to the complete cessation of importing.

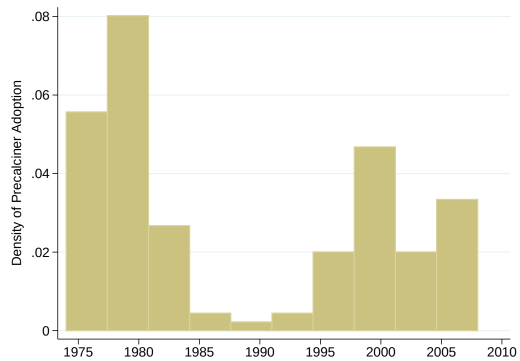

Figure 2: Empirical Distribution of Precalciner Adoption
Notes: The histogram is based on 7,540 kiln-year observations over 1974-2008. There are 445 unique wet, long dry, and preheater kilns in the sample, of which 132 are replaced with precalciner technology.

4.2 Variable definitions

4.2.1 Dependent variable

Our dependent variable captures the adoption of precalciner technology. We create an indicator variable at the kiln-year level that equals one under the joint conditions that (i) it is the final year of production for the kiln, and (ii) the plant constructs a precalciner kiln within a four-year window starting the prior year. These timing assumptions help capture instances in which the replacement of older kilns is not immediate. However, most replacements are immediate and the empirical results are virtually unchanged if alternative windows are used. Our approach restricts the baseline regression sample to wet, long dry, and preheater kilns in the years 1974-2008. There are 7,540 such kiln-year observations, featuring 445 unique kilns that could be upgraded to precaliner technology.

Figure 2 plots the empirical distribution of the dependent variable over time. We observe 132 instances overall in which an older kiln is replaced with precalciner technology. The number of upgrades exceeds the total number of precalciner kilns (e.g., see Table 1) because plants sometimes replace multiple wet or long dry kilns with a single precalciner kiln. Adoption predominately occurs during the first decade of the sample (i.e., 1974-1983) and during the last decade of the sample (i.e., 1999-2008). These periods coincide with higher fossil fuel prices. The timing of precalciner adoptions is thus consistent with perhaps the most basic prediction of the theoretical model: the incentive for new technology adoption is amplified when the new technology provides greater benefit.

4.2.2 Competition and fuel costs

We measure the competition that a kiln faces using two variables that reflect the degree of domestic and import competition, respectively. The first, which we refer to as *Rival Capacity*, is the total capacity at competing plants within 400 miles. Because the variable increases with the both number and capacity of competitors, it builds on the theoretical model by incorporating that larger plants are likely to exert more competitive pressure than smaller plants. That said, our empirical results are robust to an alternative competition measure based on competitor counts. We select the baseline distance threshold of 400 miles based on the finding that cement rarely is shipped farther than 200 miles (Miller and Osborne (2014)), which implies that plants separated by more the 400 miles are unlikely to compete for customers. We also develop results using alternative distance thresholds.

We measure import competition using *Import Proximity*, defined as the inverse distance between the kiln and the nearest active customs district (at which foreign imports can arrive). The variable equals one for a kiln located at the customs district, and decreases as the miles between the kiln and the customs district grows large. Because imports become economically viable around 1980 due to innovations in transoceanic freighter technology, we set *Import Proximity* to zero over the period 1974-1979. The relevant distance changes over the sample period, even for a given kiln, as the set of active customs districts expands.

The theory indicates that competition affects new technology adoption through its interaction with the magnitude of the technological opportunity. To measure this opportunity, we first calculate the fuel costs of the technological frontier based on precalciner technology and the cheapest fossil fuel available. We then define the variable *Fuel Cost Gap* as the difference between the fuel costs of incumbent kilns and those at the technological frontier. Appendix A contains details on how we calculate fuel costs. The three main regressors of interest are *Fuel Cost Gap*, which should positively affect precalciner adoption, and the interactions *Fuel Cost Gap*×*Rival Capacity* and *Fuel Cost Gap*×*Import Proximity*, which have a negative effect on adoption.

4.2.3 Control variables

We use a number of control variables in our estimation. These include kiln age, kiln capacity, fixed effects for the kiln technology (i.e., indicators for wet, long dry and preheater kilns), and a linear time trend. The definitions of these variables are straight-forward. We also define a variable, *Demand*, that captures the demand for portland cement among nearby counties. The variable is a linear combination of construction employment and building permits, which we observe at the county-year level. The combination is based on a regression of state-level consumption, which is available in the *Minerals Yearbook*, on construction employment and building permits aggregated to the state-level. These two regressors have a great deal of explanatory power in the consumption regression: the resulting R^2 is 0.89. We apply the regression coefficients to the county-level data on construction employment and building permits to obtain county-level predictions on consumption. The specific formula is $CONS = 0.018 \times PER + 0.012 \times EMP$ where $CONS$ is county-level predicted consumption, PER is building permits, and EMP is construction employment. The control variable $Demand$ then is defined for each kiln-year observation as the sum of predicted consumption among counties within 400 miles. The main results hold when construction employment and building permits are included independently, but the high degree of correlation between the two control variables makes interpretation of their coefficients difficult.

5 Empirical Model

5.1 Framework

Our estimation strategy follows the two-stage approach of the theoretical model. In the first stage, producers determine whether to adopt precalciner technology. In the second stage, these producers compete, taking the outcomes of the first stage as given. We conceptualize producers as playing this two-stage game each year (or period), so as to exploit the annual observations in our panel data. We assume that producers do not consider how their decisions affect subsequent periods. This framing is analogous to the static games of entry estimated elsewhere in the literature (e.g., Bresnahan and Reiss (1991); Berry (1992); Toivanen and Waterson (2005); Ciliberto and Tamer (2009); Perez-Saiz (2015)). The approach avoids the simplifying restrictions required to accommodate forward-looking producers.[18]

Denote the profit generated by kiln j in the second stage of period t as Π^i_{jt}, where the superscript i equals 1 if precalciner technology is adopted in the first stage, and 0 otherwise. We decompose this profit as follows:

$$\Pi^i_{jt} = \pi^i(x'_{jt}\beta) + \epsilon^i_{jt}, \tag{6}$$

[18] Consider that the "state space" of the industry is high-dimensional and includes at least the location and owner of each kiln, the kiln technologies, local demand conditions, import proximities, and fossil fuel prices. Our approach allows us to capture empirically the most relevant salient market forces. Dynamic estimation would require the sacrifice of this realism to reduce the dimensionality of the state space.

The functions $\pi^i()$ determine how profit is affected by fuel costs and competition: x_{jt} is a vector of regressors and β is a vector of parameters. The fixed costs associated with the decision $i \in \{0, 1\}$ are captured by the profit shock ϵ^i_{jt}, which we assume is unobservable and additively separable from the variable profit function. To estimate the reduced-form, we impose the normalization that $\pi^0_{jt} = 0$ and assume that fixed costs are stochastic with an extreme value distribution. The probability of adoption is

$$\Pr(\mathit{Adoption}) \quad = \quad \frac{\exp(\pi^1(x'_{jt}\beta)}{1 + \exp(\pi^1(x'_{jt}\beta)} \tag{7}$$

We estimate the logit model with standard maximum likelihood techniques, and cluster standard errors at the kiln level to account for autocorrelation and heteroskedasticity.

The error term in the regression has the interpretation of being an unobserved driver of precalciner adoption. The key identifying assumption, then, is that this error term is orthogonal to fuel costs and our measures of competition. The exogeneity of fuel costs seems straight-forward. Fossil fuel prices do not follow the pro-cyclical pattern of cement consumption (e.g., see Figure B.2), cement accounts for a small fraction of the fossil fuels used in the U.S., and there is no reason to suspect that fuel prices would be correlated with labor expenses or other costs of production. The exogeneity of domestic competition is more difficult to establish, and usually the cost and demand instruments are invalid when estimating profit functions. However, if some regions have unobservable and persistent profit shocks (e.g., high demand or low costs) then this would bias the regression against the result that domestic competition is a deterrent to precalciner adoption.[19]

5.2 Summary Statistics

Table 3 provides summary statistics and a matrix of correlation coefficients. We highlight that the mean value of the dependent variable, labeled *Adoption*, is 0.018. Despite the fact that 132 of the 445 unique kilns in the regression sample are upgraded to precalciner technology, the chance of upgrade in a specific year is less than two percent for the average

[19]There are a number of other reasons to think that our results are not subject to strong omitted variable bias. First, the results indicate that the impacts of domestic competition and foreign competition (which is more clearly exogenous) are qualitatively similar. Second, we obtain nearly identical results when using a two-year lag of *Rival Capacity* as an instrument. While this procedure would only partially mitigate bias due to persistent unobserved profit shocks, the fact that results are unchanged indicates that perhaps bias is not present. Third, given that the baseline specification includes a control for demand that explains nearly 90% of state-level consumption, it is plausible that the error term is dominated by idiosyncratic variation in fixed costs and investment costs that is unrelated to the competitive structure of the industry.

kiln-year observation. This has implications for how to interpret the marginal effects of the regressors, as even small effects become substantial when aggregated over time. The average kiln is 30 years old with an annual capacity of 250 thousand metric tonnes. Its fuel cost gap is $6.74, and has nearly 12MM metric tonnes of rival capacity and 13MM metric tonnes of predicted consumption within 400 miles. The *Fuel Cost Gap* variable and its interaction with *Rival Capacity* have a relatively high correlation coefficient of 0.821. To investigate the possibility that multicollinearity could distort standard errors in estimation, we calculate the variance inflation factor (VIF) of each regressor.[20] An econometric rule of thumb is that multicollinearity is potentially problematic with VIF statistics that exceed ten (e.g., Kutner, Nachtsheim and Neter (2004)). Our regressors are well below this threshold.

[20]The VIF is calculated by (i) regressing the variable of interest on the other explanatory variables; (ii) obtaining the R^2 from that regression; and (iii) applying the formula $VIF = 1/(1 - R^2)$. The VIF informs how much smaller the standard error on the coefficient of the regressor would be if that regressor were uncorrelated with other explanatory variables.

Table 3: Summary Statistics and Correlation Matrix

		Mean	St. Dev.	VIF	Correlation Coefficients (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	Adoption	0.018	(0.131)	·	1.000								
(2)	Fuel Cost Gap	6.74	(6.34)	4.52	0.088	1.000							
(3)	Fuel Costs Gap × Rival Capacity	79.31	(92.44)	3.41	0.047	0.821	1.000						
(4)	Fuel Costs Gap × Import Proximity	0.17	(1.53)	1.10	-0.003	0.223	0.098	1.000					
(5)	Demand	12.66	(7.28)	1.30	0.010	-0.235	-0.071	0.011	1.000				
(6)	Kiln Age	29.87	(15.85)	1.83	0.081	-0.062	-0.040	0.084	0.143	1.000			
(7)	Kiln Capacity	0.26	(0.26)	1.65	-0.046	-0.227	-0.162	-0.016	0.112	-0.428	1.000		
(8)	Rival Capacity	11.89	(5.65)	·	-0.011	-0.023	0.427	-0.086	0.298	0.054	0.069	1.000	
(9)	Import Proximity	0.017	(0.082)	·	-0.002	0.107	-0.009	0.799	0.011	0.084	-0.016	-0.159	1.000

Notes: Based on the regression sample of 7,540 kiln-year observations over 1974-2008. *Adoption* is an indicator that equals one during the final year of a kiln's operation if the kiln is replaced with precalciner technology within a four-year window. *Fuel Cost Gap* is the difference between the kiln's fuel costs and that of the technological frontier. *Rival Capacity* is the total competitor capacity located within 400 miles of the kiln. *Import Proximity* is the inverse distance between the kiln and the nearest active customs district. *Demand* is total predicted consumption among counties within 400 miles of the kiln. *Fuel Cost Gap* is in real 2010 dollars per metric tonne, while *Rival Capacity*, *Demand*, and *Kiln Capacity* are in millions of metric tonnes. VIF statistics are reported for each variable in the baseline specification.

Table 4: Main Logit Regression Results

	(i)	(ii)	(iii)	(iv)	(v)
Fuel Cost Gap	0.118***	0.108***	0.114***	0.107***	0.072***
	(0.017)	(0.015)	(0.015)	(0.016)	(0.012)
Fuel Cost Gap × Rival Capacity	-0.004***	-0.003**	-0.004***	-0.003***	
	(0.001)	(0.001)	(0.001)	(0.001)	
Fuel Cost Gap × Import Proximity	-0.131***	-0.112**	-0.132***		-0.107**
	(0.034)	(0.036)	(0.032)		(0.032)
Control Variables	yes	no	yes	yes	yes
Time Trend	yes	yes	no	yes	yes
Psuedo-R^2	0.079	0.047	0.071	0.075	0.072

Notes: The regression sample includes 7,540 kiln-year observations over 1974-2008. The dependent variable is an indicator that equals one if during the year that the kiln is replaced for precalciner technology. The technology fixed effects include indicators for wet and long dry kilns. Control variables include *Kiln Age*, *Kiln Capacity*, *Demand*, and indicators for wet and long dry kiln technology. A linear time trend also is included where indicated. The standard errors, shown in parentheses, are clustered at the kiln level to account for autocorrelation and heteroskedastity. Statistical significance at the 10%, 5%, and 1% levels are denoted with *, **, and ***, respectively.

6 Results

6.1 Main regression analysis

Table 4 provides the main regression results. Column (i) shows the baseline specification. The main coefficients are statistically significant and take the signs predicted by the theoretical model. The *Fuel Cost Gap* coefficient indicates that the adoption of precalciner technology is positively related to the fuel cost benefits of adoption. The negative coefficients on the interaction terms show that this relationship is mitigated both by domestic and import competition; they also capture that the (negative) impact of competition on adoption is larger in magnitude when *Fuel Cost Gap* is large. These results are robust to different specification choices: columns (ii) and (iii) shows that the results hold when the control variables or the time trend are excluded from the regression model, while columns (iv) and (v) shows that the effects of domestic and import competition are independent.[21]

The economic implications of the coefficients are substantial. We calculate kiln-specific effects using the baseline specification. A one standard deviation increase in *Fuel Cost*

[21] Appendix Table B.1 shows the coefficients and standard errors for the control variables. We omit them from the main regression table for brevity. Among the controls, only *Kiln Age* has a robust statistically significant effect. *Demand* enters positively if the time trend is excluded from the specification.

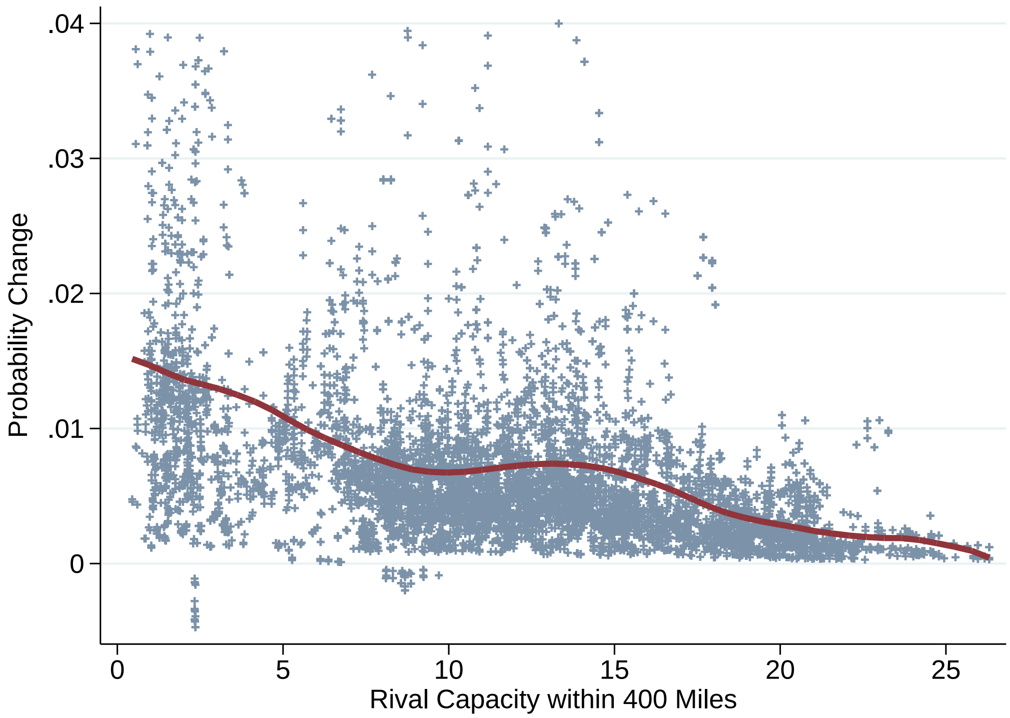

Figure 3: Effect of *Fuel Cost Gap* on the Likelihood of Precalciner Adoption

Notes: The figure shows the impact of a one standard deviation increase in *Fuel Cost Gap* on the likelihood of precalciner adoption. Effects are calculated for each kiln-year observation in the regression sample and shown as blue + symbols. The solid red line summarizes how the derivatives change with *Rival Capacity* and is calculated using a kernel-weighted local polynomial regression.

Gap increases the likelihood of precalciner adoption by an median amount of 0.005 which, evaluated against frequency of adoption, represents a 28 percent increase.[22] This effect interacts with competition. Figure 3 provides a scatterplot of the kiln-specific effects against *Rival Capacity*, our measure of domestic competition. The dark red line shows the fit from a nonparametric regression, and illustrates that the positive effect of the fuel cost gap matters much more kilns that face little competition. Among kilns in the lowest quartile of *Rival Capacity*, the median effect of a one standard deviation increase in *Fuel Cost Gap* is 0.007 (41 percent) while among kilns in the highest quartile the median effect is 0.002 (15 percent).

To further explore the impact of competition, we calculate how a one standard deviation increase in *Rival Capacity* changes the likelihood of precalciner adoption. The mean impact is a reduction in the adoption probability of 0.0035 which, evaluated against the observed frequency of adoption, represents an 18 percent decrease. A tremendous amount

[22]The calculation is $(0.018 + 0.0047)/0.018 = 0.28$.

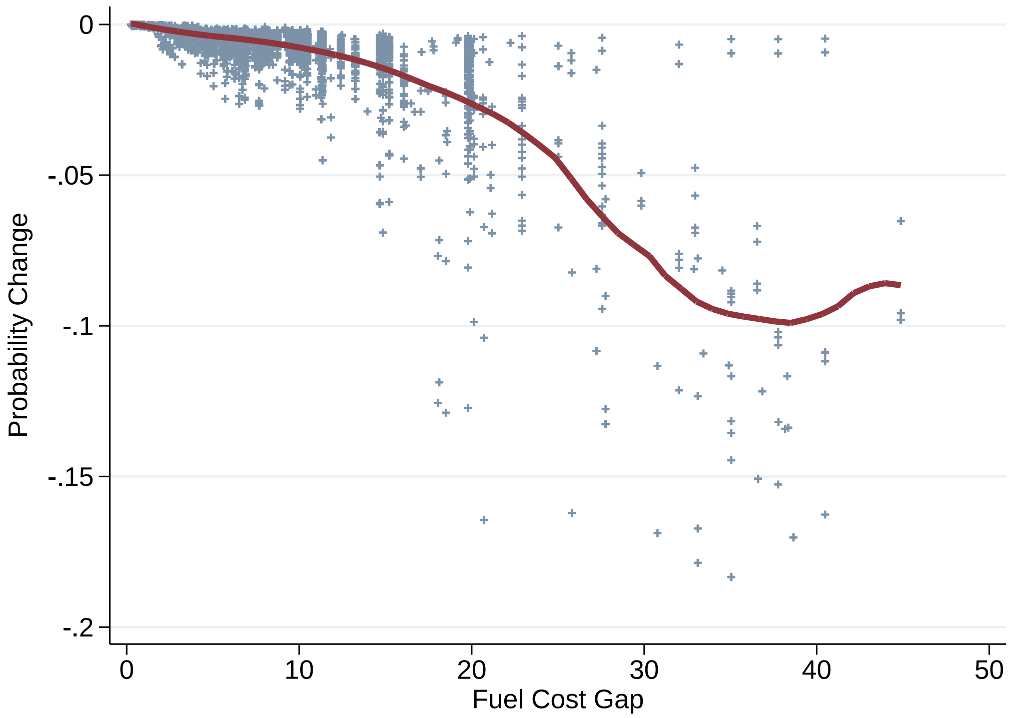

Figure 4: Effect of *Rival Capacity* on the Likelihood of Precalciner Adoption

Notes: The figure shows the impact of a one standard deviation increase in *Rival Capacity* on the likelihood of precalciner adoption. Effects are calculated for each kiln-year observation in the regression sample and shown as blue + symbols. It is assumed that the rival capacity has fuel costs that correspond to the national average during the relevant year. The solid red line summarizes how the impact changes with *Fuel Cost Gap* and is calculated using a kernel-weighted local polynomial regression.

of heterogeneity is present, however. Figure 4 provides a scatterplot of effect against *Fuel Cost Gap*. Competition affects precalciner adoption precisely when the fuel cost benefits from adoption are large. This heterogeneity is consistent with the theoretical model and has a simple intuition: if the benefit of adoption is small then so is the likelihood of adoption; and there is little remaining scope for competition to have a deterring effect.

Identifying an effect of competition on precalciner technology requires that competition enter the specification through its interaction with the fuel cost gap. To illustrate, Table 5 shows the results of more standard "concentration-innovation" regressions, in which we regress precalciner adoption on *Rival Capacity* and *Import Proximity*, along with *Fuel Cost Gap* and the control variables. In each column, we define *Rival Capacity* using a different distance threshold. The competition coefficients are uniformly negative. Their statistical significance is much diminished relative to the baseline specification, however, and results are sensitive to the distance threshold. It is also possible to add *Rival Capacity* and *Import*

Table 5: Basic Concentration Regressions

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Fuel Cost Gap	0.071***	0.070***	0.071***	0.070***	0.071***	0.069***	0.071***	0.069***
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)
Rival Capacity	-0.020	-0.040	-0.041	-0.042*	-0.035*	-0.045**	-0.017	-0.020
	(0.036)	(0.036)	(0.026)	(0.025)	(0.018)	(0.019)	(0.014)	(0.014)
Import Proximity	-1.295*	-1.287	-1.424*	-1.328	-1.615**	-1.533*	-1.505**	-1.443
	(0.747)	(0.934)	(0.734)	(0.904)	(0.746)	(0.917)	(0.763)	(0.936)
Psuedo-R^2	0.071	0.071	0.073	0.072	0.074	0.075	0.072	0.072
Distance Threshold	200	200	300	300	400	400	500	500
Diesel-Adjusted	no	yes	no	yes	no	yes	no	yes

Notes: The regression samples include 7,540 kiln-year observations over 1974-2008. The dependent variable is an indicator that equals one if during the year that the kiln is replaced for precalciner technology. All regressions include *Demand*, *Kiln Age*, and *Kiln Capacity* as control variables, as well as fixed effects for the kiln technology and a linear time trend. The standard errors, shown in parentheses, are clustered at the kiln level to account for autocorrelation and heteroskedastity. Statistical significance at the 10%, 5%, and 1% levels are denoted with *, **, and ***, respectively.

Proximity as regressors in the baseline specification, together with the interactions terms. When we do so, the baseline coefficients of Table 4 are virtually unchanged, while the statistical significance of *Rival Capacity* and *Import Proximity* again are sensitive to the distance threshold and other specification choices.

6.2 Robustness analysis

Table 6 presents results from additional regressions. The specification in column (i) allows for a nonlinear impact of domestic competition by incorporating the interactions of *Fuel Cost Gap* with both *Rival Capacity* and its square. The signs of these coefficients are consistent with a nonlinear effect. To evaluate further, we calculate the contribution of domestic competition terms to the adoption incentive.[23] Appendix Figure B.1 plots the results. There is no identifiable range over which competition increases the likelihood of adoption. Thus, the result of the baseline specification that competition mitigates adoption incentives (with considerable heterogeneity) appears robust through the range of the data.

Column (ii) adds *Rival Fuel Costs* as additional regressor. The variable is defined as the average fuel costs among competing plants within 400 miles. With some additional algebra, the theoretical model can be shown to imply that this variable should have a positive impact

[23] $Contribution = 0.012 \times \textit{Fuel Cost Gap} \times \textit{Rival Capacity} - 0.001 \times \textit{Fuel Cost Gap} \times \textit{Rival Capacity}^2$

Table 6: Additional Regression Results

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Fuel Cost Gap	0.043	0.118***	0.111***	0.106***	0.114***	0.123***	0.114***
	(0.035)	(0.016)	(0.020)	(0.014)	(0.015)	(0.018)	(0.015)
Fuel Cost Gap × Rival Capacity	-0.012	-0.005***	-0.005**	-0.008***	-0.006***	-0.003***	-0.005***
	(0.008)	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
Fuel Cost Gap × Rival Capacity^2	-0.001*						
	(0.000)						
Fuel Cost Gap × Import Proximity	-0.141***	-0.127***	-0.132***	-0.104*	-0.107*	-0.135***	-0.122**
	(0.033)	(0.031)	(0.038)	(0.032)	(0.033)	(0.034)	(0.034)
Rival Fuel Costs		0.097***					
		(0.020)					
Distance Threshold	400	400	400	200	300	500	400
Diesel-Adjusted	no	no	no	no	no	no	yes
Instruments	no	no	yes	no	no	no	no
Psuedo-R^2	0.074	0.093	0.084	0.080	0.081	0.074	0.083

Notes: The dependent variable in all regressions is an indicator that equals one if during the year that the kiln is replaced for precalciner technology. Column (i)-(ii) and columns (iiv)-(vii) show the results of standard logit regression, based on 7,540 kiln-year observations over 1974-2008. Column (iii) shows results when *Rival Capacity* and *Rival Fuel Costs* are treated as endogenous variables: two-year lags of those variables are used as instruments. The sample in column (ii) includes 6,682 kiln-year observations over 1976-2008. All regressions include *Demand*, *Kiln Age*, and *Kiln Capacity* as control variables, as well as fixed effects for the kiln technology and a linear time trend. The standard errors, shown in parentheses, are clustered at the kiln level to account for autocorrelation and heteroskedastity. Statistical significance at the 10%, 5%, and 1% levels are denoted with *, **, and ***, respectively.

on technology adoption; the intuition is that obtaining a return on investment is easier with less efficient competitors. The regression supports this prediction as well, which reinforces that the main results are well motivated by the theoretical model.

Column (iii) shows results obtained with instrumental variables. Specifically, we instrument for *Fuel Cost Gap* $\times$ *Rival Capacity* using a two-year lags of the variable. While this procedure should only partially mitigate bias due to persistent unobserved profit shocks, the fact that the IV results are virtually unchanged relative to the baseline indicates that bias may not be present in the first instance. Columns (iv)-(vii) show that the main results hold under a variety of different distance thresholds that determine the circumference at which competing plant are incorporated into *Rival Capacity*.

The main results also are robust to a host of alternative modeling and specification changes that we omit from the tables in order to conserve space. Competitors need not be weighted by capacity in the construction of *Rival Capacity*, though we think such weighting is appropriate. Additional controls can be added to the specification, including GDP growth, the national average cement price, and state fixed effects. Fuel costs can be calculated with an adjustment for waste fuels. The logit framework itself can be abandoned entirely in favor of hazard rate regressions. None of these robustness checks cast doubt on the empirical relationships obtained from the baseline regression.[24]

7 Conclusion

Coming soon.

[24]In Appendix Table B.2 we list the precalciner kilns constructed over 1974-1981. These examples of early adoption should occur in locales that are relatively insulated from competition, given the econometric results. The table shows the value of *Rival Capacity* for each kiln alongside the average value of *Rival Capacity* among kiln observations from the same year. For 13 of the 17 precalciner kilns, the amount of nearby competitor capacity indeed is lower than the corresponding national average. Thus, a simple "eyeball check" on the raw data corroborates the econometric analysis described above.

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Appendix Materials

A Measuring Fuel Costs

We calculate the fuel costs of each kiln as the price of the primary fuel (dollars per mBtu) multiplied by the energy requirements of production (mBtu per metric tonne of cement). Figure B.2 shows the fraction of industry capacity that uses bituminous coal, petroleum coke, and natural gas as a primary fossil fuel (panel A), as well as the price of those fuels (panel B). In the early years of the sample, bituminous coal and natural gas are the most common primary fuel. Due a change in relative prices, however, natural gas quickly phases out and is replaced by bituminous coal and petroleum coke.

We ascertain the energy requirements from the labor-energy input surveys of the PCA. Conditional on kiln technology, there is no discernible change in energy efficiency over 1990-2010, and we calculate the energy requirements of production to be 4.13, 4.32, 5.54, and 6.37 mBtu per metric tonne of cement for precalciner kilns, preheater kilns, long dry kilns, and wet kilns, respectively, during that period. Our calculations are corroborated by a recent USGS survey of cement plants (Van Oss (2005)). Efficiency improvements are evident over 1974-1990 within kiln type, and we assume that these are realized linearly.

Despite the transparency with which fossil fuel prices affect fuels costs, some difficulties arise in calculating fuel costs. We highlight two here. First, plants on occasion list multiple primary fuels in the PCA Plant Information Survey, and we use a simple decision rule in those instances. We calculate fuel costs with the coal price of coal is listed. Otherwise we use coke prices if coke is among the primary fuels. Otherwise we use natural gas prices if natural gas is listed. The exception to the above decision rule is when plants use a mix of coal and petroleum coke – there we assign equal weights to coal and petroleum coke prices. This decision rule reflects the relative rates at which these fuels are used (e.g., see Figure B.2). In related research, we experiment with more sophisticated allocations and the underlying empirical relationships are unaffected (Miller, Osborne and Sheu (2015b)).

Second, our methodology does not incorporate secondary fuels, the most popular of which are waste fuels such as solvents and used tires. We do not have data on the prices of waste fuels, but understand them to be lower on a per-mBtu basis than fossil fuels. The labor-energy surveys indicate that waste fuels account for around 25% of the energy used in wet kilns and 5% in dry kilns. Our results are robust to the use of a fuel cost measure in which fossil fuel requirements are scaled down in accordance with the survey data.

B Appendix Figures and Tables

Table B.1: Control Variables for the Main Logit Regressions

	(i)	(ii)	(iii)	(iv)	(v)
Demand	0.018		0.027**	0.016	0.009
	(0.013)		(0.012)	(0.013)	(0.012)
Kiln Age	0.028***		0.032***	0.027***	0.027***
	(0.007)		(0.006)	(0.007)	(0.007)
Kiln Capacity	-0.421		0.074	-0.498	-0.572
	(0.784)		(0.701)	(0.796)	(0.811)
Wet Kiln	0.367		0.351	0.351	0.329
	(0.377)		(0.373)	(0.383)	(0.389)
Long Dry Kiln	0.698*		0.564	0.598*	0.526
	(0.361)		(0.357)	(0.363)	(0.371)
Time Trend	0.019	0.040***		0.019	0.024*
	(0.013)	(0.011)		(0.013)	(0.013)

Notes: The regression sample includes 7,540 kiln-year observations over 1974-2008. The dependent variable is an indicator that equals one if during the year that the kiln is replaced for precalciner technology. The technology fixed effects include indicators for wet and long dry kilns. The standard errors, shown in parentheses, are clustered at the kiln level to account for autocorrelation and heteroskedastity. Statistical significance at the 10%, 5%, and 1% levels are denoted with *, **, and ***, respectively.

Table B.2: Precalciner Kilns Constructed 1974-1981

Year	Firm	City	State	*Rival Capacity*	Mean *Rival Capacity*
1974	Southwestern	Fairborn	OH	24.58	12.36
1978	Lehigh	Mason City	IA	10.83	11.73
1979	Kaiser	San Antonio	TX	7.91	11.76
1979	Ideal Basic	Knoxville	TN	20.96	11.76
1980	Texas Cement	New Braunfels	TX	8.16	11.06
1980	Medusa	Charlevoix	MI	8.08	11.06
1980	Martin Marietta	Lyons	CO	3.25	11.06
1980	General	New Braunfels	TX	8.23	11.06
1981	Genstar	Redding	CA	3.61	11.36
1981	Marquette	Cape Girardeau	MO	20.79	11.36
1981	Lonestar	Santa Cruz	CA	9.67	11.36
1981	California Cement	Mojave	CA	8.12	11.36
1981	Martin Marietta	Leamington	UT	3.28	11.36
1981	Martin Marietta	Buffalo	IA	19.17	11.36
1981	Ideal Basic	Theodore	AL	6.57	11.36
1981	Alamo	San Antonia	TX	8.97	11.36
1981	Kaiser	Permanente	CA	8.09	11.36

Notes: *Rival Capacity* is the sum of capacity among competing plants within 400 miles, in millions of metric tonnes. The mean shown is the national average of *Rival Capacity* during the first year of the kiln's operation.

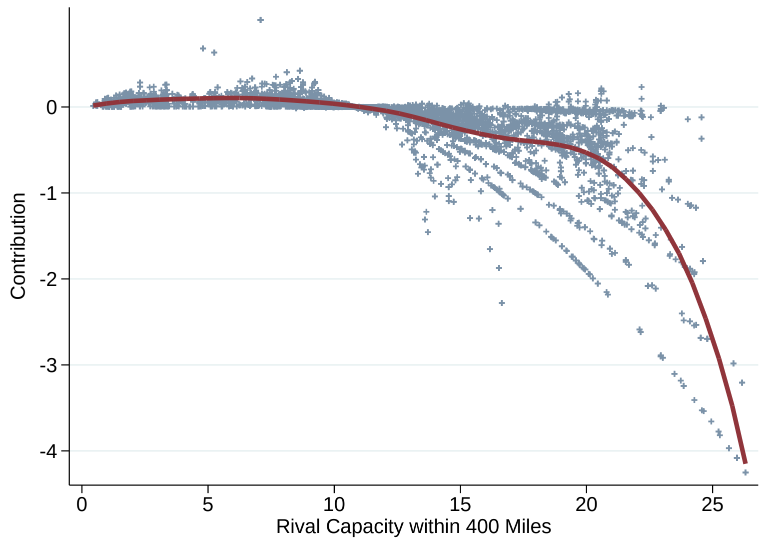

Figure B.1: Nonlinearities in the Effect of Competition

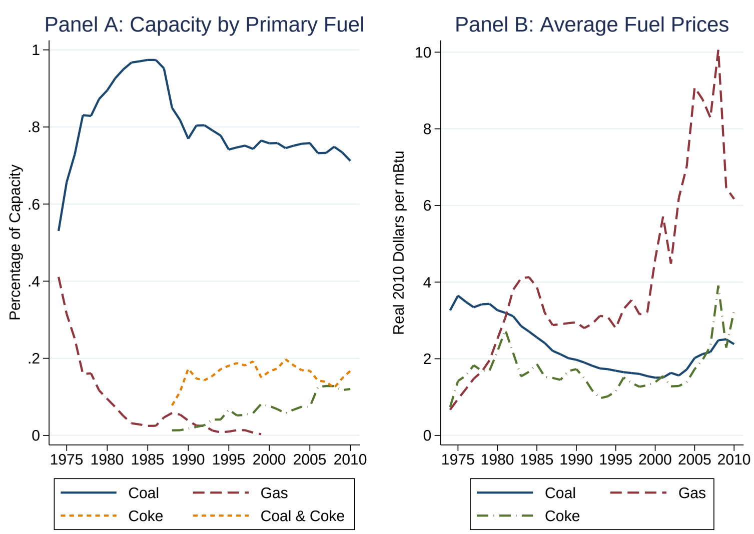

Figure B.2: Primary Fuels and Fuel Prices

Notes: Panel A plots the fraction of kiln capacity that burns as its primary fuel (i) bituminous coal, (ii) natural gas, (iii) petroleum coke, and (iv) bituminous coal and petroleum coke. Data are obtained from the PCA Plant Information Surveys. Panel B plots the average national prices for these fuel in real 2010 dollars per mBtu. Coal prices are obtained from the Coal Reports of the Energy Information Agency (EIA); other prices are obtained from the State Energy Data System of the EIA.