Technology Adoption in the Cement Industry*

Jeffrey Macher[†]
Georgetown University

Nathan H. Miller[‡]
Georgetown University

Matthew Osborne[§]
University of Toronto

December 8, 2019

Abstract

We examine the adoption of fuel-efficient precalciner kilns in the cement industry using the universe of adoption decisions in the United States over 1973-2013. We find that plants are more likely to adopt the technology if fuel costs are high, nearby competitors are few, and local demand conditions are favorable. We relate the findings to the "induced innovation" literature on whether higher factor prices induce efficiency improvements, and propose that firms may be most responsive to factor prices under advantageous competitive and demand conditions.

Keywords: technology adoption, innovation, competition, cement
JEL classification: L1, L5, L6

*We thank Philippe Aghion, Jasmina Chauvin, Alberto Galasso, Richard Gilbert, Devesh Raval, Chris Rider, Carl Shapiro, Mihkel Tombak, Francis Vella, and seminar participants at University of Colorado (Boulder), Georgetown University, Harvard University, University of Kentucky, University of Pennsylvania, and University of Toronto for helpful comments. We have benefited from conversations with Hendrick van Oss of the USGS and other industry participants. The authors are solely responsible for any errors or omissions.

[†]Georgetown University, McDonough School of Business, 37th and O Streets NW, Washington DC 20057. Email: jeffrey.macher@georgetown.edu.

[‡]Georgetown University, McDonough School of Business, 37th and O Streets NW, Washington DC 20057. Email: nathan.miller@georgetown.edu.

[§]University of Toronto, Rotman School of Management, 105 St. George Street, Toronto, ON, Canada M5S 3E6. Email: matthew.osborne@rotman.utoronto.ca.

1 Introduction

The social benefit of technical invention accrues only as it is employed. This basic observation motivates a substantial empirical literature on the determinants of technology adoption.[1] In this paper, we quantify the importance of several drivers of technology adoption in a rich empirical setting: the portland cement industry. The commercial adoption of the technology in question—the fuel-efficient precalciner kiln—has played out over the last four decades. The pace of adoption has been uneven, however, varying both over time and across geographic regions. We seek to make sense of this empirical variation and, specifically, to characterize the market conditions which appear to have facilitated speedier adoption of the technology.

Our contribution derives from the richness of the data, which allows us to separately identify the role of input costs, the competitive environment, and demand conditions within the same reduced-form model. This provides a holistic view of technology adoption and has practical policy relevance. To illustrate, a number of recent articles find empirical support for the "induced innovation" hypothesis that firms adopt efficient technologies in response to higher factor prices, with implications for carbon taxes.[2] We corroborate the finding: cement plants are more likely to adopt precalciner technology when fuel costs are high. Our results, however, also indicate that the most responsive plants may be those best positioned to recoup the sunk costs of technology adoption—in particular, those facing advantageous competitive and demand conditions. Further, higher fuel costs are associated not only with technology adoption but also with plant exit. Our results thus both suggest heterogeneity in firms' responses to carbon taxes and provide an understanding of this heterogeneity.[3]

The cement industry is ideal for our purposes because transportation costs are large relative to product value (Miller and Osborne (2014)), so the gradual diffusion of precalciner technology occurs amidst relevant spatial variation in demand and competition. Our main

[1]Aghion and Tirole (1994) refer to the Schumpeterian hypothesis regarding the impact of firm size and market structure on innovation as the second most tested relationship in industrial organization. Even the literature reviews are daunting (e.g., Kamien and Schwartz (1982); Baldwin and Scott (1987); Cohen and Levin (1989); Cohen (1995); Gilbert (2006); Cohen (2010); Shapiro (2012)). Regarding technology adoption specifically, much of the early literature provides reduced-form evidence on the impact of competition and firm size (e.g., Oster (1982); Hannan and McDowell (1984); Rose and Joskow (1990); Schmidt-Dengler (2006)). More recent contributions rely on dynamic structural models to interpret the data (e.g., Goettler and Gordon (2011); Fowlie et al. (2016); Igami (2017); Igami and Uetake (2019); Langer and Lemoine (2018)).

[2]The empirical literature includes Newell et al. (1999), Popp (2002), Linn (2008), Hanlon (2015), and Aghion et al. (2016). A substantial theoretical literature that establishes the conditions under which we should expect induced innovation to occur (e.g, Hicks (1932); Nordhaus (1973); Acemoglu (2002, 2007)).

[3]Van Oss and Padovani (2003) estimate that cement production accounts for roughly five percent of global anthropogenic CO_2 emissions. According to the most recent *Minerals Yearbook* of the United States Geological Survey (USGS), 84.7 million metric tonnes of cement were produced in the United States in 2016.

data set begins in 1973, one year before the first precalciner adoption. By 2013, the final year of our data, plants with precalciner kilns account for 74 percent of industry capacity. As precalciners also relax capacity constraints, we observe a contemporaneous industry shakeout in which the number of plants decreases from 159 to 95 and the number of kilns decreases from 429 to 140. We relate the technology adoption and kiln retirement decisions of firms to localized demand and competitive conditions and to fuel costs, taking advantage of rich cross-sectional and time-series variation in the data.

We focus on a flexible reduced-form approach because our objective is to explore and understand the determinants of technology adoption and kiln retirement without imposing strong *a priori* restrictions.[4] We develop an empirical model based on a two-stage game in which plants first determine whether to adopt precalciner technology, maintain their incumbent kiln, or retire their incumbent kiln, and then compete in prices or quantities. We derive multinomial probit regression equations that can be taken to the data. Three independent variables emerge from an analysis of Cournot competition as important determinants: fuel costs, the number of competitors, and demand conditions. We address the endogeneity of competition using the control function approach of Rivers and Vuong (1988). The stochastic properties of the unobserved error term affect the validity of candidate instruments and, accordingly, we explore a number of alternative identifying assumptions.

Our main findings indicate that the likelihood of precalciner adoption increases with fuel costs and the strength of local demand conditions, and decreases with the number of nearby competitors. These coefficients are statistically significant and robust across a range of specifications and identifying assumptions. We also find that kiln retirement increases with fuel costs, decreases with the strength of demand conditions, and increases with competition. The coefficients we obtain are also large in magnitude. For example, a one percent increase in fuel costs raises the adoption probability by 1.9 percent each year, which accumulates to 17 percent if projected over ten years. Cement plants benefiting from advantageous demand and competitive conditions appear to be more responsive to fuel costs.

We discuss the theoretical mechanisms that are consistent with these reduced-form results. Acemoglu (2002, 2007) shows that higher prices on a variable factor lead firms to adopt efficiency-improving technology adoption if substitutability among the variable factors is low, as is the case with cement. We expect our fuel cost results would generalize

[4]The main advantage of a more structural approach derives from the ability to support counterfactual simulations. However, counterfactual simulations can be computationally impossible with large state spaces and, given current methodologies, it would be difficult to (i) allow for both technology adoption and kiln retirement and (ii) account for the spatial differentiation observed in the data.

to other settings with low factor substitutability. In regard to demand and competition, one mechanism rationalizes both results: the benefits of cost-reducing technology increase with plant output (e.g., Gilbert (2006)). We therefore suspect that more demand and less competition positively affect technology adoption for the simple reason of increasing plant output. Other mechanisms, such as preemption with adoption and strategic delay with retirement, might also affect technology choices.

Our research builds on a large empirical literature that uses reduced-form techniques to examine the determinants of technology adoption, including the aforementioned induced innovation articles. Earlier research focused more on the role of market concentration and firm size (e.g., Oster (1982); Hannan and McDowell (1984); Rose and Joskow (1990); Karshenas and Stoneman (1993); Colombo and Mosconi (1995)). The results on concentration are mixed, perhaps because modern econometric techniques often are not employed to establish causality, or because mechanisms differ across markets and technologies. More robust support is found for larger firms being more likely to adopt new technology—consistent with our conjecture that demand and competition matter in the cement industry because they affect equilibrium output. Relative to this literature overall, our research is distinguished by the richness of the empirical setting, which allows for a more complete analysis.

Our reduced-form approach also complements research that applies structural methodologies to study dynamic firm choices. Consider Fowlie et al. (2016), which estimates a model of the cement industry in which plants make capacity and exit decisions. Simulations indicate that market-based regulation of carbon (e.g., carbon taxes) would induce exit and capacity reductions, and that regulatory design affects the magnitudes of these effects. These are the sorts of nuanced results that structural methodologies are uniquely able to deliver. However, as is common with structural research, a number simplifying assumptions are maintained to reduce computational burden. From our perspective, one important simplification is that the model does not incorporate efficiency-improving technology adoption, a margin of adjustment that our reduced-form regressions reveal as important. The reduced-form approach allows us to quantify the impact of a number of different drivers of adoption without imposing strong restrictions on firm behavior; moreover, our findings may be helpful in motivating future structural research which could incorporate technology adoption.

The paper proceeds as follows. We provide some background on the portland cement industry in Section 2, and also detail our data sources. We describe the empirical model and discuss identification in Section 3. We then define the regressors and instruments in Section 4, and provide the empirical results in Section 5. Finally, Section 6 discuss the theoretical mechanisms that are consistent with the empirical results, and Section 7 concludes.

2 The Portland Cement Industry

2.1 Institutional Details

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 technology 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, design and installation costs are large: publicly-available estimates place the total cost of building a modern cement plant at around \$800 million.[5]

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.[6] 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.[7]

Table 2 provides average fuel costs among kilns in each technology class. Statistics are again reported at five-year increments over the sample period. Fuel costs depend on 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 A. Comparing across columns, fuel costs of precalciner kilns are low relative to those of wet kilns and long dry kilns. Within each

[5]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.

[6]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.

[7]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*.

column, fuel costs are somewhat lower in the 1990s due to favorable fossil fuel prices. The final column provides the national average price of 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 (e.g., 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 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

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 cement. Fuel costs are based on authors' calculations as detailed in Appendix A. Prices are obtained from the USGS *Minerals Yearbook*. All statistics are in real 2010 dollars per metric tonne of cement output.

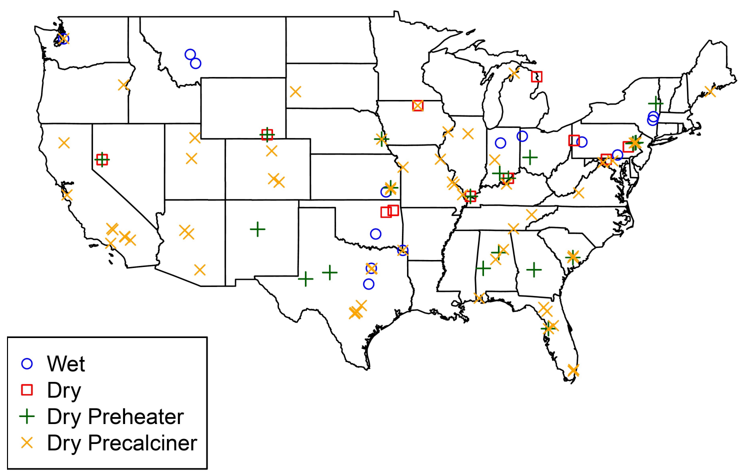

Figure 1: Portland Cement Plants in the Contiguous United States, in 2010

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.

2.2 Data 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

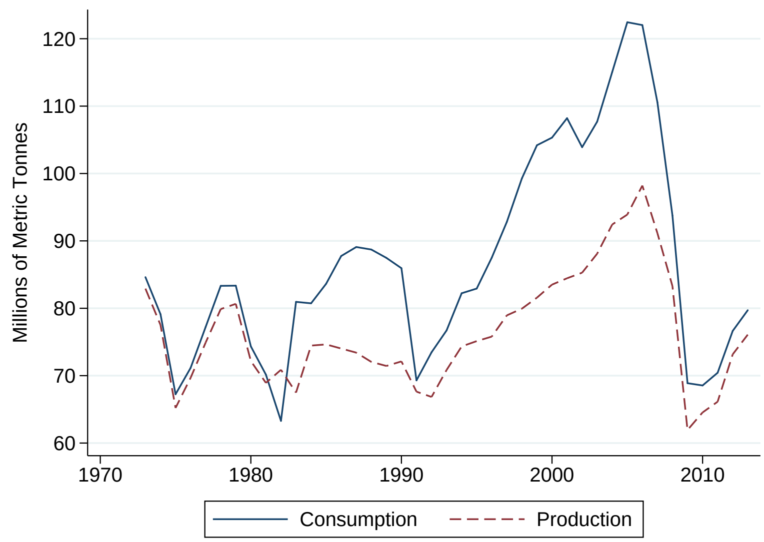

Figure 2: Consumption and Production in the United States, 1973-2013

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*.[8]

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 the measurement error associated with imputing withheld state-level data. We obtain retail

[8]We thank Mark Chicu for making these data available. See Chicu (2012) for details on the data.

gasoline prices from the EIA's *Monthly Energy Review*.[9]

We use county-level data on construction employment and building permits from the Census Bureau to account for demand-side fluctuations.[10] 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.[11] 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.[12] 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.

3 Empirical Model

3.1 Technology Choice

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

[9]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.

[10]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.

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

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

[13]Multiple equilibria may be present in the first stage of the game if, for example, more than one plant would prefer to adopt, but only if competitors do not adopt. This can lead to coherency problems in the statistical model. Ciliberto and Tamer (2009) show that inequality constraints allow for robust inference. We are unsure that the benefits of such methodological complication justify the costs in our application.

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 adoption 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 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 the (ζ_t, χ_t) terms.

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. Under the assumption that $(\epsilon^A, \epsilon^0, \epsilon^S)$ have a multivariate normal distribution, the model can be estimated using multinomial probit regression. As we develop below, control functions can be incorporated to obtain consistency in the presence of endogenous regressors.

3.2 Specification

The explanatory variables include fuel costs, the number of nearby competitors, and local demand conditions. Economic intuition and the institutional details of the industry suggest these are the natural arguments in the $b(\cdot;\theta)$ and $\pi(\cdot;\theta)$ functions. To provide a formalization, we examine a model of Cournot competition in which firms produce an undifferentiated product in some local market. Let there be $n = 1, \ldots, N$ firms, of which some number $L \geq 0$

produce with the marginal cost of c_1 while the remaining $N - L$ firms with the marginal cost $c_0 \equiv c_1 + \Delta c$ for $\Delta c > 0$. The low cost firms can be conceptualized as having adopted precalciner technology; the high cost firms as having not.

We assume a linear demand curve with unit slope for simplicity. Prices are determined according to the schedule $P(Q) = a - Q$ where $a > c_0$, $Q = \sum_{n=1}^{N} q_n$, and q_n is the quantity of firm n. Each firm selects its q_n to maximize profit conditional on its competitors' quantities. Standard solution techniques provide that the equilibrium quantities and markups of adopters ($c_n = c_1$) and non-adopters ($c_n = c_0$) are given by:

$$q^*(c_n; a, N) = P^* - c_n = \frac{a - c_n + N(\overline{c} - c_n)}{(N+1)} \tag{4}$$

in which $\overline{c} \equiv \frac{Lc_1 + (N-L)c_0}{N}$ is the average marginal cost.

Within the context of the empirical model, the technology choice of any non-adopter depends on: (i) the profit it would earn if it maintains its technology; and (ii) the increase in profit it would obtain if it adopts precalciner technology. Letting π_0^* and π_1^* denote the profit of adopters and non-adopters in Cournot equilibrium indicates:

$$\pi_0^*(N, a, c_1, c_0) = \left(\frac{a - c_0 + N(\overline{c} - c_0)}{(N+1)} \right)^2 \tag{5}$$

Defining the benefit of adoption as $b \equiv \pi_1 - \pi_0$ further indicates:

$$b(N, a, c_1, c_0) \;\; = \;\; \left(1 + \frac{N-1}{N+1} \right) q^*(\widehat{c}; a, N) \Delta c \tag{6}$$

in which $\widehat{c} = \frac{1}{2}(c_0 + c_1)$ is the midpoint between high and low marginal costs. The latter equation obtains with an application of the envelop theorem and a few lines of algebra.

In the empirical implementation, we define variables to reflect the observed spatial differentiation (e.g., see Figure 1), rather than adhering strictly to Cournot. Nonetheless, equations (5) and (6) motivate our focus on fuel costs, the number of nearby competitors, and local demand conditions. In principle, we could seek to differentiate between fuel costs (c_0), which is important in the profit function, and the change in fuel costs (Δc), which is important in the benefits function. Empirically the two variables are highly correlated with each other, and also with average costs ($\overline{c}$), so we focus on fuel costs exclusively.

3.3 Identification

We use the two-step approach of Rivers and Vuong (1988) to account for potential endogeneity in the number of nearby competitors. In the first step, the number of competitors is regressed on the exogenous variables and at least one excluded instrument. The residuals from the first step regression are then included in the second step Probit model, and act as a control function that absorbs confounding variation and allows for causal inference.[14]

The stochastic properties of the unobserved terms affect the validity of candidate instruments. We examine three stylized variance structures and discuss implications for identification. Each incorporates spatial and inter-temporal correlations, which together generate a connection between the unobserved shocks of a plant and the previous adoption/retirement decisions of its competitors. To start, and focusing on the adoption equation for simplicity, 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 are as follows:

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; instruments are not required.

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 induce 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 $T > S$.

[14]We discuss the econometric details in Appendix B.

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.

We explore each of these identification strategies in estimation, with a focus on the use of lagged exogenous and lagged endogenous regressors as instruments. The preceding analysis suggests lagged exogenous regressors allow for consistent estimation under weaker conditions. Still, lagged endogenous regressors may be preferable to the extent that: (i) they are highly relevant; and (ii) any imperfection is small (DiTraglia (2016)). However, it is unnecessary to form strong theoretical priors because similar results are obtained.

4 Variables and Summary Statistics

4.1 Regressors

Fuel Costs: 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 A. 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 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.[15]

Local 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.

Other Variables: We control for kiln age and kiln capacity. We also 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 strong effects on domestic 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.[16]

[15] 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)).

[16] The purpose of the import control variables is to distinguish those plants that are relatively proximate

4.2 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 step 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 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 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.
- We also consider lags of import availability as candidate instruments; imports can be interpreted as shifting the residual demand curve for domestic cement. We exploit the relevant USGS data back to 1958, which allows for 15-year lags on the import regressors. Because we use a simple cut-off rule to define when ports become active, we supplement with 10-year and 5-year lags.

Finally, we consider the number of commercial limestone quarries located within a 400

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.

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

[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.

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.

distance (miles $\times$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 would 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 and thus may soak up any confounding variation.

4.3 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 coeffi-

[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 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.

cients are relatively low.[20] Appendix Figure C.1 provides decadal histograms for the count of nearby competitors. Cross-sectional variation is due to dispersion in plant locations, while inter-temporal 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 may not affect local competition much due to antitrust oversight.[21]

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 step regression. To start, a test for whether the instruments are jointly significant in the first step generates an $F-$Statistic of 569. The residuals from the first step 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 step residuals produce a positive and significant coefficient in the precalciner technology adoption equation, consistent with unobserved regional shocks affecting both

[20] 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.

[21] Unfortunately it is difficult to say more about the extent of localized market power without placing more structure on the competitive game. The matter is a focus of an ongoing research project by the authors.

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)
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

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 kiln age, kiln capacity, and 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.

adoption and the number of competitors. By contrast, there is little support for endogeneity in the incumbent technology retirement equation.

The coefficient on fuel costs is positive and statistically significant in both the adoption and shutdown equations. 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 raises the probabilities of adoption and retirement by 1.90 and 0.28 percent, respectively, in any given year. The cumulative effect is substantial: projected over decade, the results imply that a persistent one percent increase in fuel costs raises the adoption probability by 17.46 percent and the retirement probability by 2.77 percent. The effects are consistent with higher fuel costs both: (i) increasing the benefits of investing in fuel-efficient technology; and (ii) decreasing the profitability of production.

Next, the coefficient on competition 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. In terms of magnitudes, the regression coefficients imply that competition elasticities of -1.77 percent for adoption and 0.77 percent for retirement, and construction elasticities of 1.56 percent for adoption and -0.83 percent for retirement. These effects become economically large when projected over multiple years. A single mechanism may generate all of these effects: firms may be more likely to invest in lowering marginal costs, and less likely to exit, if equilibrium output is greater (Section 6).

Figure 3 plots the effect of a one standard deviation increase in fuel costs on adoption probabilities, for different levels of competition (Panel A) and construction activity (Panel B). All other regressors are held fixed at their mean. The results suggest that plants are more responsive to fuel costs if they face fewer competitors and advantageous demand conditions. For example, the fuel cost increase raises the probability that a plant with six nearby competitors (the 10th percentile) adopts by roughly 2.5 percentage points. This is large relative to the unconditional adoption probability of 1.8 percent. By contrast, adoption for a plant with 37 nearby competitors (the 90th percentile) is virtually unaffected by fuel costs. These results suggest that the ability to recoup the sunk costs of technology adoption may play an important role in determining equilibrium response to changes in fuel costs.

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. The relevant coefficient is negative in 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. The coefficients on the first step 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.[22]

[22]If the 20-year competition lag is an imperfect instrument, in the sense that it is *less* correlated with the error term than unlagged competition, then the estimated coefficient provides an upper bound on the

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)
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 kiln age, kiln capacity, and 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-step 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.

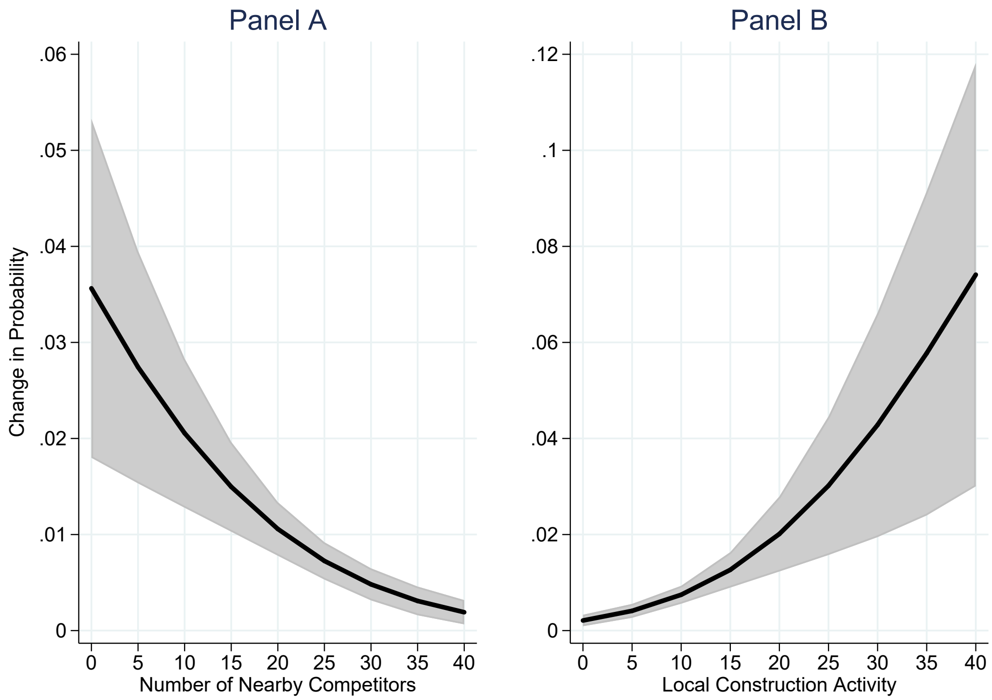

Figure 3: The Effect of Fuel Costs on Precalciner Adoption

Notes: The figures plot the change in precalciner adoption probabilities due to a one standard deviation increase in fuel costs of \$9.63.Results are allowed to with the number of competitors (Panel A) and local construction activity (Panel B). Other explanatory variables are held at their respective means. The shaded regions provide 95% confidence intervals.

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.[23] 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.

population parameter (Nevo and Rosen (2012)).

[23] This entails two first-step 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)			
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 kiln age, kiln capacity, the distance to active Top 5 and Top 10 customs districts, and the residual(s) from the first step regression(s). The first step 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.

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 C.1 and C.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. 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 Mechanisms

6.1 Fuel Costs and Technology Adoption

A substantial theoretical literature on induced innovation explores the conditions under which an increase in the price of a variable factor of production would induce firms to economize on that factor via the adoption of efficiency-improving technology (e.g., Hicks (1932); Nordhaus (1973); Acemoglu (2002, 2007)). The key insight of the literature is that the effect of factor prices depend on firms' ability to substitute among the variable factors of production. For intuition, consider a firm which uses two variable factors in production: labor and materials. If production is Leontief in the variable factors then firms benefit more from labor-saving capital investments when wages are high.[24] However, if instead materials can readily substitute for labor in production, then higher wages can reduce the benefits of labor-saving capital investments, as less labor is employed and any efficiency-improvements affect fewer workers.

In our empirical application, we find that higher fuel costs are associated with greater adoption rates for fuel-efficient precalciner technology. We interpret the finding as consistent with the theoretical literature on induced innovation because, 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. We expect the result would generalize to other settings in which the substitutability of variable factors is weak. Interestingly, empirical evidence from other settings also suggests 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)).

6.2 The Effects of Competition and Demand

The empirical results indicate that plants with more nearby competitors are less likely to adopt precalciner technology and more likely to retire kilns; further, construction activity has the opposite effects of increasing adoption and decreasing retirement. We find one particular mechanism compelling because it provides a simple explanation for all of the effects. Consider that the profit effect of a variable cost reduction increases with the amount of output (Gilbert (2006)).[25] Thus, holding demand fixed, firms with fewer competitors may benefit more from cost-reducing technology because they produce more in equilibrium. Similarly, holding competition fixed, advantageous demand conditions allow firms to benefit more from cost-reducing technology. At the same time, in standard Bertrand or Cournot models, profit increases with demand and decreases with the number of competitors, in part due to the effects on equilibrium output. Considering these arguments together, a single

[24]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)).

[25]This connection features in a number of articles (e.g., Dasgupta and Stiglitz (1980); Flaherty (1980); Shaked and Sutton (1987); Klepper (1996)).

mechanism generates the associations that we obtain in the cement application.

If this interpretation of the results is correct then there are interesting policy implications. Take the case of merger review: we can analyze whether a merger between two nearby competitors increase the likelihood of precalciner adoption. At first glance, our empirical results suggest an answer in the affirmative, as the merger would reduce the number of competitors. However, consideration of the theoretical mechanism may flip this prediction if (as seems reasonable) the merger does not allow adoption costs to be economized. The reason is that in standard models of Cournot or Bertrand competition, merging firms find it profitable to reduce output, absent efficiencies. This has the effect of lowering the benefits of cost-reducing technology, as any cost savings would be spread across fewer units.

The necessary caveat is that a number of other mechanisms may be in play, and our empirical analysis is not designed to assess the relative importance of these. For example, 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)).[26] The relationship between competition and adoption in such preemption games 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)). Further, Chicu (2012) finds some support for the role of preemption in the cement industry.

7 Conclusion

This paper contributes an empirical study of technology adoption in the cement industry. The technology in question—the precalciner kiln—improves the fuel efficiency of production. The pace of adoption, which started in the early 1970s and continues to this day, has been uneven, varying both over time and across geographic regions. This affords a distinctly good opportunity to explore the market environments that facilitate adoption, as it is possible to correlate adoption with changing cost, demand, and competitive conditions. Reduced-form analyses suggest that the likelihood of technology adoption increases with fuel costs and the strength of demand, and decreases with the number of nearby competitors. These results connect to the underlying mechanisms that give rise technology adoption, including the induced-innovation hypothesis of Hicks (1932).

[26]Similarly, with regard to the kiln retirement decision, Fudenberg and Tirole (1986) examine a "war of attrition" in which firms strategically delay exit in an attempt to outlast their competitors.

The reduced-form approach we employ does not impose (much) structure on the data, which has both advantages and disadvantages. The latter suggests paths for future research. For instance, our results suggest that higher fuel prices lead some plants to install fuel-efficient kilns and others to shutter kilns, but do not inform the adjustment path. These dynamics are both interesting and important: competitive conditions soften as plants shutter kilns, which makes it easier for remaining plants to justify upfront adoption costs; yet competitive conditions intensify as plants adopt technology, which may induce other plants to shutter kilns. How these feedback effects play out in equilibrium remains an intriguing question that could be addressed by matching the data to a dynamic economic model. Another benefit of structure is that welfare effects could be examined. We are curious particularly about how closely the timing of observed adoption aligns with the social optimum. We hope the research presented here informs future attempts to address these topics.

References

Acemoglu, Daron, "Direted Technical Change," *Review of Economic Studies*, 2002, *69* (4), 781–809.

_ , "Equilibrium Bias of Technology," *Econometrica*, 2007, *75* (5), 1371–1409.

Aghion, Philippe and Jean Tirole, "The Management of Innovation," *Quarterly Journal of Economics*, 1994, *109*, 1185–1209.

_ **, Antoine Dechezlepretre, David Hemous, Ralf Martin, and John Van Reenen**, "Carbon Taxes, Path Dependency and Directed Technical Change: Evidence from the Auto Industry," *Journal of Political Economy*, 2016, *124* (1), 1–51.

Argenziano, Rossella and Philipp Schmidt-Dengler, "Competition, Timing of Entry, and Welfare in a Preemption Game," *Economics Letters*, 2013, *120* (3), 509–512.

_ **and** _ , "Clustering in N-Player Preemption Games," *Journal of the European Economic Association*, 2014, *12* (2), 368–396.

Baldwin, William L. and John T. Scott, "Market Structure and Technological Change," 1987. In Lesourne and Sonnenschein (Eds.), *Fundamentals of Pure and Applied Economics*. Chur, Switzerland, and London: Harwook Academic Publishers.

Berry, Steven, "Estimation of a Model of Entry in the Airline Industry," *Econometrica*, 1992, *60*, 889–917.

Bouis, Romain, Kuno J.M. Huisman, and Peter M. Kort, "Investment in Oligolopy under Uncertainty: The Accordian Effect," *International Journal of Industrial Organization*, 2009, *27*, 320–331.

Bresnahan, Timothy F. and Peter C. Reiss, "Entry and Competition in Concentrated Industries," *Journal of Political Economy*, 1991, *99* (5), 977–1009.

Busse, Meghan R., Christopher R. Knittel, and Florian Zettelmeyer, "Are Consumers Myopic? Evidence from New and Used Car Purchases," *American Economic Review*, 2013, *103* (1), 220–256.

Carbon War Room, "Gigatron Analysis of the Cement Industry," 2011.

Chicu, Mark, "Dynamic Investment and Deterrence in the U.S. Cement Industry," 2012. Job Market Paper, Northwestern University.

Ciliberto, Federico and Elie Tamer, "Market Structure and Multiple Equilibria in Airline Markets," *Econometrica*, 2009, *77*, 1791–1828.

Cohen, Wesley M., "Empirical Studies of Innovative Activity," 1995. In Stoneman, P. (Ed.), *Handbook of the Economics of Innovation and Technical Change*. Oxford: Basil Blackwell.

_ , "Fifty Years of Empirical Studies of Innovative Activity and Performance," 2010. In Arrow, K.J. and Intriligator, M.D. (eds), *Handbook of the Economics of Innovation*, Volume 01. Elsevier.

_ **and Richard C. Levin**, "Empirical Studies of Innovation and Market Structure," 1989. In Schmalensee, R. and Willig, R. (Eds.), *Handbook of Industrial Organization*. Amsterdam: North-Holland.

Colombo, Massimo G. and Rocco Mosconi, "Complementarity and Cumulative Learning Effects in the Early Diffusion of Multiple Technologies," *Journal of Industrial Economics*, 1995, *43*, 13–48.

Dasgupta, Partha and Joseph E. Stiglitz, "Industrial Structure and the Nature of Innovative Activity," *The Economic Journal*, 1980, *90* (358), 266–293.

DiTraglia, Francis, "Using Invalid Instruments on Purpose: Focused Moment Selection and Averaging for GMM," *Journal of Econometrics*, 2016, *195* (2), 187–208.

Fine, J. P. and R. J. Gray, "A Proportional Hazards Model for the Subdistribution of a Competing Risk," *Journal of the American Statistical Association*, 1999, *94*, 496–509.

Flaherty, M. Therese, "Industry Structure and Cost-Reducing Investment," *Econometrica*, 1980, *48* (5), 1187–1209.

Fowlie, Meredith, Mar Reguant, and Stephen P. Ryan, "Market-Based Emissions Regulation and Industry Dynamics," *Journal of Political Economy*, 2016, *124* (1), 249–302.

Fudenberg, Drew and Jean Tirole, "Preemption and Rent Equalization in the Adoption of New Technology," *Review of Economic Studies*, 1985, *52* (3), 383–401.

_ **and** _ , “A Theory of Exit in Duopoly,” *Econometrica*, 1986, *54* (4), 943–960.

Gilbert, Richard, “Looking for Mr. Schumpeter: Where Are We in the Competition-Innovation Debate?,” 2006. In Jaffe, A.B., Lerner, J. and Stern, S. (Eds.), *Innovation Policy and the Economy.* Boston: The MIT Press, 159-215.

Goettler, Ronald and Brett Gordon, “Does AMD Spur Intel to Innovate More?,” *Journal of Political Economy*, 2011, *119* (6), 1141–1200. Mimeo.

Gowrisankaran, Gautum and Joanna Stavins, “Network Externalities and Technology Adoption: Lessons from Electronic Payments,” *RAND Journal of Economics*, 2004, *35* (2), 260–276.

Hanlon, W. Walker, “Necessity is the Mother of Invention: Input Supplies and Directed Technical Change,” *Econometrica*, 2015, *83* (1), 67–100.

Hannan, Timothy H. and John M. McDowell, “The Determinants of Technology Adoption: The Case of the Banking Firm,” *RAND Journal of Economics*, 1984, *15* (3), 328–335.

Hassler, John, Per Krusnell, and Conny Olovsson, “Energy-Saving Technical Change,” 2011. NBER Working Paper no. 18456, NBER, Cambridge, MA.

Hausman, Jerry A., “Specification Tests in Econometrics,” *Econometrica*, 1978, *46*, 1251–1271.

Hicks, John R., 1932. *The Theory of Wages.* London: Macmillan.

Igami, Mitsuru, “Estimating the Innovator’s Dilemma: Structural Analysis of Creative Destruction in the Hard Disk Drive Industry, 1981-1998,” *Journal of Political Economy*, 2017, *125* (3), 798–847.

_ **and Kosuke Uetake**, “Mergers, Innovation, and Entry-Exit Dynamics: The Consolidation of the Hard Disk Drive Industry, 1996-2015,” *Review of Economic Studies*, 2019. Forthcoming.

Kamien, Morton I. and Nancy L. Schwartz, *Market Structure and Innovation*, Cambridge: Cambridge University Press, 1982.

Karshenas, Massoud and Paul L. Stoneman, "Rank, Stock, Order, and Epidemic Effects in the Diffusion of New Process Technologies: An Empirical Model," *RAND Journal of Economics*, 1993, *24* (4), 203–528.

Klepper, Steven, "Entry, Exit, Growth, and Innovation over the Product Life Cycle," *American Economic Review*, 1996, *86* (3), 562–583.

Langer, Ashley and Derek Lemoine, "Designing Dynamic Subsidies to Spur Adoption of New Technologies," 2018. NBER Working Paper No. 24310.

_ and Nathan H. Miller, "Automakers' Short-Run Responses to Changing Gasoline Prices," *Review of Economics and Statistics*, 2013, *95* (4), 1198–1211.

Linn, Joshua, "Energy Prices and the Adoption of Energy-Saving Technology," *The Economic Journal*, 2008, *118*, 1986–2012.

Mela, Carl F. and Praveen K. Kopalle, "The Impact of Collinearity on Regression Analysis: The Asymmetric Effect of Negative and Positive Correlations," *Applied Economics*, 2002, *34*, 667–677.

Miller, Nathan H. and Matthew Osborne, "Spatial Differentiation and Price Discrimination in the Cement Industry: Evidence from a Structural Model," *RAND Journal of Economics*, 2014, *45* (2), 221–247.

_ , _ , and Gloria Sheu, "Pass-Through in a Concentrated Industry: Empirical Evidence and Regulatory Implications," *RAND Journal of Economics*, 2017, *48* (1), 69–93.

Nevo, Aviv and Adam Rosen, "Identification with Imperfect Instruments," *Review of Economics and Statistics*, 2012, *94* (3), 659–671.

Newell, Richard G., Adam B. Jaffe, and Robert N. Stavins, "The Induced Innovation Hypothesis and Energy-Saving Technological Change," *Quarterly Journal of Economics*, 1999, *114* (3), 941–975.

Nordhaus, W, "Some Skeptical Thoughts on the Theory of Induced Innovation," *Quarterly Journal of Economics*, 1973, *87* (2), 208–219.

Oss, Henrik G. Van and A.C. Padovani, "Cement Manufacture and the Environment, Part II: Environmental Challenges and Opportunities," *Journal of Industrial Ecology*, 2003, *7* (1), 93–126.

Oster, Sharon, "The Diffusion of Innovation among Steel Firms: The Basic Oxygen Furnace," *The Bell Journal of Economics*, 1982, *13* (1), 45–56.

Perez-Saiz, Hector, "Building New Plant or Entering by Acquisition? Firm Heterogeneity and Entry Barriers in the U.S. Cement Industry," *RAND Journal of Economics*, 2015, *46* (3), 625–649.

Popp, David, "Induced Innovation and Energy Prices," *American Economic Review*, 2002, *92* (1), 160–181.

Rivers, Douglas and Quang H. Vuong, "Limited Information Estimators and Exogeneity TTest for Simultaneous Probit Models," *Journal of Econometrics*, 1988, *39*, 347–366.

Rose, Nancy and Paul L. Joskow, "The Diffusion of New Technologies: Evidence from the Electric Utility Industry," *RAND Journal of Economics*, 1990, *21* (3), 354–373.

Ryan, Stephen, "The Costs of Environmental Regulation in a Concentrated Industry," *Econometrica*, 2012, *80* (3), 1019–1062.

Schmidt-Dengler, Philip, "The Timing of New Technology Adoption: The Case of MRI," 2006. Working Paper.

Shaked, Avner and John Sutton, "Product Differentiation and Industrial Structure," *Journal of Industrial Economics*, 1987, *36* (2), 131–146.

Shapiro, Carl, "Competition and Innovation: Did Arrow Hit the Bull's Eye?," 2012. In Josh Lerner and Scott Stern (eds), *The Rate and Direction of Economic Activity Revisited*.

Syverson, Chad, "Market Structure and Productivity: A Concrete Example," *Journal of Political Economy*, 2004, *112*, 1181–1222.

Toivanen, Otto and Michael Waterson, "Market Structure and Entry: Where's the Beef?," *RAND Journal of Economics*, 2005, *36* (3), 680–699.

Van Oss, Hendrik G., "Background Facts and Issues Concerning Cement and Cement Data," 2005. Open-File Report 2005-1152, U.S. Department of the Interior, U.S. Geological Survey.

Appendices for Online Publication

A 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 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 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 A.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

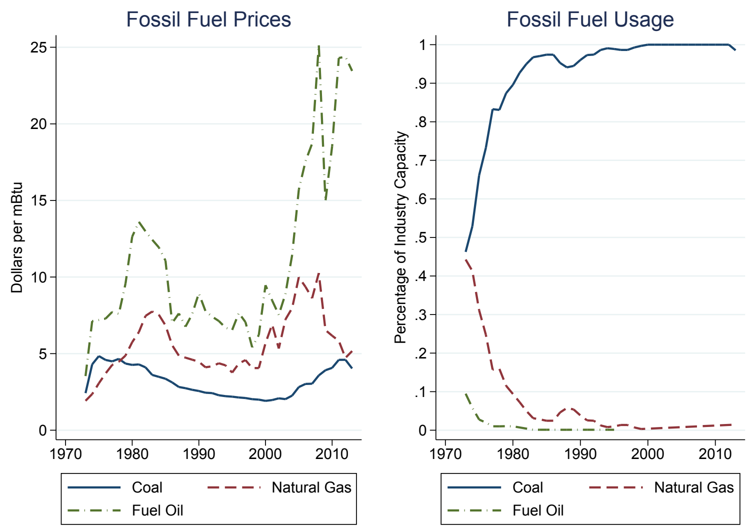

Figure A.1: Fossil Fuel Prices and Usage 1973-2013

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 sensitive to the adjustment.

B 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:

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

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:

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

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,

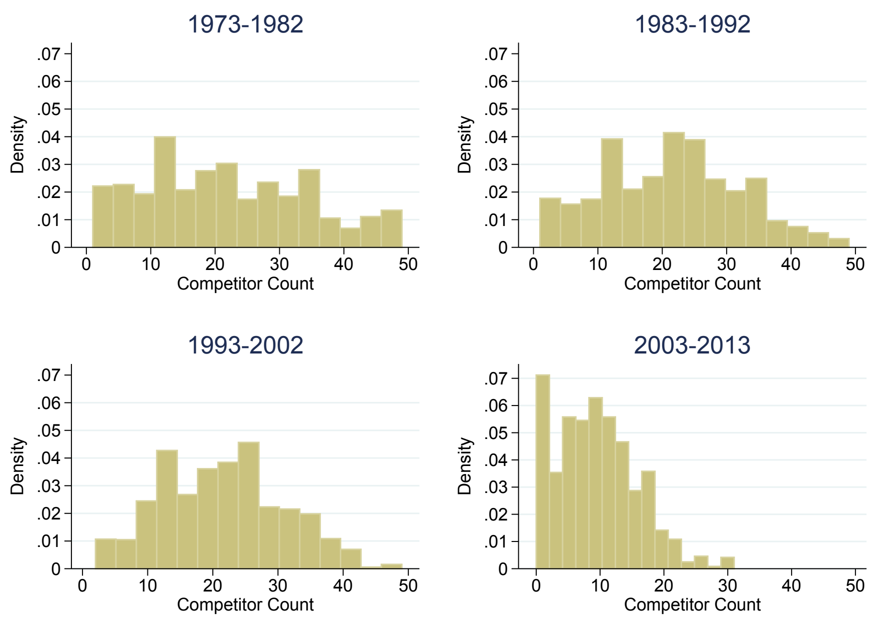

Figure C.1: Count of Competitors within a Distance of 400 by Decade

conditional on X_{it}, with the finite positive definite covariance matrix:

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

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 steps:

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.

C Additional Figures and Tables

Table C.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)
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 kiln age, kiln capacity, and 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 C.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)			
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 kiln age, kiln capacity, the distance to active Top 5 and Top 10 customs districts, and the residual(s) from the first step regression(s). The first step 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.