# Who Bears the Burden of Cap-and-Trade? Evidence from an Emissions-Intensive Industry*

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**Abstract**

There is ongoing debate about applying market-based regulation to greenhouse gas emissions. An important question is how revenues should be disbursed among market participants. We estimate the effect of fuel costs on prices in the portland cement industry, which globally accounts for five percent of $CO_2$ emissions. Robust statistical evidence supports that industry-wide cost changes are more than completely passed through to prices. Our estimates imply that 85% of the burden of regulation would accrue downstream, and that cement manufacturers could be fully compensated with disbursements representing only 22% of the revenues levied through regulation.

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# 1 Introduction

There is ongoing political debate about applying market-based regulation to greenhouse gas emissions. One of the more serious points of contention relates to how government revenues obtained through regulation should be disbursed among market participants. Multiple claimants exist. Firms subject to regulation experience direct adverse effects because regulation increases production costs. Downstream firms and consumers experience adverse effects indirectly if higher upstream costs are transmitted through the supply-chain in the form of higher prices. In compensating market participants, regulators have imperfect information regarding the relative magnitudes of the direct and indirect effects.[1]

Market-based regulation typically is proposed in the form of an emissions trading system (i.e., "cap-and-trade" regulation), in which permits are traded at auction. Whether regulated firms are required to buy permits at auction, or whether permits are grandfathered in some fashion to incumbent producers, largely determines how market participants are compensated. The European Union, which implemented cap-and-trade regulation in 2006, only recently has required firms to purchase permits at auction. In the United States, the Waxman-Markey Bill that passed the House of Representatives in 2009 specified that 85% or more of permits initially would be grandfathered to regulated firms.[2] To our knowledge, these determinations were made without a careful treatment of the direct and indirect costs of regulation, and instead were the product of political bargaining among vested interests.

We shed light on the subject by estimating the effect of production costs on prices in an emissions-intensive industry. This cost pass-through relationship largely determines who bears the burden of market-based regulations. We base our analysis on data on market outcomes that span the contiguous United States over 1980-2010. The industry in question, portland cement, globally accounts for five percent of anthropogenic $CO_2$ emissions (Van Oss and Padovani (2003)). We apply our regression results to determine how market-based regulation would affect producer and consumer surplus. In these calculations, we account for market power and oligopoly interactions, leveraging the theoretical insights of Weyl and Fabinger (2013). The analysis has clear implications for the political economy of environmental regulation and specifically on the question of how revenues obtained from regulation

[1] Even with perfect information, the existence of deadweight loss means that typically it is impossible to fully compensate all participants if only funds obtained through regulation are used.

[2] More recent action from the Environmental Protection Agency (EPA) places the regulation of greenhouse emissions from the power sector in the hands of states. It is possible that the cap-and-trade programs used in California and New England could serve as a model for this regulation. California grandfathers 90 percent of its permits, while in New England firms must purchase permits.

should be disbursed.

Our starting point is an empirical model of oligopoly interactions in which the equilibrium price of each plant is expressed, to a linear approximation, as a function of its marginal costs and those of its competitors. The linearity of the model facilitates aggregation. We obtain a reduced-form regression equation that allows for the estimation for firm-specific pass-through rates using price data that, for data reporting purposes, are available as region-year observations. We regress the region-year prices on plant-specific fuel costs, which we aggregate in a manner that preserves the microfoundations of the model. Estimation incorporates 773 region-year observations on price and 3,445 plant-year observations on fuel costs. The obtained regression coefficients provide reasonable estimates of pass-through because fuel comprises a substantial fraction of overall variables costs and there are no viable substitutes for fuel in the production process. Empirical variation in fuel costs arises due to (i) observable heterogeneity in the fuel efficiency of plants; and (ii) fluctuations in fossil fuel prices that arise over the sample period. This variation is sufficient to obtain precise estimates of how prices respond to industry-wide cost changes.

Our primary econometric result is that industry-wide cost changes are, on average, more than completely transmitted downstream in the form of higher prices. The confidence intervals we obtain are sufficiently tight to reject the possibility that industry pass-through is substantially incomplete. This result is robust across a range of specifications and modeling choices, and indicates immediately that substantial indirect adverse effects of market-based regulation are likely to accrue downstream of cement manufacturers. That industry pass-through could exceed unity is reconciled easily with economic theory.[3] Indeed, the theoretical ambiguity on this point serves to motivate the empirical analysis.

To evaluate the effects of market-based regulation in greater detail, we combine our pass-through results with estimates of margins and demand elasticities taken from the academic literature. We focus on carbon taxation for ease of analysis. Our calculations generalize to emissions trading programs in which permits are allocated with a uniform price auction.[4] With demand elasticities and margins that fall in the middle of the feasible ranges, our pass-through estimates indicate that cement manufacturers collectively would lose $13 million in producer surplus per dollar of carbon tax. This becomes meaningful in practice. For instance, the loss is $528 million under a $40 carbon tax, compared to industry revenues

[3]As the number of firms increases in standard Cournot models, industry pass-through converges to unity from above if the market demand schedule is convex (e.g., ten Kate and Niels (2005)).

[4]These two methods of implementation are equivalent economically because they both create a single price for carbon emissions.

of roughly \$7 billion in 2012.[5] The indirect losses that accrue downstream nonetheless are much larger. Our estimates imply losses of consumer surplus of \$73 million per dollar of carbon tax, meaning that 85% of the burden of market-based regulation is distributed downstream among at least ready-mix concrete plants, construction firms, and end users. The revenue obtained per dollar of carbon tax is roughly \$60 million, based on the 2012 level of output. Thus, cement manufacturers could be fully compensated with disbursements that represent 22% of revenues levied through regulation.

These calculations embed specific assumptions on margins and demand elasticities, about which there is some uncertainty. Nevertheless, we show that the qualitative conclusion that most losses accrue downstream is robust over feasible ranges, and we provide tables that allow readers to examine alternative assumptions. We also note that our calculations assume that only domestic producers are subject to regulation. If the regulation design mitigates substitution to imported cement (i.e., "leakage"), then the loss of producer surplus would diminish and the burden of regulation would shift downstream, to an even greater extent than our calculations indicate. While our results pertain strictly to the portland cement industry, Fabra and Reguant (2014) estimate that Spanish electricity plants exhibit similarly high rates of pass-through. Thus there is an empirical basis to believe that our results may extend to other emissions-intensive sectors.

Our research is complementary to the recent article of Fowlie, Reguant, and Ryan (2014), which uses a dynamic structural model to explore the effects market-based regulation on abatement and welfare in the cement industry. We are able to address a different set of questions because our pass-through estimates allow us to identify how the burden of regulation is distributed across producers and consumers, whereas this split is largely predetermined in the structural model. Further, we determine that the constant elasticity demand schedules imposed in the structural model generate implicit industry pass-through rates that are roughly consistent with our empirical estimates. This allows us to confirm a previously untested modeling assumption that has first order implications for pass-through and the welfare effects of market-based regulation.

A substantial empirical literature on pass-through exists. Our research builds especially on those articles that examine the effects of industry-wide costs changes on prices. This work has exploited cost variation that arises from a number of factors, including exchange rates (e.g., Campa and Goldberg (2005); Gopinath, Gourinchas, Hsieh, and Li (2011)), sales

[5] Official estimates of the social cost of carbon range from \$12 to \$129 per metric tonne for the year 2020, depending on the social discount rate (Working Group on Social Cost of Carbon (2013)). We use standard methods to obtain $CO_2$ emissions per metric tonne of cement.

taxes (e.g., Barzel (1976); Poterba (1996); Besley and Rosen (1998); Marion and Muehlegger (2011)), and input prices (e.g., Borenstein, Cameron, and Gilbert (1997) Genesove and Mullin (1998); Nakamura and Zerom (2010)). That pass-through is useful for policy evaluation is underscored by recent empirical research on health care markets (e.g., Cabral, Geruso, and Mahoney (2014); Duggan, Starc, and Vabson (2014)).

Important caveats apply, and we highlight two here. First, the experimental design uses historical pass-through relationships to predict the effects of policy on future market outcomes. While we provide statistical evidence that pass-through has been reasonably stable over decades, there is no guarantee that this will continue, especially for cap-and-trade programs that increase marginal costs well above historical levels. Yet this concern should not be overly limiting. Some assumptions must be made, and the Monte Carlo evidence indicates that using pass-through to inform predictions often affords greater accuracy than simulation techniques (Miller, Remer, Ryan, and Sheu 2013). Second, our baseline calculations presume that market-based regulation affects all portland cement plants equally, reflecting the dearth of plant-specific demand elasticities in the academic literature. Nonetheless, we are able to provide some evidence that the heterogeneity of markup effects is limited. Thus, our empirical work provides little support for the notion that market-based regulation impacts substantially the distribution of producer surplus among portland cement plants.

The paper proceeds as follows. Section 2 sketches the relevant institutional details of the portland cement industry, and describes the data that support our empirical work. Section 3 contains the empirical model. Section 4 presents the estimation strategy, defines the regressors, and develops simple empirical relationships. Section 5 presents the regression results, and Section 6 uses these regressions results in an analysis of market-based $CO_2$ regulation. Section 7 concludes.

# 2 The Portland Cement Industry

## 2.1 Production technology

Portland cement is a finely ground dust that forms concrete when mixed with water and coarse aggregates such as sand and stone. Concrete, in turn, is an essential input to many construction and transportation projects. The production of cement involves feeding limestone and other raw materials into rotary kilns that reach peak temperatures of 1400-1450° Celsius. Plants burn fossil fuels – mostly coal and petroleum coke – to produce these extreme kiln temperatures. Emissions of $CO_2$ range from 0.86 to 1.05 metric tonnes per metric tonne

Table 1: Plants and Kilns in the Cement Industry

| | Number of Plants | Number of Kilns | Total Capacity | Capacity Share: Wet Kilns | Long Dry Kilns | Dry with Preheater | Dry with Precalciner |
|---|---|---|---|---|---|---|---|
| 1980 | 142 | 319 | 77,100 | 49% | 27% | 16% | 8% |
| 1985 | 126 | 250 | 77,046 | 36% | 24% | 16% | 24% |
| 1990 | 109 | 208 | 72,883 | 32% | 23% | 19% | 27% |
| 1995 | 107 | 203 | 74,655 | 28% | 22% | 19% | 30% |
| 2000 | 107 | 196 | 82,758 | 24% | 20% | 17% | 39% |
| 2005 | 105 | 181 | 93,968 | 15% | 14% | 17% | 54% |
| 2010 | 101 | 153 | 103,482 | 8% | 9% | 14% | 70% |

Notes: Total capacity is in thousands of metric tonnes. All data are for the contiguous United States and are obtained from the PCA Plant Information Survey.

of cement, depending on the kiln technology. Of this, roughly 0.51 metric tonnes arise from the chemical conversion of calcium carbonate into lime and carbon dioxide. The combustion of fossil fuels accounts for most of the remainder.[6]

Capital investments over the last forty years have increased the industry's capacity and productive efficiency. Table 1 provides snapshots of the industry over 1980-2010. The number of plants falls from 142 to 101 and the number of kilns falls from 319 to 151. Total industry capacity increases from 77 million metric tonnes per year to more than 100 million tonnes as older wet kilns are retired and replaced with higher-capacity dry kilns. Today most cement is produced in dry kilns equipped with gas-suspension preheaters and precalciners.[7] This auxiliary equipment uses exhaust gases from the kiln to preheat the raw material. This allows calcination, one of the major chemical reactions required in clinker production, to occur partially or fully outside the rotary kiln. The process is supplemented with an additional combustion chamber if a precalciner is present.

[6] The $CO_2$ emissions rates are 1.05, 0.98, 0.87, and 0.86 for wet, long dry, dry preheater and dry precalciner kilns, respectively. Our calculations are consistent with the Cement $CO_2$ Protocol, developed by leading cement firms for the Cement Sustainability Initiative of the World Business Council for Sustainable Development. We scale this up the impact of converting calcium carbonate to 0.525, in order to account for $CO_2$ emitted during the calcination of cement kiln dust. We add to this the $CO_2$ emitted from the burning of coal, based on an emissions factor of 0.095 metric tonnes per mBtu and the kiln energy requirements reported in Appendix A. We then scale down total emission by five percent to convert units of clinker to units of cement. Similar calculations underly the analysis in Fowlie, Reguant, and Ryan (2014).

[7] For wet kilns, the raw materials are wet-ground to form a slurry, but for dry kilns the raw materials are dry-ground to form a powder. More fuel is required in the wet process to evaporate the added water. There is no systematic relationship between the kiln technology and the primary fossil fuel use to fire the kiln. Adjustment costs limit the profitability of switching fuels in response to changing relative prices.

Cement manufacturers sell predominately to ready-mix concrete producers and large construction firms. Contracts are privately negotiated and relatively short term (often around one year in duration). They specify a free-on-board price at which cement can be obtained from the plant, along with discounts that reflect the ability of the customer to source cement from competing manufacturers.[8] Most cement is trucked directly from the plant to the customer, though some cement is transported by barge or rail first to distribution terminals and only then trucked to customers. Transportation accounts for a substantial portion of purchasers' total acquisition costs, because portland cement is inexpensive relative to its weight. Miller and Osborne (2014) estimate transportation costs to be \$0.46 per tonne-mile, and determine that these costs create market power for spatially differentiated plants. Accordingly, the academic literature commonly models the industry using a number of geographically distinct local markets (e.g., Ryan (2012); Fowlie, Reguant, and Ryan (2014)). Aside from these spatial considerations, cement is viewed as a commodity.

## 2.2 Data sources

We draw data from numerous sources. Chief among these is the *Minerals Yearbook*, an annual publication of the Unites States Geological Survey (USGS), which summarizes a census of portland cement plants.[9] The price data are aggregated to protect the confidentiality of census respondents, and reflect the average free-on-board price obtained by plants located in distinct geographic regions. The USGS frequently redraws boundaries to ensure that each region includes at least three independently owned plants. This "rule of three" prevents any one firm from backward engineering the business data of its competitors. Thus, the regions are not intended to approximate local markets in any economic sense. The *Minerals Yearbook* also contains aggregated production and consumption data.

Our second source of data is the *Plant Information Survey*, an annual publication of the Portland Cement Association (PCA), which provides information on the plants and kilns in the United States. We obtain the location, owner, and primary fuel of each plant, as well as the annual capacity of each rotary kiln and the type of technology employed. In total, there are 3,494 plant-year observations over 1980-2010, of which 3,445 are active and 49 are idle. We also make use of the PCA's *U.S. and Canadian Portland Cement Labor-Energy Input Survey*, which is published intermittently and contains information on the energy

[8]While some cement manufacturers are vertically integrated into ready-mix concrete markets, Syverson and Hortaçsu (2007) show that this has little impact on plant- and market-level outcomes.

[9]The census response rate is typically well over 90 percent (e.g., 95 percent in 2003), and USGS staff imputes missing values for the few non-respondents based on historical and cross-sectional information.

requirements of clinker production and the energy content of fossil fuels burned in kilns. We have data for 1974-1979, 1990, 2000, and 2010.

We obtain data on 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 1980-1984 using historical data on national average free-on-board prices of bituminous coal published in the 2008 *Annual Energy Review* of the EIA. We provide details on backcasting in Appendix A. We obtain national data on the 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.[10] We obtain data on the national average price of unleaded gasoline over 1980-2010 from the Bureau of Labor Statistics, in order to better model the spatial configuration of the industry. We convert this series to an index that equals one in 2000. Lastly, to help control for demand, we obtain county-level data from the Census Bureau on construction employees and building permits. We provide details on data sources and related topics in Appendix A.

# 3 The Empirical Model

We develop a general empirical model that allows us to relate region-level prices to firm-specific costs. We take as given that single-plant cement firms set free-on-board prices according to some pricing function that can be conceptualized as the equilibrium strategy for a consumer demand schedule and a competitive game. The product of each cement plant is differentiated due to geographic dispersion and transportation costs. Let there be $j = 1 \dots J_t$ cement plants in period $t$ and let $c_{jt}$ denote fuel costs per unit of output. A linear approximation to the equilibrium price of plant $j$ is given by

$$p_{jt} = \rho_{jjt} c_{jt} + \sum_{k \neq j} \rho_{jkt} c_{kt} + x'_{jt}\gamma + \mu_j + \tau_t + \epsilon_{jt}, \tag{1}$$

where $x_{jt}$ includes observable demand and cost variables, $\mu_j$ and $\tau_t$ are plant and year fixed effects, respectively, and $\epsilon_{jt}$ is a pricing residual that summarizes unobservable demand and cost conditions. The fuel cost coefficients are linear approximations to own and cross pass-

[10]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. We also obtain state-level data on fossil fuel prices. There are many missing values at that level of reporting, and we impute these as described in Appendix A. When included together in regressions, fuel cost variables based on national fossil fuel prices dominate fuel cost variables based on state-level prices. This could be a statistical artifact due to noise introduced by the imputation of missing values in the state-level data.

through. Industry pass-through is $\rho_{jt}^M = \sum_k \rho_{jkt}$. We include among the controls nearby construction employment and building permits (which account for demand), indicators for the technology of the plant and the technology of nearby competitors (which account for non-fuel cost differences between kilns), and nearby competitor capacity.

Equation (1) is quite general but cannot be estimated, even with plant-level data, because the number of pass-through terms exceeds the number of observations. We impose restrictions on pass-through in order to facilitate estimation, leveraging the reasonable assumption that cross pass-through is greater between plants that are closer competitors.[11] In particular, we construct a "distance metric" that summarizes the closeness of competition and impose that, for plants $j \neq k$, cross pass-through is given by

$$\rho_{jkt} = \begin{cases} \beta / d_{jkt} & \text{if } j \neq k \text{ and } d_{jkt} < \overline{d} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where $d_{jkt}$ is the distance metric and $\overline{d}$ is a distance threshold that determines the maximum distance at which one plant's costs affect the other's prices. This approach is attractive for the cement industry because a distance metric can be constructed as the interaction of gasoline prices and the miles between plants, which proxies well for transportation costs.[12]

Next, we let heterogeneity in own pass-through be determined by the degree of spatial differentiation, motivated by the theoretical result of ten Kate and Niels (2005) that own pass-through diminishes with the number of competitors in Cournot oligopoly models. In particular, we specify that

$$\rho_{jjt} = \alpha_0 + \alpha_1 \sum_{k \neq j,\, d_{jkt} < \overline{d}} 1/d_{jkt} \tag{3}$$

If $\alpha_1$ is negative then the extent to which plants pass through plant-specific cost changes to customers diminishes with the number and proximity of competitors; the opposite effect arises if the parameter is positive. Together, restrictions (2) and (3) solve the dimensionality problem by reducing the number of pass-through parameters, while still allowing for the estimation of reasonable pass-through behavior.

[11] Cross pass-through is intrinsically linked to the concept of strategic complementarity in prices, in the sense of Bulow, Geanakoplos, and Klemperer (1985), and in most standard demand systems the strength of strategic complementarity depends on the degree to which consumer view products as substitutes (e.g., Miller, Remer, and Sheu (2013)).

[12] Equation (2) is analogous to the assumption of Pinske, Slade, and Brett (2002) that the strategic complementarity of prices in wholesale gasoline markets decreases in the geographic distance between terminals. Further, the approach generalizes to markets with non-spatial differentiation provided that a reasonable Euclidean distance in attribute-space can be calculated (e.g., as in Langer and Miller (2013)).

The linear approximation in equation (1) makes aggregation to the regional level mathematically tractable. Suppose there exist $m = 1 \dots M$ regions defined by the USGS for data reporting purposes. The USGS regions need not comport with the local economic markets. Many regions may include multiple markets, and many markets may span multiple regions. Instead, conceptualize regions as sets of plants loosely defined based on geographic criteria. Denote as $\mathscr{J}_{mt}$ the set of plants that are in region $m$ in period $t$. Then the average price that arises is $P_{mt} = \sum_{j \in \mathscr{J}_{mt}} \omega_{jmt} p_{jt}$, where $\omega_{jmt}$ is the fraction of the region's total production accounted for by plant $j$. Maintaining restrictions (2) and (3), a linear approximation to equilibrium prices at the regional-level then is given by

$$\begin{aligned} P_{mt} &= \alpha_0 \sum_{j \in \mathscr{J}_{mt}} \omega_{jmt} c_{jt} + \alpha_1 \sum_{j \in \mathscr{J}_{mt}} \omega_{jmt} c_{jt} \sum_{k \neq j,\, d_{jkt} < \overline{d}} 1/d_{jkt} \\ &+ \beta \sum_{j \in \mathscr{J}_{mt}} \omega_{jmt} \sum_{k \neq j,\, d_{jkt} < \overline{d}} c_{kt}/d_{jkt} \\ &+ \sum_{j \in \mathscr{J}_{mt}} \omega_{jmt} x'_{jt} \gamma + \sum_{j \in \mathscr{J}_{mt}} \omega_{jmt} (\mu_j + \tau_t) + \overline{\epsilon}_{mt} \end{aligned} \tag{4}$$

where the region-year pricing residual is $\overline{\epsilon}_{mt} = \sum_{j \in \mathscr{J}_{mt}} \omega_{jmt} \epsilon_{jt}$. Equation (4) provides the theoretical foundation for our reduced-form regression equation. To implement, we assume that production within regions is proportional to capacity, which yields proxies for the weights. This assumption, necessitated by the lack of plant-level production data, also is used by the EPA in its economic analysis of the industry (EPA (2010)).

# 4 Estimation

## 4.1 Methodologies

We estimate the empirical model with OLS. The regression coefficients provide unbiased estimates of the average effect of fuel costs on prices, under the assumption of orthogonality between the regressors and the region-year pricing residual. We believe this assumption is appropriate. While bias could arise if fossil fuel prices are correlated with unobserved components of cement demand, this is unlikely because the cement industry accounts for a small fraction of the fossil fuels consumed in the United States.[13] If anything, we expect unobserved costs to dominate the residuals, rather than unobserved demand, due to

[13]Consistent with this, bituminous coal and petroleum coke prices do not follow the pro-cyclical pattern of cement consumption.

the predictive accuracy of our demand-side control variables. Unobserved costs should be uncorrelated with fuel costs because we include fixed effects for kiln technology.

Two caveats are noteworthy. First, average pass-through can diverge from theoretical notions of pass-through, especially if pass-through is not constant and the cost distribution is asymmetric (MacKay, Miller, Remer, and Sheu (2014)). While constant pass-through arises only for certain demand systems (e.g., Bulow and Pfleiderer (1983); Fabinger and Weyl (2014)), in robustness tests we do not find statistical support for variable pass-through in our setting. Second, we take as given the capacity and location of kilns. In our data, the median kiln age at retirement is 37 years, whereas prices adjust rapidly due to the prevalence of short-term supply contracts. We therefore consider it unlikely that capacity and the geographic configuration of plants would be strongly correlated with the region-year pricing residual, especially in the presence of the demand control variables.

## 4.2 Regressors

We calculate the fuel costs of each plant based on (i) the energy requirements of the plant's least efficient kiln, (ii) the primary fuel burned at the plant, and (iii) the price of the primary fuel. Formally, the fuel costs per metric tonne of cement for plant $j$ in year $t$ equals

$$\text{Plant Fuel Cost}_{jt} = \text{Primary Fuel Price}_{jt} \times \text{Energy Requirements}_{jt} \div 1.05,$$

where the fuel price is in dollars per mBtu and the energy requirements are those of the least efficient kiln and are in mBtu per metric tonne of clinker. We scale down by five percent to reflect that a small amount of gypsum is ground together with clinker to form cement. We believe this to be the most reasonable methodology for calculating fuel costs, given the data available, and accept that it is impossible to measure perfectly the fuel costs at every kiln.[14]

Estimation exploits two main sources of empirical variation in fuel costs. First, the energy requirements of production vary according to kiln technology employed, both intertemporally (e.g., see Table 1) and across regions. The available variation is substantial: the energy requirements per metric tonne of clinker are 3.94, 4.11, 5.28, and 6.07 mBtu, for dry precalciner, dry preheater, long dry, and wet kilns, respectively. Second, the price of coal and petroleum coke varies over the sample period, as we illustrate in Figure 1. The mean

[14] We focus on the least efficient kiln because it provides the most accurate measure of marginal fuel cost. The coal price data are in dollars per metric tonne, and we use the conversion factor of 23 mBtu per metric tonne, which is the average energy content of bituminous coal obtained by cement plants based on the labor-energy input surveys. We discuss two specific sources of possible measurement error in Appendix A.

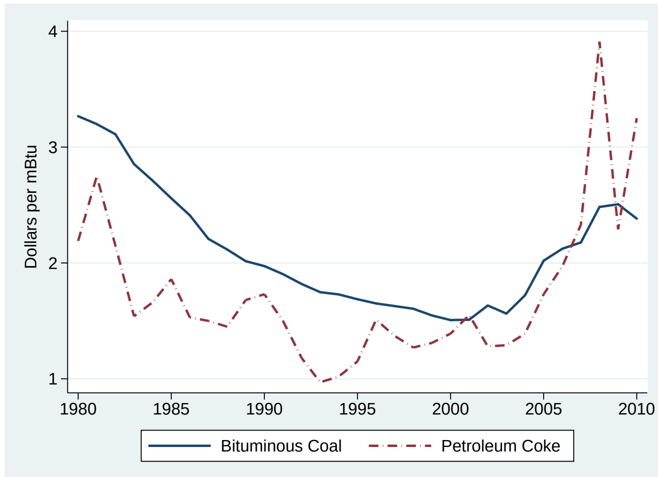


Figure 1: Primary Fuels and Fuel Prices

Notes: The figure plots the average national price of bituminous coal and petroleum coke over 1980-2010, in real 2010 dollars per mBtu. Coal prices are obtained from the Coal Reports of the Energy Information Agency (EIA) and petroleum coke prices are obtained from the State Energy Data System of the EIA.

price of coal is \$2.10 per mBtu, in real 2010 dollars, relative to a maximum of \$3.27 and a minimum of \$1.51. Fluctuations in the price of fuel affects plants differentially, based on the kiln technologies. While other sources of empirical variation exist, these are secondary and should not have much effect on results.[15]

We aggregate plant-level fuel costs to the region-level following equation (4). There are numerous sources of variation available that separately identify cross pass-through (i.e., $\beta$) from the baseline own pass-through (i.e., $\alpha_0$), and we demonstrate each in Appendix B using simple examples. Own pass-through heterogeneity (i.e., $\alpha_1$) is separately identified from cross pass-through if plants have different fuel costs than their nearby competitors. In our data sample, the aggregation process eliminates most of this empirical variation, making it difficult to estimate own pass-through heterogeneity and cross pass-through with econometric precision. The underlying problem is one of near multi-collinearity between the heterogeneity term and the cross pass-through term. Nevertheless, we are able to precisely estimate industry pass-through, which has direct bearing on market-based regulation. Further, our estimates of industry pass-through are not sensitive to the inclusion or exclusion of the heterogeneity and cross pass-through regressors.

Figure 2 explores the empirical distributions of regional prices and fuel costs over the sample period of 1980-2010. Panels A and B show the univariate distributions. The price

[15]A handful of plants use natural gas or oil as their primary fuel, and the prices of those fuels vary over time. Empirical variation also is created as those plants convert to coal and/or petroleum coke.

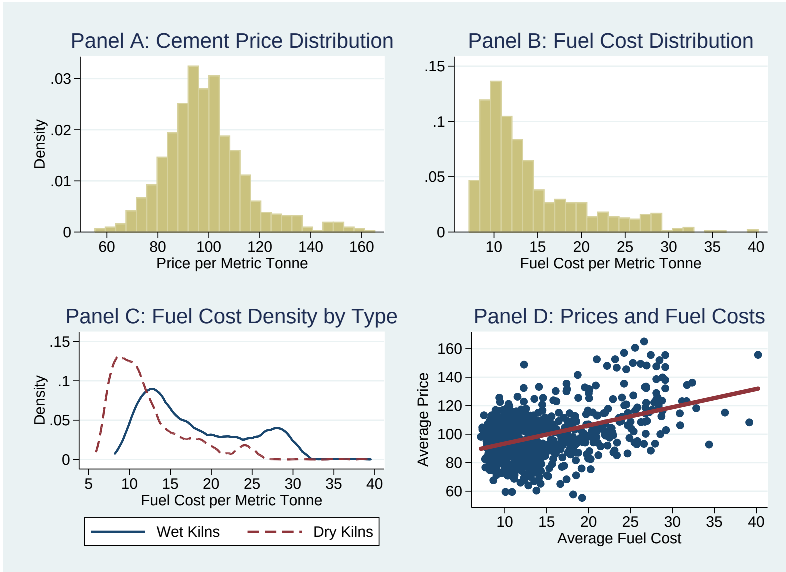


Figure 2: Regional Prices and Fuel Costs over 1980-2010

Notes: Panels A and B show the empirical distributions of cement price and fuel costs, and are based on 773 region-year observations. Panel C shows the kernel density of fuel costs, separately for plants with wet and dry kilns, and is based on 3,445 plant-year observations. Panel D shows a scatterplot of regional cement prices and fuel costs, as well as a line of best fit, and is based on 773 region-year observations. All prices and fuel costs are in real 2010 dollars per metric tonne of cement.

distribution is nearly symmetric around the mean of \$98.62 per metric tonne. The fuel cost distribution is tighter and left-centered. The relative tightness of the fuel cost distribution arises because fuel cost is one of many determinants of prices. Panel C provides separate kernel density estimates for plants with wet and dry kilns. Panel D provides a scatterplot of the 773 region-year observations on prices and fuel costs. Observations with higher fuel costs also have higher prices – the correlation coefficient is 0.4554.

We construct a number of control variables at the plant-level that account for demand, cost and competitive conditions relevant to pricing, including

- Construction employment in counties with $d_{ja} < \overline{d}$
- Building permits in counties with $d_{ja} < \overline{d}$
- Indicator variables for the kiln technology
- The count of competitors with $d_{jk} < \overline{d}$, weighted by inverse distance $d_{jk}$
- The count of competitors with $d_{jk} < \overline{d}$, by kiln type, weighted by inverse distance $d_{jk}$
- Total capacity among competitors with $d_{jk} < \overline{d}$

We aggregate all of the plant-level variables listed above to the region-level following equation (4) in order to preserve the micro-foundations of the empirical model.[16] While we include all of the above variables in our regressions, inference on pass-through does not change meaningfully if the controls are excluded. Inference also does not change much if we add regressors based on squares and interactions of the plant-level variables terms prior to aggregation.

# 5 Regression Results

Table 2 summarizes the regression results. Columns (i)-(iii) isolate *Fuel Costs* as the sole pass-through regressor. Columns (iv) and (v) incorporate heterogeneity in own pass-through and cross pass-through effects. Columns (vi) and (vii) test for the existence of structural breaks in the data. The distance metric is miles times the gasoline price index. The columns differ in the specification of the control variables. The "linear" specification includes all the control variables enumerated in the previous section. The "quadratic" specification also includes squares and interactions of the demand and competition variables. The baseline distance threshold is 400, but in columns (iii), (v), and (vi) we also include control variables constructed with a threshold of 200, which increases the flexibility of the model. We report results for the pass-through coefficients and for median industry pass-through, which we derive by applying the coefficients to the plant-year observations. The standard errors and confidence intervals are calculated using a Newey-West correction for first degree autocorrelation among observations from the same region.

The *Fuel Cost* coefficient ranges from 1.16 to 1.28 in columns (i)-(iii), for which it is the only pass-through regressor, and it is precisely estimated in each column. The specifications impose that each plant has identical pass-through because the heterogeneity and cross terms are suppressed. The 95% confidence intervals for industry pass-through have a range from about 0.90 to 1.50, summarizing across the three columns. That industry pass-through could exceed unity in equilibrium is a standard prediction of economic theory. For example, ten Kate and Niels (2005) prove that with Cournot competition among $N$ firms, pass-through is given by

$$\rho_{jj} = \frac{1}{N+1-z} \qquad \text{and} \qquad \rho^M = \frac{N}{N+1-z} \tag{5}$$

where $\rho_{jj}$ is own pass-through, $\rho^M$ is industry pass-through, and $z$ is positive with convex

[16] We provide formal definitions of the regressors, along with selected summary statistics, in Appendix C. The data we employ on building permits and construction employment are highly predictive of portland cement consumption. In state-level regressions, they explain nearly 90% of the variation in consumption.

Table 2: Regression Results

| | (i) | (ii) | (iii) | (iv) | (v) | (vi) | (vii) |
|---|---|---|---|---|---|---|---|
| Fuel Costs | 1.28 | 1.16 | 1.24 | 1.26 | 1.43 | 1.24 | 1.45 |
| | (0.14) | (0.16) | (0.16) | (0.19) | (0.18) | (0.20) | (0.27) |
| Fuel Costs × Inverse Rival Distance | | | | -5.71 | -5.52 | | |
| | | | | (1.37) | (1.54) | | |
| Rival Fuel Costs × Inverse Rival Distance | | | | 5.45 | 4.97 | | |
| | | | | (1.81) | (1.90) | | |
| Fuel Costs × (Year≥1990) | | | | | | -0.07 | |
| | | | | | | (0.16) | |
| Fuel Costs × (Year≥2000) | | | | | | 0.23 | |
| | | | | | | (0.15) | |
| Controls | none | linear | quadratic | linear | quadratic | quadratic | none |
| Distance Threshold | n/a | 400 | 200, 400 | 400 | 200, 400 | 200, 400 | n/a |
| *Derived Statistics: Industry Pass-Through* | | | | | | | |
| Median | 1.28 | 1.16 | 1.24 | 1.22 | 1.36 | 1.24 | 1.45 |
| | (1.02,1.56) | (0.87,1.48) | (0.94,1.57) | (0.91,1.51) | (1.04,1.65) | (0.73,1.77) | (0.96,1.98) |

Notes: The sample in columns (i)-(vi) includes 773 region-year observations over 1980-2010. The sample in column (vii) includes 270 region-year observations over 2000-2010. The dependent variable is the cement price. The distance metric is miles times the gasoline price index. The distance threshold used to construct *Fuel Costs* × *Inverse Rival Distance* and *Rival Fuel Costs* × *Inverse Rival Distance* is 400. Columns (ii)-(vi) feature control variables constructed with a distance threshold of 400. Columns (iii), (v), and (vi) also includes control variables constructed with a distance threshold of 200. The "quadratic" controls used in columns (iii), (v), and (vi) included regressors constructed by squaring and interacting the plant-level demand and competition control variables, and then aggregating these to the region level. Standard errors are calculated using a Newey-West correction for first-order autocorrelation within regions. The derived pass-through statistics, along with 95% confidence intervals, are calculated by applying the regression coefficients to the 3,445 plant-year observations.

demand, negative with concave demand, and zero with linear demand. Within this model, own pass-through converges to zero as the number of firms grows large, while industry pass-through converges to unity from below or above, depending on the curvature of demand.[17]

Columns (iv) and (v) incorporate heterogeneity in own pass-through and cross pass-through effects. The *Fuel Cost* coefficients are 1.26 and 1.43, respectively, and remain precisely estimated. This provides both the own and industry pass-through for any plant with no competitors within the distance threshold (i.e., for a local monopolist). The point estimates for *Fuel Costs* $\times$ *Inverse Rival Distance* are negative, consistent with own pass-through decreasing in the number and proximity of competitors, while the point estimates for *Rival Fuel Costs* $\times$ *Inverse Rival Distance* are positive. Because the magnitude of the heterogeneity term exceeds somewhat that of the cross pass-through term, industry pass-through decreases with the number and proximity of competitors. The median industry pass-through is 1.22 and 1.36, respectively, and corresponding 95% confidence intervals are (0.91, 1.51) and (1.04, 1.65).

These pass-through patterns reconcile easily with theory, and especially with the Cournot predictions in equation (5).[18] We note however that the collinearity between the two pass-through interaction terms, once aggregated to the region-level, exceeds standard econometric thresholds. While this does not bias the point estimates, the standard errors we report for those coefficients are understated because the regressors affect prices with opposite signs (e.g., Mela and Kopalle (2002)).[19] The regression results therefore do not enable robust statistical inference about own pass-through heterogeneity and cross pass-through. The empirical variation available at the region level is sufficient to estimate the net effect, meaning the presence of collinearity does not affect statistical inferences regarding industry pass-through. Further, our industry pass-through estimates are not affected much by the inclusion or exclusion of the heterogeneity and cross pass-through terms. We show in Section 6 how industry pass-through – the primary object of interest in this application – can be

[17]Specifically, $z = -\left(Q\frac{\partial^2 P}{\partial^2 Q}\right) \Big/ \left(\frac{\partial P}{\partial Q}\right)$, where $Q$ and $P$ are the market quantity and price, respectively. The derivation does not require that marginal costs be homogeneous across firms.

[18]The regression results are robust across a range of modeling choices. For the sake of brevity, we quickly enumerate some of the checks that we have conducted: (1) results are unchanged with alternative distance thresholds such as 300 and 500; (2) results are unchanged when we exclude particularly influential observations, as measured by Cook's $D$, a statistic that identifies possible outliers; (3) industry pass-through remains above unity if the model is estimated with feasible generalized least squares; (4) industry pass-through is around unity if plant and year fixed effects are incorporated, with the caveat that this exacerbates collinearity concerns; (5) regressors constructed based on squared plant-level fuel costs, designed to test for variable pass-through, produce small and statistically insignificant coefficients.

[19]To our knowledge, the econometric literature has not coalesced around a methodology that corrects standard errors for the presence of collinearity.

Table 3: Industry Pass-Through in Selected EPA Markets

| | | Theoretical Predictions | | |
|---|---|---|---|---|
| | N | $\epsilon^D = 1.0$ | $\epsilon^D = 1.5$ | $\epsilon^D = 2.0$ |
| Atlanta | 6 | 1.20 | 1.13 | 1.09 |
| Birmingham | 5 | 1.25 | 1.15 | 1.11 |
| Chicago | 4 | 1.33 | 1.20 | 1.14 |
| Cincinnati | 3 | 1.50 | 1.29 | 1.20 |
| Detroit | 2 | 2.00 | 1.50 | 1.33 |

Notes: Theoretical predictions are derived from a model of Cournot competition among firms with constant but heterogenous marginal costs and a constant elasticity market demand schedule. We denote the number of firms with active plants in the EPA market in 2010 as $N$ and the market elasticity as $\epsilon^D$.

used to evaluate the effects of market-based $CO_2$ regulation.

We turn now to whether there are structural breaks in pass-through that arise in the data. In column (vi), we report the results obtained with a specification that includes the interactions of fuel costs with indicators for whether the region-year observation occurs over 1990-2010 and over 2000-2010. Weak statistical support is identified for somewhat higher pass-through in the most recent years, as the relevant coefficient is statistically significant at the 10 percent level. In column (vii), we show the results of a univariate regression estimated only on observations over 2000-2010. The pass-through coefficient of 1.45 exceeds what is obtained from the full sample, again consistent with somewhat higher pass-through in more recent years, but the differences are not statistically significant. Our conclusion based on these latter two regressions is that there is little statistical support for a conjecture that high pass-through rates are a historical phenomenon with limited contemporary relevance.

Lastly, before turning to the market-based regulation of $CO_2$, we evaluate an implicit pass-through assumption that is made in recent articles on the portland cement industry (e.g., Ryan (2012); Fowlie, Reguant, and Ryan (2014)). The structural models used in those articles feature (i) Cournot competition among firms in local markets and (ii) constant elasticity market demand curves. Pass-through in this context is fully determined by the number of firms and the elasticity of demand. In Table 3, we list the theoretical industry pass-through implied by the model, for selected local markets delineated by the EPA and used in Fowlie, Reguant, and Ryan (2014), over a range of elasticities considered in that article.[20] The similarity between the theoretical predictions and our empirical estimates is apparent, and supports the validity of the structural models.

[20]The authors can provide results for all 20 EPA markets upon request.

# 6 Market-Based Regulation

Our regression results have direct bearing on the implications of $CO_2$ regulation on profit, consumer surplus, and deadweight loss. In our analysis below, we model market-based regulation as a uniform carbon tax. This is economically equivalent to a cap-and-trade program in which permits are allocated with a uniform price auction. Our quantitative focus is on the short run and, in our calculations, we assume that the carbon tax is imposed only on domestic producers – this best utilizes our pass-through estimates, which relate domestic costs to domestic prices. We then discuss qualitatively how results would change in the long run and if importers are subject to the tax.

We first consider a general model of symmetric oligopoly. Denote industry pass-through as $\rho^M$, the industry elasticity of demand as $\epsilon^D$, and the price-cost margins of firms as $m$. Normalize the demand elasticity to be positive. The change in producer surplus due to an arbitrarily small output tax $t$ is given by

$$\frac{\partial \pi}{\partial t} = \left[\rho^M \left(1 - m\epsilon^D\right) - 1\right] Q \qquad (6)$$

This equation is derived in Atkin and Donaldson (2014) and appears as a "principle of incidence" in Weyl and Fabinger (2013). It is useful because it expresses the change in producer surplus in terms of industry pass-through, which we estimate, together with margins and the domestic industry elasticity of demand, which have been estimated elsewhere in the literature. Assuming substitutes, it must be that $m\epsilon^D \in [0, 1]$ with zero representing price-taking behavior and one representing monopoly.[21] We translate the output tax into a $CO_2$ tax using the conversion detailed in Section 2.

We calculate results for margins that range from 0.20 to 0.50, and for demand elasticities that range from 0.60 to 1.60. The results of Miller and Osborne (2014) imply average margins of 31% when applied to single-plant firms, and a recent analysis conducted by the EPA constructed kiln-specific variables costs for each of 20 local markets; the costs imply an average margin of 43% when paired with the reported market prices (EPA (2009)). On the domestic industry elasticity of demand, Jans and Rosenbaum (1997) report an estimate of

[21] The product $m\epsilon^D$ is mathematically equivalent to the Rothschild Index (Rothschild (1942)), a measure of monopoly power based on the ratio of the industry elasticity to the firm-specific elasticity. The Rothschild index equals $1/N$ with Cournot competition, so calculating the change in producer surplus does not require knowledge of margins or demand elasticities. While we prefer to treat margins and elasticities independently, when we apply the Cournot framework and average over the 20 EPA local markets discussed in Section 5, we obtain results that are nearly identical to those reported in the text for a margin of 0.35 and a domestic elasticity of 0.80. This conveys an additional robustness to our results.

0.87, Miller and Osborne (2010) report an estimate of 1.11, and Fowlie, Reguant, and Ryan (2014) report estimates ranging between 0.89 and 2.03. Consumer substitution away from domestic cement is captured predominately by importers (Miller and Osborne (2010)).

Table 4 shows the changes in short run producer surplus, per dollar of carbon tax, that arise over the ranges of margins and demand elasticities considered. Panel A uses an industry pass-through rate of 1.20, which we select based on our regression results. Panels B and C use an industry pass-through of 0.90 and 1.30, respectively. Producer surplus loss increases with margins and the elasticity of demand, and decreases with industry pass-through.[22] With margins of 0.35, an elasticity of 1.00, and industry pass-through of 1.20, the loss is \$13.21 million per dollar of carbon tax. This becomes meaningful in practice. For instance, the loss is \$528 million with a \$40 dollar carbon tax, assuming a constant pass-through rate, relative to industry revenues of roughly \$7 billion in 2012.

We calculate the loss of consumer surplus to be \$73 million per dollar of carbon tax, assuming industry pass-through of 1.20, following the methodology of Weyl and Fabinger (2013). This exceeds producer surplus loss for every combination of margins and elasticities examined. With margins of 0.35 and an elasticity of 1.00, which we view as a reasonable middle ground, it follows that about 85% of the burden of cap-and-trade regulation falls on downstream customers. With industry pass-through of 0.90 or 1.30 instead, the loss of consumer surplus remains substantial, at \$54 million and \$78 million, respectively. How surplus loss is distributed downstream, among at least ready-mix concrete plants, construction firms, and end users, goes beyond the scope of our data.

We now relax the assumption of symmetry and analyze the differential effects of market-based regulation. We focus on markup and price effects, rather than producer and consumer surplus, because the plant-specific demand elasticities that would be required for surplus statements are not readily available in the literature.[23] We rely on column (iv) from Table 2, which incorporates pass-through heterogeneity and cross pass-through effects. An important caveat is that these effects are not precisely estimated due to the collinearity in the aggregated data. If anything, we expect the analysis to overstate the degree of heterogeneity present.[24]

[22]For some combinations of margins, elasticities and pass-through, producer surplus increases with the carbon tax (see Panel C). This is recognized as a theoretical possibility (Kimmel (1992)), but one that cannot be true globally as it implies infinite consumer surplus.

[23]In principle, one could obtain plant-specific elasticities by applying the structural estimates of Miller and Osborne (2014), which are obtained based on data from the U.S. Southwest over 1983-2003, to the entire country based on the geographic configuration in 2010.

[24]This is because the estimated pass-through heterogeneity and cross pass-through effects are large enough in magnitude, possibly due in part to collinearity, that plants with many nearby competitors are predicted to have negative own pass-through rates. This is inconsistent with economic theory and suggests to us that

Table 4: Change in Producer Surplus ($MM) Per Dollar of Carbon Tax

Panel A: Industry Pass-through of 1.20

| | Domestic Elasticity of Demand | | | | | |
|---|---|---|---|---|---|---|
| Margins | 0.60 | 0.80 | 1.00 | 1.20 | 1.40 | 1.60 |
| 0.20 | 3.36 | 0.48 | -2.40 | -5.29 | -8.17 | -11.05 |
| 0.30 | -0.96 | -5.29 | -9.61 | -13.97 | -18.26 | -22.58 |
| 0.35 | -3.12 | -8.17 | -13.21 | -18.26 | -23.31 | -28.35 |
| 0.40 | -5.29 | -11.05 | -16.82 | -22.58 | -28.35 | -34.12 |
| 0.50 | -9.61 | -16.82 | -24.03 | -31.23 | -38.44 | -45.65 |

Panel B: Industry Pass-through of 0.90

| | Domestic Elasticity of Demand | | | | | |
|---|---|---|---|---|---|---|
| Margins | 0.60 | 0.80 | 1.00 | 1.20 | 1.40 | 1.60 |
| 0.20 | -12.49 | -14.66 | -16.82 | -18.98 | -21.14 | -23.31 |
| 0.30 | -15.74 | -18.98 | -22.22 | -25.47 | -28.71 | -31.95 |
| 0.35 | -17.36 | -21.14 | -24.93 | -28.71 | -32.50 | -36.28 |
| 0.40 | -18.98 | -23.31 | -27.63 | -31.95 | -36.28 | -40.60 |
| 0.50 | -22.22 | -27.63 | -33.04 | -38.44 | -43.85 | -49.25 |

Panel C: Industry Pass-through of 1.30

| | Domestic Elasticity of Demand | | | | | |
|---|---|---|---|---|---|---|
| Margins | 0.60 | 0.80 | 1.00 | 1.20 | 1.40 | 1.60 |
| 0.20 | 8.65 | 5.53 | 2.40 | -0.72 | -3.84 | -6.97 |
| 0.30 | 3.96 | -0.72 | -5.41 | -10.09 | -14.78 | -19.46 |
| 0.35 | 1.62 | -3.84 | -9.31 | -14.78 | -20.24 | -25.71 |
| 0.40 | -0.72 | -6.97 | -13.21 | -19.46 | -25.71 | -31.95 |
| 0.50 | -5.41 | -13.21 | -21.02 | -28.83 | -36.64 | -44.45 |

Notes: Calculations are based on a general model of symmetric oligopoly. Units are in millions of real 2010 dollars. We aggregate to the industry level based on the 2011 industry output of 67.90 million metric tonnes. We use the industry average ratio of 0.88 metric tonnes of $CO_2$ per metric tonne of cement to convert from an output tax to a carbon tax. Margins refer to $(P-C)/P$ where $P$ is price and $C$ is marginal cost. The domestic elasticity of demand is the percentage change in total domestic cement output with respect to a one percent increase in the domestic price. The ranges shown for margins and domestic elasticity reflect the existing literature on the portland cement industry.

Table 5: Change in Markup Per Dollar of Carbon Tax

| Kiln Type | Mean | 5% | 25% | 50% | 75% | 95% |
|---|---|---|---|---|---|---|
| Wet | 0.12 | -0.41 | 0.19 | 0.21 | 0.25 | 0.27 |
| Long Dry | 0.13 | -0.27 | 0.18 | 0.22 | 0.24 | 0.25 |
| Dry with Preheater | 0.19 | 0.05 | 0.19 | 0.22 | 0.23 | 0.14 |
| Dry with Precalciner | 0.23 | 0.13 | 0.21 | 0.22 | 0.23 | 0.35 |

Notes: Calculations are obtained using plant-specific pass-through effects. Markup refers to price less marginal cost.

Table 5 reports summary statistics regarding the change in markups that arise per dollar of carbon tax, taking into account asymmetry in pass-through. Markups increase with the carbon tax on average because, in our baseline Bayesian regression, industry pass-through just exceeds unity. Plants that utilize less efficient kiln technology see smaller markup increases, though the differences are not large. Thus, unless inefficient plants face more elastic demand than other plants, our calculations provide little support for the notion that market-based regulation impacts substantially the distribution of producer surplus among technology classes. There also is some heterogeneity within technology classes. The wet plants that experience markup decreases are near efficient competitors, and the precalciner plants that experience the largest markup increases are near inefficient competitors.

# 7 Conclusion

We provide empirical evidence that industry-wide cost increases are more than fully pass-through by portland cement manufacturers. We pair this result with information on margins and demand elasticities, culled from the academic literature, to disentangle how the adverse effects market-based regulation of greenhouse gases would be distributed along the supply-chain. Our calculations indicate that pass-through is sufficiently large that most adverse effects accrue downstream of manufacturers. This has clear implications how government revenues obtained from regulation should be disbursed, especially given the normative objective that compensation should be commensurate with adverse effects. Specifically, our results indicate that cement manufacturers can be fully compensated with a small fraction of the revenues obtained. Broad-based disbursement of the remainder, via tax credits, rebates, or other means, then becomes appropriate.

the true coefficients are smaller in magnitude. Even in the extreme instances of negative own pass-through, we predict that a carbon tax increases price, due to the larger cross pass-through effects.

While we focus on the market-based regulation of greenhouse gases, a number of extensions are possible. We outline two here. First, the cement industry is a major source of local pollutants, such as particulate matter and mercury, and controversial new regulations are set to take force in September of 2015. EPA analyses indicate that the monetized health benefits of regulation outweigh economics costs (EPA (2009); EPA (2010)), which deal with the pass-through of compliance costs. Our estimates could be used to cross-check the EPA predictions. Second, a merger two large cement manufacturers is currently is under antitrust review. Our pass-through results could be used to calculate likely merger price effects, following Jaffe and Weyl (2013) and Miller, Remer, Ryan, and Sheu (2013). Together, these possibilities reinforce recent theoretical work (e.g., Weyl and Fabinger (2013)) that develops the usefulness of pass-through in understanding market outcomes.

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# Appendix for Online Publication

## A Details on the Data Collection

We discuss details of the data collection process here in order to assist replication. We start with the *Plant Information Survey* (PIS) of the PCA. Our sample includes annual observations over 1980-2010. The PIS is published annually over 1980-2003 and also semi-annually in 2004, 2006, 2008 and 2010. We make use of all of the publications with the exception of 1981. The data provide snapshots as of December 31 of each year. We impute values for the capacity, technology, and primary fuel of each kiln in the missing years based on the preceding and following data. In most instances, imputation is trivial because capacity, 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 for each kiln the year of construction. We remove from the analysis 198 kiln-year observations for which the kiln is identified in the PIS as being idled. These occur mostly in the late 1980s and over 2009-2010. There are 49 plant-year observations – out of 3,494 – for which all kilns at a plant are observed to be idled. A handful of kilns drop out of the PIS and then reappear in later years. We treat those observations on a case-by-case basis, leveraging detailed qualitative and quantitative information provided in the *Minerals Yearbook* of the USGS. We detail the available evidence and the selected treatment in our annotated Stata code. Lastly, we remove from the analysis a small number of kilns that produce white cement, which takes the color of dyes is used for decorative purposes. Production requires higher kiln temperatures and iron-free raw materials, and the resulting cost differential makes it a poor substitute for gray cement in most instances.

We obtain data on delivered bituminous coal prices for the industrial sector from the annual *Coal Reports* of the Energy Information Agency (EIA). Averages are available at the national, regional and state levels over 1985-2012. We convert prices from dollars per short ton to dollars per metric tonne using the standard conversion factor. Many of the state values are withheld and must be imputed. We first use linear interpolation to fill in missing strings no longer than three years in length. We then calculate the average percentage difference between the observed data of each state and the corresponding national data, and use that together with the national data to impute missing values. For 14 states, all or nearly all of the state-level data are withheld, and we instead set the state price equal to the regional price.[25] We backcast the coal price data to the period 1980-1984 using data on the national average free-on-board (FOB) price of bituminous coal over 1980-2008 published in the 2008 *Annual Energy Review* of the EIA. Backcasting is based on (1) the state-specific average percentage differences between the delivered state and national prices; and (2) the percentage differences between the delivered national prices and the FOB national prices over the 1985-1990. The coal price data are reported in dollars per metric tonne. We convert to dollars per mBtu using the conversion factor of 23 mBtu per metric tonne of bituminous coal, which we calculate based on the labor-energy input surveys of the PCA.

We obtain state-level data on the 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 imputation of missing values is required only for petroleum coke. To perform the imputation, we first calculate average percentage difference between the observed data of each state and the corresponding national data, and use that together with the national data to impute missing values. In five states with active kilns, all or nearly all of the state-level data are withheld so we base imputation instead on the average petroleum coke prices that arise in adjacent states and nationwide.[26] The SEDS data are in dollars per mBtu.

Plants sometimes list multiple primary fuels in the Plant Information Survey. There is little data available on the mix of primary fuels in those instances, however, and we allocate such plants based on a simple decision rule. We calculate fuel costs with the price of coal if coal is among the primary fuels. If not, we use petroleum coke prices if coke is among primary fuels. Otherwise we use natural gas prices if natural gas is among the multiple fuels. We use oil prices only if oil is the only fossil fuel listed. 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. We have experimented with more sophisticated methodologies, leveraging data published in the *Minerals Yearbook* of the USGS on the total amounts of each fossil fuel burned by cement plants nationally. These methodologies are not fully satisfactory because, among other reasons, the USGS numbers include fuel burned (especially natural gas) to reheat kilns after maintenance periods. Our regression results are not sensitive to methodology on this subject and, given this, we prefer the simple rule.

[25] These states are Connecticut, Delaware, Louisiana, Massachusetts‘, Maine, Mississippi, Montana, North Dakota, New England, New Jersey, New Mexico, Nevada, Oregon and Vermont.

[26] We use the national price here because the prices in many adjacent states similarly are withheld. We impute the price of Maine using the national price because data for adjacent states are withheld (there are no kilns in adjacent states). We impute the price of Iowa using the arithmetic mean of the Illinois price and the national price. We impute the price of Nevada and Arizona using the arithmetic mean of the California price and the national price. We impute the price of Kansas using the arithmetic mean of the Oklahoma price, the Missouri price, and the national price.

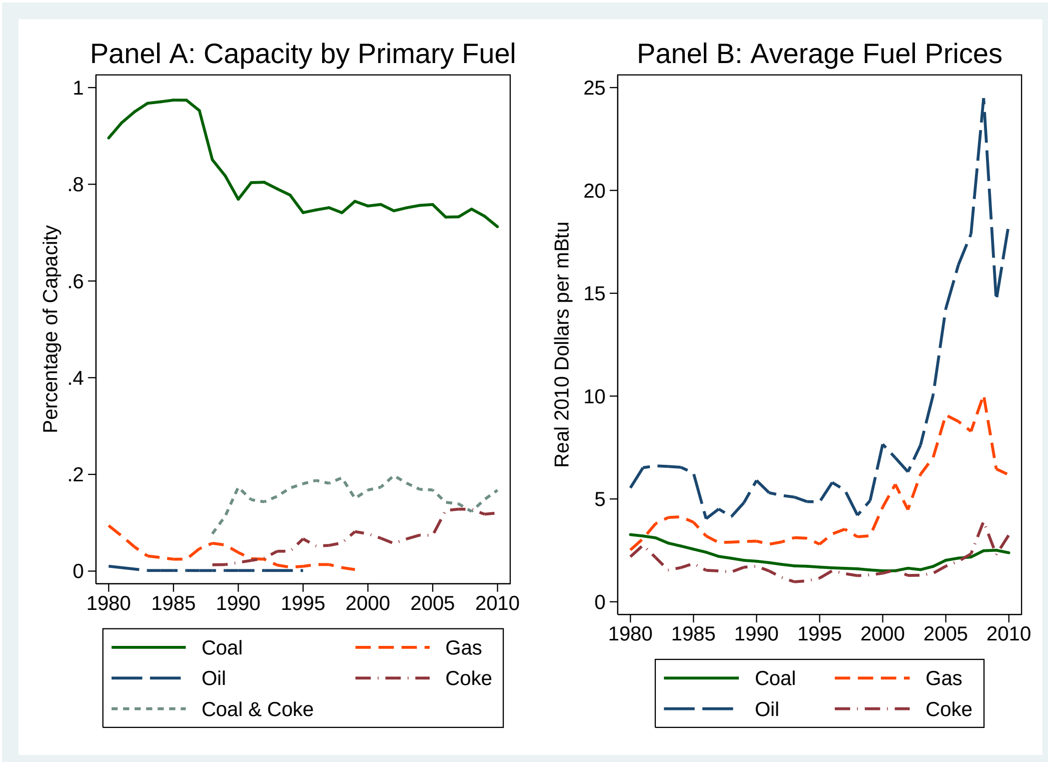


Figure A.1: Primary Fuels and Fuel Prices

Notes: Panel A plots the fraction of kiln capacity that burns as its primary fuel (i) bituminous coal, (ii) natural gas, (iii) fuel oil, (iv) petroleum coke, and (v) 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); the remaining prices are obtained from the State Energy Data System of the EIA.

Figure A.1 plots in Panel A the fraction of industry capacity that uses each fossil fuel as its primary source of energy, based on this methodology. The dominant primary fuel sources are coal and petroleum coke, which complete displace natural gas and oil midway through the sample period. Panel B shows why coal and petroleum coke are used: one a per-mBtu basis, they are more cost efficient than natural gas and oil. The variation in fuel choices and fuel prices, together with the heterogeneous kiln technologies, produces variation in fuel costs that we exploit in the empirical analysis.

We calculate energy requirements of each kiln technology based on the labor-energy input surveys of the PCA. There is no discernible change in the energy requirements of production, conditional on the kiln type, over 1990-2010. We calculate the average mBtu per metric tonne of clinker required in 1990, 2000, and 2010, separately for each kiln type, and apply these averages over 1990-2010. These requirements are 3.94, 4.11, 5.28, and 6.07 mBtu per metric tonne of clinker for dry precalciner kilns, dry preheater kiln, long dry kiln, and wet kilns, respectively. A recent survey of the USGS accords with our calculations (Van Oss (2005)). By contrast, technological improvements are evident over 1974-1990, conditional on kiln type. The labor-energy surveys indicate that in 1974 the energy requirements were 6.50 mBtu per metric tonne of clinker at dry kilns (a blended average across dry kiln types), and 7.93 mBtu per metric tonne of clinker at wet kilns. We assume that technological improvements are realized linearly over 1974-1990 and scale the energy requirements over the early years of the sample period accordingly.

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

The USGS *Minerals Yearbook* publishes average prices per region. In total, there are 56 regions, fully contained in the contiguous United States, that appear at least once.[27] In Table A.1, we list the number times we observe each region over the sample period 1980-2010. Only five regions are observed in every year – Alabama, Illinois, Maine/New York, Missouri, and Ohio. Regions more commonly are observed for a portion of the sample. The regions exhibit numerous features that make it difficult to interpret them as local markets. We highlight two here. First, regions are not always contiguous. An example is Georgia, which in 14 years is grouped with Virginia and West Virginia but not with South Carolina. Second, the regions exhibit little constancy over the sample period. An example is Nevada, which in 19 years is grouped with Idaho, Montana and Utah and in nine years is grouped with Arizona and New Mexico. Nonetheless, the data provide useful information on prices throughout the United States and serve to motivate our empirical framework, which we develop to accommodate such data.

[27]We do not include regions that incorporate states and territories outside the contiguous United States. For example, we exclude Oregon/Washington/Alaska/Hawaii, which exists over 1983-1985.

Table A.1: Number of Observations by USGS Region

| Region | Observations | Region | Observations |
|---|---|---|---|
| AL | 31 | GA/TN | 9 |
| IL | 31 | OK | 9 |
| ME/NY | 31 | SD | 9 |
| MO | 31 | AR/MS/LA | 7 |
| OH | 31 | MD/VA/WV | 6 |
| FL | 30 | KY/VA/WV | 6 |
| East PA | 30 | WA | 6 |
| West PA | 30 | ID/MT | 5 |
| North TX | 29 | ID/MT/UT | 5 |
| South TX | 29 | AZ/CO/UT/NM | 3 |
| North CA | 29 | GA/SC | 3 |
| South CA | 29 | ID/MT/WY | 3 |
| KS | 28 | IN/KY | 3 |
| IN | 28 | KS/NE | 3 |
| SC | 28 | KY/NC/VA | 3 |
| CO/WY | 26 | MD/WV | 3 |
| AR/OK | 22 | NE/WI | 3 |
| MI | 21 | TN | 3 |
| MD | 20 | UT | 3 |
| AZ/NM | 19 | AR/MS | 2 |
| IA/NE/SD | 19 | CA | 2 |
| ID/MT/NV/UT | 19 | GA | 2 |
| KY/MS/TN | 19 | GA/MD/VA/WV | 2 |
| GA/VA/WV | 14 | LA/MS | 2 |
| OR/WA | 13 | OR/NV | 2 |
| IA | 12 | TX | 2 |
| MI/WI | 10 | CO/NE/WY | 1 |
| AZ/NM/NV | 9 | PA | 1 |

Notes: The table provides the number of observations and the mean number of active plants for each USGS region over the period 1980-2010. In total there are 56 regions and 773 region-year observations. We do not include regions that incorporate states and territories outside the contiguous United States.

We obtain county-level data from the Census Bureau on construction employees and building permits to help control for demand. 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.[28] 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.[29] We base the permits variable on the number of units so that, for example, a 2-unit permits counts twice as much as a 1-unit permit. 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.

# B Identification

We highlight here the sources of empirical variation that separately identify the own and cross pass-through parameters. We highlight here the sources of empirical variation that separately identify the own and cross pass-through parameters. The empirical variation we use to disentangle the own pass-through heterogeneity parameters (i.e., $\alpha_1$) from the cross pass-through parameter (i.e, $\beta$), is straightforward – plants often have different fuel costs then their nearby competitors – and needs no further explanation. Instead, we focus on the empirical variation that distinguishes the baseline fuel cost parameter (i.e., $\alpha_0$) from the cross pass-through parameter. There we can identify four distinct sources of identification (i) time-series variation in the distance metric, (ii) heterogeneity of capacity shares within a region, (iii) variation in fuel costs of plants in neighboring regions, and (iv) variation in the spatial composition of regions. We illustrate each source with simple examples below.

First, suppose that data consist of a single region and two plants with equal capacity. The linear approximation to regional prices then can be expressed

$$P_t = (\alpha_0 + \beta/d_{12t}) \frac{c_{1t} + c_{2t}}{2} + \bar{\varepsilon}_t, \tag{B.1}$$

where we have normalized $\alpha_1 = \gamma = 0$, without loss of generality. Absent inter-temporal variation in the distance metric, the coefficients $\alpha_0$ and $\beta$ are not separately identifiable. This remains true if more firms are incorporated, provided that plant capacity is homogeneous.

[28]See http://www.census.gov/econ/cbp/download/, last accessed April 16, 2014.
[29]See http://socds.huduser.org/permits/, last accessed April 16, 2014.

However, time-series variation in the distance metric is sufficient for identification. Periods with greater effective plant dispersion (i.e., a bigger $d_{12t}$) exhibit lower rates of industry pass-through due to more muted cross pass-through. We introduce time-series variation in the distance metric by interacting the miles between plants with the gasoline price index.

Second, suppose that the distance metric is constant over time, but that capacities differ for the two plants in the single region. Regional prices then take the form

$$P_t = \alpha_0(\omega_1 c_{1t} + \omega_2 c_{2t}) + \beta/d_{12}(\omega_2 c_{1t} + \omega_1 c_{2t}) + \bar{\varepsilon}_t, \quad \text{(B.2)}$$

The higher-capacity plant exercises greater influence on the own pass-through regressor, while the lower-capacity plant exercises greater influence on the cross pass-through regressor.[30] This is sufficient for identification, provided non-collinearity in the plants' fuel costs, which exists in regions containing plants that utilize different kiln technology. Identification through this channel becomes stronger with the inter-temporal changes in capacity weights that occurs with the retirement and introduction of kilns.

Third, the fuel costs of a plant can affect prices in a region even if the plant is not located in that region. Suppose that capacity shares of our two plants are equal, and the distance measure does not vary over time. Suppose further that we observe costs and distance for a third plant, denoted as plant 3, which is outside the region in the data. In this case, regional prices take the form:

$$P_t = \alpha_0(c_{1t} + c_{2t}) + \beta((1/d_{12})c_{1t} + (1/d_{12})c_{2t} + (1/d_{13} + 1/d_{23})c_{3t}) + \bar{\varepsilon}_t \quad \text{(B.3)}$$

The third plant's fuel costs affect the cross pass-through regressor but not the own pass-through regressor, and this is sufficient for identification if the fuel costs of the third plant are not collinear with the fuel costs of the first two plants. Identification through this channel becomes stronger, the closer is the third plant to the first and second plants.

Turning to the final source of variation in the data, identification is assisted by having multiple regions in the data. Consider a case with two regions and four plants. Plants 1 and 2 are in region A and plants 3 and 4 are in region B. Stripping away all other sources of identifying variation, assume that capacity is homogeneous and constant, there is no inter-temporal variation in the distance metric, plants do not affect prices outside their region,

[30]If capacity shares are equal then the two data vectors will be $0.5c_{1t} + 0.5c_{2t}$ and $(0.5c_{1t} + 0.5c_{2t})/d_{12}$, respectively, and collinearity causes identification to fail.

and the fuel costs of all plants are equal and collinear. Regional prices then take the form

$$\begin{bmatrix} P_{At} \\ P_{Bt} \end{bmatrix} = \begin{bmatrix} \alpha_0 + \beta/d_{12} \\ \alpha_0 + \beta/d_{34} \end{bmatrix} c + \begin{bmatrix} \bar{\varepsilon}_{At} \\ \bar{\varepsilon}_{Bt} \end{bmatrix}. \tag{B.4}$$

Identification is possible if $d_{12} \neq d_{34}$, as regions with greater plant dispersion exhibit lower rates of industry pass-through. Having multiple regions also amplifies the identifying variation available through the other channels enumerated above.

# C Regressors

Table C.1 defines the regressors explicitly. We use two variables to control for demand. *Construction Employment* and *Building Permits* are constructed by (i) calculating, for each plant, the total construction employment and building permits among all counties with centroids that are within the distance threshold, and (ii) aggregating to the region-level. We use two variables to control for competitive conditions. *Inverse Rival Distance* is constructed by calculating, for each plant, the count of competitors' plants within some distance threshold. In this calculation, we divide competitors' plants by their distance from the plant in question, so that closer competitors have greater influence. The variable increases in both the number and proximity of competitors. *Rival Capacity* is constructed by calculating, again for each plant, the total capacity at competitors' plants within some distance threshold. We omit from Table C.1 our controls for non-fuel costs, which are relatively straight-forward and seldom statistically significant in our regression analysis. The controls are based on plant-level indicator variables for the technology of the marginal kiln, i.e., whether the least efficient kiln at a plant is wet, long dry, dry with a preheater or dry with a precalciner. These plant-level variables are aggregated to the region-level, again using the capacity share weights. We also include as controls the count of competitor kiln types, within the distance threshold from each plant, aggregated to the region-level.

We use three main variables to capture pass-through, based on how restrictions (2) and (3) manifest in equation (4). *Fuel Costs* is constructed as the weighted average fuel cost of plants in the region, where plant fuel costs are calculated as described in the previous subsection and weights are by capacity share. *Fuel Costs* × *Inverse Rival Distance* is constructed based on the interactions of the fuel costs of each plant with the plant-level version of the *Inverse Rival Distance* variable, and allows for own pass-through to change based on the number and proximity of competitors. *Rival Fuel Costs* × *Inverse Rival Distance* captures cross pass-through and is constructed by calculating, for each plant, the sum of its competitors' fuel costs normalized by distance. This captures cross pass-through. The total influence of cross pass-through, summing across competitors, varies with the number and proximity of competitors.

Our baseline specifications employ a distance metric defined by the interaction of the gasoline price index and the miles between plants, and a distance threshold of 400. This approach reflects the predominant role of trucking in distribution.[31] 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)). The baseline threshold follows prior findings that 80-90 percent of portland cement is trucked less than 200 miles (Census Bureau (1977); Miller and Osborne (2014)), so that plants separated by more than 400 miles are unlikely to compete for many customers. In robustness checks, similar results are obtained with a distance metric defined by miles (i.e., not interacted with the gasoline price index), and with distance thresholds of 300 and 500.

[31] A fraction of cement is shipped to terminals by train (6% in 2010) or barge (11% in 2010), and only then is trucked to customers. Some plants may be closer than our metric indicates if, for example, both are located on the same river system.

Table C.1: Definitions and Summary Statistics for Selected Regressors

| Regressor | Definition | Mean | St. Dev. | Description |
|---|---|---|---|---|
| *Control variables* | | | | |
| Construction Employment | $\sum_{j\in\mathscr{J}_{mt}} \omega_{jmt} \sum_{d_{ajt}<\bar{d}} EMP_{at}$ | 835.27 | (556.03) | Total construction employment in nearby counties, aggregated to the region level. |
| Building Permits | $\sum_{j\in\mathscr{J}_{mt}} \omega_{jmt} \sum_{d_{ajt}<\bar{d}} PER_{at}$ | 216.35 | (150.03) | Total building permits in nearby counties, aggregated to the region level. |
| Inverse Rival Distance | $\sum_{j\in\mathscr{J}_{mt}} \omega_{jmt} \sum_{k\neq j,\, d_{jkt}<\bar{d}} 1/d_{jkt}$ | 0.23 | (0.23) | The count of competitors normalized by distance, aggregated to the region level. |
| Rival Capacity | $\sum_{j\in\mathscr{J}_{mt}} \omega_{jmt} \sum_{d_{jkt}<\bar{d}} CAP_{kt}$ | 11.03 | (6.35) | Total nearby competitor capacity, aggregated to the region level. |
| *Own pass-through variables* | | | | |
| Fuel Costs | $\sum_{j\in\mathscr{J}_{mt}} \omega_{jmt} c_{jt}$ | 16.08 | (5.79) | Fuel costs of the plant as defined in the text, aggregated to the region level. |
| Fuel Costs $\times$ Inverse Rival Distance | $\sum_{j\in\mathscr{J}_{mt}} \omega_{jmt} c_{jt} \sum_{k\neq j,\, d_{jkt}<\bar{d}} 1/d_{jkt}$ | 3.07 | (3.48) | Fuel costs times the count of competitors normalized by distance, aggregated to the region level. |
| *Cross pass-through variables* | | | | |
| Rival Fuel Costs $\times$ Inverse Rival Distance | $\sum_{j\in\mathscr{J}_{mt}} \omega_{jmt} \sum_{k\neq j,\, d_{jkt}<\bar{d}} c_{kt}/d_{jkt}$ | 3.11 | (3.46) | Summation of competitors' fuel costs normalized by distance, aggregated to the region level. |

Notes: Aggregation to the region level is conducted with the weights $\omega_{jmt}$, which are approximated with capacity shares. In all equations, $c_{jt}$ is the fuel cost of plant $j$ in period $t$, $d_{jkt}$ is the distance between plants $j$ and $k$ in period $t$, $d^c_{ajt}$ is the distance between county $a$ and plant $j$ in period $t$, $PER_{at}$ and $EMP_{at}$ are building permits and construction employment in county $a$ in period $t$, respectively, and $CAP_{kt}$ is the capacity of plant $k$ in period $t$. Summary statistics are calculated from 773 region-year observations.