

Pass-Through in a Concentrated Industry: Empirical Evidence and Regulatory Implications*

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Abstract

We estimate pass-through with thirty years of data from a concentrated industry. The empirical model accounts for oligopoly interactions, yet facilitates estimation with aggregate price data. Robust statistical evidence supports that industry-wide cost changes are more than completely transmitted downstream, and that this “industry pass-through” is largely unaffected by competitive conditions. The industry in question, portland cement, is a major focus of environmental and antitrust regulators. We use our pass-through estimates to (i) evaluate the welfare consequences of market-based CO₂ regulation; (ii) predict the magnitude and location of price effects due to a merger under review by antitrust authorities; and (iii) corroborate the simulation-based analysis of the EPA regarding its impending regulation of local pollutants.

Keywords: pass-through, cap-and-trade, mergers, regulation, portland cement
JEL classification: K3, L1, L5, L6

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1 Introduction

Recent theoretical literature extends the principles of incidence elucidated by Marshall (1890) to imperfectly competitive environments (e.g., Weyl and Fabinger (2013)). Within the field of industrial economics, it now is understood that pass-through is central to a wide range of analyses, including price discrimination (e.g., Aguirre, Cowan, and Vickers (2010)), merger analysis (e.g., Jaffe and Weyl (2013)) and the economics of platforms (e.g., Weyl (2009)). The empirical literature, with some notable exceptions, has lagged in applying the theoretical insights to study real-world markets. Here our objective is to demonstrate how pass-through can yield insights that are relevant to regulatory and policy decisions.

We estimate pass-through based on more than 30 years of data, in a manner that allows for realistic oligopoly interactions, and apply the results to study three specific regulatory questions. The industry in question, portland cement, is a major focus of environmental policy-makers because it accounts for roughly five percent of global anthropogenic CO₂ emissions (Van Oss and Padovani (2003)) and is also a major source of local pollutants such as particulate matter and mercury (e.g., EPA (2009); EPA (2010)). Firms exercise localized market power (e.g., (Miller and Osborne 2014)), and there is some prospect that this market power could be enhanced by the recently proposed merger of two dominant manufacturers. We use pass-through to analyze (i) the welfare effects of market-based CO₂ regulation, (ii) the magnitude of merger price effects; and (iii) the consequences of proposed EPA action to reduce local hazardous air pollutants.

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 generates a reduced-form regression equation that allows for the estimation of pass-through using price data that are available only as region-year observations. This empirical strategy, while natural, is novel in the empirical literature. In our application, the obtained regression coefficients provide reasonable estimates of cost pass-through because fuel comprises a substantial fraction of overall variables costs, and because 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 empirical variation allows for precise estimates of how prices respond to industry-wide cost fluctuations, and how this “industry pass-through” is affected by competition.¹

¹How prices respond to cost fluctuations specific to a firm or competitor (“own pass-through” and “cross pass-through”) are identified theoretically but imprecisely estimated due to the aggregation process.

Our primary econometric results are that (i) industry-wide cost changes are, on average, more than completely transmitted downstream; and (ii) this pass-through is largely unaffected by the degree of competition. The confidence intervals we obtain are sufficiently tight to reject the possibility that industry pass-through is substantially incomplete. These results are robust across a range of specifications and modeling choices. That industry pass-through exceeds unity reconciles easily with economic theory. For instance, as the number of firms increases in standard Cournot models, industry pass-through converges to unity from above if the market demand schedule is sufficiently convex (e.g., see Kate and Niels (2005)). Indeed, theoretical ambiguity on this point serves to motivate the empirical analysis. Our point estimates also are suggestive that firm-specific own pass-through decreases with competition, but this effect is imprecisely estimated due to multicollinearity in the data, and we treat firm-specific pass-through with caution in the regulatory applications that follow.

Our first application examines the welfare effects of market-based CO₂ regulation. We use the analytical framework of Weyl and Fabinger (2013) to interpret our pass-through results, together with estimates of margins and demand elasticities taken from the academic literature, in a way that accounts for market power and oligopoly interactions. We show that cement manufacturers bear only 15% of the burden of market-based regulation, with the remainder accruing downstream among agents such as ready-mix concrete plants, construction companies, and end users. Cement manufacturers could be fully compensated for the adverse effects of regulation with 22% of the revenues obtained. The deadweight loss of market-based regulation has the same order of magnitude as the social value of abatement, absent production-based reallocations of permits or other design mechanisms that encourage production. Our pass-through estimates imply only limited within-industry heterogeneity in the effects of regulation on the producer surplus of cement plants.

The second application is to the proposed merger of Holcim and Lafarge, which currently is under review by antitrust authorities. We apply the theoretical framework of Jaffe and Weyl (2013) to translate the pass-through estimates into first order approximations to merger price effects. We believe this to be the first academic application of this methodology, though Monte Carlo evidence is suggestive that first order approximation typically outperforms merger simulation when pass-through is measured accurately (e.g., Miller, Remer, Ryan, and Sheu (2013)). Our calculations indicate price elevations of 3%-7% at many plants, based on an industry snapshot in 2010, the final year of our data. However, accounting for the merging firms' recent plant divestitures and closures, which just postdate our sample, eliminates most of these effects. Remaining price increases are relatively modest, arise at only a handful of plants, and affect customers predominately in the Northeast and

Great Plains. These price elevations likely could be eliminated through the divestiture of two plants, one for each geographic area.

Our final regulatory application is to recent regulation promulgated by the EPA to reduce emissions of hazardous air pollutants (HAPs), including particulate matter, mercury, hydrocarbons, and hydrogen chloride. The regulation is scheduled to take effect in September 2015, after more than two years of litigation and renegotiation. The EPA indicates that the monetized health benefits of regulation outweigh economics costs (EPA (2009); EPA (2010)), the latter of which can be first order in oligopoly models with market power (e.g., Buchanan (1969)). Our analysis corroborates the simulation results developed by the EPA. The pass-through estimates imply average price increases of \$4.49 across 20 local markets, relative a simulation average of \$4.66. Further, there is a high degree of correlation in the predictions market-by-market. We believe this is attributable to a fortuitous choice of functional forms in the EPA simulation model, and would not occur with simulations generally.

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 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)).

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, presents the estimation strategy, and defines the regressors. Section 4 presents the pass-through regression results. Sections 5, 6, and 7 provide respectively the applications to the market based regulation of CO₂, the merger of Holcim and Lafarge, and the EPA regulation of hazardous air pollutants. Section 8 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 CO₂ range from 0.86 to 1.05 metric tonnes per metric tonne 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.²

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.³ Today most cement is produced in dry kilns equipped with gas-suspension preheaters and precalciners. 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.

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.⁴ 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 rela-

²The CO₂ 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 CO₂ Protocol, developed by leading cement firms for the Cement Sustainability Initiative of the World Business Council for Sustainable Development. We scale up the impact of converting calcium carbonate to 0.525, in order to account for CO₂ emitted during the calcination of cement kiln dust. We add to this the CO₂ 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 emissions by five percent to convert units of clinker to units of cement. Similar calculations underly the analysis in Fowlie, Reguant, and Ryan (2014).

³For 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 which primary fossil fuel is used to fire the kiln. Adjustment costs limit the profitability of switching fuels in response to changing relative prices.

⁴While 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.

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 Precaliner
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.

tive 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 United States Geological Survey (USGS), which summarizes a census of portland cement plants.⁵ 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

⁵The 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.

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 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.⁶ 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 Model and Estimation

3.1 Empirical Model

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

⁶The 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.

the equilibrium price of plant j is given by

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

where x_{jt} includes observable demand and cost variables, μ_j and τ_t are plant and year fixed effects, respectively, and ϵ_{jt} is a pricing residual that summarizes unobservable demand and cost conditions. The fuel cost coefficients are linear approximations to own and cross pass-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.⁷ 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

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

where d_{jkt} is the distance metric and \bar{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.⁸

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

⁷Cross 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 consumers view products as substitutes (e.g., Miller, Remer, and Sheu (2013)).

⁸Equation (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)).

particular, we specify that

$$\rho_{jkt} = \alpha_0 + \alpha_1 \sum_{k \neq j, d_{jkt} < \bar{d}} 1/d_{jkt} \quad (3)$$

If α_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.

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 \mathcal{J}_{mt} the set of plants that are in region m in period t . Then the average price that arises is $P_{mt} = \sum_{j \in \mathcal{J}_{mt}} \omega_{jmt} p_{jkt}$, where ω_{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

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

where the region-year pricing residual is $\bar{\epsilon}_{mt} = \sum_{j \in \mathcal{J}_{mt}} \omega_{jmt} \epsilon_{jt}$. 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)).

3.2 Estimation

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.⁹ If anything, we expect unobserved costs to dominate the residuals, rather than unobserved demand, due to 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.

3.3 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.¹⁰

Estimation exploits two main sources of empirical variation in fuel costs. First, the

⁹Consistent with this, bituminous coal and petroleum coke prices do not follow the pro-cyclical pattern of cement consumption.

¹⁰We 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.

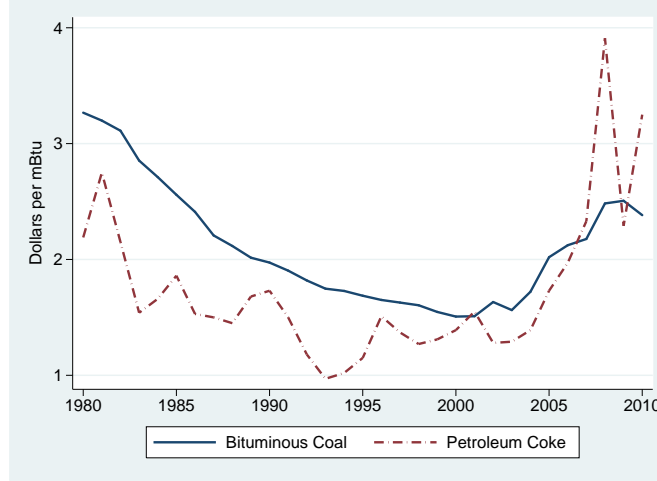


Figure 1: Primary Fuels and Fuel Prices

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.

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 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.¹¹

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., β) from the baseline own pass-through (i.e., α_0), and we demonstrate each in Appendix B using simple examples. Own pass-through heterogeneity (i.e., α_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 impossible 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.¹² Nevertheless, the data support precise

¹¹A 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.

¹²To provide perspective on this multicollinearity problem, the univariate correlation coefficient between

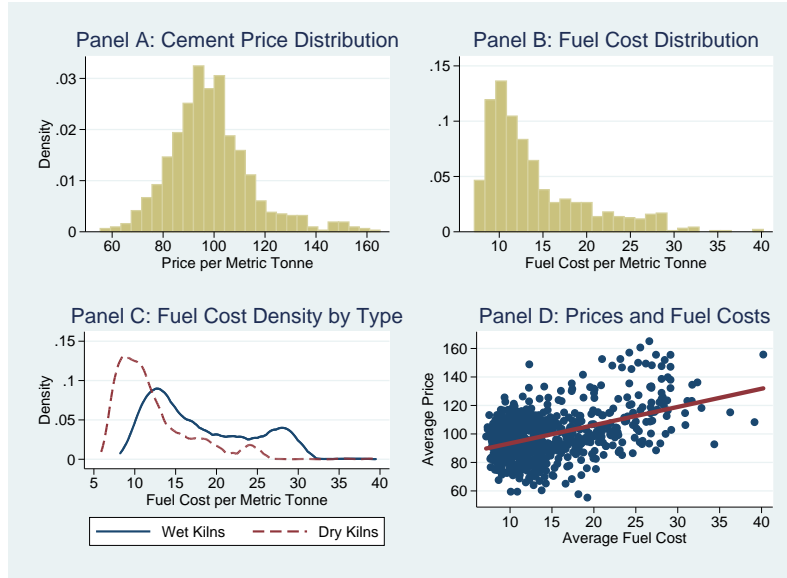


Figure 2: Regional Prices and Fuel Costs over 1980-2010

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.

estimates of industry pass-through, including how competition affects industry pass-through, and this has direct bearing on cap-and-trade regulation and the NESHAP amendments. Plant-specific pass-through is most relevant for the merger application, and there we conduct robustness checks to explore different pass-through scenarios.

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 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

the own pass-through heterogeneity and cross pass-through regressors is 0.924 in the plant-level data, but 0.995 in the region-level data. Estimates of industry pass-through are not sensitive to the inclusion or exclusion of these regressors.

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

We include the above variables in our baseline regressions. Precise mathematical definitions are provided in Appendix Table A.2. Inference on pass-through does not change meaningfully if some or all of 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.¹³ We use 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.¹⁴ 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 distance 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 distance thresholds of 300 and 500.

4 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

¹³The 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.

¹⁴A 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.

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

$$\rho_{jj} = \frac{1}{N + 1 - z} \quad \text{and} \quad \rho^M = \frac{N}{N + 1 - z} \quad (5)$$

where ρ_{jj} is own pass-through, ρ^M is industry pass-through, and z is positive with convex 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.¹⁵

¹⁵Specifically, $z = - \left(Q \frac{\partial^2 P}{\partial^2 Q} \right) / \left(\frac{\partial P}{\partial Q} \right)$, where Q and P are the market quantity and price, respectively. The derivation does not require that marginal costs be homogeneous across firms.

Table 2: Regression Results

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Fuel Costs	1.28 (0.14)	1.16 (0.16)	1.24 (0.16)	1.26 (0.19)	1.43 (0.18)	1.24 (0.20)	1.45 (0.27)
Fuel Costs \times Inverse Rival Distance				-5.71 (1.37)	-5.52 (1.54)		
Rival Fuel Costs \times Inverse Rival Distance				5.45 (1.81)	4.97 (1.90)		
Fuel Costs \times (Year \geq 1990)						-0.07 (0.16)	
Fuel Costs \times (Year \geq 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
<i>Derived Statistics: Industry Pass-Through</i>							
Median	1.28 (1.02, 1.56)	1.16 (0.87, 1.48)	1.24 (0.94, 1.57)	1.22 (0.91, 1.51)	1.36 (1.04, 1.65)	1.24 (0.73, 1.77)	1.45 (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* \times *Inverse Rival Distance* and *Rival Fuel Costs* \times *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.

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).¹⁶ We note 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)). The regression results therefore should not be interpreted as enabling precise inferences regarding pass-through heterogeneity and cross pass-through. The empirical variation available at the region level is sufficient to estimate the net effect, and the presence of collinearity does not affect statistical inferences regarding industry pass-through. Further, the 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 ?? how industry pass-through – the primary object of interest in this application – can be used to evaluate the effects of market-based CO₂ 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

¹⁶The 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.

Table 3: Industry Pass-Through in Selected EPA Markets

	N	Theoretical Predictions		
		$\epsilon^D = 1.0$	$\epsilon^D = 1.5$	$\epsilon^D = 2.0$
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 ϵ^D .

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 CO₂, 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.¹⁷ The similarity between the theoretical predictions and our empirical estimates is apparent, and supports the validity of the structural models.

5 Market-Based Regulation

Our regression results have direct bearing on the implications of CO₂ 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

¹⁷The authors can provide results for all 20 EPA markets upon request.

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 and production-based updating of permit allocation is not employed. This best utilizes our pass-through estimates, which relate domestic costs to domestic prices. We then discuss how inferences extend to cap-and-trade programs with more sophisticated mechanisms, such as border tax adjustments (BTAs) and production-based updating.

5.1 Symmetric oligopoly

We first consider a general model of symmetric oligopoly. Denote industry pass-through as ρ^M , the industry elasticity of demand as ϵ^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

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

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.¹⁸ We translate the output tax into a CO₂ 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. A recent analysis conducted by the EPA constructed kiln-specific variable costs for each of 20 local markets; the costs imply an average margin of 43% when paired with reported market prices (EPA (2009)). On the domestic industry elasticity of demand, Jans and Rosenbaum (1997) report an estimate of 0.87, Miller and Osborne (2010) report an estimate of 1.11, and Fowlie, Reguant, and Ryan

¹⁸The 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 4, 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.

(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.¹⁹ 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. While how surplus loss is distributed downstream (e.g., among ready-mix concrete plants, construction firms, and end users), cannot be informed by our data, a reasonable conclusion is that broad-based disbursements are more likely to align compensation with the adverse effects felt by market participants.

Table 5 shows the deadweight loss (Panel A) and the social value of abatement (Panel B), both per dollar of carbon tax. Both depend on the elasticity of demand, while deadweight loss also depends on margins and the social value of abatement also depends on the social cost of carbon ("SCC").²⁰ Calculations use an industry pass-through of 1.20. The deadweight loss of regulation is of the same magnitude as the social value of abatement. This is due to market power, which amplifies deadweight loss in oligopoly models with (e.g., Buchanan (1969)). The deadweight loss is \$25 million with margins of 0.35 and an elasticity of 1.00. The comparable value of abatement is \$29 million with an SCC of \$40 and \$71 with an SCC

¹⁹For 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.

²⁰Official 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 CO₂ emissions per metric tonne of cement.

Table 4: Change in Producer Surplus (\$MM)

Panel A: Industry Pass-through of 1.20						
Margins	Domestic Elasticity of Demand					
	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						
Margins	Domestic Elasticity of Demand					
	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						
Margins	Domestic Elasticity of Demand					
	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: All numbers are in millions of real 2010 dollars per dollar of carbon tax. Calculations are based on a general model of symmetric oligopoly. 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 CO₂ 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: Deadweight Loss and Abatement (\$MM)

Panel A: Deadweight Loss						
Margins	Domestic Elasticity of Demand					
	0.60	0.80	1.00	1.20	1.40	1.60
0.20	8.65	11.53	14.42	17.30	20.18	23.06
0.30	12.97	17.30	21.62	25.95	30.27	34.60
0.35	15.14	20.18	25.23	30.27	35.32	40.36
0.40	17.30	23.06	28.83	34.60	40.36	46.13
0.50	25.95	28.83	36.06	43.25	50.45	57.66

Panel B: Social Value of Abatement						
SCC	Domestic Elasticity of Demand					
	0.60	0.80	1.00	1.20	1.40	1.60
20	5.55	11.40	14.25	17.10	19.95	22.80
40	17.10	22.80	28.50	34.20	39.90	45.60
60	25.65	34.20	42.75	51.30	59.85	68.40
100	42.75	57.00	71.25	85.50	99.75	113.99

Notes: All numbers are in millions of real 2010 dollars per dollar of carbon tax. Calculations are based on a general model of symmetric oligopoly. 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 CO₂ 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. An industry elasticity of 1.20 is used. In panel B, SCC refers to the social cost of carbon.

of \$100. Calculations based on higher (lower) industry pass-through increase (decrease) both deadweight loss and the social value of abatement mechanically, preserving the relative magnitudes.

5.2 Asymmetric oligopoly

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

Table 6: 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.

statements are not readily available in the literature.²¹ 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 present in the aggregated data. If anything, we expect the analysis to overstate the degree of heterogeneity present.²²

Table 6 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.

Figure 3 maps the county-level price changes that arise per dollar of carbon tax. Our objective is to inform the geographic dispersion of effects. We approximate county-level price effects as weighted averages of the plant-level price changes, with weights that are proportional to the inverse miles between the plant and the county centroid. Counties with larger price increases are shown with deeper shades of blue. The distribution of price

²¹In 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.

²²This 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 the true coefficients are smaller in magnitude. That stated, we predict that a carbon tax increases prices even in the extreme instances of negative own pass-through, due to the larger cross pass-through effects.

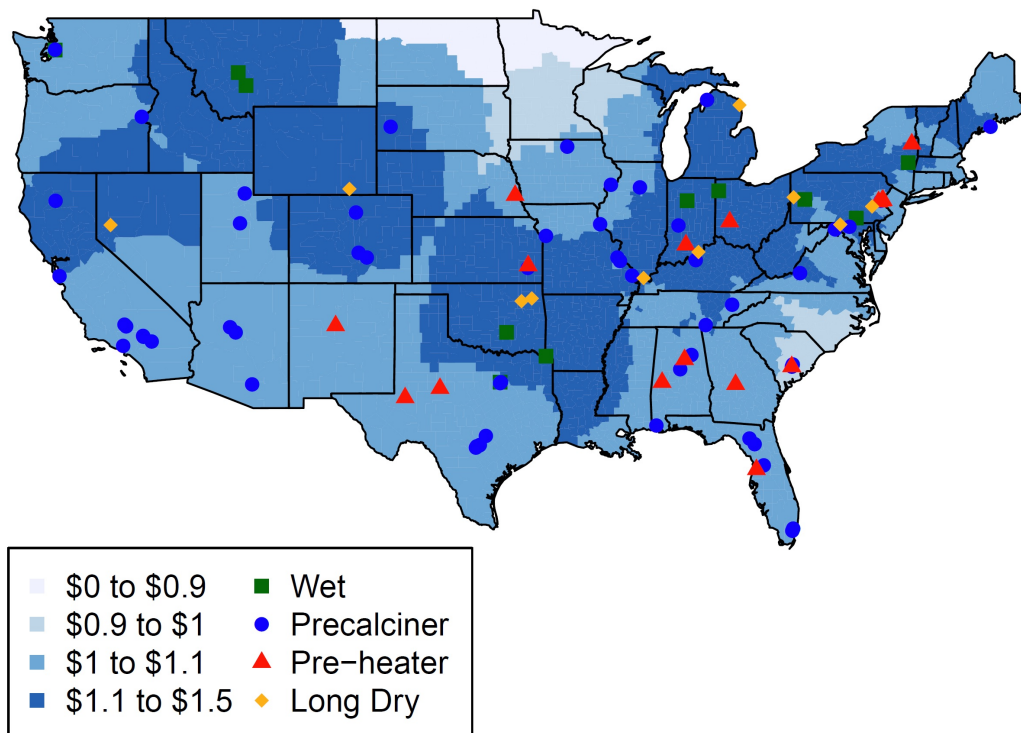


Figure 3: County-Level Price Changes per Dollar of Carbon Tax

Notes: County-level price changes are calculated as a weighted average of the plant-level price changes, with weights that are proportional to the inverse miles between the plant and the county centroid.

increases exhibits a modest degree of dispersion – nearly all counties experience increases between \$1.00 and \$1.50. The counties with larger price increases typically are near relatively inefficient cement plants. Smaller price increases arise in the southwest and southeast, where cement is produced in kilns that utilize modern technology.

5.3 Discussion

Our analysis of carbon taxes yields three main insights: (i) the burden of market-based regulation falls predominantly downstream, rather than on portland cement manufacturers; (ii) the deadweight loss of market-based regulation has the same order of magnitude as the social value of abatement; and (iii) market-based regulation is unlikely to substantially affect the distribution of producer surplus among existing plants. Our calculations embed specific assumptions on margins and demand elasticities, about which there is some uncertainty, but

the conclusions appear robust over the feasible ranges.²³ The incorporation of border tax adjustments (BTAs) to mitigate substitution to unregulated importers would reinforce our calculations, as the loss of producer surplus would diminish and the burden of regulation would shift downstream, to an even greater extent than our calculations indicate.

These insights have direct bearing the implementation of market-based regulation. First, insofar as the objective to compensate market participants for the burden of regulation, our results indicate that the broad-based disbursement of government revenue most closely aligns compensation with adverse effects. The result is useful because policy-makers typically have imperfect information about how the adverse effects of regulation are distributed through the supply chain. To our knowledge, previous determinations regarding the allocation of revenues have been made without a careful treatment these issues, and instead were the product of political bargaining among the vested interests.²⁴

Second, our results underscore the importance of regulatory design mechanisms that mitigate deadweight loss. Existing cap-and-trade programs, as well as the proposed program under the Waxman-Markey Bill, utilize production-based updating of permit allocations in order to motivate firms to expand production. Absent such mechanisms, our results indicate that the social gains due to abatement are substantially offset deadweight loss. Whether production-based updating can be implemented in a way that is consistent with a “fair” allocation of revenues is an interesting question that we plan to address in the next draft.

Lastly, we note that our findings in this section are 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 new 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 their structural model. Further, we determine that the constant

²³The external validity of our results is not guaranteed. That said, the finding of Fabra and Reguant (2014) that Spanish electricity plants exhibit similarly high rates of industry pass-through provides an empirical basis to speculate that our results may extend to other emissions-intensive sectors.

²⁴Market-based regulation typically takes 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. More recent action from the Environmental Protection Agency (EPA) places the regulation of greenhouse emissions from the electricity generation sector in the hands of states. An existing cap-and-trade program in California grandfathers 90 percent of its permits, while in New England firms must purchase permits.

elasticity demand schedules imposed in their 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.

6 Merger Analysis

Here we predict the price effects of the proposed merger of Holcim and Lafarge, the first- and third-largest cement firms in the United States, by clinker capacity in the final year of the data. We believe this represents the first academic application of first order approximation (FOA) in the study of merger price effects. The core logic is that horizontal mergers generate opportunity costs because, for each merging firm, a lower price requires it to forgo some profit that otherwise would be earned by its merging partner (Farrell and Shapiro (2010)). Price changes can be approximated by multiplying these opportunity costs by a relevant notion of pass-through (Jaffe and Weyl (2013)), and Monte Carlo evidence supports the accuracy of this calculation in the merger context (Miller, Remer, Ryan, and Sheu (2013)).²⁵

Our analysis accounts for two complications. First, the merging firms divested and closed a number of unprofitable plants after the final year of our data. We therefore provide separate predictions based on (i) an industry snapshot in 2010, for which we have complete data; and (ii) a 2014 snapshot in which the status of Holcim and Lafarge plants is updated from press releases, but the status of other plants is left as in 2010. Second, first order approximation as we apply it here requires information on firm-specific pass-through rates. We show results based on the imprecisely estimated point estimates, and also with firm-specific pass-through calculated with damped own pass-through heterogeneity and cross pass-through coefficients.²⁶

The requisite inputs for FOA are pass-through and what is known as “upward pricing pressure” or “UPP” among antitrust economists. UPP equals the opportunity cost created

²⁵We provide mathematical details on FOA in Appendix C. In our application, the approach has notable advantages over most simulation methodologies. Modeling the industry based on Cournot competition in local markets would be inappropriate because mergers are not profitable, except to monopoly, unless additional complicating factors are invoked. The alternative of modeling the industry based on Bertrand competition with spatial differentiation, as in Miller and Osborne (2014), is computationally difficult and requires an assumption on the functional form of demand that partially determines the magnitude of the merger effects. By contrast, our present calculations are both simple and consistent with profitable mergers, spatial differentiation, and arbitrary demand functions.

²⁶These robustness checks will be provided with the next draft of the paper. Damping the heterogeneity and cross terms together maintains the core econometric findings on industry pass-through.

by the merger and can be calculated from diversion – the fraction of sales lost by each merging firm, due to a price increase, that shift to the other merging firm – and the margins of the merging firms. Diversion and margins often are available to antitrust agencies through confidential business data, but we must rely on publicly available data and informed assumptions. Namely, we let diversion be proportional to the inverse distances between plants, we set margins to 30 percent, and we obtain measures of pre-merger prices based on the USGS regions in which plants are located, following Fowlie, Reguant, and Ryan (2014).²⁷

Table 7 shows results for each the 16 Holcim and Lafarge plants with a nonzero predicted price change in either the pre-divestiture and post-divestiture samples. Our calculations indicate that, but for the post-recession divestitures and closures, the merger would have resulted in substantial price elevations, on the order of 5%-7% at many Holcim plants and 3%-7% at many Lafarge plants. Accounting for changes in plant status, the predicted effects are more modest, at 3%-4%, and these exist only for five plants.

In Figure 4, we map the county-level distribution of price effects, both pre-divestiture (map A) and post-divestiture (map B). We calculate these county-level price changes based on a weighted-average of the plant-level price changes, with weights that are proportional to the inverse distance between the plants and the county centroids. While this a crude correspondence, we nonetheless consider it a useful way to examine the geographic dispersion of effects. The pre-divestiture map shows substantial price elevations in the Northeast, Southeast, and Great Plains. These effects arise due to Holcim and Lafarge plants, shown in orange circles and red diamonds, that are in close proximity to each other. The post-divestiture map, however, shows that price elevations are confined to the Northeast and the Great Plains, and that these elevations are smaller in magnitude. Although we do not investigate the matter formally, we suspect that each remaining pocket of harm could be remedied with a single divestiture.²⁸

²⁷To illustrate the diversion assumption, consider a simple model with three firms. The distances between firm A and its competitors, firms B and C, is 50 and 150 miles, respectively. Our working assumption is that 75% of firm A’s customers view firm B as their next best option and 25% view firm C as their next best option. The same diversion rates emerge if distance instead is measured in miles times the gasoline price because the gasoline price affects both distances proportionally.

²⁸Our calculations also do not inform whether these price effects could be mitigated by cost efficiencies or other factors, and we leave such considerations to the antitrust authorities.

Table 7: Predicted Price Effects of a Holcim/Lafarge Merger

City	State	Capacity	Pre-Merger Price	Pre-Divestiture Price	Pre-Divestiture Price Effects	Post-Divestiture Price	Post-Divestiture Price Effects
<i>Holcim Plants</i>							
Bloomsdale	MO	3,720	82.50	5.42	6.6%	3.88	4.70%
Midlothian	TX	2,126	91.00	0.06	0.0%	.	.
Holly Hill	SC	1,860	86.78	5.48	6.3%	.	.
Theodore	AL	1,503	83.00	6.84	8.2%	.	.
Catskill	NY	572	83.00	7.42	8.1%	.	.
Ada	OK	524	97.38	7.02	7.2%	.	.
Hagerstown	MD	512	84.16	3.83	4.5%	3.57	4.2%
Mason City	IA	363	103.13	0.08	0.0%	.	.
<i>Lafarge Plants</i>							
Ravena	NY	1,680	91.72	6.82	7.4%	2.30	2.5%
Calera	AL	1,403	83.00	3.09	3.7%	.	.
Grand Chain	IL	1,014	89.07	2.72	3.1%	2.67	3.0%
Harleyville	SC	978	86.78	2.38	2.7%	.	.
Buffalo	IA	975	103.13	6.84	6.6%	3.08	3.0%
Sugar Creek	MO	943	82.50	3.30	4.0%	.	.
Whitehall	PA	702	95.00	1.27	1.3%	0.61	0.1%
Tulsa	OK	580	97.38	4.75	4.9%	.	.

Notes: Predicted price effects are obtained from first order approximation. Prices are in real 2010 dollars. Capacity is in thousands of metric tonnes of clinker per year. Plants for which no price change is predicted do not appear, including Holcim plants in Florence CO, Morgan UT and Three Forks MT, and Lafarge plants in Alpena MI, Paulding OH and Seattle WA. The divestitures are based on Holcim's and Lafarge's consummated plant sales over 2011-2013.

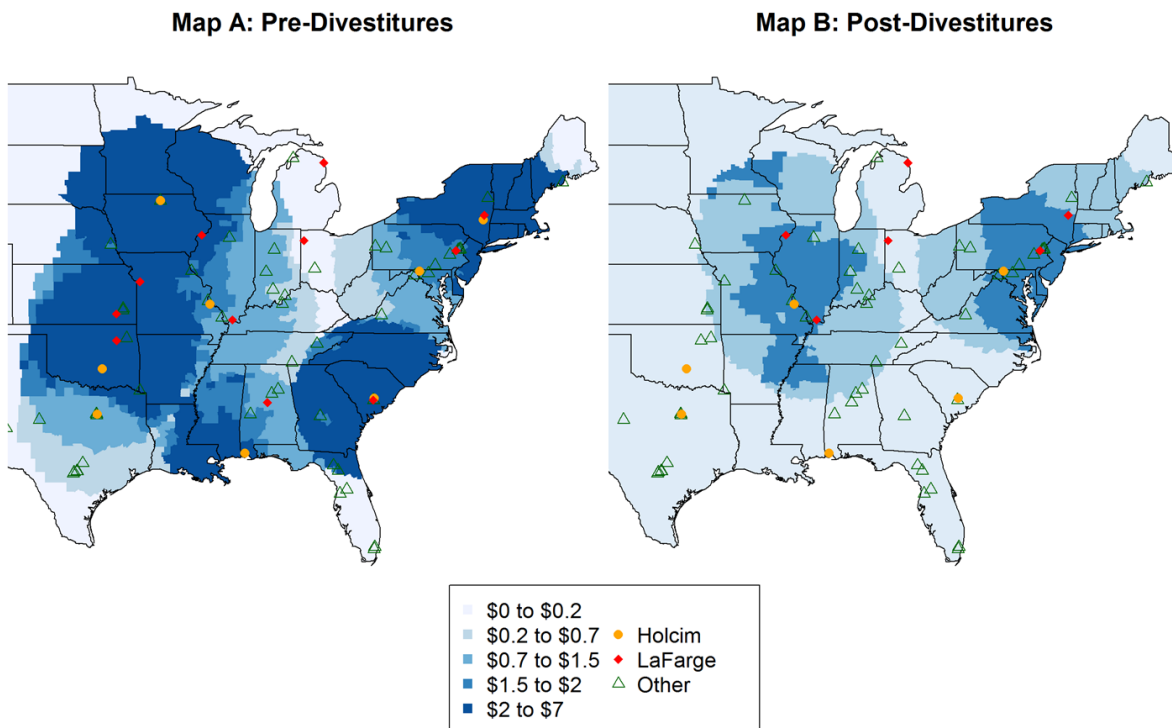


Figure 4: County-Level Predicted Price Effects of a Holcim/Lafarge

Notes: County-level price changes are calculated as a weighted-average of the plant-level price changes obtained from first order approximation. The weights are proportional to inverse distance. The distance metric employed is the log of one plus the miles between the plant and the county centroid. The distance threshold is 400. Price changes are in real 2010 dollars.

7 NESHAP Amendments

We turn now to an economic analysis of recent regulation promulgated by the EPA that reduces dramatically the legally permissible emissions of hazardous air pollutants (HAPs) including particulate matter, mercury, hydrocarbons, and hydrogen chloride. EPA analysis indicates that monetized health benefits, which it predicts exceed \$7-\$18 billion, far outweigh economic costs (EPA (2009); EPA (2010)). We revisit the price predictions of the EPA using our pass-through estimates. The EPA relies on a Cournot model of competition to simulate the effect of regulation in each of 20 local markets based on conditions in 2005. The model incorporates a constant elasticity market demand curve and, for markets that are adjacent to a customs office, a constant elasticity import supply curve. It is calibrated to elasticity estimates in the existing literature. Details on the model and calibration are provided in Appendix D.

We are able to fully replicate the EPA modeling results, up to the restriction that the

EPA makes compliance costs public only at the market-average level. We then update the analysis to 2010, the most recent year of our sample, and compare the price predictions to an alternative based on our pass-through estimates. Because the economic costs of concern result from the pass-through of compliance costs to customers, empirical estimates of pass-through usually provide more accurate short run predictions than model-based simulations (Miller, Remer, Ryan, and Sheu (2013)). While the EPA approach is grounded in modeling techniques and functional forms that are standard in the literature of industrial organization (e.g., Fowlie, Reguant, and Ryan (2014)), the drawback is that pass-through is fully determined by functional forms and the first order properties of the system. Relying on empirical estimates of pass-through relaxes these assumptions and allows the data to inform predictions more directly.

Figure 5 provides a scatter-plot of market-specific predictions from the EPA’s Cournot model (on the vertical axis) and the predictions from our pass-through estimates (on the horizontal axis). Across the 20 local markets, the Cournot model yields average price increases of \$4.66 per metric tonne and the pass-through calculations yield average increases of \$4.49. The predictions are highly correlated, with a univariate correlation statistic of 0.88.²⁹ The similarity between the two methodologies arises because the industry pass-through that is implicit in the EPA model is close to the industry pass-through that estimate (e.g., see Table 3). To our knowledge, the quality of this match between the EPA model and empirical pass-through is coincidental. Interpreted in that light, our results allow us to confirm a previously untestable assumption on demand curvature that has first order implications for pass-through and the price effects of regulation.

8 Conclusion

Our objectives in conducting the research described herein are twofold: First, we have intended to demonstrate that the estimation of pass-through is feasible, even without access to large quantities of price data at the firm/product level, and in a manner consistent with the oligopoly interactions of concentrated markets. Second, we have intended to reinforce theoretical findings about how pass-through can be used to better understand markets. In our view, the value of empirical research on pass-through is great, and we hope that our own work helps spur endeavors elsewhere. With that in mind, we offer some caveats that are relevant to our own research, and that are likely to generalize to other settings.

²⁹The exceptions are Pittsburgh, for which the EPA under-predicts by \$3.30 relative to the pass-through calculation, and Cincinnati, for which the EPA over-predicts by \$2.70 relative to the pass-through calculation.

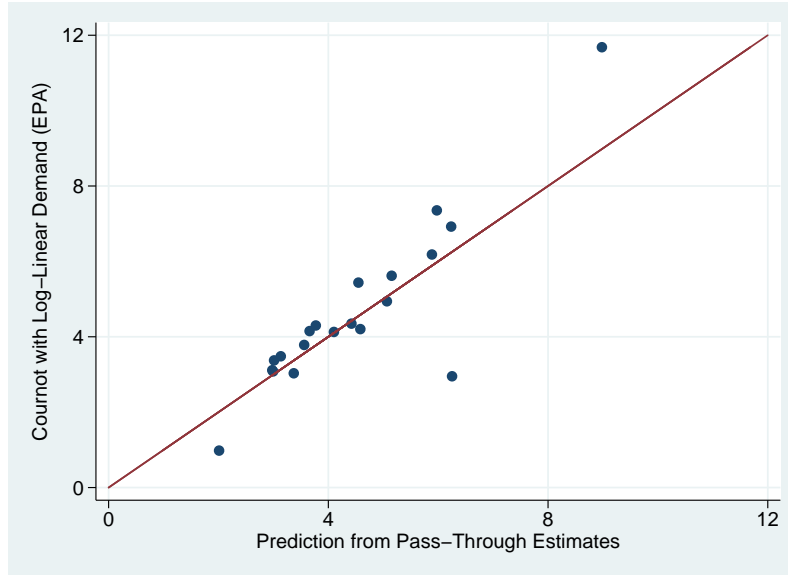


Figure 5: Price Effects of NESHAP Amendments for Portland Cement
Notes: Each dot represents the price predictions based on (i) the EPA model of Cournot competition between firms facing a constant elasticity demand curve and (ii) our estimates of pass-through. Also shown is a 45-degree line.

Estimates of pass-through typically are obtained with reduced-form regressions of price on a cost shifter. These regressions are vulnerable to bias from measurement error and omitted variables. Care must be taken in constructing the regressors, and in considering factors that correlate with both price and the cost shifter. In our application, the electricity price stands out as one such factor, but bringing it into the regression does not affect inference. Regression coefficients, even if unbiased, provide information on the average short run pass-through that arises in the data. These can diverge from long run pass-through, which typically is more interesting from a policy standpoint, if menu costs exist or if firms use simple rule-of-thumb pricing rules. Further, because equilibrium pass-through depends on higher order properties of the cost and demand functions, whether average pass-through corresponds to a theoretical notion of pass-through, at any equilibrium point, is unclear. It is possible to investigate this latter point, as we do in our application, but tests can be limited by the amount of empirical variation present.

Caution also must be taken when applying pass-through to analyze counter-factual scenarios. It is an open question whether historical pass-through are helpful in evaluation events that increase marginal costs well above historical levels. Yet this concern should not be overly limiting. In counter-factual scenarios, some assumptions must be made, and the existing Monte Carlo evidence indicates that using pass-through to inform predictions

typically improves accuracy (Miller, Remer, Ryan, and Sheu 2013). Finally, the theoretical ambiguities that exist with respect to pass-through make external validity challenging, absent careful consideration of institutional details. With these caveats in mind, we reiterate our belief in the value of empirical pass-through research.

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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.³⁰ 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.³¹ 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.

³⁰These states are Connecticut, Delaware, Louisiana, Massachusetts, Maine, Mississippi, Montana, North Dakota, New England, New Jersey, New Mexico, Nevada, Oregon and Vermont.

³¹We 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.

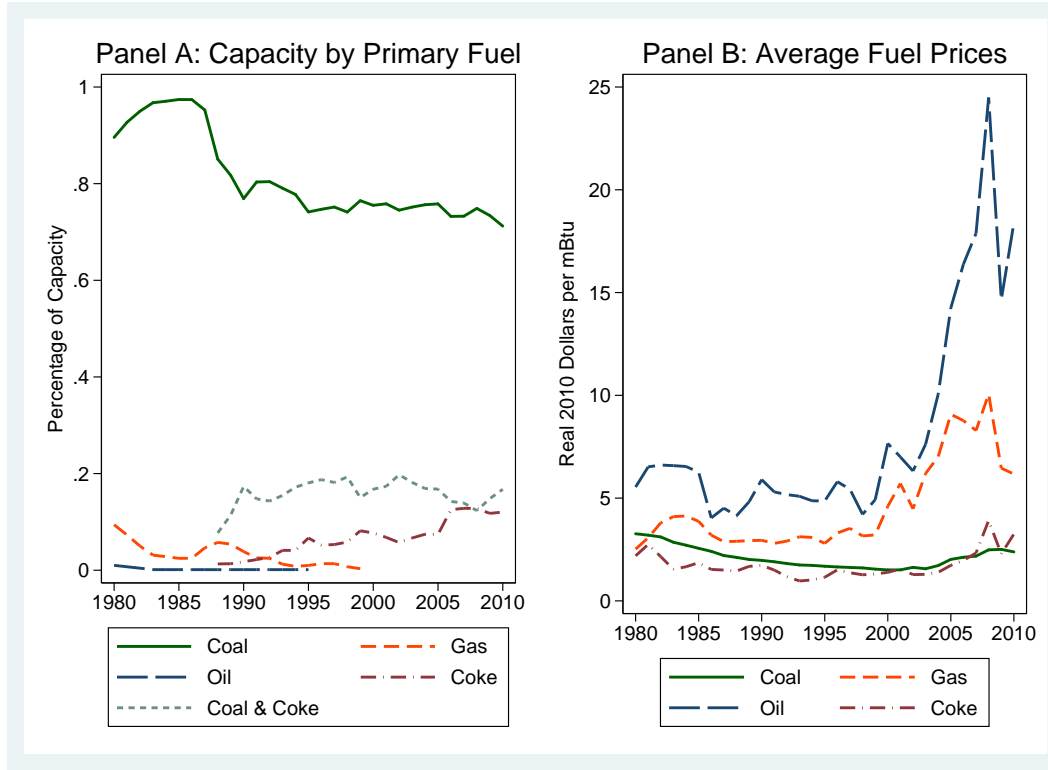


Figure A.1: Primary Fuels and Fuel Prices

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.³² 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.

³²We 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.³³ 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.³⁴ 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.

Table A.2 defines selected regressors mathematically, and provides summary statistics. In each instance, plant-level variables are aggregated to the region-level, following equation (4), in order to preserve the micro-foundations of the empirical model.

³³See <http://www.census.gov/econ/cbp/download/>, last accessed April 16, 2014.

³⁴See <http://socds.huduser.org/permits/>, last accessed April 16, 2014.

Table A.2: Definitions and Summary Statistics for Selected Regressors

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

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., α_1) from the cross pass-through parameter (i.e., β), is straightforward – plants often have different fuel costs than their nearby competitors – and needs no further explanation. Instead, we focus on the empirical variation that distinguishes the baseline fuel cost parameter (i.e., α_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

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

where we have normalized $\alpha_1 = \gamma = 0$, without loss of generality. Absent inter-temporal variation in the distance metric, the coefficients α_0 and β are not separately identifiable. This remains true if more firms are incorporated, provided that plant capacity is homogeneous. 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.³⁵ 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

³⁵If 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.

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

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

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 First Order Approximation

We sketch in this appendix the mathematics of first order approximation (FOA) as it pertains to merger price effects. Greater detail is provided in Jaffe and Weyl (2013) and Miller, Remer, Ryan, and Sheu (2013). The starting point for FOA is the first order condition that characterizes profit-maximization. Let cement firms set free-on-board prices to maximize profit, taking as given the prices of other firms. Then the first order conditions of any firm

i can be expressed

$$f_i(P) \equiv - \left[\frac{\partial Q_i(P)^T}{\partial P_i} \right]^{-1} Q_i(P) - (P_i - MC_i) = 0, \quad (\text{C.1})$$

where P_i is a vector of firm i 's plant prices, P is a vector of all prices, $Q_i(P)$ is a demand schedule and MC_i is a vector of firm i 's plant marginal costs. The post-merger first order conditions then can be expressed

$$h_i(P) \equiv f_i(P) + g_i(P) = 0, \quad (\text{C.2})$$

where, for a merger of firms j and k ,

$$g_j(P) = - \underbrace{\left(\frac{\partial Q_j(P)^T}{\partial P_j} \right)^{-1} \left(\frac{\partial Q_k(P)^T}{\partial P_j} \right)}_{\text{Diversion from } j \text{ to } k} \underbrace{(P_k - MC_k^1)}_{\text{Markup of } k}, \quad (\text{C.3})$$

the form of $g_k(P)$ is analogous, and $g_i(P) = 0$ for $i \neq j, k$. The g function captures the opportunity costs, or “upward pricing pressure,” created by the merger.³⁶ Notice that it enters the post-merger first order conditions in the same way as a cost shock. To a first order approximation, the resulting price changes equal

$$\Delta P = - \left(\frac{\partial f(P)}{\partial P} + \frac{\partial g(P)}{\partial P} \right)^{-1} \bigg|_{P=P^0} g(P^0), \quad (\text{C.4})$$

where P^0 is the vector of pre-merger equilibrium prices. In this expression, the Jacobian of the post-merger first order conditions – “merger pass-through” – depends on the first and second derivatives of demand. Given knowledge of the first derivatives, it is possible to infer the second derivatives from cost pass-through based on the formula

$$\rho = - \left(\frac{\partial f(P)}{\partial P} \right)^{-1} \quad (\text{C.5})$$

Merger pass-through then can be calculated with the first and second demand derivatives. In our application, the large number of plants makes it numerically difficult to identify the

³⁶Each firm in the merger, when making a sale, forgoes with some probability a sale by the other firm. The diversion matrix represents the fraction of sales lost by firm j 's products that shift to firm k 's products due to an increase in firm j 's prices. When multiplied by firm k 's markups, this yields the value of diverted sales; the more these sales are worth, the greater incentive a firm has to raise price following a merger.

second derivatives. We instead use cost pass-through to proxy merger pass-through. Price predictions then are based on the matrix multiplication of the pass-through matrix and the vector of upward pricing pressure. This simplification is proposed in Jaffe and Weyl (2013) and shown in Miller, Remer, Ryan, and Sheu (2013) to cause little loss of predictive accuracy.

D EPA Analysis of NESHAP Amendments

The EPA relies on a Cournot model of competition to simulate the effect of regulation in each of 20 local markets based on conditions in 2005. The model incorporates a constant elasticity market demand curve and, for markets that are adjacent to a port, a constant elasticity import supply curve. It is calibrated to elasticity estimates in the existing literature. We provide details on the model here. After the implementation of regulation, the first order conditions of firm i can be expressed

$$dMC_i = dP \left[1 + \frac{s_i}{\eta} \right] + dq_i \left[\frac{P}{\eta} \frac{1}{Q} \right] - dQ \left[\frac{P}{\eta} \frac{q_i}{Q^2} \right], \quad (\text{D.1})$$

P is the market price, s_i is the share of sales for plant i , q_i is the quantity sold by plant i , Q is market consumption including imports, MC is marginal cost, and η is the elasticity of consumption with respect to price. Thus the object dMC is the compliance cost of regulation. Equation D.1 governs how compliance costs, represented by dMC_i , affect output and, in turn, market price. Imports are supplied according to an elasticity ϕ , such that

$$dI = \phi \left(\frac{dP}{P} \right) I, \quad (\text{D.2})$$

where I is the quantity of imports. Total consumption in a market (again including imports) evolves according to

$$dQ = \eta \left(\frac{dP}{P} \right) Q. \quad (\text{D.3})$$

Finally, the model is closed with supply equaling demand,

$$dQ = \sum_i dq_i + dI. \quad (\text{D.4})$$

The EPA calibrates the model with a price elasticity of consumption of 0.88, based on EPA (1998), an import elasticity of 2.0, based on Broda, Limao, and Weinstein (2008). Prices and plant-level production are calculated by manipulating the region-level data published in

the *Minerals Yearbook* of the USGS, following a methodology that is detailed in Section A.1 of EPA (2009). We are able to replicate the calibration process exactly so that discrepancies between our predictions and those of the EPA are due solely to the decision of the EPA not to publish plant-level compliance costs.