**How Does State-Level Carbon Pricing in the United States Affect Industrial Competitiveness?**

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## Abstract

Pricing carbon emissions from an individual jurisdiction may harm the competitiveness of local firms, causing the leakage of emissions and economic activity to other regions. Past research concentrates on national carbon prices, but the impacts of subnational carbon prices could be more severe due to the openness of regional economies. We specify a flexible model to capture competition between a plant in a state with electric sector carbon pricing and plants in other states or countries without such pricing. Treating energy prices as a proxy for carbon prices, we estimate model parameters using confidential plant-level Census data, 1982–2011. We simulate the effects on manufacturing output and employment of carbon prices covering the Regional Greenhouse Gas Initiative (RGGI) in the Northeast and Mid-Atlantic regions. A carbon price of $10 per metric ton on electricity output reduces employment in the regulated region by 2.7 percent, and raises employment in nearby states by 0.8 percent, although these estimates do not account for revenue recycling in the RGGI region that could mitigate these employment changes. The effects on output are broadly similar. National employment falls just 0.1 percent, suggesting that domestic plants in other states as opposed to foreign facilities are the principal winners from state or regional carbon pricing.

**Keyword*:***

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## 1. Introduction

The adoption of carbon pricing in an individual jurisdiction raises the possibility that some economic activity, especially in energy intensive and trade exposed (EITE) industries, may shift production to areas with lower costs. This relocation of economic activity in response to a carbon price, known as a "competitiveness" effect, is often proxied by reductions in output, employment or profit in the carbon pricing jurisdiction. Emission leakage results when the emissions reduction in the carbon pricing region are offset by emissions increases elsewhere. Past research has concentrated on national carbon prices, but the competitiveness and leakage effects of sub-national carbon pricing could be more severe due to the free flow of goods across states.

Increasingly, carbon prices vary across jurisdictions that trade goods with one another. In the United States, California has capped most state-wide carbon emissions since 2012. Multiple Northeast and mid-Atlantic states have capped carbon emissions from the electricity sector via the Regional Greenhouse Gas Initiative (RGGI) since 2009. As of May 2020 California's allowance prices are trading below $18 per metric ton, while RGGI allowance prices are trading below $6 per metric ton. Other states are considering adopting a carbon price (either an emissions tax or cap) or increasing the scope or stringency of existing carbon pricing regimes for electricity generation, transportation, and other sectors.[2]

A central insight of the growing literature on competitiveness and leakage effects – largely at the national and international levels -- is that the extent of adverse effects depends on the degree of competition between firms in areas that impose a carbon price versus those that do not.[3] The impacts of subnational carbon prices, particularly for EITE industries, could be more severe due to the openness of regional economies.[4] Despite the prominence of such policies, however, the literature has not previously examined this possibility.

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[2] For example, as of late 2018, Oregon was considering pricing carbon and linking its program with California's, and many states in the Mid-Atlantic and Northeast were also considering the expansion of RGGI.

[3] For example, see Fowlie, Reguant, and Ryan (2016); Fischer and Morgenstern (2009); Fischer and Fox (2012); and Boehringer, Fischer, and Rosendahl (2010).

[4] In the U.S., electricity accounts for less than 2 percent of total manufacturing costs. However, for aluminum, chemicals, cement, and certain other energy intensive industries the cost share is considerably higher - suggesting proportionately larger negative effects of higher electricity prices. While some plants combust fuels directly, virtually all facilities consume electricity.

The fact that states sell a large share of their manufacturing output beyond the local market makes them sensitive to competition from other states and countries. In 2012, about two-thirds of U.S. manufacturing output (by value) was shipped more than 100 miles and a similar proportion was shipped to another state or country. The domestic competitive pressures faced by manufacturing plants in a particular state suggest that even a modest carbon price applied to only that state could be costly and lead to a reduction in output and employment, as well as emissions leakage.

We develop a model that links plant-level outcomes, including employment and output, to energy prices. We decompose the effect of a regional carbon price on a plant's outcome into two channels: a) the change of the national average outcome for the corresponding industry; and b) the deviation in the plant's outcome from that national average outcome. The first channel is estimated using an approach similar to Aldy and Pizer (2015).[5]

Estimating the second channel is the primary literature contribution of our empirical analysis. This empirical component contains several features that make it particularly suitable for the analysis of state-level carbon pricing. First, and most importantly, we control separately for the energy prices a plant faces and the energy prices faced by competing plants in other states and countries. This allows us to show transparently how carbon pricing in one state affects outcomes in that state and others. Second, we allow the effects of energy prices on output and employment to vary across industries and in a flexible manner. We partially relax assumptions that other studies have imposed on the relationships between a plant's energy cost share and the elasticity of its output and employment to energy prices.[6] Third, because some states (e.g., California) price carbon emissions from electricity and fuels whereas other states (e.g., New York) price carbon only for electricity, the model includes separate measures of electricity and fuels prices.

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[5] Aldy and Pizer (2015) use national-level data to estimate the effects of energy prices on manufacturing employment. They use their results to infer the effects of a hypothetical national carbon price, finding that a carbon tax of $15 per ton would increase net imports by up to 0.8 percent for the most energy intensive industries. Because they use national-level data, their results reflect only competition among US and international manufacturing plants. Although Kahn and Mansur (2013) estimate the effect of electricity prices on employment by comparing adjacent counties, their analysis does not directly translate to a statewide carbon price, which would affect energy prices at the state and not the county level. The general equilibrium literature (e.g., Boehringer, Fischer, and Rosendahl 2010; Fischer and Fox 2012; and Adkins et al. 2012) lacks the geographic resolution necessary to address state-level competitiveness issues.

[6] For example, Linn 2008, 2009; and Aldy and Pizer 2015.

In contrast, some empirical studies aggregate electricity and fuels.[7] Further, the model accounts for the energy embedded in materials inputs and also for demand and labor cost shocks. This model extends the work of Gray, Linn, and Morgenstern (2016) in several ways: including all sectors rather than selected energy-intensive, trade-exposed industries in the analysis; including all fuels rather than just natural gas; and controlling for indirect energy use. These advances make it possible to evaluate a wide range of actual or hypothetical state carbon pricing policies.

We use plant-level Census data from 1982–2011 to estimate a short-run (annual) reduced-form model of energy prices and the economic outcomes of interest (employment and output). The parameter estimates largely conform to intuition. The effects of a plant's own energy prices on its output and employment are generally negative -- reflecting the decrease in competitiveness for a plant that faces higher energy prices, all else equal. The effects of competing plants' energy prices are typically positive for the same reason. Energy-intensive industries are typically more adversely affected by energy prices than other industries.

We simulate the output and employment effects of a $10 allowance price in RGGI as well as an expanded program to include New Jersey and Pennsylvania. These states were chosen because they border the RGGI region and have previously belonged to RGGI or have considered joining; both states have substantial levels of manufacturing employment.

Our main finding is that RGGI loses 2.7 percent of manufacturing employment, and other non-RGGI states gain 0.8 percent. National employment falls just 0.1 percent, suggesting that domestic plants in other states as opposed to foreign facilities are the principal winners from state or regional carbon pricing. Thus, the geographical shifts in economic activity associated with jurisdiction-level carbon pricing are estimated to be greater in magnitude than those from a national carbon price, especially for the EITE industries. It is important to note that state policymakers can and do take steps to reduce the adverse effects of carbon pricing on the competitiveness for their manufacturing sector; for example, RGGI members use some allowance auction revenue to subsidize energy efficiency investments at industrial facilities.[8].

[7] For example, Aldy and Pizer (2015).

[8] In particular, states can use tax revenue (or in the case of a cap-and-trade program, allocate emissions credits rather than auction them) to compensate firms and reduce the likelihood of employment and output losses and the risk of emissions leakage. For example, California allocates emissions credits to certain industries based on their energy intensity and exposure to international competition. In addition, states can use tax revenue or revenues from

Because our employment and output estimates do not include the effects of these subsidies, they may overstate the adverse competitiveness effects of a carbon price.

Section 2 develops an analytical framework that links energy prices to output and employment, which are the key measures of competitiveness. Section 3 describes the data. Section 4 presents the empirical results of the statistical analysis, including the relevant elasticities of output and employment with respect to energy prices. Section 5 uses the statistical model to simulate the effects of alternative carbon prices on manufacturing industries in RGGI and surrounding states. Section 6 concludes.

## 2. Analytical Framework

This section presents the analytical framework used, including the decomposition of the effects of a regional carbon price and the estimation of both the deviations from the national average effects and the national average effects.

### 2.1 Decomposing the Effects of a Regional Carbon Price

As noted in the introduction, Aldy and Pizer (2015) estimate the effects of national average energy prices on national employment, and they use the results to make inferences on the effects of a hypothetical national carbon price on national employment. One expects that a national carbon price would affect employment in a given industry in the same direction across all regions of the country, although the magnitude of the effect could vary across states due to regional differences in energy intensity or other factors. In our context, by contrast, a regional carbon price would not have such uniform effects. A carbon price in the Northeast, for example, could reduce employment in the Northeast but increase employment in other regions. The effects of regional carbon prices are more likely to vary in direction across regions with a greater degree of competition among plants.

This possibility suggests decomposing into two terms the effects of a regional carbon price on the outcomes of plant $i$ in industry $j$. The first term is the effect of the regional carbon price on the national average of that outcome for the industry, $\Delta y_j$. This term captures competition

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allowance auctions to subsidize energy efficiency investments at energy consuming businesses, potentially reducing competitiveness effects. In 2017, almost two-thirds of the RGGI auction revenue supported energy efficiency and clean and renewable investments, mostly focused on the business and residential sectors.

among domestic and foreign plants in the industry. If plants in the industry compete closely with foreign plants, the national average effect should be negative—but if competition is purely domestic, the national average effect could be zero.

The second term in the decomposition is the plant's deviation from the corresponding national average, $\Delta y_{ij}$. This term captures domestic competition. If the region imposes a carbon price, the deviation should be negative, as the carbon price causes plants in the region to be less competitive compared to other domestic plants. If the region does not impose a carbon price, the deviation should be positive because the plants in the region are more competitive compared to plants in the regulated region.

Aldy and Pizer (2015) estimate the first term in this decomposition. Identifying the second term is the main focus of our empirical analysis, as discussed below.

**2.2 Estimating Deviations from National Average Effects**

This subsection describes the short-run econometric model that links a manufacturing plant's economic activity to the energy prices it faces and the energy prices of its competitors. The effects of energy prices on an individual manufacturing plant depend on where the plant is located. For example, suppose Massachusetts adopts a carbon price that raises energy prices, and that no other states adopt a carbon price. In that case, the energy costs of plants located in Massachusetts increase relative to competing plants elsewhere. In contrast, for a plant located outside the Bay State, the energy prices it faces do not change, while the prices paid by its competitors increase. The increase in energy prices in Massachusetts, therefore, can create a competitive advantage for plants located outside the state.

For either a plant in Massachusetts or a plant outside the state, we can express output or employment ( $y$ ) as a function of the energy prices faced by the plant and the energy prices of its competitors:

$$\ln(y) = \beta_1 s * \ln(p) + \beta_2 s * \ln(p_R) \tag{1}$$

where $s$ is the cost share of energy, $p$ is the energy price the plant faces, and $p_R$ is the energy price faced by plants in other states. The energy cost share is multiplied by the energy price because a given energy price increase should have a greater effect on the outcomes for energy-intensive industries than for other industries. We expect $\beta_1$ to be negative because a plant facing higher costs should produce less output and have lower profits, and these negative effects should increase in magnitude with the cost share. In principle, if energy and labor are strong enough substitutes, the coefficient could be positive for employment.

In the case where output is on the left-hand side of Equation (1), this particular functional form (in which we interact the cost shares with the energy prices) represents a generalization of a Cobb-Douglas production function. If the plant has a Cobb-Douglas production function, the output would be directly proportional to the interaction of the cost share with the price, and $\beta_1$ would equal –1.

The parameter $\beta_2$ should be positive because an increase in the energy prices of competing plants makes the plant more competitive relative to those plants. For example, a Massachusetts energy price increase would increase the competitiveness of plants outside the state that compete with Massachusetts plants, causing their output ( $y$ ) to increase. Note that we could express the outcome variable as a function of the price of energy faced by the Massachusetts plant relative to the price of energy in other states (i.e., $p / p_R$), which would be equivalent to setting $\beta_1 = -\beta_2$ in Equation (1).

To arrive at the estimating equation, we relax several assumptions embedded in Equation (1). First, Equation (1) includes aggregate energy prices but the specific policies we consider affect electricity and natural gas prices in different ways. Consequently, we distinguish between the consumption of electricity and the consumption of fuels, which primarily include natural gas and petroleum products for the manufacturing industries studied here.

Second, Equation (1) includes the assumption that energy prices affect economic activity in proportion to the cost share of energy. Aldy and Pizer (2015) and others in the literature make a similar assumption. However, given the available data we can partly relax this assumption. We define eight industry groups based on their energy cost shares and we allow the coefficient on their cost shares to vary across groups. For industries belonging to the same group, energy prices affect economic activity in proportion to the energy cost shares, but we do not assume any proportionality across groups. This approach allows the data to determine whether energy prices have larger effects for high-consuming groups than for other groups. It also allows for non-loglinear relationships among energy prices and outcomes.

Third, we account for indirect energy use. In the short run, with the capital stock fixed, plants select inputs of energy, labor, and materials. Linn (2009) shows that energy prices can affect economic activity directly, by raising the energy costs faced by a plant, as well as indirectly, by affecting the prices of materials inputs. Ganapati, Shapiro, and Walker (2017) show that energy prices affect marginal costs and output prices for certain industries, providing further evidence that energy prices can affect a plant indirectly via intermediate materials prices.[9] Consistent with these studies, we assume that the indirect effect depends on the energy intensity of the inputs a plant uses. For example, an increase in crude oil prices causes prices of petroleum products to increase, which affects production costs more for plants that use petroleum products than for those that do not. As described below, we use input-output relationships between industries to compute the average electricity and fuels cost shares of the materials each plant consumes. We interact the electricity and fuels cost share variables with their corresponding prices.

Fourth, we control for the plant's labor costs. We allow the coefficient on labor costs to differ across the energy cost share groups. Further, we recognize that energy prices may be correlated with product demand. Energy price increases often accompany or precede macroeconomic downturns, which would bias estimates of the effects of energy prices on economic activity. We control flexibly for national industry-level demand shocks by including interactions of industry- and year-fixed effects. We adopt two methods to control for subnational demand shocks. Using an approach that builds on Ellison and Glaeser (1999), we control for product demand of an individual plant based on input-output relationships between industries as well as a plant's proximity to demanding industries. In addition, we include interactions of fixed effects for Census region and year to allow for regional demand shocks. These interactions control for regional changes in input costs, regional product demand shocks, as well as international supply

[9] Ganapati, Shapiro, and Walker (2017) estimate the pass-through of energy prices to marginal costs and output prices. Our assumption on pass-through regards the pass-through of the carbon price to energy prices, and not output prices for the manufacturing plants. Fabra and Reguant (2014), among others, provide evidence on full pass-through of a carbon price to energy prices.

and demand shocks that affect each industry proportionately. The next section describes the construction of these variables in detail.[10]

After making these modifications to Equation (1), we arrive at the estimating equation:

$$\begin{aligned}\ln(y_{ijt}) = \beta_0 &+ \beta_1^E s_j^E \ln(p_{ijt}^E) + \beta_2^E s_j^E \ln(p_{R,ijt}^E) + \beta_1^F s_j^F \ln(p_{ijt}^F) + \beta_2^F s_j^F \ln(p_{R,ijt}^F) \\ &+ \delta_1^E m_j^E \ln(p_{ijt}^E) + \delta_2^E m_j^E \ln(p_{R,ijt}^E) + \delta_1^F m_j^F \ln(p_{ijt}^F) + \delta_2^F m_j^F \ln(p_{R,ijt}^F) \\ &+ \gamma_1^E \ln(p_{ijt}^E) + \gamma_2^E \ln(p_{R,ijt}^E) + \gamma_1^F \ln(p_{ijt}^F) + \gamma_2^F \ln(p_{R,ijt}^F) + \mu_1 LCOST_{ijt} \\ &+ \mu_2 DEMAND_{ijt} + \delta_{rt} + \delta_{jt} + \varepsilon_{ijt}\end{aligned} \tag{2}$$

where the dependent variable is employment or output by plant *i* in industry *j* and year *t*. Equation (2) includes interactions of the log of the plant's electricity price ($p_{ijt}^E$) with the industry's electricity cost share ($s_j^E$), as well as the interaction of the log of the electricity price of competing plants $\left(p_{R,ijt}^E\right)$ with the cost share. We use the industry's rather than the plant's cost share to address potential concerns about the endogeneity of the plant's cost share to unobserved plant-specific productivity. The equation includes corresponding terms for fuel prices, where the superscript *F* indicates a fuels price index rather than electricity (*E*). The second line in the equation includes the interactions of the energy price variables with the indirect energy use shares ($m_j^E$ and $m_j^F$). The variables are average electricity or fuels cost shares of the industry's materials. The equation includes the principal effects of electricity and fuels prices, with these effects being absorbed by the corresponding industry-year interactions ($\delta_{jt}$). The variables $LCOST_{ijt}$ and $DGROWTH_{ijt}$ indicate labor costs and a demand index; $\delta_{rt}$ are region–year interactions; and $\varepsilon_{ijt}$ is an error term. The next section describes the definitions of the competing energy prices, as well as the construction of the measures for indirect energy use, labor costs, and demand.

We estimate Equation (2) separately for each energy cost share group, omitting group subscripts in the equation to simplify the notation. Because we perform a separate estimation for

[10] In principle, we could add plant fixed effects to control for time-invariant unobservables at the plant level. Unfortunately, after including plant fixed effects there is insufficient remaining energy price variation to identify the coefficients.

each group, we allow for cross-group heterogeneity in the effects on economic activity of electricity prices, fuels prices, indirect energy use, labor costs, and demand. For symmetry, we allow for the possibility that the effect of a competitor's energy prices varies across groups—for example, if the industry's energy cost share is correlated with the degree of competition with nearby plants.

The industry-year interactions play an important role in the identification and interpretation of the coefficients on the variables that include energy prices. These interactions control for the effects of energy prices on the average of the outcome for each industry and year. Consequently, the coefficients are identified by deviations from industry-year means of energy prices interacted with cost shares. For this reason, the coefficients capture precisely the second term in the decomposition introduced in the previous subsection—that is, the deviations from the national averages of the effects of energy prices on a plant's outcomes. The region-year interactions control for regional output or employment trends, and the energy price coefficients are identified by energy price variation across states within a region.

Based on the intuition from Equation (1), within a cost share group, we expect that a plant's electricity and fuels prices negatively affect the outcomes, and that the negative effects are larger in magnitude for plants with higher cost shares—that is, the interaction terms for the plant's energy prices are negative. Likewise, we expect positive coefficients for the interaction terms involving energy prices of competing plants. We expect the signs on the indirect energy use interactions to be the same as the signs of the corresponding direct energy use interactions.

### 2.3 Estimating National Average Effects

Equation (2) identifies a plant's deviations from national industry average effects of energy prices. To estimate the total effect of a carbon price, we therefore need to estimate the effects of energy prices on national averages of the four outcomes. To accomplish this, we take an approach similar to that of Aldy and Pizer (2015) and estimate an industry-level regression

$$\ln(y_{jt}) = \theta_0 + \theta_1^E c_j^E \ln(p_t^E) + \theta_1^F c_j^F \ln(p_t^F) + \rho_1 LCOST_{jt} + \rho_2 DEMAND_{jt} + \tau_t + \tau_j + \varepsilon_{jt} \quad (3)$$

where the dependent variable is employment or output by industry $j$ and year $t$. The equation includes the interaction of the industry's electricity or fuels cost share with the log of the average price of electricity or fuels in year $t$. Because there is less price variation in the aggregate than in the plant-level data, we add the direct and indirect cost shares in Equation (2) to create a combined cost share, $c$, in Equation (3). The variables for labor costs and demand are defined similarly to Equation (2), except that they are aggregated across plants. The equation includes year and industry fixed effects, and an error term.

The coefficients on the cost share–energy price interactions are the key estimates of interest. They are identified by time series variation in energy prices interacting with cross-industry variation in cost shares. For example, if the price of electricity increases between one year and the next, the interaction coefficient is identified by cross-industry variation in the response of the dependent variable to the price increase. One expects an electricity price increase to have a larger negative effect for industries that consume more electricity than others (either directly or indirectly via intermediate materials), in which case the interaction coefficient is negative. Note that the equation omits the main effects of the cost shares and energy prices because they are absorbed by the industry and year fixed effects. The year fixed effects control for average energy prices in other countries and any other global demand or supply shocks that affect all industries proportionately. Therefore, the energy price coefficient captures the effects of domestic energy prices, holding international prices fixed. This is an important aspect of the estimation because the simulations implicitly hold international prices fixed. The labor cost and demand variables account for supply and demand shocks that vary across industries.

Although Equation (3) is broadly similar to Aldy and Pizer (2015), there are a few important differences. First, and most importantly, we estimate separate effects for electricity and fuels prices. This is consistent with Equation (2) and enables us to simulate carbon prices that affect electricity prices only, as well as carbon prices that affect both electricity and fuels prices. Second, we include only industry and year fixed effects rather than interactions of year fixed effects with aggregated industry fixed effects. Including only the year fixed effects rather than additional controls is for consistency with the simulations discussed below. Third, we use aggregate energy prices rather than industry-specific energy prices to reduce concerns about endogeneity. Fourth, we account for both direct and indirect energy use, which is consistent with the empirical analysis cited above as well as the plant-level estimation in Equation (2), and allows for the possibility of indirect effects of energy prices acting through intermediate materials prices. Finally, we omit controls for oil prices, physical capital, and human capital. These choices are motivated primarily by parsimony to focus on the key coefficients of interest. In practice, these differences do not appear to substantially affect the results; we obtain similar estimates to those reported in Section 5 if we use a specification more similar to Aldy and Pizer (2015).

## 3. Data and Summary Statistics

Our analysis is based on confidential plant-level data collected by the Census Bureau in the Census of Manufactures (CMF) and the Annual Survey of Manufactures (ASM), which provide data on output, revenue, employment, and expenditures. The CMF is conducted every five years and includes data from all manufacturing plants; we use all years of the CMF from 1982–2007. The ASM samples small plants and includes all large plants; we use the ASM data from 1983–2011. The ASM and CMF records are linked together over time in the Longitudinal Business Database, as described in Jarmin and Miranda (2002). Our final dataset includes about 2.5 million plant-year observations, covering all manufacturing industries except those that shifted in or out of the manufacturing sector during the 1997 switch from the Standard Industry Classification (SIC) to the North American Industry Classification System (NAICS) industry definitions.

To measure economic activity, the ASM/CMF data provide the dependent variables for our analysis: employment and output. Employment is measured as the plant's total employment including both production and nonproduction workers. Output is measured as the plant's total value of shipments, deflated by the industry's price deflator for shipments from the NBER-CES Manufacturing Industry Database.[11]

Our key explanatory variables are related to energy costs. The ASM/CMF data provide annual plant-level expenditures separately for electricity and fuels and also report the quantity of electricity purchased. We calculate average (rather than marginal) plant-level electricity prices as

[11] https://www.nber.org/data/nberces.html. At the time of our analysis, these data were only available through 2011.

the ratio of electricity expenditure to the quantity of purchased electricity.[12] Using the 1992 CMF, we calculate the average share of electricity or fuels in the value of shipments by industry. Under the standard assumption that plants earn zero economic profits in the long run, these shares equal the corresponding cost shares.

Because the ASM/CMF data do not include quantities of purchased fuels throughout the sample, we use state-level industrial prices for five fuels (coal, natural gas, distillate fuel oil, residual fuel oil, and liquefied natural gas) from the US Energy Information Administration. The computed fuels price varies by industry, state, and year, equaling the average of the five fuel prices for each state-year, weighted by each industry's expenditure shares of those fuels, taken from the 1981 ASM.

We use geocoded Census data from the Longitudinal Business Database to approximate cross-state competition among plants. First, we randomly select 10,000 ASM/CMF plant observations from each state. If at least 1,000 of the businesses in one state are located within 500 miles of 1,000 businesses in another state, those two states are deemed to be neighbors. The choice of the 500-mile radius is motivated by the fact that according to the Commodity Flow Survey (CFS), manufacturing goods are typically shipped less than 500 miles. Thus, using this radius allows us to characterize the set of plants in other states that are likely to compete with plants in a particular state. We calculate neighbor electricity and fuels prices for each plant in our sample as the average of the electricity and fuels prices across all plants in the same industry in neighboring states. These neighbor prices vary by industry, state, and year, and they account for geographic concentration of plants within a state.

The labor cost index is computed from the labor cost for plants in the same industry and state, as well as plants in the same industry in neighboring states. The index is the total payroll for all such plants divided by their total employment, using the 500-mile definition to define the set of neighboring plants and excluding the plant's own payroll and employment.

The demand index varies by plant and year and is based on downstream economic activity and shipping patterns. First, input-output (IO) tables from the US Bureau of Economic

[12] The ratio could be measured with error, which would bias estimated coefficients. We have performed data quality checks on both the expenditure and quantity variables used to calculate prices.

Analysis (BEA) identify for every "making" industry how much of its output is purchased by each "using" industry. We use both the 1992[13] (SIC-based) and 2007[14] (NAICS-based) IO tables, and use concordances between the BEA industry codes and the SIC/NAICS industry codes to link the IO tables to each of our plants in each year, identifying which other industries (both manufacturing and nonmanufacturing industries, including final demand) purchase that plant's products. Second, the 2002 CFS identifies the distances traveled by shipments from plants in each industry, reported by three-digit NAICS industry of the shipped products.[15] For each three-digit NAICS industry, we compute the share of shipments traveling less than 250 miles, the share of shipments traveling between 250 and 1,000 miles, and the share of shipments traveling more than 1,000 miles. Third, annual state-level industry output data from BEA identifies the activity level of different "using" industries around the country, with final demand proxied by personal income in the state.[16]

For each plant in our dataset and for each industry that uses the products of that plant, we calculate the amount of that industry's production that is located in states within 250 miles of the plant (including the plant's own state), between 250 and 1,000 miles from the plant, or more than 1,000 miles from the plant. We then use the IO data to predict the demand for the plant's products, aggregated over all these "using" industries, at each of the three distances. We calculate the annual growth rate in product demand at each distance and weight those three growth rates using the CFS weights for the share of the plant's shipments expected to travel those distances, yielding a weighted projected demand growth. Finally, we transform these growth rates into an index of the demand level by assigning them all a value of 150 in 1987.[17]

We allow for differences among groups of industries in our estimation models, based on the energy intensity of each industry as published in the 1992 CMF (total expenditure on electricity and fuels divided by total value of shipments). We split the industries into 8 separate groups, with finer detail in the grouping for industries with higher energy intensity. Group 1 includes the bottom half of all 6-digit NAICS industries based on their energy intensity, with

[13] http://www.bea.gov/industry/io_benchmark.htm.
[14] http://www.bea.gov/industry/io_annual.htm.
[15] http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/commodity_flow_survey/index.html.
[16] http://www.bea.gov/regional/index.htm.
[17] The starting value of 150 in 1987 was chosen so that the demand index numbers would remain positive throughout the sample for all industries.

each of Groups 2–4 including the next 10 percent of industries and each of Groups 5–8 including 5 percent of industries. Table 1 shows some key information for each group, such as its share of the plants in our data sample[18] and its average energy cost shares. Plants in more energy intensive (higher-numbered) groups tend to have higher expenditures on both electricity and fuels but otherwise don't differ significantly in their average employment or shipments.

We define high-energy industries as those belonging to Groups 5–8, which collectively include the top quintile of energy-intensive industries. Figure 1 shows the variation over our time period in average energy prices and cost shares as well as output and employment for the entire manufacturing sector and for high-energy manufacturing industries. The cost share of high-energy industries declined by half over the period (from about 6 to 3 percent), and energy cost shares declined by about one-third in the manufacturing sector as a whole (from about 3 to 2 percent). In contrast, energy prices followed similar trends for high-energy industries and all industries. Output growth was noticeably slower for high-energy industries as compared to others, while the decline in employment over the period was similar in both groups. Figure 2 shows geographic and temporal variation of electricity prices. Among RGGI or potential RGGI states, New Hampshire, Connecticut, and Massachusetts have the highest electricity prices; while there are common movements in electricity prices across Census divisions, despite the fact that regional energy markets have become increasingly integrated, there is also noticeable variation over time, particularly for New England. The cross-sectional variation across divisions helps identify the coefficients on the own and competing energy prices, since by construction a plant's competitors are often located in other divisions.

## 4. Estimation Results

This section presents the results of the estimations, both the national average effects and the deviations from the national average effects.

### 4.1 Deviations from National Average Effects

[18] These plant-based sample shares differ from the industry shares mentioned in the previous sentence, since industries have differing numbers of plants.

Recall that equation (2) includes multiple coefficients on energy prices and energy price interaction terms. There are separate terms for electricity and fuels prices; interactions of those prices with corresponding cost shares; prices for competing plants and interaction terms; as well as for direct and indirect energy use; with a separate set of coefficients estimated for each of the 8 groups, for a total of 96 energy-related coefficients. The results are presented in Appendix Tables A2 and A3, but not discussed here because of the large number of coefficients. Instead we focus on the overall elasticities for each group with respect to energy prices, which include both the direct effect of energy purchased by the plant and the indirect effect via the energy-intensity of its purchased materials.

Figure 3 plots the elasticities for employment and output by group for electricity prices, and Figure 4 provides the analogous information for fuels prices. The figures illustrate separately the elasticities with respect to the plant's own energy prices as well as the energy prices of competing plants in neighboring states. The figures show the elasticities and confidence intervals for each group. (The underlying regressions were estimated with clustering by industry-year to allow for correlation of the error term across plants and states.) As expected, the confidence intervals get wider as the groups get smaller, going from 1 to 8, although even our smallest groups include nearly 100,000 observations (for reference, see Table 1 for the cost shares for each group).

The own electricity price elasticities in Figure 3 (panels A and B) are typically negative and increase in magnitude, moving from the low cost-share groups to the high cost-share groups. The increase is not perfectly monotonic, and there are deviations for Group 6 (employment) and Group 7 (output). The mean employment elasticities range from -0.07 to -0.90 across the 8 groups, while the output elasticities range from -0.07 to -1.19, with all of them statistically significant at the 5-percent level. The fact that there are a few positive elasticities is perhaps not surprising, given the flexible functional form of Equation (2) and the large number of estimated coefficients (that is, one could expect that by chance there might be a few positive coefficients).

The own fuels price elasticities in Figure 4 (panels A and B) are also typically negative (3 of 16 are positive but only one of those is significant, while 12 of the 13 negative elasticities are significant), but they are smaller and less precisely estimated than the electricity elasticities. The relationships between the cost shares and the elasticities of the groups are weaker than for electricity. The significant negative elasticities range from -0.08 to -0.29 for employment and from -0.10 to -0.32 for output across the 8 groups.

Overall, for most industry groups the own-electricity elasticities are negative and the magnitudes increase with the cost share. The neighbor elasticities tend to be positive but there is not a correlation between the magnitude of the elasticities and the cost share. Own-fuel elasticities tend to be negative and neighbor-fuel elasticities tend to be positive, although there are a few exceptions to these patterns.

These elasticities are similar to those found in Gray, Linn, and Morgenstern (2016), in which we applied a similar model to plant-level data for 49 energy-intensive, trade-exposed industries and found average elasticities with respect to electricity prices of -0.6 for employment and -0.8 for output. Two other papers in the literature estimate own-price elasticities but not neighbor elasticities. Aldy and Pizer (2015) find a somewhat lower elasticity of output with respect to energy prices of -0.4, using national-level industry data from 1986–1994. Kahn and Mansur (2013) use County Business Patterns data and report estimates similar to ours, finding an elasticity of output with respect to electricity prices ranging from -0.2 for their average industry to -2.2 for their most electricity-intensive industry (primary metals). Note that more than 100 6-digit industries are included in the high-energy category and that many industries in group 5 have energy cost shares below 5 percent. If we had focused exclusively on group 8 we certainly would have found larger effects, but then we could not report state-level results due to Census confidentiality rules.

The elasticities for competitors' energy prices, seen in panels C and D of Figures 3 and 4, are typically positive for both electricity and fuels. As with the own-energy price elasticities, the elasticities with respect to neighbors' electricity prices are larger in magnitude and more precisely estimated than those for fuels. This difference between electricity and fuels elasticities is similar to that reported in Gray, Linn, and Morgenstern (2016) for electricity and natural gas, and it could reflect the lesser variation across states in prices for fuels or the greater measurement error of fuels prices. Across the 8 groups, the majority of the elasticities with respect to neighbors' energy prices have the expected positive sign and are statistically different from zero.

### 4.2 National Average Effects

Table 2 reports the estimates of Equation (3), for which we regress the variable indicated in the column heading on electricity and fuels prices interacted with cost shares. Recall that the energy price variables include both the direct and indirect effects. For each dependent variable, the coefficient estimates are negative, which is as expected and consistent with the literature. Unfortunately, we do not have sufficient variation to precisely estimate the electricity coefficients. The fuel coefficients are estimated at the 5-percent confidence level or better.

## 5. Simulation Results

### 5.1 Main Scenarios

The objective of the simulations is to illustrate the effects of state carbon pricing on competitiveness. In this subsection we define the two main scenarios that we analyze in comparison to a no-policy baseline scenario.

The baseline scenario uses the observed energy prices and other independent variables across the entire estimation sample. We use Equation (3) to predict national average outcomes for each industry and Equation (2) to predict deviations from the national averages. To ensure that the scenarios are consistent with the energy price variation used to identify the key coefficients, we use the entire estimation sample. By construction, the predicted values in the baseline are equal to the observed sample means.

To compare with the baseline, in the first policy scenario we add a carbon price of $10 per ton of $CO_2$ that raises electricity prices in the RGGI region, which includes Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont. For simplicity, we assume that the carbon price raises electricity prices in proportion to the emissions rate of a natural gas–fired unit. Consequently, electricity prices increase by 0.6 cents per kilowatt hour in the RGGI states.[19] We also assume that the carbon price does not affect electricity prices in other states or fuels prices in any states. Consequently, for plants in

[19] The effect of the carbon price on electricity prices is broadly consistent with estimates reported in Linn and Muehlenbachs (2018), who estimate the effect of fuels prices on wholesale electricity prices using data from the 2000s. For traditionally regulated states, we are assuming that regulators allow the firm to pass the carbon price through to regulated retail electricity prices.

RGGI, their own electricity prices rise and the electricity prices of competing plants are unchanged. For plants close to RGGI, their own electricity prices are unchanged and the electricity prices of competing plants rise.[20]

Equation (2) and these counterfactual plant-level electricity prices are used to predict deviations from national averages of employment and output. For consistency with equation (2), these deviations are normalized so that the national means are zero. We use Equation (3) to predict national average changes for each industry. The price increases for RGGI and the share of RGGI plants in national employment are used to compute the change in national average electricity prices. Because RGGI plants account for about 10 percent of national employment on average across all industries, national average electricity prices increase by about 2 percent for the average industry. We combine the results of Equations (2) and (3) for each plant in the dataset, and then compute percent changes in the outcomes for each plant, relative to the no-policy baseline.

Based on the estimation results reported in the previous section, we expect the RGGI carbon price to reduce employment and output in RGGI states and increase those outcomes in surrounding states. The total effect across the entire country should be negative, because national average electricity prices increase. Because the plant-level elasticities (in Equation 2) tend to be larger in magnitude than the industry-level elasticities (in Equation 3), we expect the carbon price to induce shifts of employment and output to unregulated states.

The second carbon price scenario expands the RGGI carbon price to New Jersey and Pennsylvania. The plant-level outcomes are computed similarly to the first scenario. Relative to the no-policy scenario, we expect lower employment and output in the expanded RGGI region. Relative to the original RGGI scenario, we expect less of a reduction in employment and output since the average electricity prices of competing plants increase by less in the expanded RGGI scenario than in the original RGGI scenario.

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[20] In principle, a carbon price in RGGI could affect electricity prices outside the region, particularly if transmission lines connect the regions. The carbon price raises the cost of producing electricity in RGGI, which could increase generation from outside the region, causing marginal costs and electricity prices to increase. Shawhan et al. (2014) suggest that for a carbon price of $10 per ton of $CO_2$, this effect would be small compared to the increase in electricity prices in the RGGI region. However, Fell and Maniloff (2018) find empirical evidence of leakage despite the low carbon price that has persisted in the market. For simplicity, the simulations do not include this effect.

## 5.2 Main Results

The main results are presented in a series of maps that illustrate the changes relative to the baseline scenario, showing state-specific effects on employment and output for the eastern half of the country, which includes all states that are neighbors of RGGI. In addition to the maps, Table 3 shows the average effects of each scenario for employment and output in various groups of states. We focus on percentage changes for each state rather than levels because the percentage indicates the importance relative to the state's total manufacturing employment and output. Because employment and output levels vary across states, we also report national average percent changes, which are the employment or output weighted percent changes across states.

The results of the simulations generally follow the expected pattern, with reductions in employment and output in the RGGI states and increases in neighboring states. The effects tend to be larger for RGGI states such as New York, Maryland, and Delaware that are located closer to non-RGGI states. The output effects tend to be larger than the employment effects, which is consistent with the elasticities seen in Figures 3 and 4. In Table 2 for the first scenario, the RGGI carbon price reduces average manufacturing employment in those states by 2.7 percent, and raises average employment in New Jersey and Pennsylvania by 0.8 percent (the increases are smaller in other eastern states). However, the maps show some variation in effects that are uncorrelated with the distance from RGGI states. For example, Figure 5 shows larger output changes for Kentucky and Tennessee than for some other states that are closer to RGGI. These variations could arise because of the specific mix of industries operating in RGGI and non-RGGI states, since relative energy prices only matter if there are competing plants in neighboring states to take advantage of the energy price differential. Thus, in Figure 5C we see larger output effects for Kentucky and Tennessee than for some other states that are closer to more RGGI states.

The effects of the carbon price on the high-energy industries are generally larger than for the average industry, as expected. The average employment in those industries falls by 7.1 percent in the RGGI states and output falls by 10.5 percent. The increases in employment and output in neighboring non-RGGI states are also larger than for the average industry, although still only about 0.5 percent. These larger effects make it easier to identify differences across particular states, including the variation across states within the regions shown in Table 3, which again shows Kentucky and Tennessee with larger output effects than those found for some other states closer to RGGI.

The results for the second scenario, where Pennsylvania and New Jersey join RGGI and adopt carbon prices, are as expected. The results are shown in Table 3 and Figure 6. Because of their location, those states now form a buffer between some of the original RGGI states and the neighboring non-RGGI states, and the effects on their employment and output are somewhat smaller on average than they were in the first scenario. The average across industries is a decline of 2.2 percent in employment and 3.4 percent in output, with similar reductions for the high-energy industries. The average declines in employment and output for Pennsylvania and New Jersey are larger than those for the original states, with a 3.3 percent decline in average employment and a 4.9 percent decline in average output across all industries. The estimated effects on high-energy industries are also larger than those in the original RGGI states. The increases in the non-RGGI states are also larger than they were in the first scenario, reflecting the greater number of neighboring states with carbon prices.

## 6. Conclusions

A substantial literature has analyzed empirically and theoretically the potential for international emissions leakage, in which a country or set of countries imposes a carbon price that raises emissions in other countries. Accompanying the emissions leakage would be corresponding shifts of employment and output to firms located in unregulated countries, representing the adverse competitiveness effects of the carbon price.

In the United States, certain states have adopted or are considering adopting a carbon price. The high degree of trade of manufactured goods across state lines raises the possibility of substantial leakage of economic activity (and emissions) across states. In the state-level policy context, leakage would be concerning not only because it would undermine the climate objectives of a carbon pricing policy but also because it would imply losses of local jobs and production. As policies evolve in this area, it is important to understand the magnitudes of potential leakage under state-level carbon pricing policies.

Clearly, it is not simply a matter of energy or carbon price differences across jurisdictions—the industry mix in different areas is also a major factor. Carbon pricing by a jurisdiction that has a monopoly or near monopoly on particular production capabilities would likely result in minimal competitiveness effects in that jurisdiction. Thus, to estimate the employment or output sensitivity to the direct energy price effects of a particular jurisdiction requires consideration of multiple state- and region-specific factors of the type included in our modeling. Similarly, estimating the full consequences of either national or subnational carbon pricing requires going beyond the direct energy price effects and also considering the extent of the potentially offsetting effects of recycling the carbon pricing revenues.

Our modeling decomposes the effects of a carbon price on employment and output into two effects: the change in the national average level of those variables for all plants in the corresponding industry, and the individual plant's deviation from the national industry average. The first part is estimated via similar methods as Aldy and Pizer (2015). We use a novel model and unique data to estimate the second part. Specifically, we link a plant's outcome deviations to the energy prices it faces as well as the energy prices of competing plants. This model thereby captures differing effects of the carbon price across plants in the same industry. For plants in the regulated region, the carbon price raises energy prices, making them less competitive, while plants outside the regulated region become more competitive. The model is further distinguished by separating the effects of electricity and fuels, and by allowing for indirect effects of energy prices to affect a plant via the prices of the energy-intensive materials that it uses in its production process.

The model parameters are estimated with confidential plant-level data from the Census Bureau from 1982–2011. As expected, higher energy prices at a plant typically reduce its employment and output, with the magnitude of the effects generally increasing with energy intensity. Higher energy prices at competing plants tend to increase a plant's employment and output.

Focusing on the RGGI program, which prices carbon emissions from the electricity sector in the Northeast, we use the estimated parameters from the model to simulate the effects of regional carbon prices. A carbon price of $10 per ton reduces employment by 2.7 percent in the RGGI region, with comparable changes in output. The same carbon price raises those outcomes in the surrounding states, with a 0.8 percent increase in employment. The national-level outcomes are relatively small, with employment declining by 0.1 percent, confirming that a substantial amount of the shift of output and employment flowing out of RGGI leaks into surrounding states rather than to other countries. We also show that expanding RGGI to include New Jersey and Pennsylvania would reduce the adverse competitiveness effects within the original RGGI region.

These results imply that state policymakers can reduce the degree of leakage—and the associated environmental and economic costs—by expanding their programs to include other states. The benefits of linking programs across states can be substantial, due to the fact that states' economies are so intertwined with such a high degree of cross-state trade of manufactured goods.

Finally, we note a few caveats regarding our analysis. First, as with most other studies in the literature, we use industry responses to past changes in energy prices to derive estimates of the effects of future carbon policy. That is, we assume that manufacturing plants would respond similarly to energy price increases induced by a carbon price as they have responded to historical price changes. The high degree of persistence of historical energy prices and carbon prices supports this assumption. Second, our analysis covers the short run, in which capital stocks are fixed and there is no entry and exit of plants. Modeling long-run effects that include capital investment, entry, and exit would be a useful direction for future research. Third, the recycling of revenues, which are not included in our modeling, can affect the overall employment and output changes caused by a carbon price. Going forward, additional research in these areas could be helpful as states and regions debate designs of carbon pricing schemes.

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**Table 1. Mean Values by Group**

| Group | # of obs. (rounded) | Share of sample | Energy cost share | Electricity cost share | Fuel cost share | Log of employment | Log of shipments |
|---|---|---|---|---|---|---|---|
| 1 | 1,289,000 | 0.51 | 0.011 | 0.007 | 0.004 | 3.716 | 8.494 |
| 2 | 208,000 | 0.08 | 0.016 | 0.010 | 0.007 | 4.182 | 9.030 |
| 3 | 306,000 | 0.12 | 0.019 | 0.012 | 0.008 | 3.524 | 8.453 |
| 4 | 262,000 | 0.10 | 0.025 | 0.013 | 0.011 | 3.987 | 8.912 |
| 5 | 191,000 | 0.08 | 0.036 | 0.019 | 0.017 | 3.980 | 9.164 |
| 6 | 87,000 | 0.03 | 0.055 | 0.022 | 0.032 | 4.076 | 8.636 |
| 7 | 87,000 | 0.03 | 0.083 | 0.029 | 0.054 | 3.600 | 8.802 |
| 8 | 96,000 | 0.04 | 0.177 | 0.078 | 0.099 | 3.959 | 8.585 |
| | | | | | | | |
| Full sample | 2,527,000 | 1.00 | 0.030 | 0.015 | 0.015 | 3.797 | 8.646 |
| (std. dev.) | | | (0.041) | (0.022) | (0.026) | (1.443) | (1.866) |

Note: Groups based on industry energy cost share (electricity plus fuel costs, divided by shipments).

**Table 2. Effects of Energy Prices on National Outcomes**

Dependent variable

| | Log of real value of shipments | Log of employment |
|---|---|---|
| Log of electricity price | -0.01 | -0.04 |
| * cost share | (0.11) | (0.06) |
| | | |
| Log of fuels price | -0.15 | -0.04 |
| * cost share | (0.07) | (0.02) |
| | | |
| Number of observations | 13,749 | 13,749 |
| R-squared | 0.92 | 0.92 |

Notes: The table reports coefficient estimates from Equation (3), with standard errors in parentheses clustered by three-digit NAICS industry and year. See text for details.

**Table 3. Simulation Results for $10 Carbon Price Applied to RGGI States Including Variation with PA and NJ added to RGGI**

| Coverage | Carbon price | Industries | Outcome | RGGI states | PA+NJ | Near RGGI | Far RGGI |
|---|---|---|---|---|---|---|---|
| RGGI | electricity | all | employ | -2.71% | 0.83% | 0.29% | 0.12% |
| RGGI | electricity | all | output | -3.81% | 0.67% | 0.20% | 0.06% |
| RGGI | electricity | high-energy | employ | -7.08% | 1.76% | 0.61% | 0.37% |
| RGGI | electricity | high-energy | output | -10.51% | 1.01% | 0.56% | 0.42% |
| RGGI_PA_NJ | electricity | all | employ | -2.22% | -3.32% | 0.67% | 0.28% |
| RGGI_PA_NJ | electricity | all | output | -3.37% | -4.91% | 0.52% | 0.18% |
| RGGI_PA_NJ | electricity | high-energy | employ | -5.73% | -7.82% | 1.59% | 0.85% |
| RGGI_PA_NJ | electricity | high-energy | output | -9.64% | -11.01% | 1.42% | 0.94% |

Notes: Simulation results based on coefficients estimated in Equations (2) and (3). The table shows change in average outcome variable for plants located in specified regions, comparing no-policy scenario ($0 carbon price) with a $10 carbon price applied to electricity prices (or both electricity and fuels prices) faced by all plants located in the RGGI region (expanded in some simulations to include Pennsylvania and New Jersey). Results are shown separately for all manufacturing industries and those designated as high-energy-cost industries (groups 5-8 in Table 1).

RGGI states: CT, DE, MA, MD, ME, NH, NY, RI, VT.
Near-RGGI states: IN, KY, MI, NC, OH, VA, WV.
Far-RGGI states: AL, FL, GA, IL, MS, SC, TN, WI.

**Figure 1. Comparison of All-Manufacturing and High-Energy-Cost-Industry Trends**

**Figure 1A. Energy Price and Energy Cost Share**

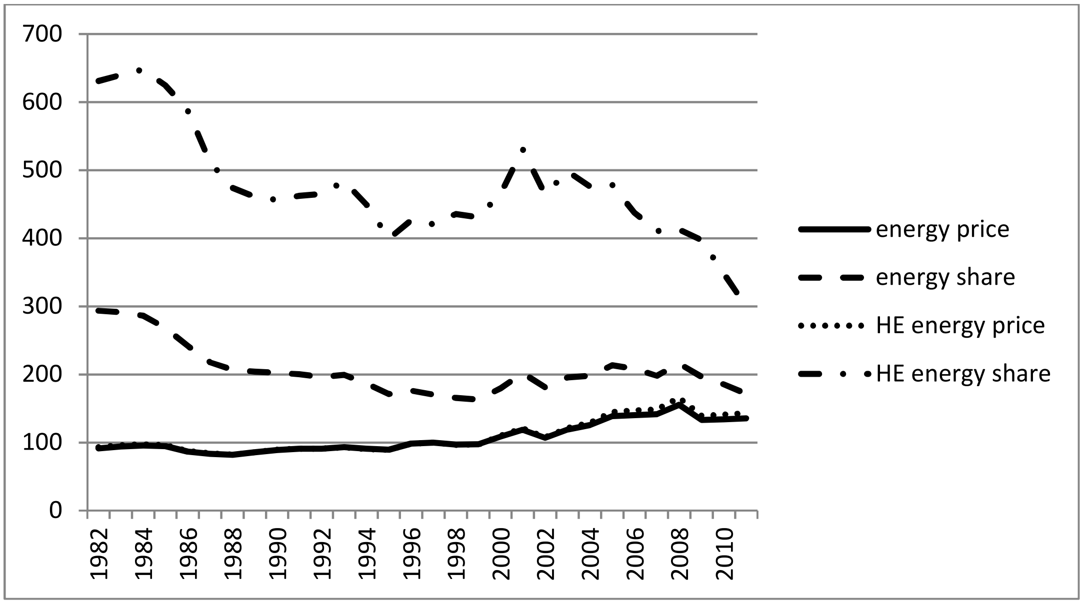
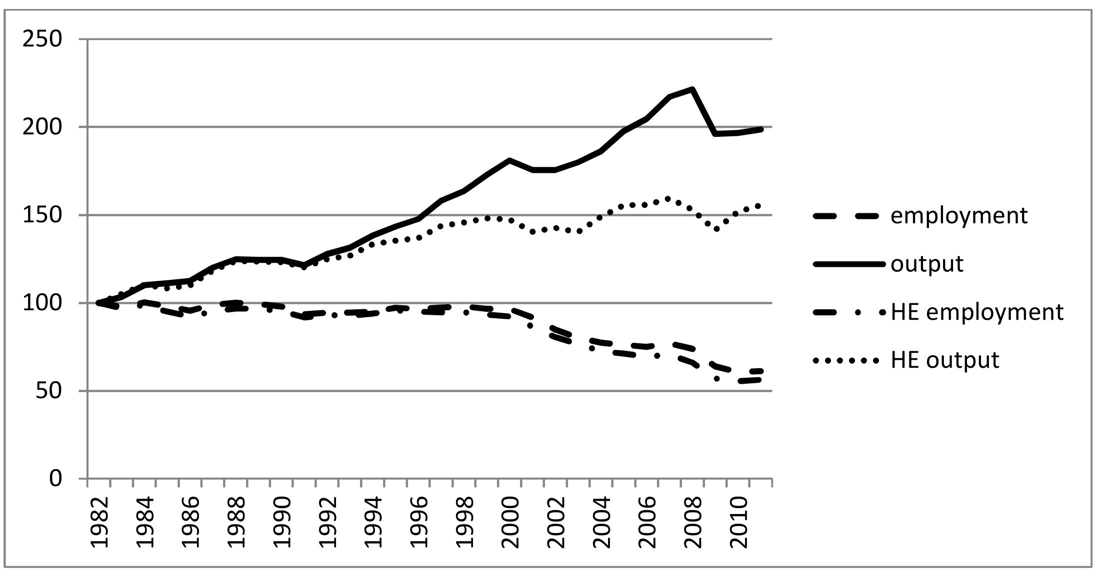



**Figure 1B. Employment and Output**




Notes: These figures compare the average values for all manufacturing industries with the average values for the high-energy-cost industries in Groups 5–8. Energy cost shares are scaled, setting 100 = one percent cost share; all other variables are normalized to 100 in 1982. All numbers based on industry-level data from NBER-CES Manufacturing Industry Database.

**Figure 2. Energy Price Variation Across States in 2011**
**Figure 2A. 2011 Electricity Prices**

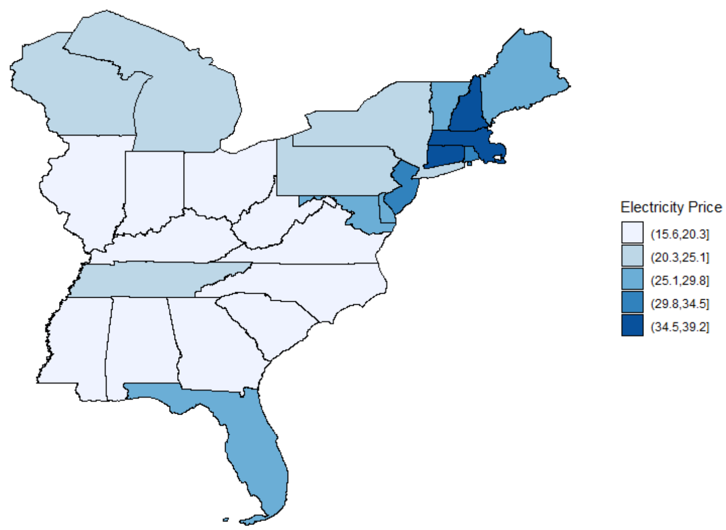
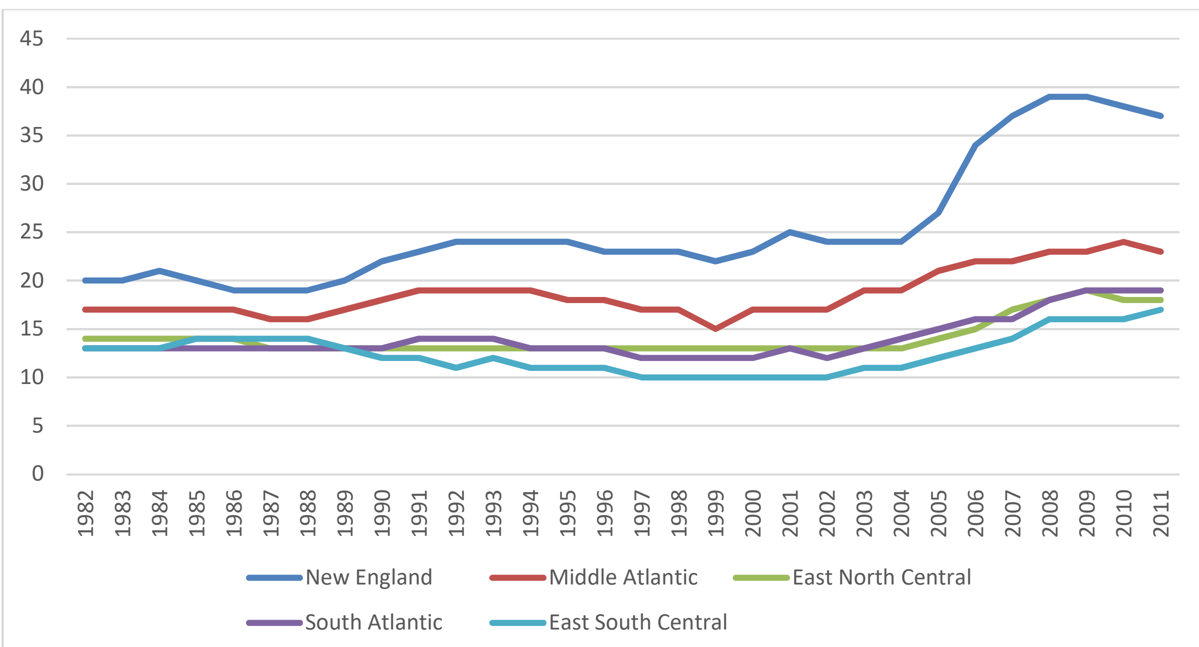
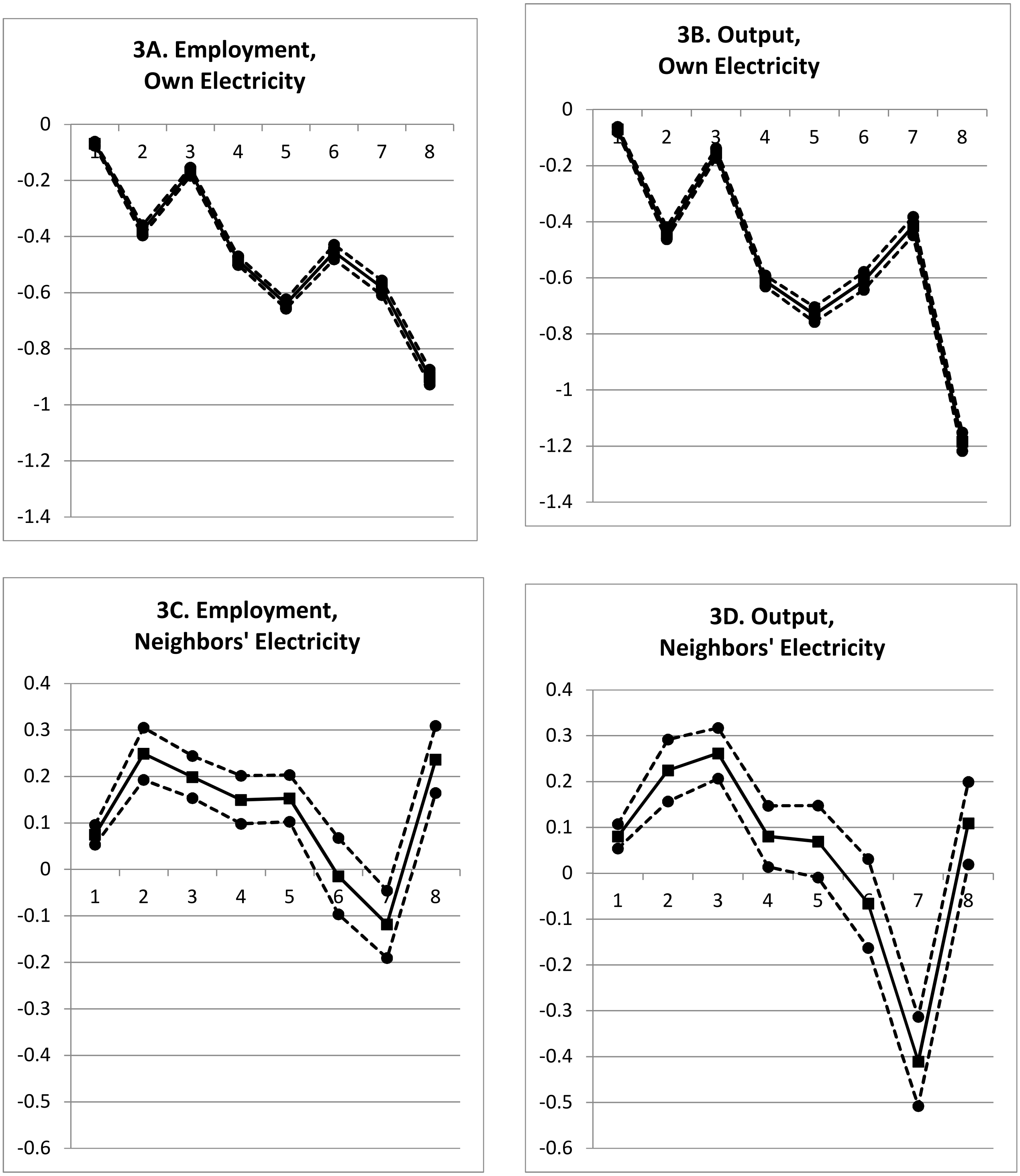



**Figure 2B. Electricity Prices by Census Division 1982-2011**



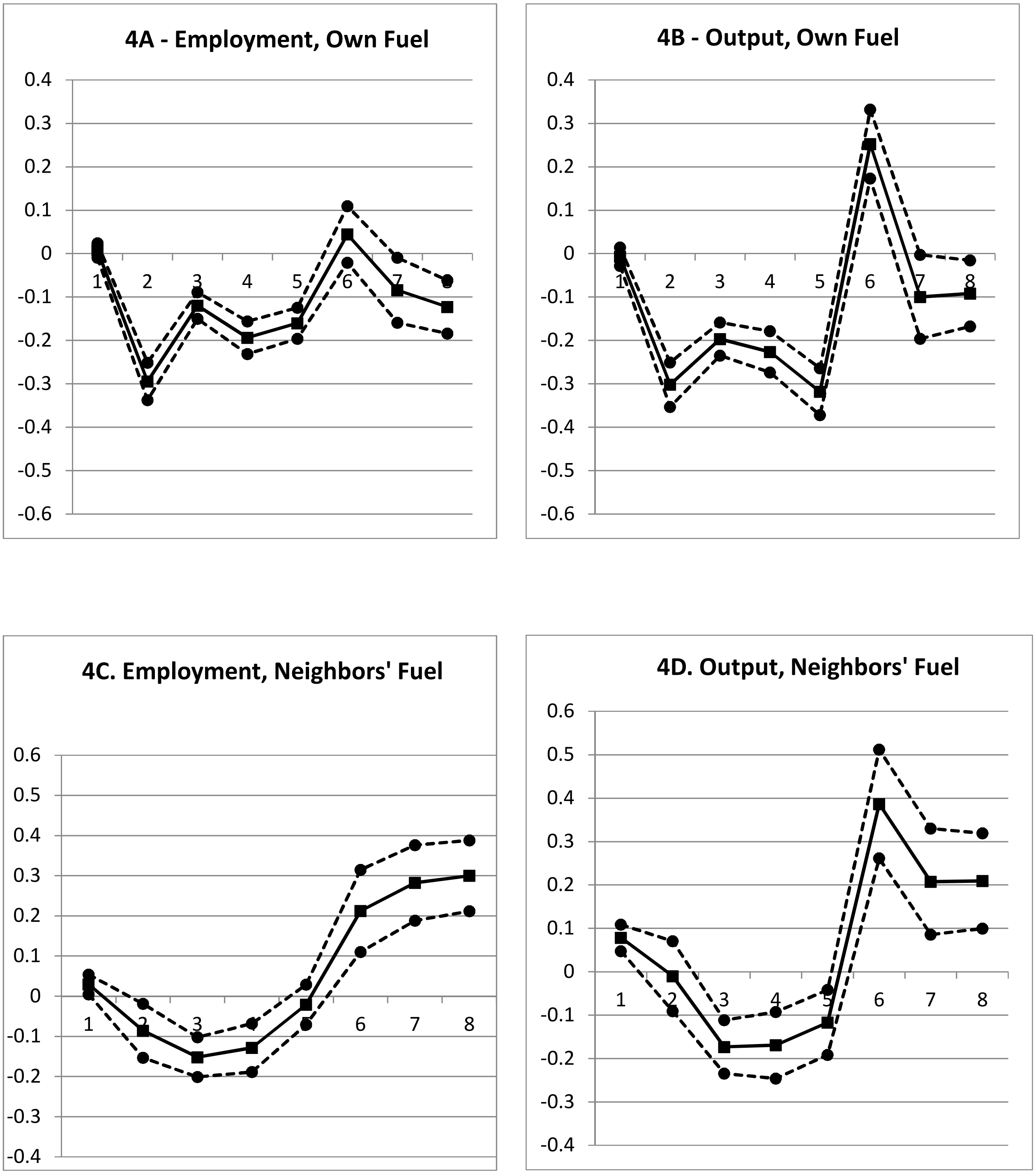

Notes: Electricity prices come from the State Energy Data System (SEDS) provided by the US Energy Information Administration (https://www.eia.gov/state/seds/) expressed in dollars per million BTU. Electricity price paid by industrial consumers, aggregated by Census division.

**Figure 3. Employment and Output Elasticities with Respect to Electricity Prices**




Notes: Estimated elasticity of outcome variables with respect to electricity prices (both own price and neighbor price), based on coefficients from Equation 2, which is estimated separately for 8 industry groups shown in Table 1 (Group 1 is lowest energy cost share; Group 8 is highest).

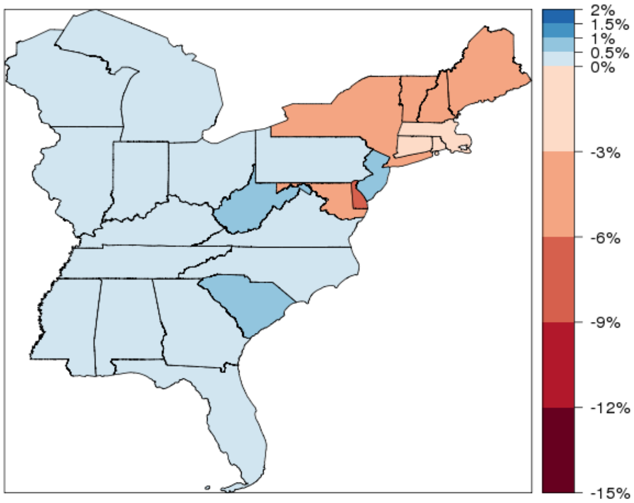
Figure 4. Employment and Output **Elasticities with Respect to Fuels Prices**



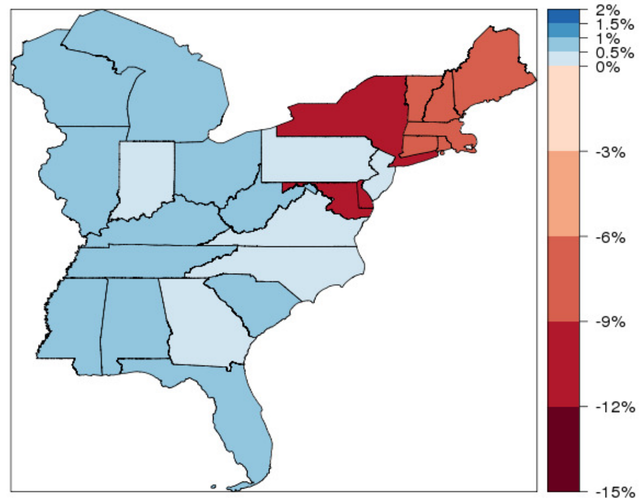

Notes: Estimated elasticity of outcome variables with respect to fuels prices (both own price and neighbor price), based on coefficients from Equation 2, which is estimated separately for 8 industry groups shown in Table 1 (Group 1 is lowest energy cost share; Group 8 is highest).

Figure 5. Employment and Output Changes with $10 Carbon Price on Electricity

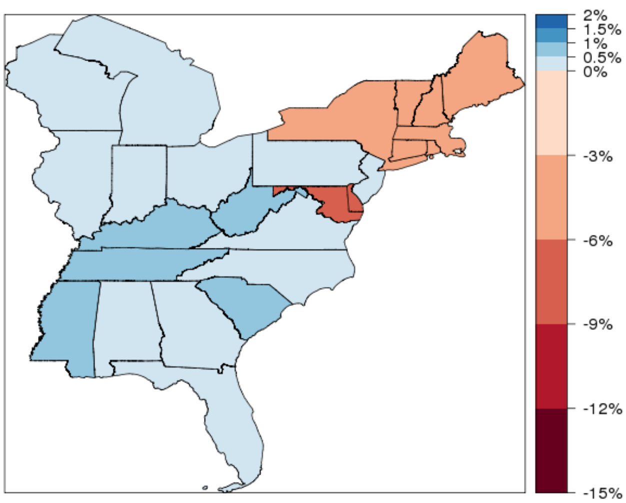
**5A. Employment, All Industries**



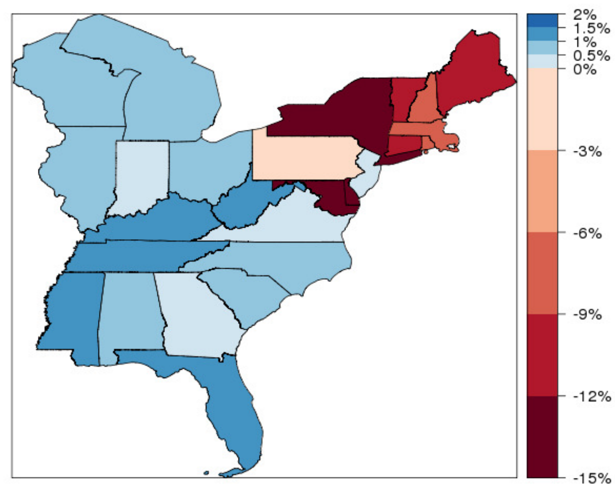

**5B. Employment, High-Energy Industries**




**5C. Output, All Industries**



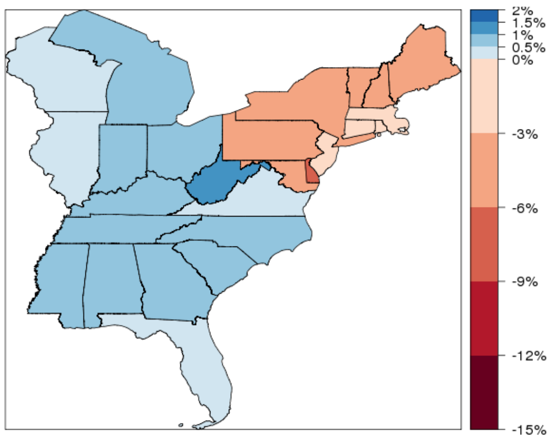

**5D. Output, High-Energy Industries**



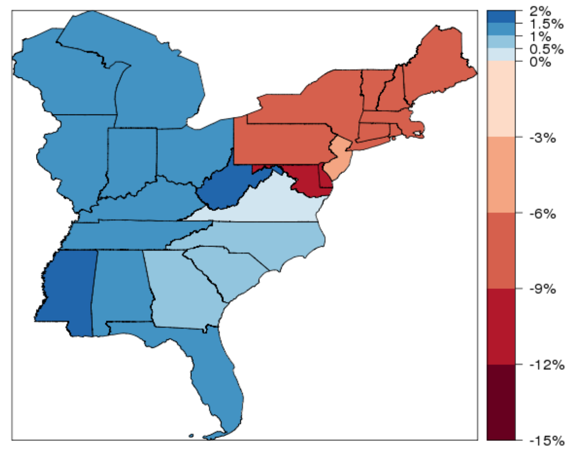

Notes: Simulation results based on coefficients estimated in Equations (2) and (3). The figures show the change in average employment and output for plants located in each state, comparing no-policy ($0 carbon price) with a $10 carbon price applied to electricity prices faced by all plants located in the RGGI region. Results shown separately for all manufacturing industries and those designated as high-energy industries (Groups 5-8 in Table 1).

**Figure 6. Employment and Output Effects: Adding PA and NJ to RGGI with $10 Carbon Price on Electricity**

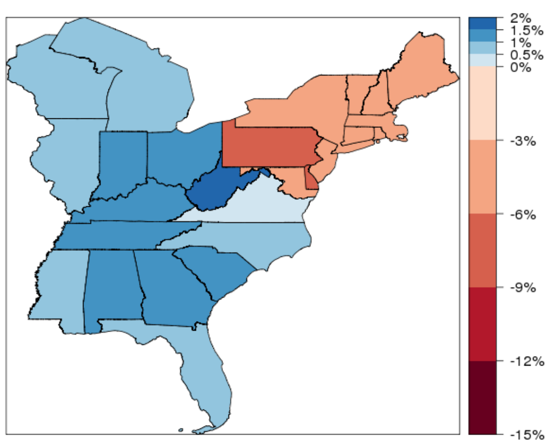
**6A. Employment, All Industries**



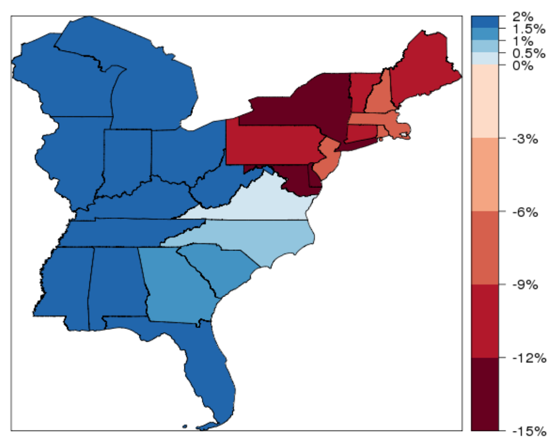

**6B. Employment, High-Energy Industries**




**6C. Output, All Industries**




**6D. Output, High-Energy Industries**




Notes: Simulation results based on coefficients estimated in Equations (2) and (3). The figure shows the change in average employment and output for plants located in each state, comparing no-policy ($0 carbon price) with a $10 carbon price applied to electricity prices faced by all plants located in the RGGI region as well as Pennsylvania and New Jersey. Results shown separately for all manufacturing industries and those designated as high-energy industries (Groups 5-8 in Table 1).

## Appendix Table A1 – Summary Statistics

| variable | mean | std. dev. |
|---|---|---|
| value of shipments ($ 1997) | 39,400 | 579,000 |
| log(value of shipments) | 8.646 | 1.866 |
| employment | 134.3 | 434.8 |
| log(employment) | 3.797 | 1.443 |
| electricity price (cents/kWh) | 0.0717 | 0.0277 |
| log(electricity price) | -2.703 | 0.3668 |
| fuel price ($/mmBTU) | 5.679 | 3.092 |
| log(fuel price) | 1.622 | 0.457 |
| neighbors electricity price | 0.0656 | 0.0144 |
| log(neighbors electricity price) | -2.749 | 0.2209 |
| neighbors fuel price | 5.725 | 2.914 |
| log(neighbors fuel price) | 1.643 | 0.4303 |
| industry electricity cost share | 1.525 | 1.49 |
| industry fuel cost share | 0.7465 | 0.97 |
| industry indirect electricity intensity | 0.8345 | 0.69 |
| industry indirect fuel intensity | 0.4131 | 0.46 |
| labor cost index | 32.98 | 12.91 |
| log(labor cost index) | 3.42 | 0.3972 |
| demand index | 100.7 | 5.846 |
| log(demand index) | 4.596 | 0.343 |
| observations (rounded) | 2,527,000 | |

## Appendix Table A-2 - Employment Regressions

| | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 |
|---|---|---|---|---|---|---|---|---|
| log(own electricity price) | -0.07548*** | 1.271*** | 1.018*** | 0.1208** | 0.06205 | 0.07835 | 0.1182 | -0.8715*** |
| | (0.01832) | (0.06110) | (0.05521) | (0.03840) | (0.04655) | (0.06126) | (0.07312) | (0.02273) |
| log(own electricity price)* | 0.115 | -123.9*** | -85.60*** | -28.07*** | -28.71*** | -7.602*** | -20.41*** | 4.509*** |
| electricity cost share | (1.834) | (4.571) | (3.854) | (1.987) | (2.267) | (1.817) | (1.671) | (0.2457) |
| log(own electricity price)* | 0.8954 | -7.481*** | -9.926*** | -10.41*** | -9.641*** | -32.78*** | -3.376 | -42.50*** |
| indirect electricity cost share | (0.6293) | (1.678) | (1.082) | (0.8231) | (0.7023) | (1.747) | (4.398) | (2.654) |
| log(own fuel price) | 0.05384* | -0.2257*** | -0.03436 | 0.05605 | 0.05177 | -0.7689*** | -0.5279*** | -0.2117*** |
| | (0.02173) | (0.05232) | (0.04512) | (0.04082) | (0.04314) | (0.07036) | (0.08066) | (0.05601) |
| log(own fuel price)* | -15.33* | -49.53*** | -36.02*** | -55.84*** | -22.43*** | 17.68*** | 9.324** | -1.317 |
| fuel cost share | (6.097) | (10.56) | (6.913) | (5.529) | (3.214) | (3.569) | (2.883) | (1.136) |
| log(own fuel price)* | -0.2957 | 44.91*** | 47.45*** | 27.40*** | 13.55*** | 222.9*** | 60.60*** | 50.19** |
| indirect fuel cost share | (1.749) | (5.717) | (4.460) | (3.052) | (3.259) | (14.92) | (16.14) | (16.28) |
| log(neighbors electricity price) | -0.01565 | -1.029*** | 0.1232 | -0.1767* | 0.3079** | 1.437*** | -0.6831*** | 0.2349*** |
| | (0.03792) | (0.1522) | (0.1255) | (0.08794) | (0.1166) | (0.1584) | (0.1575) | (0.05513) |
| log(neighbors electricity price)* | 15.12*** | 95.69*** | 19.34* | 10.73* | -7.047 | -36.50*** | 18.65*** | 4.262*** |
| electricity cost share | (3.837) | (11.34) | (8.560) | (4.784) | (5.461) | (4.749) | (3.530) | (0.7905) |
| log(neighbors electricity price)* | -6.435*** | 6.384 | -27.60*** | 15.35*** | -1.085 | -30.52*** | -7.848 | -35.81*** |
| indirect electricity cost share | (1.456) | (3.924) | (2.673) | (2.160) | (1.580) | (3.917) | (10.34) | (5.765) |

| | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 |
|---|---|---|---|---|---|---|---|---|
| log(neighbors fuel price) | -0.02089 | 0.3331*** | 0.03773 | 0.02982 | 0.3025*** | -0.01956 | 0.7988*** | 0.4431*** |
| | (0.03111) | (0.08445) | (0.07363) | (0.06597) | (0.07114) | (0.1156) | (0.1148) | (0.08505) |
| log(neighbors fuel price)* | -0.997 | -75.03*** | -13.99 | -15.47 | -16.76** | -27.62*** | -26.92*** | -4.231* |
| fuel cost share | (8.930) | (17.13) | (11.12) | (8.952) | (5.170) | (6.180) | (4.516) | (1.722) |
| log(neighbors fuel price)* | 17.75*** | -27.07** | -27.62*** | -16.18** | -26.75*** | 193.3*** | 70.03** | 4.764 |
| indirect fuel cost share | (2.994) | (9.640) | (7.130) | (5.199) | (5.288) | (25.75) | (25.25) | (25.48) |
| log(labor cost index) | 0.2711*** | 0.5472*** | 0.4701*** | 1.093*** | 0.3831*** | 0.3701*** | 0.4076*** | 0.5083*** |
| | (0.01261) | (0.02967) | (0.02707) | (0.03097) | (0.02967) | (0.04681) | (0.04364) | (0.05518) |
| log(demand index) | 1.849*** | 1.819 | 0.06681 | -0.4490** | 0.02742 | 0.001581 | -0.5044 | -1.315 |
| | (0.4881) | (2.976) | (0.1981) | (0.1526) | (0.01601) | (0.01999) | (6.885) | (4.131) |
| R-square | 0.334 | 0.3487 | 0.3622 | 0.3074 | 0.28 | 0.4427 | 0.4253 | 0.4899 |
| Observations (rounded) | 1,289,000 | 208,000 | 306,000 | 262,000 | 191,000 | 87,000 | 87,000 | 96,000 |

Note: Regressions also include industry-year and region-year dummies, following Equation (2). Standard errors in parentheses are clustered by industry-year.

# Appendix Table A-3 – Output Regressions

| | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 |
|---|---|---|---|---|---|---|---|---|
| log(own electricity price) | -0.2065*** | 1.610*** | 1.253*** | 0.2533*** | -0.02186 | 0.2052** | 0.1838* | -0.9412*** |
| | (0.02202) | (0.07327) | (0.06728) | (0.04640) | (0.05841) | (0.07295) | (0.09201) | (0.02743) |
| log(own electricity price)* | 17.36*** | -153.8*** | -107.9*** | -39.69*** | -29.00*** | -11.25*** | -19.20*** | 2.476*** |
| electricity cost share | (2.206) | (5.481) | (4.696) | (2.401) | (2.845) | (2.164) | (2.103) | (0.2965) |
| log(own electricity price)* | -1.093 | -11.65*** | -3.186* | -11.11*** | -16.19*** | -43.03*** | -5.37 | -49.74*** |
| indirect electricity cost share | (0.7566) | (2.012) | (1.318) | (0.9948) | (0.8812) | (2.080) | (5.535) | (3.202) |
| log(own fuel price) | 0.03795 | -0.3159*** | -0.1159* | 0.03465 | 0.1216* | -0.5620*** | -0.5249*** | -0.1217 |
| | (0.02613) | (0.06274) | (0.05498) | (0.04933) | (0.05413) | (0.08379) | (0.1015) | (0.0676) |
| log(own fuel price)* | -13.83 | -21.93 | -37.71*** | -67.21*** | -31.93*** | 18.23*** | 3.784 | -0.5776 |
| fuel cost share | (7.331) | (12.66) | (8.424) | (6.682) | (4.033) | (4.250) | (3.628) | (1.371) |
| log(own fuel price)* | -2.69 | 32.82*** | 52.61*** | 32.76*** | 9.231* | 168.6*** | 104.1*** | 16.87 |
| indirect fuel cost share | (2.103) | (6.855) | (5.434) | (3.689) | (4.089) | (17.76) | (20.32) | (19.65) |
| log(neighbors electricity price) | 0.1988*** | -1.293*** | -0.02349 | -0.2739** | -0.03429 | 1.665*** | -0.4692* | 0.02434 |
| | (0.04560) | (0.1825) | (0.1530) | (0.1063) | (0.1463) | (0.1886) | (0.1982) | (0.06654) |
| log(neighbors electricity price)* | -1.416 | 115.3*** | 44.26*** | 11.86* | 9.3 | -46.63*** | 16.21*** | 7.659*** |
| electricity cost share | (4.614) | (13.60) | (10.43) | (5.782) | (6.852) | (5.655) | (4.442) | (0.9540) |
| log(neighbors electricity price)* | -15.72*** | 6.512 | -41.06*** | 16.28*** | -4.010* | -26.77*** | -56.14*** | -48.28*** |
| indirect electricity cost share | (1.751) | (4.706) | (3.257) | (2.611) | (1.982) | (4.664) | (13.01) | (6.958) |

| | Group 1 | Group 2 | Group 3 | Group 4 | Group 5 | Group 6 | Group 7 | Group 8 |
|---|---|---|---|---|---|---|---|---|
| log(neighbors fuel price) | 0.07712* | 0.4395*** | -0.1102 | -0.09122 | 0.3790*** | 0.2511 | 1.017*** | 0.3844*** |
| | (0.03741) | (0.1013) | (0.08972) | (0.07973) | (0.08926) | (0.1376) | (0.1445) | (0.1026) |
| log(neighbors fuel price)* | -20.03 | -69.55*** | 3.418 | 0.2504 | -29.09*** | -31.84*** | -34.66*** | -3.347 |
| fuel cost share | (10.74) | (20.54) | (13.55) | (10.82) | (6.487) | (7.359) | (5.683) | (2.078) |
| log(neighbors fuel price)* | 22.65*** | -40.55*** | -24.77** | -26.50*** | -23.02*** | 158.3*** | 76.81* | -13.57 |
| indirect fuel cost share | (3.600) | (11.56) | (8.689) | (6.283) | (6.635) | (30.66) | (31.78) | (30.75) |
| log(labor cost index) | 0.4447*** | 0.7521*** | 0.6312*** | 1.659*** | 1.049*** | 0.8365*** | 0.9163*** | 0.9143*** |
| | (0.01516) | (0.03558) | (0.03298) | (0.03743) | (0.03723) | (0.05575) | (0.05491) | (0.06659) |
| log(demand index) | 2.096*** | 2.762 | 0.205 | -0.5131** | 0.04628* | 0.03793 | 16.88 | -3.377 |
| | (0.5869) | (3.568) | (0.2413) | (0.1844) | (0.02009) | (0.02381) | (8.664) | (4.986) |
| R-square | 0.4156 | 0.4008 | 0.3859 | 0.3801 | 0.4331 | 0.5279 | 0.3841 | 0.6747 |
| Observations (rounded) | 1,289,000 | 208,000 | 306,000 | 262,000 | 191,000 | 87,000 | 87,000 | 96,000 |

Note: Regressions also include industry-year and region-year dummies, following Equation (2). Standard errors in parentheses are clustered by industry-year.