# Do Local Energy Prices and Regulation Affect the Geographic Concentration of Employment? A Border Pairs Approach

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**Abstract**

Manufacturing industries differ with respect to their energy intensity, labor-to-capital ratio and their pollution intensity. Across the United States, there is significant variation in electricity prices and labor and environmental regulation. This paper uses a border-pairs approach to examine whether the basic logic of comparative advantage can explain the geographical clustering of U.S. manufacturing. We document that energy-intensive industries concentrate in low electricity price counties, labor-intensive industries avoid pro-union counties, and pollution-intensive industries locate in counties featuring relatively lax Clean Air Act regulation. We use our estimates to predict the likely employment impacts of state greenhouse gas mitigation efforts.

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# 1. Introduction

Between 1998 and 2006, aggregate U.S. manufacturing jobs declined by 19 percent while the total production of this industry grew by 24 percent.[1] This loss of manufacturing jobs has important implications for the quality of life of the middle class. Despite public concerns about the international outsourcing of jobs, over eleven million people continue to work in the U.S. manufacturing sector.[2] The ability of local areas to attract and retain such manufacturing jobs continues to play an important role in determining the vibrancy of their local economy.

Ongoing research examines the role that government regulations and local factor prices play in attracting or deflecting manufacturing employment. A leading example of this research is Holmes' (1998) study that exploited sharp changes in labor regulation at adjacent state boundaries. He posited that counties that are located in Right-to-Work states have a more "pro-business" environment than their nearby neighboring county located in a pro-union state. He used this border-pairs approach to establish that between 1952 and 1988 there has been an increasing concentration of manufacturing activity on the Right-to-Work side of the border. A recent *Wall Street Journal* piece claimed that, between the years 2000 and 2008, 4.8 million Americans moved from union states to Right-to-Work states.[3]

[1] The US Bureau of Labor Statistics reports employment by sector. From 1998 to 2006, manufacturing employment fell from 17.6 million to 14.2 million. (http://data.bls.gov/timeseries/CES3000000001?data_tool=XGtable). The United Nations Statistics division reports gross value added by kind of economic activity at constant (2005) US dollars. From 1998 to 2006, manufacturing value went from $1448 billion to $1695 billion (http://data.un.org/Data.aspx?d=SNAAMA&f=grID%3a202%3bcurrID%3aUSD%3bpcFlag%3a0%3bitID%3a12).

[2] In March, 2011, 11.67 million people worked in manufacturing (NAICS 31-33) (source: http://www.bls.gov/iag/tgs/iag31-33.htm).

[3] Arthur B. Laffer and Stephen Moore. "Boeing and the Union Berlin Wall." http://online.wsj.com/article/SB10001424052748703730804576317140858893466.html

In this paper, we build on Holmes' core research methodology along three dimensions. First, we focus on the modern period from 1998 to 2006. During this time period, the manufacturing sector experienced significant job destruction as intense international competition has taken place (Davis, Faberman and Haltiwanger 2006, Bernard, Jensen, and Schott 2006). Second, we generalize the border-pair methodology to study three key determinants of the geographic concentration of manufacturing jobs in one unified framework. Past research has documented that industrial concentration is affected by energy prices (Carlton 1983), environmental regulation (Becker and Henderson 2000, Greenstone 2002), and labor regulation and general pro-business policies (Holmes 1998, Chirinko and Wilson 2008). We estimate an econometric model that allows us to study all three of these factors. Third, we examine the heterogeneity of industries' response to these policies. Our identification strategy exploits within border-pair variation in energy prices and regulation to tease out the role that each of these factors play in influencing the geographical patterns of manufacturing employment.

This paper studies where different manufacturing industries cluster across different types of counties. We disaggregate manufacturing into 21 three-digit NAICS industries. We model each three-digit NAICS industry as a point in a three-dimensional attribute space; its energy consumption per unit of output, its labor-to-capital ratio, and its pollution intensity. We model each county as embodying three key bundled attributes; its utility's industrial electricity price, its state's labor regulation, and the county's Clean Air Act regulatory status.

The basic logic of comparative advantage yields several testable hypotheses. In a similar spirit as Ellison and Glaeser (1999), we test for the role of geographical "natural advantages" by studying the sorting patterns of diverse industries. Energy-intensive industries should avoid high electricity price counties.[4] Labor-intensive manufacturing should avoid pro-union counties. Pollution-intensive industries should avoid counties that face strict Clean Air Act regulation. We use a county-industry level panel data set covering the years 1998 to 2006 to document evidence supporting all three of these claims.

The paper also examines the relationship between energy prices and employment for specific industries. For 21 manufacturing industries and 15 major non-manufacturing industries, we estimate this relationship. We find that energy prices are not an important correlate of geographical concentration for most non-manufacturing industries. However, employment in expanding industries such as Credit Intermediation (NAICS 522), Professional, Scientific and Technical Services (NAICS 541), and Management of Companies and Enterprises (NAICS 551) is responsive to electricity prices with implied elasticities of approximately -.25. In comparison, the most electricity-intensive manufacturing industry, primary metals, has an elasticity of -1.3.

Finally, we use our estimates of the effect of electricity prices on local employment to judge the possible consequences of regional carbon mitigation policies. Given the failure of the U.S. Congress to pass significant carbon mitigation legislation, states such as California and regions such as the Northeast are unilaterally proceeding with carbon mitigation legislation. Critics have argued that carbon regulation will lead to higher local electricity prices (as the externality of producing power using fossil fuel is priced) and this in turn will repel energy-intensive industries away from these states. We use our estimates to provide new results on the likely effects of carbon regulation that places a price of $15 per ton of carbon dioxide ($CO_2$). We predict that states such as Ohio, with energy-intensive manufacturing and that rely heavily on

[4] Energy-intensive industries will also attempt to avoid high oil, coal, and natural gas prices, as well. However, our identification strategy examines differences between neighboring counties and while there are regional differences in coal and natural gas, these differences are likely to be small between neighboring counties.

coal for generating power, could lose as many as 28,000 manufacturing jobs. Other states such as California will experience a much smaller manufacturing job loss.

## 2. Empirical Framework

Our empirical work will focus on examining the correlates of the geographic clusters of employment and establishments by industry starting in 1998. Building on Holmes' (1998) approach, we rely heavily on estimating statistical models that include border-pair fixed effects.

Comparing the geographic concentration of employment within a border pair controls for many relevant cost factors. Manufacturing firms face several tradeoffs in choosing where to locate, how much to produce, and which inputs to use. To reduce their cost of production, they would like to locate in areas featuring cheap land, low quality-adjusted wages, lax regulatory requirements and cheap energy. They would also like to be close to final consumers and input suppliers in order to conserve on transportation costs. Within a border pair, we posit that local wages are roughly constant as are location amenities and proximity to input suppliers and final consumers.

Our unit of analysis will be a county/industry/year. First we study the geographic concentration of 21 manufacturing industries using the U.S. County Business Patterns (CBP) data over the years 1998 to 2006.[5] The CBP reports for each county and year the employment count, establishment count and establishment count by employment size. This last set of

[5] County Business Patterns (http://www.census.gov/econ/cbp/download/index.htm). We use 1998 as our start date because this was the first year in which NAICS rather than SIC codes where used. All data use the 2002 NAICS definitions.

variables is important because the CBP suppresses the actual employment count and reports a "0" for many observations (Isserman and Westervelt 2006).[6]

Within each local labor market, we study where the 21 different manufacturing industries cluster. While labor pooling represents an important reason why firms will cluster within local commuting range (say within fifteen miles), it alone does not explain *where* the cluster will take place. We posit that long run differentials in input prices and regulations influence where specific industries cluster.

Throughout this paper, we assume that each industry differs with respect to its production process (and hence in their firms' response to electricity prices and regulation) but any two firms within the same industry have the same production function. In general, energy inputs and environment technology may be either substitutes or complements with labor in a given industry. We measure the overall effect of these policies, which potentially include factor substitution as well as scale effects.

Our main econometric model is presented in equation (1). The unit of analysis is by county $i$, county-pair $j$, industry $k$, and year $t$. County $i$ is located in utility $u$ and state $s$. In most of the specifications we report below, we will focus on counties that are located in metropolitan areas.

[6] The CBP suppress employment counts to protect firms' privacy in certain cases. In 35 percent of our observations, employment equals zero despite there being a positive count of establishments in that county, industry and year. To address this issue, we impute the employment data using the establishment count data when suppression occurs. The CBP provides the counts of establishments by firm size category. We take the midpoint of employment for each of these categories and use the county/industry/year establishment count data across the employment size categories (1-4, 5-9, 10-19, 20-49, 50-99, 100-249, 250-499, 500-999, 1000-1499, 1500-2499, 2500-4999 and 5000+ ) to impute the employment count for observations that are suppressed. We top code the 5000+ employment observations at 6000. Our regressions focus on county pairs in which both counties are part of metropolitan areas, where we expect that suppression is less likely to take place.

$$emp_{ijuskt} = \beta_1 P_{ut}^{elec} + \beta_2 P_{ut}^{elec} Index_{kt} + \beta_3 Right_s LK_{kt} + \beta_4 NonA_{it} + \beta_5 NonA_{it} HighPoll_k \quad (1)$$
$$+\beta_6 NoMon_i + \beta_7 NoMon_i HighPoll_k + \theta_1 Index_{kt} + \theta_2 Right_s + \theta_3 LK_{kt}$$
$$+\theta_4 HighPoll_k + f(Poll_{it}) + \boldsymbol{\delta Z}_i + \alpha_j + \gamma_{kt} + \pi_{st} + \varepsilon_{ijuskt}.$$

In this regression, the dependent variable will be a measure of county/industry/year employment. The first term on the right side of equation (1) presents the log of the average electricity prices that the industry faces in a specific county. The second term allows this price effect to vary with the industry's electricity-intensity index. In the regressions, the electricity-intensity index is normalized to range from 0 to 1 for ease in interpreting the results. Third is an interaction term between whether state *s* has Right-to-Work laws (*Right*) and the industry's labor-to-capital ratio (*LK*). Finally, we examine the effect of environmental policy. This includes the interaction of an indicator of nonattainment status (*NonA*) and an indicator of high-polluting industries (*HighPoll*). We also examine the interaction effect of an indicator of whether a county does not monitor the pollutant of interest (*NoMon*) and the *HighPoll* dummy variable.

In estimating these policy-relevant variables, we try to control for potentially confounding factors. There are several variables that we would estimate in a traditional difference-in-differences model, including the direct effects of *Index*, *Right*, *LK*, and *HighPoll*: $\theta_1$- $\theta_4$. However, all of these are perfectly collinear with the various fixed effects that we estimate. For example, the direct effect of Right-to-Work states cannot be separately identified given the inclusion of state-year fixed effects. We do control for a flexible function of pollution concentration levels, $poll_{it}$.[7] The $\boldsymbol{Z}$ vector has county variables: a county's population in 1970, its distance to the nearest metropolitan area's Central Business District (CBD), the county's land

[7] Counties are more likely to be assigned to nonattainment status if their ambient air pollution levels in the recent past have been higher. If booming counties have high regulation levels, then a researcher could conclude that regulation raises employment levels when in fact reverse causality is generating this relationship. To sidestep this problem, we include a flexible function of the county's ambient pollution level.

area, and the log of the 1990 housing values.[8] In the core specifications we control for a county-pair fixed effect, industry-year fixed effects and state-year fixed effects. We rely heavily on these border-pair fixed effects to soak up spatial variation in local labor market conditions, climate amenities, and proximity to intermediate input providers and final customers. Past studies such as Dumais, Ellison and Glaeser (2002) have emphasized the importance of labor pooling as an explanation for why firms in the same industry locate close together. The industry-year fixed effects control for any macro level changes in demand due to shifting national consumption trends or world trade.[9] The state-year fixed effects control for any state policy that affects a firm's propensity to locate within a state. For example, some states have low taxes such as Missouri while others such as California do not.[10]

We use several different dependent variables. We begin by examining the number of manufacturing employees. We also present results that focus on an industry's percentage of total county employment. In another specification, we report results for the natural log of employment, which is estimated only for observations with positive employment. As discussed below, 16 percent of our observations have no establishments and thus no employees.

[8] Adjacent counties are unlikely to be "twins." The classic monocentric model of urban economics predicts that counties closer to a major Central Business District will feature higher population densities and higher land prices than more suburban counties. We have also estimated specifications that included other county attributes such as a dummy indicating whether the county is the metropolitan area's center county and another dummy that indicates whether the county is adjacent to an Ocean or a Great Lake. The results are robust to controlling for these variables and are available on request. In Appendix Table A1, we present formal tests of whether our explanatory variables included in the **Z** vector are "balanced." We find that these covariates vary by treatment for high electricity prices, labor regulation, and environmental regulation. In a regression reported in Table 5, we include linear trends for each covariate to test whether our results are robust.

[9] Linn (2009) documents that linkages between manufacturing industries amplify the effect of a macro energy price shock. Given that energy-intensive industries are important input suppliers to other industries, there could be industry-year effects driven by such linkages. Including the industry-year fixed effects helps to address this issue. For more on the macroeconomics impacts of energy price changes see Killian (2008).

[10] Recent empirical work has documented that minimum wage differences across states do not influence the locational choices of low skill jobs (Dube, Lester, and Reich 2010).

Estimates of equation (1) generate new findings about the long run equilibrium relationship between regulation, electricity prices and manufacturing locational choice. As we discuss below, county electricity prices are highly serially correlated over time and so are labor and environmental regulation. Thus, these three factors embody long run natural advantages of a specific location.

For each manufacturing industry, we can measure the electricity intensity and the labor-capital ratio. These data are from NBER Productivity Data Base and cover 1997 to 2005.[11] Below, we will also present results for non-manufacturing industries but cannot measure their electricity, labor, or pollution intensity. As such, our main results focus on manufacturing where we can test for the role of geographical "natural advantages."

The interaction terms presented in equation (1) allow us to test three hypotheses. The first hypothesis is that energy-intensive industries cluster on the low electricity price side of the border. The second hypothesis is that labor-intensive industries cluster on the Right-to-Work Side of the border. The third hypothesis is that high emissions industries cluster in the low environmental regulation side of the border.

We estimate equation (1) using weighted least squares. We will also present one set of results below in which we instrument for local electricity prices. Note that each county/industry/year observation enters multiple times since a county can be adjacent to several counties. We place equal weight on each county/industry/year observation with weights based on a county's number of borders.[12] Multiple entries also require standard error corrections: we need to cluster

[11] See http://www.nber.org/data/nbprod2005.html. For 2006, we use the 2005 data.

[12] The analytic weights are the inverse of the number of times a given county/industry/year enters the sample.

at this level or one that is more aggregated. We cluster by major utility to allow for serial correlation and spatial correlation.

Incumbent firms are likely to face migration costs to relocate. If large capital costs are sunk, firms may delay relocating until their existing production facility depreciates or there are large differences in operating costs across geographic locations.[13] Our estimates of equation (1) will be attenuated relative to how responsive industries would have been if they face zero migration costs. For this reason, we also report estimates in which we include county fixed effects (rather than border-pair fixed effects).

In equation (2), the unit of analysis is by county *i*, industry *k*, electric utility *u*, and year *t*. We estimate equation (2) with county, industry-year, and state-year, fixed effects:

$$emp_{iukt} = \beta_1 P_{ut}^{elec} + \beta_2 P_{ut}^{elec} Index_{kt} + \beta_3 Right_s LK_{kt} + \beta_4 NonA_{it} HighPoll_k + \beta_5 NoMon_i HighPoll_k \\ + \beta_6 NonA_{it} + \beta_7 NoMon_i + f(Poll_{it}) + \alpha_i + \gamma_{kt} + \pi_{st} + \varepsilon_{iukt}. \tag{2}$$

By exploiting within county variation over time in electricity prices and environmental regulation, these estimates can be thought of as a short term response to changes in the relevant explanatory variables. The county fixed effects regression presented in equation (2) also addresses the criticism that there are fixed county attributes that are not captured by our controls that could be correlated with the key explanatory variables. If these unobservables are time invariant, then including county fixed effects address this concern.

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[13] One example is the Ocean Spray Corporation which plans to close its 250-worker cranberry concentrate processing plant in Bordentown, New Jersey in September 2013, and move it to Lehigh or Northampton counties in Pennsylvania. The closing facility is old and high cost. The company has claimed that it is attracted to the new Pennsylvania location because of lower power, water and trucking costs (http://www.philly.com/philly/blogs/inq-phillydeals/South-Jersey-plant-to-close-250-jobs-moved-report.html).

## 3. Three Margins Affecting Geographic Concentration of Employment

A key identifying assumption in this paper is that there exists within county border pair variation in labor regulation intensity, electricity prices, and Clean Air Act intensity that allows us to observe "exogenous" variation.

### 3.1. Electricity Prices

Electricity prices vary across electric utility jurisdictions (see Figure 1 for county average prices in 1998). Adjacent counties can lie within different electric utility jurisdictions. Each of the approximately 460 U.S. electric utilities charges different electricity prices. In the ideal research design that relies on county-level employment data, each county would be served by one utility. In this case, we would have a sharp spatial regression discontinuity at each county border but this is not the case. Some major counties have multiple utilities. While other utilities span several counties. If two adjacent counties lie within the same electric utility district, then there will be no within border pair variation for these counties.[14]

Most of our border pairs are within the same utility area. However, for those pairs that cross utilities, the price differences can be significant. The median price differential is about one cent for border pair counties that lie in different utility areas. For five percent of these counties, the difference is over nine cents a kWh. For firms in electricity-intensive industries, this differential represents about seven percent of revenue. This fact highlights that there are

[14] Davis *et al*. (2008) find that, in 2000, about 60 percent of the variation in electricity prices paid by manufacturing plants can be explained by county fixed effects. The remaining differences may be due to multiple utilities serving a county, non-linear pricing where customers are charged both a usage fee and a peak consumption fee, or because of different rates negotiated with the utilities. Davis *et al*. find evidence of scale economies in delivery that are consistent with observed quantity discounts.

significant cost savings for a subset of industries for choosing to locate in the lower electricity price county within a county-pair.

Most U.S. retail electricity prices are determined through rate hearings where regulated firms can recover rates through average cost pricing. Initially in restructured markets, rates were frozen for an initial period when utilities were to recover "stranded" assets. Today the retail prices in these markets are mostly wholesale costs as passed on to consumers through retail competition. However, during our historic period, most rates were the function of past costs that had little to do with current production costs.

Our electricity price data are constructed from data available from the Energy Information Administration (EIA) form 861.[15] We determine prices by aggregating total revenue at any utility that serves industrial customers in a given county and year. We divide this total revenue by the total quantity of electricity sold by those utilities in that year.[16] For clustering, we assign the county to one of the 178 major utilities in our sample.[17]

## 3.2. Labor Regulation

We follow Holmes (1998) and assign each county to whether it is located in a Right-to-Work state or not. Today, there are 22 states that are Right-to-Work states. A Right-to-Work law secures the right of employees to decide for themselves whether or not to join or financially

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[15] See http://www.eia.doe.gov/cneaf/electricity/page/eia861.html

[16] In fact, industrial customers face a non-linear structure that has a per day fixed meter charge, an energy charge per kWh consumed, and an additional demand charge based on peak hourly consumption (kW) during a billing period. In addition, rates may differ by firm size and type. Some large firms face tariffs with a specific tariff that applies to them. Our empirical strategy imposes that firms respond to cross county average price variation when in fact firms will recognize that they face a non-linear pricing schedule.

[17] For counties with multiple utilities, the major utility is defined as the utility with the largest total sales across all of its industrial customers.

support a union. The set of states includes Alabama, Arizona, Arkansas, Florida, Georgia, Idaho, Iowa, Kansas, Louisiana, Mississippi, Nebraska, Nevada, North Carolina, North Dakota, Oklahoma, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia and Wyoming.

When we restrict our sample to the set of counties that are both in a metropolitan area, we have relatively few cases in which one county lies in a Right-to-Work state and the other county lies in non-Right-to-Work State (28 pairs comprise 36 counties). Two examples of such a "hybrid" metropolitan areas are Kansas City, Missouri and Washington D.C. Below, we also report results in which we use all U.S. counties (here, 443 pairs comprise 425 counties).

### 3.3. Environmental Regulation

The Clean Air Act assigns counties to low regulation (Attainment Status) and high regulation (Nonattainment Status) based on past ambient air pollution readings. Within county border-pairs, there is variation in environmental regulation both due to cross-sectional differences (*i.e.*, high regulated counties that are adjacent to less regulated cleaner counties) and due to changes over time (reclassification of counties from attainment to nonattainment and vice-versa). In this paper, we focus on ozone as one of the six criteria pollutants. We estimate similar models for carbon monoxide and particulate matter.[18] There were 490 ozone nonattainment counties (401 in MSAs) in 1998, while 206 (171) remained in 2006.

[18] We estimate equation (1) using two other measures of local environmental regulation intensity: a county's carbon monoxide (CO) nonattainment status; and a county's particulate matter (PM) nonattainment status. All high polluters are defined based on the data reported in Greenstone's (2002) Appendix. We classify NAICS industries 322, 324, and 331 as high CO polluters, and NAICS industries 321, 322, 327 and 331 as high PM polluters. Initially we focused just on CO, the only pollutant for which Greenstone found a significant effect on manufacturing jobs. However, we changed our focus from CO because recent progress in reducing ambient CO has led to the reclassification of many counties from "nonattainment" to "attainment" status. By the end of our sample (2006), only ten counties were in nonattainment (and there have been none at all since 2009).

We classify three of the 21 industries as “High Ozone Polluters.” These industries include Petroleum and Coal Products (NAICS 324), Plastics and Rubber Products (NAICS 326), and Nonmetallic mineral products (NAICS 327).[19] We hypothesize that these industries should be the most responsive to avoiding the nonattainment sides of the county border pair and in locating in that county within the county border pair that does not monitor ambient ozone.[20] The data indicating a county’s Clean Air Act regulatory status are from the EPA’s Greenbook.[21] Our county/year ambient air pollution data are from the U.S. EPA AIRS data base. Our regressions include a cubic function of a county’s ambient ozone level.

## 4. Results

Table 1 reports the summary statistics. The uneven distribution of manufacturing activity is revealed in the first row. The average county/industry/year observation has 721 jobs but the median is 129 and the maximum is 158,573. It is relevant to note these summary statistics are based on all counties located in metropolitan areas and excludes about 75 percent of U.S. counties. Of this sample, 84 percent have at least one employee in that county, industry, and year.

Table 2 reports the names and key statistics for the 21 manufacturing industries that we study. The rows are sorted from the most energy-intensive industry (Primary Metals) to the least energy-intensive industry (Computer and Electronic Product Manufacturing). The most energy-intensive industry uses sixteen times as much electricity per unit of output as the least electricity-

[19] This classification system is based on the emissions share data reported in Greenstone’s (2002) Table A2.

[20] Ambient air pollution is not monitored in every county. Kahn (1997) documents higher manufacturing growth rates in counties that do not monitor ambient pollution relative to those that do monitor.

[21] http://epa.gov/airquality/greenbk/

intensive industry. In the right column of Table 2, we report each industry's labor-to-capital ratio. Apparel, Leather, Textiles, and Furniture are some of the most labor-intensive industries. In contrast, the primary metals industry has a tiny labor-to-capital ratio. The cross-industry correlation between the electricity index and the labor-to-capital ratio equals -.36.

In Table 3, we report our first estimates of equation (1). Recall that each county pair consists of two metropolitan area counties that are physically adjacent. Controlling for county-pair fixed effects, industry-year fixed effects, and state fixed effects, and a vector of county attributes (log of land area, log of the distance to the closest metro area's Central Business District, the log of the county's 1970 population, and the log of the 1990 housing values), we focus on the role of electricity prices and labor and environmental regulation in determining manufacturing clusters.[22] As shown in column (1), we find evidence of a negative relationship between electricity prices and manufacturing employment activity for all manufacturing industries whose normalized electricity index is greater than 0.038.[23] This includes all of our industries except electronics (NAICS 334). We find the largest negative effects of electricity prices on primary metals employment. For this industry, we estimate a price elasticity of -2.2.[24]

Controlling for electricity prices, we find that labor-intensive manufacturing clusters on the Right-to-Work side of the county border pair. For the most labor-intensive industry

[22] For the first column, when we look at the level of manufacturing employment, we use the level of population in 1970 to be consistent. The results are similar when log historic population is used instead. Recognizing that within a county, such as Los Angeles County, firms may seek out the cheapest utility within the county, we have re-estimated our models using the minimum price in the county and find very similar results.

[23] Deschenes (2010) uses a state/year panel approach using a longer time series than we do and does not disaggregate manufacturing industries beyond; "durables" and "non-durables." Controlling for state and year fixed effects, for "non-durables" he reports a positive correlation of electricity prices and employment based on a specification with state and year fixed effects.

[24] This is the sum of the coefficient on price and the coefficient on price interacted with the index (which is normalized to range from 0 to 1, where 1 is the most electricity-intensive industry (primary metals)) all divided by the average employment in that industry in our sample: (63+(-1656)*1)/721=-2.21.

(Apparel), the coefficients imply 421 more jobs on the right-to-work side of the border, relative to an extremely capital-intensive industry like petroleum. This is approximately half of the average number of workers in a given county/industry/year. It is relevant to contrast this finding with Holmes' (1998) work. He finds that share of total employment that is in manufacturing is greater by about one third in Right-to-Work states. He did not disaggregate manufacturing into distinct industries. If the Right-to-Work status simply reflected this overall ideology then we might not observe that labor-intensive industries are more likely to cluster there. Our finding of a positive industry-average labor intensity interaction with the state's labor policies indicates a differential effect within manufacturing.

Controlling for electricity prices and labor regulation, we also study the role of environmental regulation. As expected, we find that employment in high-pollution industries is lower in high-regulation (nonattainment) counties. We also find that employment is higher for high-ozone industries in counties that do not monitor ozone.

A distinctive feature of our study is that we simultaneously study the marginal effects of energy prices, labor regulation, and environmental regulation in one unified framework. In Table 3's columns (2-4), we present our estimates for what we would find if we studied these variables individually. We find that our electricity and environmental regulation estimates are comparable to column (1), but that we would have estimated a smaller labor regulation effect on employment had we studied this factor individually.

The results in column (5) of Table 3 switch the dependent variable to the ratio of a county/year's jobs in a given industry divided by total county employment. This was Holmes' (1998) dependent variable. This measure better captures the composition of jobs within a county.

The results are quite similar to the results in column (1) except that we find no evidence of the importance of environmental regulation. For the primary metals industry, we find that a ten percent increase in electricity prices is associated with a 0.056 percentage point reduction in the share of workers in the county who works in this industry.

In Table 3's column (6), we use the log of the county/industry/year's employment and thus lose the observations for which there are zero jobs. These results are qualitatively quite similar to the results reported in equation (1). Based on this specification, we estimate an employment electricity price elasticity of -1.13 for the primary metals industry.

We can now compare the relative sensitivities of a given industry to energy prices, labor policy, and environmental policies. For an industry like petroleum—which is energy intensive, capital intensive, and a high-ozone polluter—banning Right-to-Work laws would have the same effect on employment as a four percent increase in electricity prices. In contrast, if a petroleum manufacturer's county falls into nonattainment with environmental regulations, this is akin to increasing electricity prices by 48 percent. Other industries that are not energy or pollution intensive are not as negatively affected by either higher energy prices or pollution regulation. For example, for apparel manufacturing, repealing a right-to-work law is akin to a fourfold increase in electricity prices.

In Table 4, we modify equation (1) by estimating separate coefficients on electricity prices for each manufacturing industry. In other words, we relax the index restriction on electricity prices that was imposed on the results reported in Table 3. We also estimate equation (1) separately for fifteen major non-manufacturing industries.[25] While we do not have energy

[25] We choose the 15 industries with the most employees in 1998. Wholesale electronic markets (NAICS 425) had the ninth most jobs in 1998 but the NAICS 2002 reclassifications made it difficult to track this industry. Instead, we

usage information for these industries, we use Bureau of Economic Analysis (BEA) input-output data to construct electricity cost shares.[26]

The results reported in Table 4 focus on the role of energy prices. We do not include labor or environmental regulations in these regressions. We report results for two dependent variables: log employment and the level of employment. The table reports each industry's total national employment in 1998, its national employment growth between 1998 and 2006, and the BEA electricity cost shares. For five manufacturing industries, we find negatively statistically significant correlations (at the five percent level) for both measures of employment with electricity prices: NAICS 321, 322, 324, 327, and 331.

As shown in Table 2, several of these industries are the most electricity intensive. We find a positive and statistically significant correlation for two manufacturing industries (NAICS 334 Computers and 339 Miscellaneous). These two industries each have a very low energy intensity index. Finally, we note that Tables 3 and 4 imply similar employee-weighted average elasticities across industries for each specification.[27]

The bottom panel of Table 4 reports similar regressions for non-manufacturing industries. Many of these industries employ millions of people and have experienced sharp employment growth between 1998 and 2006. Employment in expanding industries such as Credit Intermediation (NAICS 522), Professional, Scientific and Technical Services (NAICS 541), and

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added the 16th most common job in 1998, Motor Vehicle and Parts Dealers (NAICS 441). Note that the border-pair and state-year fixed effects differ by non-manufacturing industry but are pooled for manufacturing industries.

[26] See http://www.bea.gov/industry/io_benchmark.htm. Using data for 2002, we define the cost share as the ratio of an industry's dollars spent on electric power (NAICS 2211) over its total industry output.

[27] For the linear specification, the implied elasticity is -.40 in Table 3 and -.52 in Table 4. For the log specification, they are -.08 and -.13, respectively. Note that the log specification is conditional on any employment in the county/industry/year and therefore need not be the same as the linear model.

Management of Companies and Enterprises (NAICS 551) is quite responsive to electricity prices with elasticities of approximately -.25. However, for most non-manufacturing industries, we find that energy prices are not an important correlate of geographical concentration. The BEA electricity cost shares do not explain the variation in responses for non-manufacturing industries.

Estimates of equation (2) are reported in Table 5, column (1). By including county fixed effects, we exploit 1998 to 2006 variation of electricity prices within a county. We view this within-county estimate as capturing the short run effects of energy price changes. We find an elasticity of -1.4 for primary metals, which is smaller than the elasticity we reported based on estimates of equation (1). Note that the coefficient on electricity price, $\beta_1$, becomes positive and statistically significant. Based on this specification, only the five most energy-intensive industries have a negative relationship between employment and electricity prices. In column (2), we include state, but not county, fixed effects and find a small and negative $\beta_1$.

Up until this point, we focused on results based on counties located in metropolitan areas. In the column (3) of Table 5, we re-estimate equation (1) using the full sample of all U.S. counties. Relative to the metro sample, the results for the full county sample yield the same coefficient signs but the absolute value of the coefficients for electricity prices and labor regulation shrinks by more than 50 percent. The coefficients on environmental regulation indicators shrink but by a much smaller percentage. In Table 5's column (4), we include linear time trends for each control variable such as population and home values to control for the possibility that counties differ with respect to their growth trajectory. The results are robust for controlling for these trends. Column's (5) and (6) use PM and CO pollution in place of the ozone for attainment status, monitoring status, high polluter industries, and concentration ratios. We find similar coefficients as in our main results but larger standard errors.[28]

We recognize that there are cases in which a county's average electricity price could be correlated with the error term. A demand side explanation argues that a boom in local employment will result in an increase in the utility's demand. This requires more expensive power plants to operate, and electricity prices will increase. Second, industrial firms have some bargaining power in negotiating rates with the electric utility. Third, imprecise measurement of a firm's electricity price will attenuate OLS coefficient estimates. To address these concerns, we present instrumental variables results in Table 5's column (7). We construct instruments using the product of the local utility's capacity shares of coal, oil and gas-fired power plants and the respective annual average fuel price.[29] The sample size declines because we are missing fuel shares for some utilities. The F-Statistic for the first stage equals 1139. The key finding to emerge in this instrumental variables case is that all industries (even those with the lowest energy intensity) now have a negative employment elasticity with respect to energy prices and the effect is much larger. The other coefficients on labor and environmental regulation are consistent with our core hypotheses.

[28] These results are not surprising given the few number of counties in nonattainment with these pollutants.

[29] The shares data are from the EIA form 860 data for 1995. The fuel prices are from the EIA: coal prices are quantity-weighted annual averages from form 423; oil prices are spot WTI; and natural gas prices are the annual Henry Hub contract 1 prices.

The County Business Patterns data provides information for each county/industry/year on its employment count and establishment count. In Table 6, we use these two pieces of information and in addition we calculate the average employment count per establishment. We report regression estimates of equation (1) using each of these as the dependent variable. Table 6's column (1) is identical to Table 3's column (1). In column (2), we report the establishment count regression. We find that the count of establishments responds to both electricity prices and to environmental regulation. Establishments that are energy intensive avoid the high electricity price counties. We cannot reject the hypothesis that there is no correlation between labor regulation and the establishment count. In column (3), we switch the dependent variable to the log of the establishment count. In this case, we find that there are more labor-intensive establishments clustering on the Right-to-Work side of the border. We find no evidence that ozone regulation is a determinant of the log establishment count.

In columns (4) and (5) of Table 6, we report regression results for two measures of facility size: the ratio of workers per establishment, and its log. Bigger firms avoid the high electricity price county. Surprisingly, we find no statistically significant correlation between a county's Right-to-Work status and the size of facilities even for labor-intensive industries. Based on the results in column (4), smaller firms in high ozone industries are clustering in counties that do not monitor ozone.

## 5. Predicting Local Manufacturing Job Destruction Due to Carbon Pricing Pass Through

In the summer of 2010, the U.S. Senate chose not to vote on carbon cap-and-trade regulation. Opponents of carbon regulation argued that given that the rest of the world was unwilling to sign a global treaty that the United States would hurt its industrial employment base if it unilaterally enacted carbon mitigation regulation. Such regulation would raise electricity prices here and would act to push industrial activity abroad.

A similar argument has been made about the employment consequences of recent state and regional level initiatives seeking to reduce greenhouse gas emissions. Today, California is launching AB32 and the Northeast is launching RGGI.[30] Critics have argued that such regulation will lead to job loss as carbon regulation raises local electricity prices relative to other states that have not enacted such regulation.

Basic free rider logic suggests that it is futile to be a first mover and unilaterally adopt costly regulation. Over the last year, both Arizona and New Jersey have dropped out of regional carbon mitigation efforts. New Jersey's governor has expressed concerns about how coal-fired power plants in New Jersey would be affected by carbon cap-and-trade legislation.[31]

For domestic jobs "leakage" to take place, the following logic chain must hold. Carbon pricing must raise electricity prices by different amounts in different states with the largest electricity price increases taking place in states that rely on coal for generating power. In addition, manufacturing must be fairly "footloose" in how it responds to electricity price differentials across space. Our estimates are useful for judging the validity of this concern.

We simulate the effect of adopting carbon pricing on employment for each state. We begin by estimating the marginal carbon dioxide emissions in each electricity market. As in Holland and Mansur (2008), we define markets as NERC regions (during the late 1990s and

[30] See http://www.arb.ca.gov/cc/ab32/ab32.htm and http://www.rggi.org/home, respectively.

[31] http://www.environmentalleader.com/2011/05/27/new-jersey-pulls-out-of-rggi-bans-coal-plants/

early 2000s). For the years 1997 to 2000, we use data from EPA's Continuous Emissions Monitoring System on hourly power plant emissions and the Federal Energy Regulatory Commission (FERC) Form 714 data on hourly electricity consumption by utility. For each NERC region, we regress hourly aggregate carbon dioxide ($CO_2$) emissions on hourly aggregate demand, and fixed effects for month-year and hour-of-day. Standard errors are clustered by month-year. The coefficient of interest measures the marginal change in emissions rate (tons of $CO_2$ per MWh). Panel A of Table 7 reports the coefficient estimates and standard errors. Average emissions rates are also shown for comparison. For a given carbon price, we can predict the change in electricity prices assuming complete pass through and no change in the merit order of power plants (*i.e.*, the same power plant would be on the margin with and without a carbon price).

The thought experiment we run is to introduce a $15 per ton carbon tax for each regional electricity market (*e.g*., a NERC) region under the assumption that it is the only region to enact this policy. We then summarize the effects on employment at the state level.[32] In Table 7, we report simulations based on our main results in Table 3, column (1). It is important to recall that these estimates of Table 3 represent "long run" effects. For each state, Panel B reports total change in manufacturing jobs, the average normalized electricity index, and the average change in electricity prices.

[32] The effect on employment equals $(\hat{\beta}_1 + \hat{\beta}_2 Index_{kt}) \cdot (\ln(\exp(P_{ut}^{elec}) + .15\hat{\varphi}_u) - P_{ut}^{elec}))$ where $\hat{\varphi}_u$ is the estimated marginal emissions rate.

The states that are expected to be the most affected by carbon regulation are Ohio, Pennsylvania, New York, and North Carolina.[33] Ohio's predicted manufacturing job loss of roughly 27,700 jobs is likely to cause significant economic dislocation in smaller manufacturing cities. Larger cities feature more diversified economies but such smaller cities could bear much of the incidence of such new regulation.

Given our identification strategy, our estimates should only be used to judge the effects of a marginal change in electricity prices in a given county. With this caveat in mind, we view these state-level simulations as generating an upper bound on the lost employment from carbon policy as moving costs are likely to be smaller across county borders than over long distances. Furthermore, we cannot claim to have credibly recovered estimates that can be used in a general equilibrium context. Thus, we caution against summing our individual state job loss estimates to yield a national job loss estimate.

## 6. Conclusion

The basic logic of cost minimization offers strong predictions concerning where different manufacturing industries will cluster across U.S. counties as a function of regulatory policies and input prices. Using a unified framework that exploits within county-pair variation in locational attributes, we have documented that labor-intensive industries locate in anti-union areas, energy-intensive industries locate in low electricity price counties and high polluting industries seek out low regulation areas. Based on our findings, we conclude that energy prices are only a significant determinant of locational choice for a handful of manufacturing industries such as primary

[33] Deschenes (2010) uses his state level panel estimates to predict the likely employment effects of a Federal carbon mitigation policy. If such a policy would raise electricity prices by 4%, then he predicts that aggregate U.S. employment would decline by 460,000.

metals. For the typical manufacturing industry, the electricity price effects are modest. Our analysis highlights the importance of simultaneously studying multiple determinants of industrial agglomeration.

Our estimates of the relationship between local manufacturing employment and local electricity prices can be used to simulate the consequences of a new local carbon mitigation policy such as a carbon tax. A Republican Congress is highly unlikely to enact Federal carbon legislation but state and regional initiatives such as California's AB32 and the Northeast's RGGI are moving forward. Based on our estimates from calendar year 2006, we predict that the introduction of a $15 per ton cap and trade program in California under AB32 would lead to a loss of 6.6 thousand jobs for this state (a .5 percent reduction). The introduction of a $15 per ton of carbon dioxide policy in the RGGI region (ten Northeastern states) would lead to a loss of 47 thousand jobs in that region (a 3.1 percent reduction).[34] This price is only a benchmark: we recognize that actual permit prices may be very different and that carbon policies may include other incentives that will affect employment. Combining econometric evidence with policy simulations offers a fruitful path for offering credible predictions about the likely cost of environmental regulation.

[34] The Regional Greenhouse Gas Initiative regulates firms in Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island and Vermont. The RGGI region's greater percentage differential is due to the fact that this region's electric utilities have a higher carbon emissions factor and its industries are on average more energy intensive than California's.

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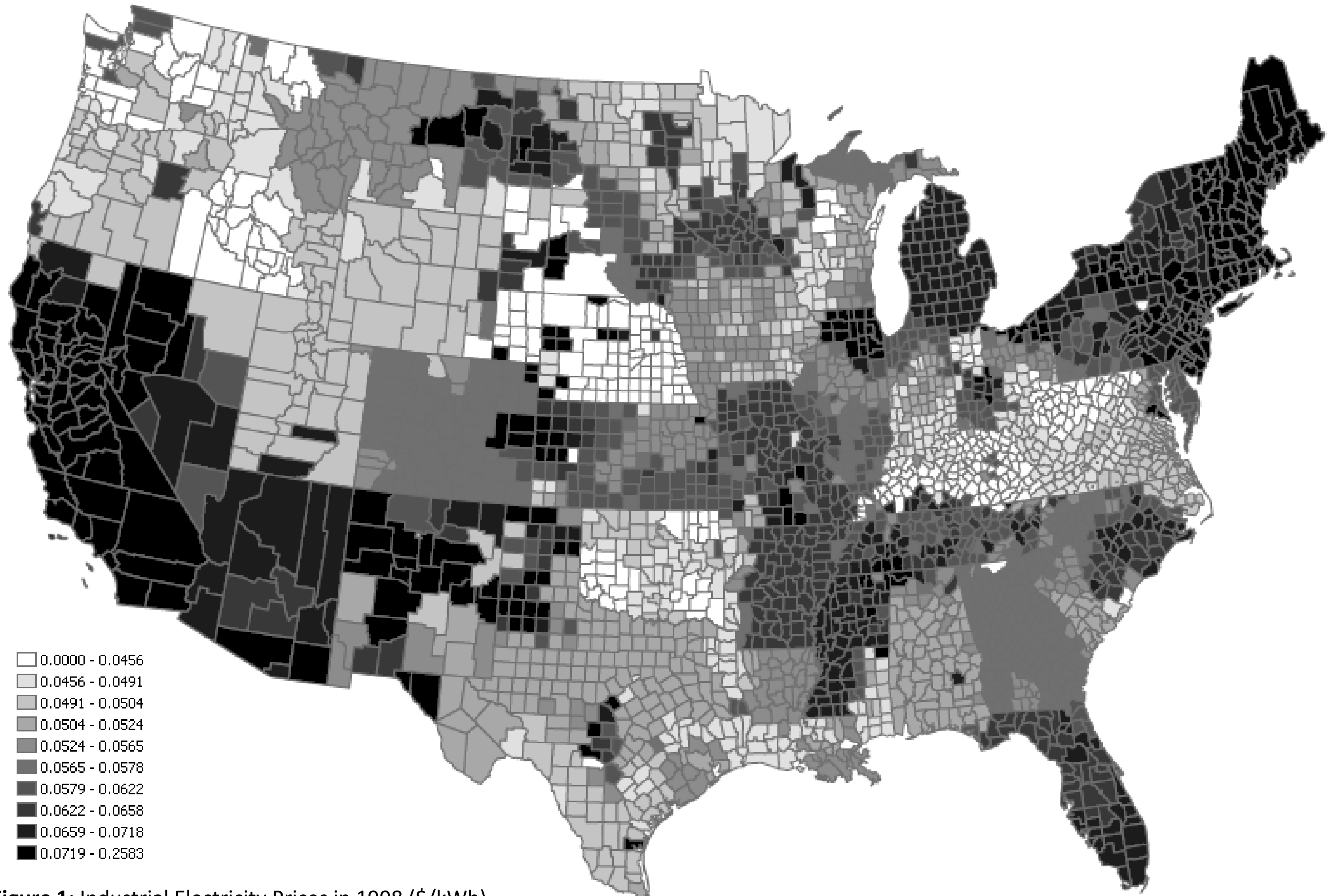


**Figure 1**: Industrial Electricity Prices in 1998 ($/kWh)

**Table 1**: Summary Statistics

| Variable | Units | Obs | Mean | Std. Dev. | Min | 1st Quartile | Median | 3rd Quartile | Max |
|---|---|---|---|---|---|---|---|---|---|
| Mnfct. Employees | workers | 138,320 | 721 | 2,508 | 0 | 10 | 129 | 573 | 158,573 |
| % Total Emp. | % | 138,320 | 0.8% | 1.8% | 0.0% | 0.0% | 0.2% | 0.7% | 56.4% |
| ln(Employment) | | 116,353 | 5.13 | 2.02 | 0.00 | 3.77 | 5.33 | 6.62 | 11.97 |
| Any Manufacturing | 0/1 | 138,320 | 0.84 | 0.37 | 0.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Suppressed Data | 0/1 | 138,320 | 0.35 | 0.48 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| Electricity Price | $/kWh | 138,320 | $0.064 | $0.023 | $0.025 | $0.050 | $0.056 | $0.068 | $0.296 |
| Electricity Index | kWh/shipments | 138,320 | 0.27 | 0.25 | 0.00 | 0.09 | 0.16 | 0.39 | 1.00 |
| Elect. Cost Share | elec. cost/ship. | 189 | 0.014 | 0.013 | 0.002 | 0.008 | 0.012 | 0.025 | 0.056 |
| Right to Work Laws | 0/1 | 138,320 | 0.43 | 0.50 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| Labor/Capital Ratio | work hrs/capital | 138,320 | 0.017 | 0.013 | 0.001 | 0.007 | 0.014 | 0.023 | 0.074 |
| Ozone Nonattain. | 0/1 | 138,320 | 0.42 | 0.49 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| PM Nonattainment | 0/1 | 138,320 | 0.05 | 0.22 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| CO Nonattainment | 0/1 | 138,320 | 0.04 | 0.20 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |

**Table 2**: Industry Details

| Industry | NAICS | Electricity Index | Normalized Electricity Index | Labor to Capital Ratio |
|---|---|---|---|---|
| Primary Metal Manufacturing | 331 | 0.816 | 1.000 | 0.007 |
| Paper Manufacturing | 322 | 0.706 | 0.856 | 0.006 |
| Textile Mills | 313 | 0.503 | 0.591 | 0.014 |
| Nonmetallic Mineral Product Manufacturing | 327 | 0.454 | 0.527 | 0.013 |
| Chemical Manufacturing | 325 | 0.402 | 0.459 | 0.004 |
| Plastics and Rubber Products Manufacturing | 326 | 0.330 | 0.364 | 0.016 |
| Wood Product Manufacturing | 321 | 0.253 | 0.265 | 0.028 |
| Petroleum and Coal Products Manufacturing | 324 | 0.245 | 0.254 | 0.002 |
| Fabricated Metal Product Manufacturing | 332 | 0.185 | 0.175 | 0.020 |
| Printing and Related Support Activities | 323 | 0.169 | 0.154 | 0.023 |
| Textile Product Mills | 314 | 0.165 | 0.149 | 0.035 |
| Food Manufacturing | 311 | 0.149 | 0.128 | 0.013 |
| Electrical Equipment, Appliance, and Component Manufacturing | 335 | 0.137 | 0.112 | 0.017 |
| Furniture and Related Product Manufacturing | 337 | 0.123 | 0.094 | 0.043 |
| Leather and Allied Product Manufacturing | 316 | 0.110 | 0.077 | 0.035 |
| Machinery Manufacturing | 333 | 0.103 | 0.068 | 0.014 |
| Apparel Manufacturing | 315 | 0.102 | 0.067 | 0.047 |
| Miscellaneous Manufacturing | 339 | 0.096 | 0.059 | 0.023 |
| Beverage and Tobacco Product Manufacturing | 312 | 0.092 | 0.053 | 0.004 |
| Transportation Equipment Manufacturing | 336 | 0.086 | 0.045 | 0.011 |
| Computer and Electronic Product Manufacturing | 334 | 0.051 | 0.000 | 0.007 |
| Correlation with Electricity Index | | | | -0.356 |
| Units | | kWh/shipments | | work hrs/capital |

*Notes*: Industries are defined by 3 digit NAICS codes.

**Table 3**: Effect of Local Energy Prices and Regulation on Manufacturing Employment

| | Manufacturing Employees (N) | | N | | N | | N | | Percent Total Employment | | ln N | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | | 2 | | 3 | | 4 | | 5 | | 6 | |
| ln Electricity Price | 62.5 | | 48.2 | | | | | | 0.15 | ** | 0.20 | * |
| | (204.6) | | (188.4) | | | | | | (0.07) | | (0.10) | |
| ln Price * Electricity Index | -1656.0 | *** | -1518.9 | ** | | | | | -0.56 | ** | -1.33 | *** |
| | (617.3) | | (587.7) | | | | | | (0.24) | | (0.31) | |
| Right to Work* Labor/Capital | 9154.4 | *** | | | 6413.0 | ** | | | 9.72 | *** | 10.05 | *** |
| | (3007.6) | | | | (2602.0) | | | | (3.55) | | (3.54) | |
| Nonattainment County | -2.0 | | | | | | 1.1 | | -0.05 | ** | 0.01 | |
| | (29.6) | | | | | | (28.9) | | (0.02) | | (0.03) | |
| NonA * HighPoll | -163.3 | *** | | | | | -152.8 | *** | 0.10 | | 0.01 | |
| | (49.0) | | | | | | (49.4) | | (0.06) | | (0.07) | |
| No Pollution Monitor | -50.0 | | | | | | -48.5 | | 0.04 | *** | 0.01 | |
| | (42.0) | | | | | | (40.7) | | (0.01) | | (0.03) | |
| NoMon * HighPoll | 175.6 | *** | | | | | 190.1 | *** | -0.03 | | -0.02 | |
| | (47.7) | | | | | | (51.9) | | (0.05) | | (0.05) | |
| $R^2$ | 0.36 | | 0.36 | | 0.35 | | 0.35 | | 0.14 | | 0.52 | |
| n | 789,267 | | 850,458 | | 850,458 | | 789,267 | | 789,009 | | 669,404 | |

* Notes: All regressions include cubic polynomials of PM concentrations, county population in 1970, miles to CBD, area of county, 1990 housing values, and county-pair, industry-year, and state-year fixed effects. High PM industries are wood products, paper, nonmetallic minerals, and primary metals. Significance is noted at the 10% (*), 5% (**) and 1% (***) levels. Standard errors clustered by utility.

**Table 4**: Electricity Price on Employment by Industry

| Industry | Employees in 1998 (1000s) | Industry growth | BEA Elect. Cost Shares | *Manufacturing Industries* | ln N Coef. | ln N S.E. | | Employees Coef. | Employees S.E. | |
|---|---|---|---|---|---|---|---|---|---|---|
| 311 | 1,464 | -.004% | 1.17% | Food | 0.10 | (0.26) | | 244 | (337) | |
| 312 | 173 | -10% | 0.79% | Beverage & Tobacco Product | 0.06 | (0.47) | | -1100 | (463) | ** |
| 313 | 385 | -51% | 2.40% | Textile Mills | -0.30 | (0.62) | | -1170 | (389) | *** |
| 314 | 217 | -28% | 0.77% | Textile Product Mills | 0.24 | (0.17) | | -1099 | (347) | *** |
| 315 | 671 | -68% | 0.54% | Apparel | 0.30 | (0.32) | | 344 | (555) | |
| 316 | 79 | -53% | 0.66% | Leather & Allied Product | -0.13 | (0.29) | | -1253 | (432) | *** |
| 321 | 580 | -1% | 1.35% | Wood Product | -0.72 | (0.27) | *** | -1222 | (367) | *** |
| 322 | 568 | -22% | 3.34% | Paper | -0.60 | (0.26) | ** | -908 | (340) | *** |
| 323 | 845 | -24% | 0.99% | Printing & Related Activities | 0.28 | (0.11) | ** | -113 | (138) | |
| 324 | 111 | -7% | 0.78% | Petroleum & Coal Products | -0.75 | (0.25) | *** | -1239 | (423) | *** |
| 325 | 901 | -11% | 3.49% | Chemical | 0.05 | (0.22) | | 59 | (370) | |
| 326 | 1030 | -13% | 1.82% | Plastics & Rubber Products | -0.26 | (0.16) | | -290 | (236) | |
| 327 | 508 | -5% | 2.20% | Nonmetallic Mineral Product | -0.42 | (0.18) | ** | -903 | (321) | *** |
| 331 | 615 | -27% | 3.40% | Primary Metal | -1.26 | (0.26) | *** | -1258 | (364) | *** |
| 332 | 1,816 | -14% | 1.42% | Fabricated Metal Product | -0.23 | (0.15) | | 1069 | (659) | |
| 333 | 1,444 | -22% | 0.47% | Machinery | -0.36 | (0.19) | * | -251 | (296) | |
| 334 | 1,681 | -37% | 0.27% | Computer & Electronic Product | 0.75 | (0.30) | ** | 2573 | (1048) | ** |
| 335 | 602 | -30% | 0.66% | Electrical Equipment, Appliance | 0.09 | (0.24) | | -746 | (286) | *** |
| 336 | 1,911 | -15% | 0.21% | Transportation Equipment | -0.95 | (0.29) | *** | -274 | (674) | |
| 337 | 604 | -10% | 0.70% | Furniture & Related Product | -0.16 | (0.15) | | -692 | (168) | *** |
| 339 | 737 | -7% | 0.49% | Miscellaneous | 0.78 | (0.12) | *** | 578 | (216) | *** |
| | | | | *Other Industries* | | | | | | |
| 238 | 8,926 | 26% | 1.28% | Specialty Trade Contractors | 0.09 | (0.07) | | -1176 | (625) | * |
| 441 | 1,757 | 11% | 1.28% | Motor Vehicle & Parts Dealers | -0.12 | (0.06) | ** | -1097 | (363) | *** |
| 445 | 2,944 | -1% | 1.28% | Food & Beverage Stores | 0.02 | (0.06) | | -1243 | (466) | *** |
| 452 | 4,263 | -34% | 1.28% | General Merchandise Stores | 0.01 | (0.10) | | -673 | (366) | * |
| 522 | 2,688 | 22% | 0.10% | Credit Intermediation & Related | -0.21 | (0.06) | *** | -717 | (424) | * |
| 524 | 2,312 | 3% | 0.11% | Insurance Carriers & Related | -0.20 | (0.15) | | -388 | (472) | |
| 541 | 6,052 | 33% | 0.19% | Professional, Scientific & Techn. | -0.25 | (0.13) | * | -5113 | (2226) | ** |
| 551 | 2,704 | 8% | 0.63% | Management of Companies | -0.26 | (0.15) | * | -2048 | (640) | *** |
| 561 | 8,366 | 27% | 0.28% | Administrative & Support | -0.11 | (0.14) | | -4344 | (1490) | *** |
| 611 | 2,324 | 28% | 2.18% | Educational Services | 0.12 | (0.13) | | -82 | (654) | |
| 621 | 4,482 | 27% | 0.35% | Ambulatory Health Care | 0.03 | (0.05) | | -264 | (573) | |
| 622 | 5,011 | 7% | 1.13% | Hospitals | -0.08 | (0.08) | | 33 | (550) | |
| 623 | 2,511 | 19% | 1.38% | Nursing & Residential Care | 0.12 | (0.07) | * | -36 | (274) | |
| 722 | 7,758 | 22% | 1.96% | Food Services & Drinking Places | -0.04 | (0.04) | | -3699 | (1429) | *** |
| 813 | 2,488 | 12% | 0.20% | Religious, Grantmaking, Civic | -0.05 | (0.04) | | -44 | (210) | |

* Notes: For manufacturing industries, we modify equation (1) so each industry has a separate price coefficient. For non-manufacturing industries, we estimate equation (1) separately for each industry. See Table 3's notes for further details.

**Table 5**: Employment Regression Results to Test for Robustness

| | No Border Pairs (County FE) | | No Border Pairs (State FE) | | Full Sample | | County Trends | | PM Regulation | | CO Regulation | | IV | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | | 2 | | 3 | | 4 | | 5 | | 6 | | 7 | |
| ln Electricity Price | 598.3 | *** | -179.0 | | 136.2 | * | -88.0 | | -214.6 | | -344.4 | | -9392.0 | *** |
| | (222.0) | | (410.2) | | (71.1) | | (205.2) | | (225.2) | | (214.8) | | (626.3) | |
| ln Price * Electricity Index | -1604.5 | *** | -1590.9 | *** | -720.1 | *** | -1652.8 | *** | -1533.5 | *** | -1280.1 | *** | -2473.3 | *** |
| | (602.4) | | (599.4) | | (263.3) | | (616.7) | | (410.9) | | (390.1) | | (95.3) | |
| Right to Work * Labor/Capital | 8858.8 | *** | 8880.1 | *** | 3951.3 | *** | 9150.8 | *** | 7320.5 | | 8740.3 | * | 9482.4 | *** |
| | (2959.2) | | (2945.5) | | (1054.9) | | (3009.9) | | (4518.4) | | (4637.1) | | (558.3) | |
| Nonattainment County | 95.4 | ** | 99.8 | * | 83.4 | *** | -44.1 | | 331.8 | | 347.4 | ** | -115.5 | *** |
| | (40.7) | | (58.7) | | (22.9) | | (34.3) | | (293.5) | | (172.2) | | (19.0) | |
| NonA * HighPoll | -173.0 | *** | -173.1 | *** | -201.2 | *** | -162.9 | *** | -644.0 | | -664.8 | | -130.9 | *** |
| | (49.6) | | (49.8) | | (41.4) | | (49.2) | | (559.5) | | (566.8) | | (21.1) | |
| No Pollution Monitor | -95.9 | *** | -63.6 | | -41.8 | ** | -15.4 | | -27.5 | | 39.3 | | -170.8 | *** |
| | (26.4) | | (51.9) | | (16.4) | | (41.0) | | (66.5) | | (177.8) | | (17.6) | |
| NoMon * HighPoll | 173.6 | *** | 173.0 | *** | 120.8 | *** | 175.8 | *** | 284.7 | *** | 686.4 | *** | 165.7 | *** |
| | (47.7) | | (47.4) | | (25.4) | | (47.7) | | (60.1) | | (85.8) | | (21.1) | |
| County Pair F.E. | | | | | Y | | Y | | Y | | Y | | Y | |
| Industry-Year F.E. | Y | | Y | | Y | | Y | | Y | | Y | | Y | |
| State-Year F.E. | Y | | Y | | Y | | Y | | Y | | Y | | Y | |
| County F.E. | Y | | | | | | | | | | | | | |
| $R^2$ | 0.37 | | 0.32 | | 0.35 | | 0.36 | | 0.33 | | 0.33 | | . | |
| n | 128,197 | | 128,197 | | 3,178,634 | | 789,267 | | 842,390 | | 835,415 | | 570,359 | |

*Notes*: Column (4) includes linear time trends for the county variables (population in 1970, miles to CBD, area of county, 1990 housing values). See Table 3's notes for further details.

**Table 6**: Effect of Local Energy Prices and Regulation on Manufacturing Establishments

| | Employees | | Establishments | | Log Establishment | | Workers per Establishment | | Log (Workers per Establishment) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | | 2 | | 3 | | 4 | | 5 | |
| ln Electricity Price | 62.5 | | 5.1 | * | 0.13 | ** | 7.9 | ** | 0.07 | |
| | (204.6) | | (2.8) | | (0.06) | | (3.7) | | (0.06) | |
| ln Price * Electricity Index | -1656.0 | *** | -50.7 | *** | -0.73 | *** | -42.0 | *** | -0.59 | *** |
| | (617.3) | | (17.5) | | (0.20) | | (13.2) | | (0.13) | |
| Right to Work* Labor/Capital | 9154.4 | *** | -48.4 | | 7.43 | *** | -46.2 | | 2.65 | |
| | (3007.6) | | (95.2) | | (1.95) | | (130.0) | | (1.87) | |
| PM Nonattainment County | -2.0 | | -0.8 | | 0.00 | | -3.9 | ** | -0.01 | |
| | (29.6) | | (0.8) | | (0.02) | | (1.7) | | (0.02) | |
| High PM * Nonattain County | -163.3 | *** | -5.1 | *** | -0.02 | | -1.6 | | 0.03 | |
| | (49.0) | | (1.1) | | (0.04) | | (4.4) | | (0.05) | |
| No PM Monitor | -50.0 | | -0.9 | | -0.01 | | 5.1 | *** | 0.03 | |
| | (42.0) | | (0.9) | | (0.02) | | (1.5) | | (0.02) | |
| High PM * No Monitor | 175.6 | *** | 5.0 | *** | 0.04 | | -11.4 | *** | -0.07 | |
| | (47.7) | | (1.5) | | (0.03) | | (4.0) | | (0.04) | |
| $R^2$ | 0.36 | | 0.43 | | 0.77 | | 0.14 | | 0.27 | |
| n | 789,267 | | 786,975 | | 667,185 | | 669,376 | | 669,376 | |

*Notes*: See Table 3's notes for further details.

**Table 7:** Simulation of Carbon Policy

**Panel A**: Regional Electricity Markets Average and Marginal Carbon Dioxide Emissions per MWh from 1997 to 2000.

| NERC | Average | Marginal | s.e. | |
|---|---|---|---|---|
| ECAR | 1.038 | 0.879 | (0.019) | *** |
| MAIN | 0.754 | 0.794 | (0.014) | *** |
| MAPP | 1.150 | 0.791 | (0.028) | *** |
| NPCC | 0.472 | 0.706 | (0.018) | *** |
| SPP | 0.889 | 0.670 | (0.026) | *** |
| SERC | 0.759 | 0.613 | (0.019) | *** |
| FRCC | 0.559 | 0.598 | (0.022) | *** |
| MAAC | 0.516 | 0.580 | (0.025) | *** |
| ERCOT | 0.693 | 0.576 | (0.010) | *** |
| WSCC | 0.351 | 0.234 | (0.014) | *** |

**Panel B:** Simulation of Carbon Policy ($15/ton of $CO_2$) by State

| State | Change in Employment | Percent Change | Average Electricity Index | Change in Electricity Price |
|---|---|---|---|---|
| Ohio | -27,736 | -4.8% | 26.9% | $0.013 |
| Pennsylvania | -25,218 | -4.7% | 28.4% | $0.010 |
| Texas | -20,471 | -2.8% | 22.3% | $0.009 |
| Indiana | -18,933 | -5.4% | 27.4% | $0.013 |
| North Carolina | -18,399 | -5.4% | 25.4% | $0.009 |
| Michigan | -16,653 | -3.4% | 21.6% | $0.013 |
| Wisconsin | -15,759 | -4.7% | 27.4% | $0.012 |
| New York | -15,146 | -3.1% | 22.4% | $0.011 |
| Georgia | -14,930 | -6.5% | 28.0% | $0.009 |
| Illinois | -14,466 | -2.6% | 26.1% | $0.012 |
| Tennessee | -13,309 | -5.8% | 26.2% | $0.010 |
| Alabama | -12,445 | -7.2% | 28.5% | $0.009 |
| New Jersey | -11,495 | -3.9% | 27.8% | $0.009 |

| | | | | |
|---|---|---|---|---|
| Missouri | -10,928 | -5.5% | 22.8% | $0.011 |
| South Carolina | -10,508 | -6.4% | 30.7% | $0.009 |
| Florida | -10,441 | -3.4% | 21.4% | $0.009 |
| Virginia | -10,396 | -6.5% | 25.7% | $0.010 |
| Minnesota | -8,498 | -3.8% | 20.8% | $0.012 |
| California | -6,648 | -0.5% | 19.5% | $0.004 |
| Kentucky | -6,642 | -5.0% | 25.2% | $0.013 |
| Maryland | -6,612 | -5.6% | 24.1% | $0.011 |
| Louisiana | -6,522 | -6.4% | 26.1% | $0.009 |

continued on next page.

**Table 7, Panel B:** Continued

| State | Change in Employment | Percent Change | Average Electricity Index | Change in Electricity Price |
|---|---|---|---|---|
| Arkansas | -5,055 | -5.9% | 26.4% | $0.009 |
| Massachusetts | -5,053 | -1.9% | 22.3% | $0.011 |
| Iowa | -4,482 | -4.9% | 23.6% | $0.012 |
| Kansas | -3,916 | -3.9% | 19.0% | $0.010 |
| Connecticut | -3,874 | -2.2% | 19.7% | $0.011 |
| Washington | -3,857 | -1.8% | 20.5% | $0.004 |
| Oklahoma | -3,613 | -3.8% | 24.3% | $0.010 |
| Colorado | -3,496 | -2.9% | 20.4% | $0.004 |
| Mississippi | -3,224 | -7.7% | 22.7% | $0.009 |
| Oregon | -3,177 | -2.3% | 21.6% | $0.004 |
| Utah | -2,353 | -2.6% | 21.2% | $0.004 |
| Nebraska | -2,159 | -4.4% | 22.1% | $0.012 |
| Rhode Island | -1,694 | -3.3% | 24.4% | $0.011 |
| Arizona | -1,503 | -0.9% | 19.3% | $0.004 |
| New Hampshire | -1,400 | -2.9% | 19.8% | $0.011 |
| South Dakota | -917 | -5.8% | 19.9% | $0.008 |

| | | | | |
|---|---|---|---|---|
| Vermont | -710 | -4.7% | 12.3% | $0.011 |
| West Virginia | -684 | -2.4% | 38.6% | $0.013 |
| New Mexico | -654 | -3.1% | 19.3% | $0.004 |
| Montana | -632 | -8.3% | 30.6% | $0.004 |
| Nevada | -584 | -1.5% | 25.7% | $0.004 |
| Idaho | -518 | -2.4% | 10.1% | $0.004 |
| Delaware | -514 | -2.9% | 26.3% | $0.009 |
| Maine | -462 | -2.1% | 28.4% | $0.009 |
| Wyoming | -454 | -10.6% | 23.7% | $0.004 |
| North Dakota | -251 | -1.8% | 20.1% | $0.012 |
| District of Columbia | 0 | 0.0% | 19.4% | $0.009 |

**Table A1:** Checks of Covariates Across Policies

| | Electricity | Prices | | |
|---|---|---|---|---|
| Variable | Low | High | T-Stat | |
| Log Pop in 1970 | 11.73 | 12.02 | 2.66 | *** |
| Log Pop in 1995 | 12.10 | 12.38 | 2.94 | *** |
| Log Miles to CBD | 2.51 | 2.48 | -0.58 | |
| Log County Area | 6.11 | 6.13 | 0.23 | |
| Log House Values 90 | 11.77 | 11.80 | 0.81 | |

| | Right to | Work | | |
|---|---|---|---|---|
| Variable | No | Yes | T-Stat | |
| Log Pop in 1970 | 12.23 | 11.17 | -8.43 | *** |
| Log Pop in 1995 | 12.49 | 11.73 | -6.62 | *** |
| Log Miles to CBD | 2.41 | 2.68 | 4.35 | *** |
| Log County Area | 6.12 | 6.21 | 0.99 | |
| Log House Values 90 | 11.90 | 11.53 | -8.48 | *** |

| | PM | Monitor | | |
|---|---|---|---|---|
| Variable | Present | Missing | T-Stat | |
| Log Pop in 1970 | 12.59 | 11.05 | -12.49 | *** |
| Log Pop in 1995 | 12.84 | 11.54 | -11.82 | *** |
| Log Miles to CBD | 2.22 | 2.82 | 10.65 | *** |
| Log County Area | 6.15 | 6.08 | -0.69 | |
| Log House Values 90 | 11.90 | 11.66 | -4.6 | *** |

| | PM | Status | | |
|---|---|---|---|---|
| Variable | Attainment | Nonattainment | T-Stat | |
| Log Pop in 1970 | 11.79 | 12.99 | 4.54 | *** |
| Log Pop in 1995 | 12.15 | 13.41 | 5.69 | *** |
| Log Miles to CBD | 2.52 | 2.19 | -2.23 | ** |
| Log County Area | 6.08 | 6.67 | 1.37 | |
| Log House Values 90 | 11.77 | 12.02 | 1.72 | * |