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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 regression discontinuity approach to examine whether the basic logic of comparative advantage can explain the geographical clustering of U.S. manufacturing. Using a unified empirical framework, 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 jobs impacts of regional carbon mitigation efforts.

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1. Introduction

Over the last 50 years, manufacturing has migrated away from the U.S. Northeast and Midwest to the South and West and overseas (Crandall 1993). Between 1969 and 2000, Ohio's total manufacturing employment fell by 380,000 and Pennsylvania lost over 650,000 manufacturing jobs. Other states such as Nevada have experienced manufacturing job growth over time. Between 1997 and 2007, U.S. total manufacturing declined by 16% while Nevada's manufacturing employment grew by 28%.[1]

Manufacturing firms face several tradeoffs in choosing where to locate. 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. Some manufacturing firms will seek out areas where other firms in their own industry have already clustered to take advantage of agglomeration effects related to labor pooling and local learning (Dumais, Ellison and Glaeser 2002, Rosenthal and Strange 2004).

Different manufacturing industries will have different rankings of the desirability of the same set of geographical areas. This paper studies the locational choice of heterogeneous manufacturing industries as they sort across diverse counties. We model each of these counties as embodying three key bundled attributes; its average industrial electricity price, its state's labor regulation, and the county's Clean Air Act regulatory status.

[1] http://www.ppinys.org/reports/jtf/manufacturingemployment.html

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 labor-to-capital ratio, its energy consumption per unit of output, and its pollution intensity. Firms in these industries choose whether to locate in a United States county and conditional on locating there, how many workers to employ.

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. Labor-intensive manufacturing should avoid pro-union counties. Energy-intensive industries should avoid high electricity price counties.[2] 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.

Our econometric approach employs a regression discontinuity strategy similar to Holmes (1998). We compare employment counts by manufacturing industry in adjacent counties. Adjacent counties share many common factors such as amenities and a common local labor market and similar access to final consumers but two adjacent counties can differ along key dimensions such as energy prices and exposure to government labor and environmental policy. We exploit this within county-pair variation in energy prices and labor and environmental regulation to provide new estimates of their effects on the locational pattern of manufacturing.

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[2] 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.

Our study unifies three independent research lines investigating the geography of manufacturing employment activity. Carlton (1983) examined how location specific factors such as average metropolitan area wages and energy prices influenced firms' locational choices. He studied where fabricated plastic products, communication transmitting equipment and electronic component factories located. He found that each of these industries were less likely to locate in metropolitan areas with higher electricity prices. Deschenes (2010) uses a state level panel data approach and fails to reject the hypothesis that there is no correlation between changes in state manufacturing employment and changes in state electricity prices. For other broad industries such as agriculture, he finds evidence of a negative correlation.

A second literature has examined the unintended consequences of labor and environmental regulation in determining county manufacturing patterns. Such regulation is not uniformly imposed across the nation. Some states have Right-to-Work laws while others do not. Holmes (1998) uses a county border pair comparison design to document that manufacturing growth is taking place on the Right-to-Work (anti-union) side of the state border. In a similar spirit, an environmental literature has exploited cross-sectional and time series variation in the Clean Air Act's regulatory intensity to test for whether high polluting industries seek out domestic pollution havens (counties not facing stringent Clean Air Act regulation). Becker and Henderson (1997), Kahn (1997) and Greenstone (2002) exploit temporal and spatial variation in Clean Air Act regulatory enforcement to document that environmental regulation deflects footloose, dirty manufacturing to less regulated areas.[3] Holmes' study covers the years 1953 to 1987 and Greenstone's from 1967 to 1987. One payoff of our integrated approach which we use

[3] Berman and Bui (2001a, 2001b) reject the hypothesis that stringent California regulation of oil refining led to local job destruction. They use trends in oil refining employment in less regulated Texas as a control group.

to study manufacturing over the years 1998 to 2006 is to test whether both of the forces that they document are still at work in the more recent period.

A third empirical literature has sought to understand why certain industries agglomerate close together (Dumais, Ellison and Glaeser 2002, Rosenthal and Strange 2003, 2004). Labor pooling and knowledge spillovers are important agglomeration sources. This literature yields insights into predicting which industries will cluster together but does not offer precise predictions over where these clusters will take place. Historical circumstances offer one possible initial condition (Krugman 1991). A location's input prices and regulatory stringency offer an alternative pathway for explaining where manufacturing clusters form. If there are significant agglomeration economies for such industries then self re-enforcing clusters will arise in counties offering an economic environment that allows specific industries to economize on expenditure for inputs that they use intensively.

By generating new estimates of the role of electricity prices on the locational choice of 21 U.S. manufacturing industries, we take a new look at the likely consequences of regional and state level efforts (such as California's AB32) to reduce greenhouse gas emissions.[4] In the summer of 2010 the Senate decided to table legislation that would have introduced a carbon cap and trade bill for electric utilities. Opponents of the bill argued that it would be a jobs killer for coal states, as electricity prices would rise in such states (due to tax pass through). They argued that this electricity price increase would deflect manufacturing jobs to states with cheaper electricity. We use our estimates to judge the merits of this claim by simulating the job loss for states and regions that unilaterally enact carbon regulation.

[4] See http://www.arb.ca.gov/cc/ab32/ab32.htm.

2. Empirical Framework

We will compare manufacturing activity in adjacent counties. In most of the econometric results we present below, we will limit our study to counties that lie within metropolitan areas. More than 75% of the nation's jobs are located in the 781 counties that lie within a metropolitan area. Given that our main econometric strategy relies on contrasting border-pairs of counties, we would ideally like these counties to be "twins". Our rationale for mainly focusing on metropolitan area counties is to avoid comparing manufacturing job counts in adjacent rural counties or in two counties for which one is located within a metropolitan area and its adjacent neighbor is not. We recognize that some might view this sample restriction as arbitrary and so we will also report results that use the full sample of all U.S. counties.

Our empirical work's unit of analysis will be a county/industry/year. We will study the spatial sorting patterns and the employment decisions of 21 manufacturing industries using the U.S. County Business Patterns data over the years 1998 to 2006.[5] Throughout this paper, we assume that each of these industries differ with respect to their production process (and hence in their response to electricity prices and regulation) but any two firms within the same industry have the same production function.[6]

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[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.

[6] If there is within industry plant level heterogeneity, then there would be two types of selection effects. Individual plants would simultaneously choose where to locate (the first selection effect), and then would make choices over what technology to adopt as a function of local input prices. In high energy price areas, such firms would be more likely to invest in energy efficient capital. This choice's impact on employment would hinge on whether workers and capital are complements or substitutes.

Each firm simultaneously chooses which county to locate in, how much output to produce, and its input choice. The firms choose their optimal location with full knowledge of their underlying production technology. In contrast, the econometrician does not know whether, for a specific industry, energy and labor are complements or substitutes. If they are substitutes, then industries located in high energy price counties may hire more workers. A county's input prices and regulatory structure induce both a selection effect (whether the firm locates there) and a treatment effect (how the representative firm within each industry responds to the local input prices). Our empirical work seeks to measure this combined effect. We will also study industry entry decisions (the selection effect) as a function of a geographical location's regulatory policies and its electricity prices.

For every county in a metropolitan area, we identify pairs of counties that are adjacent. A given county such as Cook County in Illinois can touch several counties and thus will be a member of several border pairs. Below, we will discuss our weighting scheme.

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*.

$$emp_{ijkt} = \beta_1 P_{ut}^{elec} + \beta_2 P_{ut}^{elec} Index_{kt} + \beta_3 Right_s LK_{kt} + \boldsymbol{\delta Z}_i + \alpha_j + \gamma_{kt} + \pi_s + \varepsilon_{ijkt}, \qquad (1)$$

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. The third term represents an interaction term between whether state *s* is a Right-to-Work state and the industry's labor-to-capital ratio. In the regressions, the electricity-intensity index is normalized to range from 0 to 1 for ease in interpreting the results. In equation (1), **Z** is a vector of a county's population in 1970, its distance to the nearest metropolitan area's Central Business District (CBD), the county's land area, and the log of the 1990 housing values.[7] In the core specifications we control for a county-pair fixed effect, industry-year fixed effects and state 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. Given widespread car ownership, adjacent counties represent an integrated local labor market in which workers can access many possible job opportunities. 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.[8] The state fixed effects control for any time invariant state policy that affects a firm's propensity to locate within a state.[9] For example, some states have low taxes such as Missouri while others such as California do not.

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[7] We recognize that adjacent counties are unlikely to be perfect "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.

[8] 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).

[9] Below, we will report results with and without state fixed effects.

We use several different dependent variables. We begin by examining the number of manufacturing employees. We will also present results that simply focus on industry *k* in county *i* in year *t*'s percent of total county employment. In another specification, we will report results for log(employment) which is estimated only for county/industry/year observations for who there is positive employment count. As we discuss below, roughly 50% of our observations at the county/industry/year level equal zero. We also examine log(1+employment) as the dependent variable. This dependent variable allows us to capture the total effect of entry, exit and plant growth and shrinkage. Finally, we will also present results in which dependent variable equals one if there is any employment in a given county in a given industry/year.

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 very highly serially correlated over time and so is labor and environmental regulation. Thus, these three factors embody long run natural advantages of a specific location.

Within each local labor markets, we will study where the 21 different manufacturing industries clusters. 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.[10]

[10] Arzaghi and Henderson (2008) argue that for advertising that the agglomeration benefits (as measured by average productivity) are a function of highly localized agglomeration (the count of firms within one mile of a specific firm). Rosenthal and Strange (2003) find that for firms in the computer software, apparel, food processing, printing and publishing, machinery, and fabricated metals industries that firms are agglomerating within the same zip code.

The 21 industries differ with respect to their energy intensity, labor-to-capital ratio and their pollution intensity. These three dimensions of industry heterogeneity are often bundled together. Copeland and Taylor (2004) argue that pollution-intensive industries tend to be capital intensive. This suggests that there will be a negative correlation between labor intensity and pollution intensity. Industry pollution intensity is likely to be correlated with an industry's energy intensity. Our econometric framework presented in equation (1) explicitly acknowledges this through adopting a multivariate regression framework. Our data source is the NBER Productivity Data Base from 1997 to 2005.[11]

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

The 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. We can only test for the role of factors that vary within the border pair. We first explain why there is variation in each of our key explanatory variables within a border pair and then we discuss our econometric strategy.

[11] http://www.nber.org/data/nbprod2005.html

3. Three Margins Affecting Locational Choice

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.[12]

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 9 cents a kWh. For firms in electricity intensive industries, this differential represents about 7% of revenue. This fact highlights that there are significant cost savings for a subset of industries for choosing to locate in the lower electricity price county within a pair.

[12] 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.

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.[13] 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. 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. Below, we will discuss how we attempt to address this issue. We recognize that 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.

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

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

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. Two examples of such a "hybrid" metropolitan areas are Kansas City, Missouri and Washington DC. Below, we will also report results in which we use all U.S. counties.

3.3. Environmental Regulation

The Clean Air Act assigns counties to low regulation (Attainment Status) and high regulation (Non-Attainment 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 non-attainment and vice-versa). In 1998, there were from 80 non-attainment counties while, in 2006, 51 remained.[14]

We take our 21 industries and, based on Greenstone's (2002) Table A2, we assign four industries (wood products, paper, nonmetallic minerals, and primary metals) to "High particulate matter polluters." We hypothesize that these industries should be the most responsive to avoiding

[14] In an earlier draft of this paper , we estimated the same regressions we will present below but we measured local environmental regulation intensity using a county's carbon monoxide non-attainment status. We find qualitatively similar results. The reason we dropped the carbon monoxide investigation is because in recent years only a small set of counties (10) are still in non-attainment status. Recent progress in reducing ambient carbon monoxide has led to the reclassification of many counties from "non-attainment" to "attainment" status.

the non-attainment sides of the county border pair and in locating in that county within the county border pair that does not monitor ambient particulate matter.[15] The data indicating a county's Clean Air Act regulatory status are from the EPA's Greenbook.[16] Our county/year ambient air pollution data are from the U.S. EPA AIRS data base.

4. Econometric Details

We estimate equation (1) using OLS and two stage least squares. We recognize that there are cases in which the 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. For these reasons, we instrument using average electricity prices for commercial customers in that county-year. In the footnotes of the tables below, we will report the F-statistic for the instruments. We do not instrument for labor regulation or environmental regulation. Recall that the labor regulation varies by state not by county. Thus, under the assumption that each county is "small" within a state, it will take the state's regulation as given. In the case of environmental regulation, we will present results where we control for a polynomial of the county's ambient air pollution. We recognize the possibility that counties with more pollution have more industrial activity and are thus more likely to be in non-attainment. By

[15] 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.

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

including this potentially omitted continuous variable (ambient pollution), we are exploiting a regression discontinuity design to test for the discrete effect of the regulation.

Note that because each county-industry-year observation enters multiple times (since a county can be adjacent to several counties), we need to cluster at this, or a more aggregate, level. The error term in equation (1) is clustered by utility and year, which is the level we observe electricity prices. We weight our regressions by the inverse of the number of times a county-industry-year observation enters the sample so as to avoid having counties with more neighbors be weighted more so than others.

In addition to estimating OLS and IV estimates of equation (1), we also report estimates of a long differenced version of equation (1). This specification implicitly allows for county fixed effects and estimates the impact of electricity prices using within county variation:

$$\frac{\Delta emp_{ijk}}{\overline{emp}_{ijk}} = \beta_1 \Delta P_u^{elec} + \beta_2 \Delta P_u^{elec} Index_k + \alpha_j + \gamma_k + \pi_s + \varepsilon_{ijk}, \tag{2}$$

where $\overline{emp}_{ijk}$ is the average employment in 1998 and 2006. Using a plant level panel data set, this is Greenstone's (2002) dependent variable. Such variation is generated because of changes in fuel prices (either via rate hearings or retail competition) or rate freezes implemented with the start of restructuring. We predict that any employment change responses to such electricity price changes should be smaller than long run effects.

Finally, we estimate a model that does not use a regression discontinuity framework. In equation (3), the unit of analysis is by county *i*, industry *k*, and year *t*. We estimate equation (3) with industry-year fixed effects and either county (as shown here) or state fixed effects.

$$emp_{ikt} = \beta_1 P_{ut}^{elec} + \beta_2 P_{ut}^{elec} Index_{kt} + \beta_3 Right_s LK_{kt} + \alpha_i + \gamma_{kt} + \varepsilon_{ikt}. \tag{3}$$

5. 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 642 jobs but the median is 0 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% of U.S. counties. Of this sample, 49% 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-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 fixed 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 regulation in determining manufacturing clusters.[17] 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 .15. For 11 industries (those with low electricity indices), we find a positive correlation between electricity prices and manufacturing activity.[18] We find the largest negative effects of electricity prices on primary metals employment. For this industry, we estimate a price elasticity of -3.3.[19]

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 (Apparel), the coefficients imply 308 more jobs on the right-to-work side of the boarder, relative to an extremely capital-intensive industry like petroleum. It is relevant to contrast this finding with Holmes' (1998) work. He interpreted the Right-to-Work status of a state as indicating the state's general "pro-business" viewpoint. 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

[17] 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.

[18] 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.

[19] 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: (237+(-1551)*1)/398=-3.3.

effect within manufacturing. The other covariates in the regression indicate that there are more manufacturing jobs in counties with larger year 1970 population levels and in counties with more land area. Counties further from the city center have more manufacturing jobs, though this is significant only in Columns (2), (3), and (4).[20]

The results in column (2) 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). For the primary metals industry, we find that a 10% increase in electricity prices is associated with a 2.5 percentage point reduction in the share of workers in the county who works in this industry. Columns (3) and (4) model log(manufacturing) and log(1+manufacturing). The results imply an electricity price elasticity for the most electricity-intensive industry of approximately -.85 and -.64, respectively. In column (5), we focus on the extensive margin using a dummy dependent variable that equals one if the county has any employment in a given industry/year. Our results indicate that a 10% increase in electricity prices is associated with a .5 percentage point reduction in the probability that a county has a primary metals plant opening. For labor-intensive industries, such births are more likely on the Right-to-Work side of the border.[21]

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[20] Recall that all of the counties in this regression are located within metropolitan areas. Given the cost per square foot of center city land, it is intuitive that land-intensive manufacturing activity will take place where land is relatively cheap within a metropolitan area. After all, manufacturing cannot be sited in a skyscraper.

[21] 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.

We recognize that our estimates of equation (1) are subject to 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 first differencing removes these effects. In column (6) of Table 3, we report estimates of equation (2). This long differenced regression is of the change from 1998 to 2006 in county/industry employment divided by the average employment in those years.[22] Since the set of states that are Right-to-Work states does not change over time, we lose the ability to estimate this effect. By including county fixed effects, we exploit 1998 to 2006 variation in county average electricity prices. Intuitively, we are comparing pairs of counties where one county has experienced a larger percent change over time in the price of electricity than its adjacent "twin." We view this within county estimate as capturing the short run effects of energy price changes and we find that for primary metals an elasticity of -.34 which is about half the magnitude of the "long run" elasticities reported in columns (3) and (4). For industries whose normalized energy intensity is less than .85, we cannot reject the hypothesis that there is no relationship between changes in electricity prices and changes in county employment at the 10 percent level. As shown in Table 2, all industries but Paper and Primary Metals fall into this category.

In the results in Table 3, we simultaneously study the role of labor regulation and electricity prices. In results available on request, we have also estimated the regressions and studied the role of each of these agglomeration factors on their own. The results indicate that both the absolute magnitude of the electricity price effects and the labor regulation effects are smaller when we study them separately versus jointly (the coefficients are about 80% of the size

[22] Greenstone (2002) uses this functional form in studying manufacturing firms. For his sample, he finds that this functional form implies similar elasticities as logs for firms that exist throughout. However, this functional form allows him, and us, to study births and deaths.

as compared to the main results). These results highlight the importance of simultaneously studying all of the agglomeration forces within a unified framework.

We recognize that in estimating equation (1) in the pooled specification that we have restricted the county pair fixed effects to be the same for each of the 21 three-digit NAICS industries. In reality, different industries are likely to have different rankings of the desirability of different county pair locations. Such industries will differ with regards to where their final consumers are and which geographical areas offer the greatest spillover opportunities. In Table 4, we stratify our estimates of equation (1) and estimate separate regressions by industry using three functional forms for employment (N): N, percent total employment, and ln(N). For some energy-intensive industries such as primary metals we find a large negative elasticity ranging from -.94 to -2.65, depending on functional form, while less energy-intensive industries such as printing manufacturing we find a zero price elasticity. The industries that have a large energy-intensity index and for which we find a relatively large price elasticity (the coefficient on ln(N) is greater in magnitude than .5) include: Primary Metals, Petroleum, Textile Mills, and Wood Products. Other electricity-intensive industries include Paper, Nonmetallic Minerals, Chemicals, and Plastics which were not as sensitive to electricity prices. To our surprise, we estimate some large negative price elasticities for Transportation Equipment, which is not electricity intensive. As shown in Table 4, these industry-stratified results are robust for over half of industries if we use employment, the percent of total employees, or the log of employment as the dependent variable. However, for some industries, we do find that the functional form of employment implies different signs that are significantly different from zero.[23]

[23] These industries are NAICS 312, 314, 316, 322, 332, and 335.

We now turn to studying how county-level environmental regulatory severity affects the location of manufacturing clusters. Table 5 explores this for manufacturing employment counts while Appendix Tables A1 and A2 show the results for percent total employment and log manufacturing employment, respectively. We report estimates of equation (1) with measures related to particulate matter (PM) regulation and a cubic of ambient pollution levels.[24] As shown in the first column of Table 5, controlling for ambient PM and environmental regulation has very little effect on the electricity price or labor regulation findings.

Holding county electricity prices and labor regulation constant, we test whether high PM emitting industries respond to county PM regulation status. As shown in Table 5's column (1), we find that counties assigned to non-attainment status have 276 more workers in relatively clean industries, but 426 fewer workers than an adjacent county twin who is in attainment status for the four industries that have high PM emissions. In adjacent counties where particulate matter is not monitored in one county but is monitored in the other, there are 250 more dirty jobs in the county where particulate matter is not monitored. This is consistent with Kahn's (1997) finding that there has been greater manufacturing growth in counties not monitoring air pollution.

From Table 5, we can compare the relative sensitivities of a given industry to energy prices, labor policy, and environmental policies. For an industry like primary metals—which is energy intensive, capital intensive, and a high PM polluter—banning Right-to-Work laws would have the same effect on employment as a 3.8 percent increase in electricity prices. In contrast, if

[24] Counties are more likely to be assigned to non-attainment 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 cubic of the county's ambient carbon monoxide level.

a primary metal manufacturer's county falls into non-attainment with environmental regulations, this is akin to increasing electricity prices by 34 percent. For other industries that are less energy intensive but still polluting, like wood products, labor and environmental regulations are much more costly: these policies would reduce employment to the same degree as increasing electricity prices 118 and 256 percent, respectively. Other industries that are not energy or pollution intensive are not negatively affected by either higher energy prices or pollution regulation.

The take away theme here is one of comparative advantage. The most energy-intensive industries respond to electricity prices and the most labor-intensive industries respond to labor regulation and the most pollution-intensive industries respond to environmental regulatory differentials.

Up until this point, we focused on results based on counties located in metropolitan areas. In the column (2) 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 shrinks by roughly 50%.

We recognize that our county-pair regression discontinuity estimation strategy is a non-standard approach. In columns (3) and (4) in Table 5, we re-estimate equation (1) but we drop the county-pair RD framework. Note the number of observations declines. In this case, we only have one observation per county/industry/year. In column (4), we estimate equation (3) using county fixed effects and in column (4) we estimate equation (3) controlling for state fixed effects. Perhaps surprisingly, these fixed effects results are almost identical to the RD results presented in column (1). This similarity in coefficient estimates suggests that the effects across a relatively short time period within a county are similar to differences across county pairs.

Furthermore, the similarity between columns (3) and (4) suggests that within state differences in counties are uncorrelated with our variables of interest.[25]

We now present results similar to Table 3 in which we estimate equation (1) using two stage least squares. The two stage least squares results are reported in Table 6. The first stage of TSLS highlights that commercial electricity prices are unit elastic and are strong instruments (F-stat of 165). As shown in columns (1) through (5), we find similar qualitative results as for OLS but the elasticities are slightly smaller.

6. 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. Fear of job loss in coal states facing a carbon price helped to kill the bill. Opponents of carbon regulation argued that an unintended consequence of carbon mitigation regulation would be significant "leakage" of industrial activity to nearby states that will be less affected by cap and trade legislation.[26] For such "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.

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[25] In results that are available on request, we have conducted a variety of robustness tests. The results we report in Table 3's column (1) are robust to controlling for local labor market demand.

[26] 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.

Our estimates are useful for judging the validity of this concern. First, we estimate 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 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. In Table 7, we report simulations based on our main results in Table 3, column (1). For each state, Panel B reports total change in manufacturing jobs, the average normalized electricity index, and the average change in electricity prices. The states that are expected to be the most affected are Ohio, Pennsylvania, New York, and North Carolina. We caution against summing our individual state job loss estimates to yield a national job loss estimate because we cannot claim to have credibly recovered estimates that can be used in a general equilibrium context.

7. 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 local 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 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 dominated 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 two thousand jobs for this state (a .1% 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 15 thousand jobs in that region (a 1.1% reduction).[27] This price is only a benchmark: we recognize that actual permit prices may be very different and that carbon policies may

[27] The Regional Greenhouse Gas Initiative regulates firms in Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island and Vermont.

include other incentives that will affect employment. 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. While many studies examining the costs of carbon mitigation regulation rely on computable general equilibrium models to forecast consequences, we believe that combining econometric evidence with policy simulations offers a fruitful path for offering credible predictions about the new public policies.

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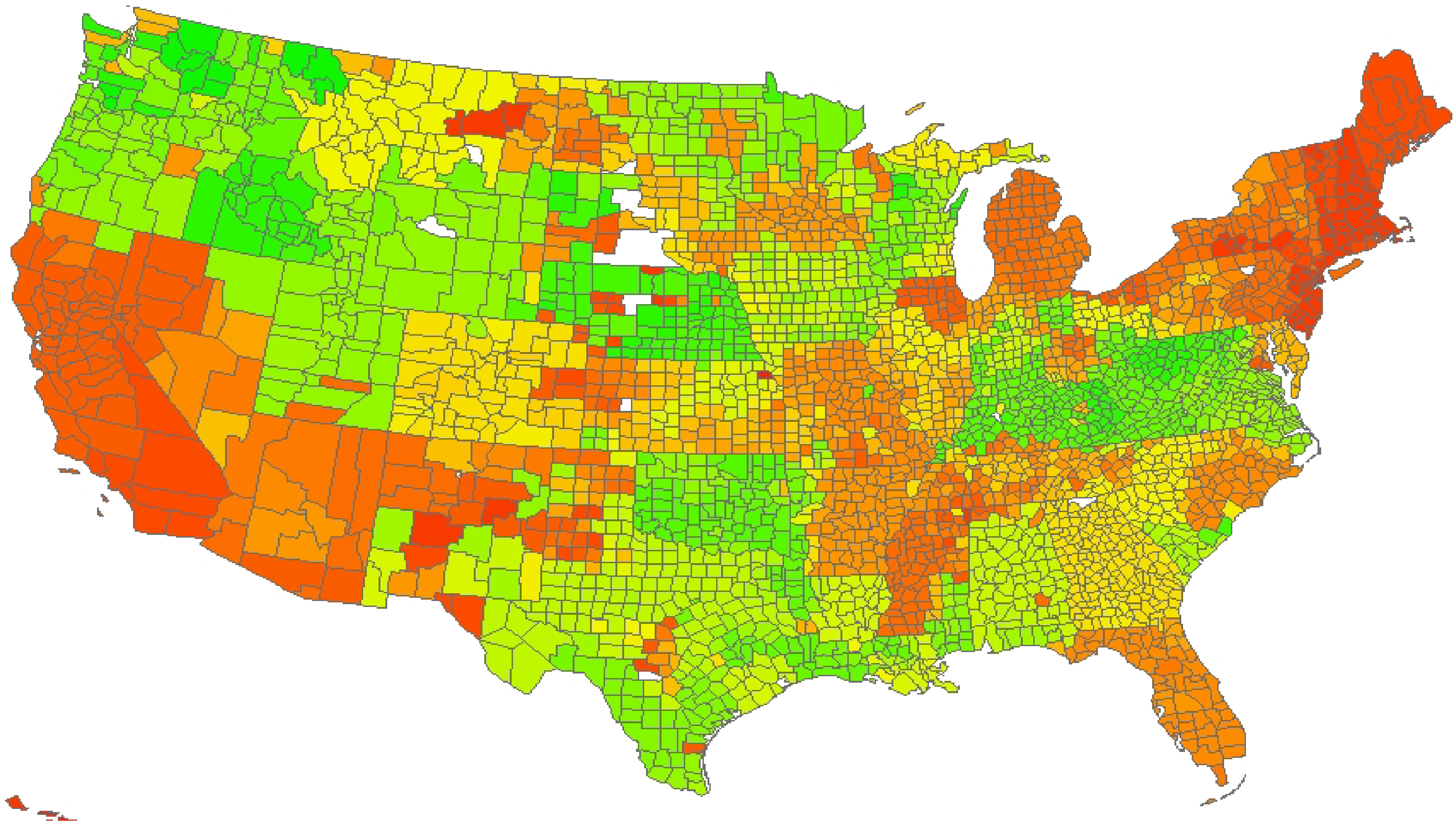

Figure 1: Electricity Prices in 1998

Table 1: Summary Statistics

Variable	Units	Obs	Mean	Std. Dev.	Min	1st Quartile	Median	3rd Quartile	Max
Mnfct. Employees	workers	138,264	642	2,485	0	0	0	463	158,573
% Total Emp.		138,264	0.5%	1.4%	0.0%	0.0%	0.0%	0.5%	56.4%
ln(N)	%	67,818	6.15	1.44	0.00	5.17	6.17	7.13	11.97
Any Manufacturing	0/1	138,264	0.49	0.50	0.00	0.00	0.00	1.00	1.00
Electricity Price	$/kWh	138,264	$0.064	$0.023	$0.025	$0.050	$0.056	$0.068	$0.296
Electricity Index	kWh/shipments	138,264	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 Law	0/1	138,264	0.43	0.50	0.00	0.00	0.00	1.00	1.00
Labor/Capital Ratio	work hrs/capital	138,264	0.017	0.013	0.001	0.007	0.014	0.023	0.074
Local Demand	%Δtotal emp	138,264	1.7%	5.2%	-53.8%	-0.5%	1.7%	3.9%	98.5%
1970 Population	in 1000s	138,264	209.3	437.0	2.4	39.2	88.6	215.1	7042.8
Miles to CBD	miles	138,264	18.21	19.81	2.28	6.73	13.39	22.75	181.91
Area of County	sq. miles	138,264	841	1,379	15	395	561	816	20,053

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 Electricity Prices on Manufacturing Employment using a Regression Discontinuity Approach

	N Manufacturing Employees		Percent Total Employment		ln N		ln (N+1)		Any N		Long Difference	
	1		2		3		4		5		6	
ln Electricity Price	236.9	***	0.109	***	0.26	***	0.15	**	0.006		0.04	
	(58.1)		(0.021)		(0.03)		(0.07)		(0.011)		(0.17)	
ln Price * Electricity Index	-1550.6	***	-0.361	***	-1.11	***	-0.79	***	-0.056	**	-0.38	*
	(212.2)		(0.060)		(0.08)		(0.18)		(0.028)		(0.20)	
Right to Work* Labor/Capital	6708.7	***	6.941	***	2.25		16.93	***	2.76	***		
	(1002.0)		(1.118)		(1.41)		(1.49)		(0.22)			
Population in 1970 (in 1000s)	2.83	***										
	(0.13)											
ln Population in 1970			0.015	***	0.74	***	1.32	***	0.15	***		
			(0.005)		(0.01)		(0.01)		(0.00)			
ln Miles to CBD	23.9		0.061	***	0.02	*	0.03		-0.01	***		
	(36.5)		(0.008)		(0.01)		(0.02)		(0.00)			
ln Area of County (Sq. Miles)	281.9	***	0.035	***	0.16	***	0.31	***	0.05	***		
	(38.4)		(0.007)		(0.01)		(0.02)		(0.00)			
Ln Housing Values in 1990	952.5	***	-0.222	***	0.39	***	0.99	***	0.14	***		
	(74.2)		(0.019)		(0.03)		(0.05)		(0.01)			
County Pair F.E.	Y		Y		Y		Y		Y		Y	
Industry-Year F.E.	Y		Y		Y		Y		Y		Y	
State F.E.	Y		Y		Y		Y		Y		Y	
R^2	0.36		0.17		0.53		0.58		0.50		0.14	
n	850,458		850,017		428,502		850,458		850,458		53,482	

* Notes: Significance is noted at the 10% (*), 5% (**) and 1% (***) levels. Standard errors clustered by utility-year. For the long difference, the dependent variable is the change in employment from 1998 to 2006 divided by the average employment in those years, and the electricity prices are the change in the log prices. The omitted category is a county in a non-Right to Work county.

Table 4: Employment Regressions by Industry

Industry	Normalized Electricity Index	Average Employment	Average % Tot Emp	Coef on N		Coef on % Total Emp		Coef on ln N	
Primary Metal Manufacturing	1.00	398	0.39	-1052.6	***	-0.368	***	-1.18	***
				(125.1)		(0.074)		(0.09)	
Paper Manufacturing	0.86	381	0.29	-741.0	***	0.109	***	-0.35	***
				(111.9)		(0.037)		(0.06)	
Textile Mills	0.59	151	0.23	-1006.2	***	-0.199	**	-0.78	**
				(135.3)		(0.077)		(0.31)	
Nonmetallic Mineral Product Manufacturing	0.53	431	0.52	-737.2	***	-0.145	***	-0.24	***
				(106.8)		(0.047)		(0.06)	
Chemical Manufacturing	0.46	787	0.62	169.9		0.250	***	0.19	**
				(135.8)		(0.096)		(0.09)	
Plastics and Rubber Products Manufacturing	0.36	847	0.88	-88.7		-0.093		-0.19	***
				(78.9)		(0.059)		(0.06)	
Wood Product Manufacturing	0.26	296	0.46	-1041.1	***	-0.197	***	-0.54	***
				(127.8)		(0.051)		(0.10)	
Petroleum and Coal Products Manufacturing	0.25	73	0.05	-1117.6	***	0.023		-1.05	***
				(147.2)		(0.031)		(0.17)	
Fabricated Metal Product Manufacturing	0.17	1,677	1.75	1226.2	***	-0.472	***	0.00	
				(237.8)		(0.101)		(0.05)	
Printing and Related Support Activities	0.15	794	0.50	67.6		0.202	***	0.37	***
				(59.6)		(0.036)		(0.05)	
Textile Product Mills	0.15	108	0.07	-911.1	***	0.125	***	0.54	***
				(121.6)		(0.029)		(0.09)	
Food Manufacturing	0.13	1,141	1.08	466.7	***	0.057		0.04	
				(124.1)		(0.148)		(0.09)	
Electrical Equipment, Appliance, and Component Manufacturing	0.11	364	0.23	-465.3	***	0.183	***	0.01	
				(92.0)		(0.031)		(0.07)	
Furniture and Related Product Manufacturing	0.09	463	0.47	-502.9	***	-0.207	***	0.05	
				(66.7)		(0.078)		(0.06)	
Leather and Allied Product Manufacturing	0.08	19	0.01	-1096.6	***	0.108	***	1.05	***
				(153.7)		(0.034)		(0.18)	
Machinery Manufacturing	0.07	1,156	1.07	-41.6		-0.301	***	-0.28	***
				(95.9)		(0.077)		(0.06)	
Apparel Manufacturing	0.07	325	0.15	561.4	***	0.258	***	1.06	***
				(209.1)		(0.044)		(0.16)	
Miscellaneous Manufacturing	0.06	723	0.45	755.3	***	0.520	***	0.83	***
				(86.0)		(0.045)		(0.06)	
Beverage and Tobacco Product Manufacturing	0.05	95	0.05	-1005.9	***	0.152	***	0.00	
				(156.2)		(0.056)		(0.20)	
Transportation Equipment Manufacturing	0.05	1,366	0.99	-86.6		-0.627	***	-0.92	***
				(236.0)		(0.099)		(0.10)	
Computer and Electronic Product Manufacturing	0.00	1,452	0.62	2749.8	***	0.848	***	0.46	***
				(378.8)		(0.087)		(0.09)	
Total		13,047	10.86						

* Notes: For each industry, we ran the main regressions separately (except for the industry interaction variables, like electricity intensity and LK*Right, which cannot be identified).

Table 5: Environmental Policies and Manufacturing Employment

	MSA Only		Full Sample		No Regression Discontinuity County FE		No Regression Discontinuity State FE	
	1		2		3		4	
Ln Electricity Price	227.0	***	128.2	***	414.3	***	21.6	
	(55.8)		(19.1)		(52.0)		(128.1)	
Ln P * Electricity Index	-1487.5	***	-622.4	***	-1482.4	***	-1471.0	***
	(189.1)		(72.2)		(189.1)		(190.2)	
Right to Work* Labor/Capital	7057.1	***	2776.8	***	7029.5	***	7135.1	***
	(1013.0)		(318.0)		(1012.5)		(1096.3)	
PM Nonattainment County	276.1	***	111.1	***	370.7	***	357.3	***
	(99.2)		(42.5)		(89.6)		(97.6)	
High PM * Nonattainment County	-702.4	***	-398.8	***	-696.9	***	-699.8	***
	(212.5)		(124.0)		(212.7)		(212.3)	
No PM Monitor	-8.7		-27.8	**	-33.0	**	28.3	
	(25.1)		(12.7)		(14.7)		(35.6)	
High PM * No Monitor	259.0	***	216.5	***	261.2	***	259.8	***
	(22.5)		(14.0)		(22.5)		(22.6)	
Other Controls	Y		Y				Y	
County Pair F.E.	Y		Y					
Industry*Year F.E.	Y		Y		Y		Y	
State F.E.	Y		Y				Y	
County F.E.					Y			
Cubic function pollution concentration	Y		Y		Y		Y	
R^2	0.36		0.35		0.38		0.33	
Counties	763		3158		763		763	
n	842,106		3,395,899		137,326		137,314	

Notes: Significance is noted at the 10% (*), 5% (**) and 1% (***) levels. Standard errors clustered by utility-year. The omitted category is a particulate matter attainment county in a non-Right-to-Work state for an industry with a low particulate matter emissions factor.

Table 6: Two-Stage Least Squares Regressions

	N (Mnfct Employees)		Percent Total Emp		ln N		ln (N+1)		Any N	
	1		2		3		4		5	
ln Electricity Price	90.4		0.07	**	0.22	***	0.06		-0.01	
	(75.6)		(0.03)		(0.04)		(0.09)		(0.01)	
ln Price * Electricity Index	-1591.6	***	-0.23	***	-0.97	***	-0.55	***	-0.02	
	(227.9)		(0.07)		(0.10)		(0.21)		(0.03)	
Right to Work* Labor/Capital	6749.2	***	6.80	***	2.02		16.66	***	2.72	***
	(1030.9)		(1.12)		(1.41)		(1.49)		(0.22)	
Other Controls	Y		Y		Y		Y		Y	
County Pair F.E.	Y		Y		Y		Y		Y	
Industry-Year F.E.	Y		Y		Y		Y		Y	
State F.E.	Y		Y		Y		Y		Y	
R^2	0.19		0.11		0.34		0.42		0.36	
N	850,458		850,017		428,502		850,458		850,458	

Notes: Significance is noted at the 10% (*), 5% (**) and 1% (***) levels. Standard errors clustered by utility-year. We instrument with commercial electricity prices plus its interaction with the electricity index. The first stage regression of electricity price on instruments and exogenous variables has an F stat on the joint significance on the instruments of 165.

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	demp	Index	ΔPrice	State	demp	Index	ΔPrice
Ohio	-11,864	0.30	$ 0.013	Arkansas	-951	0.30	$ 0.009
Pennsylvania	-10,103	0.30	$ 0.010	Oregon	-938	0.26	$ 0.004
New York	-4,752	0.28	$ 0.011	Kansas	-467	0.26	$ 0.010
North Carolina	-7,189	0.30	$ 0.009	South Dakota	-423	0.26	$ 0.008
New Jersey	-4,355	0.29	$ 0.009	Rhode Island	-399	0.29	$ 0.011
Indiana	-6,030	0.29	$ 0.013	Oklahoma	-528	0.27	$ 0.010
Michigan	-7,080	0.28	$ 0.013	New Hampshire	-464	0.29	$ 0.011
Tennessee	-4,202	0.29	$ 0.010	Mississippi	-350	0.30	$ 0.009
Illinois	-4,877	0.29	$ 0.012	Utah	-459	0.24	$ 0.004
Wisconsin	-5,541	0.30	$ 0.012	Nevada	-164	0.28	$ 0.004
Missouri	-4,133	0.27	$ 0.011	Arizona	-219	0.28	$ 0.004
Texas	-5,213	0.27	$ 0.009	Delaware	-137	0.26	$ 0.009
South Carolina	-3,544	0.29	$ 0.009	Maine	-193	0.27	$ 0.009
Georgia	-3,387	0.27	$ 0.009	New Mexico	-88	0.24	$ 0.004
Alabama	-3,083	0.27	$ 0.009	Idaho	-49	0.26	$ 0.004
Minnesota	-2,877	0.25	$ 0.012	District of Columbia	0	0.16	$ 0.009
Massachusetts	-2,293	0.30	$ 0.011	Wyoming	-2	0.26	$ 0.004
Florida	-2,725	0.24	$ 0.009	Montana	12	0.24	$ 0.004
California	-2,016	0.25	$ 0.004	Vermont	201	0.22	$ 0.011
Maryland	-1,219	0.26	$ 0.011	Louisiana	-160	0.26	$ 0.009
Colorado	-1,091	0.26	$ 0.004	North Dakota	338	0.22	$ 0.012
Washington	-1,411	0.26	$ 0.004	Iowa	288	0.27	$ 0.012
Kentucky	-1,321	0.31	$ 0.013	West Virginia	1,735	0.36	$ 0.013
Connecticut	-1,026	0.27	$ 0.011	Virginia	2,396	0.25	$ 0.010
Nebraska	-828	0.29	$ 0.012				

Table A1: Environmental Policies and Percent Total Employment

	MSA Only		Full Sample		No Reg Dis County FE		No Reg Dis State FE	
	1		2		3		4	
Ln Electricity Price	0.124	***	0.094	***	0.133	***	0.120	***
	(0.023)		(0.016)		(0.023)		(0.034)	
Ln P * Electricity Index	-0.402	***	-0.262	***	-0.399	***	-0.403	***
	(0.067)		(0.046)		(0.068)		(0.067)	
Right * Labor/Capital	7.040	***	6.084	***	7.079	***	7.079	***
	(1.121)		(0.631)		(1.126)		(1.172)	
PM Nonattainment County	-0.041	***	-0.073	***	-0.012		0.010	
	(0.011)		(0.012)		(0.014)		(0.017)	
High PM * Nonattain	0.187	***	0.292	***	0.188	***	0.187	***
	(0.065)		(0.054)		(0.065)		(0.065)	
No PM Monitor	0.004		0.008		-0.001		0.050	***
	(0.009)		(0.007)		(0.009)		(0.014)	
High PM * No Monitor	-0.033	**	0.070	***	-0.033	**	-0.034	**
	(0.016)		(0.013)		(0.016)		(0.016)	
Other Controls	Y		Y				Y	
County Pair F.E.	Y		Y					
Industry*Year F.E.	Y		Y		Y		Y	
State F.E.	Y		Y				Y	
County F.E.					Y			
Cubic f'n pollution conc	Y		Y		Y		Y	
R^2	0.17		0.10		0.17		0.12	
Counties	763		3158		763		763	
n	841,665		3,384,496		137,179		137,167	

Notes: Significance is noted at the 10% (*), 5% (**) and 1% (***) levels. Standard errors clustered by utility-year.

Table A2: Environmental Policies and Log Manufacturing Employment

	MSA Only 1		Full Sample 2		No Reg Dis County FE 3		No Reg Dis State FE 4	
Ln Electricity Price	0.27	***	0.31	***	0.33	***	0.27	***
	(0.03)		(0.03)		(0.03)		(0.07)	
Ln P * Electricity Index	-1.14	***	-1.21	***	-1.14	***	-1.21	***
	(0.09)		(0.08)		(0.09)		(0.09)	
Right * Labor/Capital	2.47	*	6.14	***	2.70	*	1.99	
	(1.40)		(1.17)		(1.41)		(1.56)	
PM Nonattainment County	0.12	***	0.09	***	0.05	**	0.16	***
	(0.02)		(0.02)		(0.02)		(0.04)	
High PM * Nonattain	0.15	***	0.20	***	0.16	***	0.14	***
	(0.03)		(0.04)		(0.03)		(0.04)	
No PM Monitor	-0.01		-0.02	*	-0.04	***	0.03	
	(0.01)		(0.01)		(0.01)		(0.02)	
High PM * No Monitor	0.14	***	0.18	***	0.14	***	0.17	***
	(0.02)		(0.02)		(0.02)		(0.02)	
Other Controls	Y		Y				Y	
County Pair F.E.	Y		Y					
Industry*Year F.E.	Y		Y		Y		Y	
State F.E.	Y		Y				Y	
County F.E.					Y			
Cubic f'n pollution conc	Y		Y		Y		Y	
R^2	0.53		0.50		0.54		0.45	
Counties	755		2497		755		755	
n	424,334		694,826		67,347		67,345	

Notes: Significance is noted at the 10% (*), 5% (**) and 1% (***) levels. Standard errors clustered by utility-year.

Table A3: Environmental Policies and Any Manufacturing Employment

	MSA Only		Full Sample		No Reg Dis County FE		No Reg Dis State FE	
	1		2		3		4	
Ln Electricity Price	0.01		0.03	***	0.02	*	0.01	
	(0.01)		(0.01)		(0.01)		(0.01)	
Ln P * Electricity Index	-0.06	**	-0.08	***	-0.06	**	-0.06	**
	(0.03)		(0.01)		(0.03)		(0.03)	
Right * Labor/Capital	2.74	***	0.83	***	2.76	***	2.77	***
	(0.23)		(0.13)		(0.23)		(0.24)	
PM Nonattainment County	-0.01	*	-0.02	***	0.00		0.00	
	(0.01)		(0.01)		(0.01)		(0.01)	
High PM * Nonattain	0.00		0.01		0.00		0.00	
	(0.01)		(0.01)		(0.01)		(0.01)	
No PM Monitor	0.01		-0.02	***	0.01		0.00	
	(0.00)		(0.00)		(0.00)		(0.00)	
High PM * No Monitor	-0.01	**	-0.02	***	-0.01	**	-0.01	**
	(0.01)		(0.00)		(0.01)		(0.01)	
Other Controls	Y		Y				Y	
County Pair F.E.	Y		Y					
Industry*Year F.E.	Y		Y		Y		Y	
State F.E.	Y		Y				Y	
County F.E.					Y			
Cubic f'n pollution conc	Y		Y		Y		Y	
R^2	0.50		0.44		0.51		0.46	
Counties	763		3158		763		763	
n	842,106		3,395,899		137,326		137,314	

Notes: Significance is noted at the 10% (*), 5% (**) and 1% (***) levels. Standard errors clustered by utility-year.