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Do Renewable Portfolio Standards Affect Manufacturing Activity Through Higher Electricity Prices? [1]

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Abstract

State-level renewable portfolio standards (RPSs) are a relatively recent but increasingly popular phenomena in the United States, enacted to encourage cleaner production of electric power. To date there has not been any research on how the adoption of an RPS affects manufacturing activity. In this paper, we estimate the impact RPS requirements have on U.S. manufacturing activity, and in particular, labor demand and production, via their effect on electricity prices faced by manufacturing facilities. We begin our analysis by modelling the adoption of state-level RPS requirements. Next, using a plant-level dataset for the entire U.S. manufacturing sector from 1990 – 2009, we model how the stringency of RPS requirements impact the electricity prices faced by manufacturing plants and then, in turn, how electricity prices affect manufacturing activity both in general and in energy-intensive, trade-exposed (EITE) sectors. The estimated effects of an RPS on electricity prices and manufacturing employment and output are small. For example, we find that electricity prices faced by plants that purchase electricity subject to an RPS that requires utilities to generate 3% of their electricity from renewable sources are approximately 3-6% higher than the electricity price faced by plants purchasing from a non-RPS utility. For the plants in EITE industries we estimate that a 6% increase in electricity prices would cause employment, production hours and output to decrease by approximately 2-3%.

[1] Disclaimer: The views expressed herein are those of the author(s) and do not necessarily represent those of the U.S. Environmental Protection Agency or the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. In addition, although the research described in this paper may have been funded entirely or in part by the U.S. Environmental Protection Agency, it has not been subjected to the Agency's required peer and policy review. No official Agency endorsement should be inferred.

1. Introduction

Renewable portfolio standards (RPSs) are a relatively recent but increasingly popular phenomena in the United States employed by states to encourage cleaner generation of power. A handful of states first enacted legislation for RPSs in the late 1990s/early 2000s (Wiser et al. 2007). As of March 2013, 29 states and the District of Columbia had enacted mandatory renewable portfolio standards. Eight others had voluntary RPSs in place (DSIRE 2013). The popularity of RPSs stems from a desire to encourage utilities to produce electricity from clean, renewable sources, including wind and solar, rather than coal and natural gas, which produce higher levels of greenhouse gas emissions associated with climate change. In addition, diversifying electricity generation is thought to enhance energy security, reducing the risk of potential disruptions in fuel supplies and vulnerability to fluctuations in fuel prices (Jaccard 2004; Schmalansee 2011). Given that until very recently renewable sources of electricity typically were more expensive than burning fossil fuels, we might expect that increasing the use of renewable energy would increase the cost of electricity (Palmer and Burtraw 2005). The U.S. Energy Information Administration (EIA) (2014) predicts that the levelized cost[2] of energy, which includes capitalization and transmission costs, for new generation resources beginning in 2019 would range from $66.3/MWh for natural gas combined cycle to $95.6/MWh (in 2012 dollars) for conventional coal, while renewables would vary from $80.3/MWh for wind to $130/MWh for solar. However, some studies suggest that the additional renewable energy use induced by RPSs could displace natural gas-fired generation, lowering both its price and electricity prices (Wiser and Bollinger 2007). Others suggest that RPS stringency is important for electricity prices as well as differences in responsiveness of renewable versus fossil-fuel generation to changes in electricity price (Fischer 2009).

One of the arguments raised against the adoption of RPS requirements is that it would put industries in the state (especially manufacturing) at a competitive disadvantage. Several recent papers, using industry-level data, examine how increased electricity prices due to other environmental regulations affect manufacturing activity (e.g., Kahn and Mansur 2012, Aldy and Pizer 2013, and Curtis 2013).[3] These papers find larger impacts on energy-intensive industries. For example, Aldy and Pizer find that a $15/ton carbon tax would reduce employment in all of manufacturing by only 0.2%, but that in the most energy-intensive industries employment would decline by 1-2%. While this literature is instructive, the effect of

[2] Levelized cost of electricity is frequently cited as a convenient summary measure of the overall competiveness of the various power generating technologies. It is the real per-kilowatthour cost of building and operating a generating plant over an assumed economic lifetime and duty cycle.

[3] None of these papers model electricity prices, they just assume a particular environmental policy increases electricity prices by some specific amount.

RPSs on industrial sector electricity prices or subsequent impacts on manufacturing activity remains an important unstudied empirical question of keen interest to policymakers.

Neoclassical microeconomic theory alone cannot answer the policy question of whether RPSs have a negative impact on manufacturing activity, specifically, labor demand. In particular, theory cannot predict the direction of the electricity price impact on labor demand since it depends on the level of substitutability between labor and energy (Deschênes, 2012). If labor and energy are highly substitutable, labor demand may rise with an increase in electricity prices; otherwise it may decline (Pindyck and Rotemberg 1998).

How likely is it that RPS requirements may have a substantial negative economic impact on manufacturing industries via their effects on electricity prices? For the manufacturing sector as a whole, electricity represents a relatively small percentage of total manufacturing costs - approximately 1 percent as reported in the 2011 Annual Survey of Manufacturers (ASM). However, electricity expenditures represent 10 to 20 percent of total costs for some energy-intensive industries such as aluminum (NAICS 331312), industrial gases (NAICS 325120), and cement (NAICS 327310). Moreover, electricity expenditures represent 2-3 percent of total costs in broader sectors within manufacturing such as textiles (NAICS 313) and primary metals (NAICS 331). Because RPS requirements are imposed at the state level, with considerable flows of manufactured goods across states, industries located in RPS states face some competitive disadvantage due to a rise in electricity prices. Furthermore, it has been argued in other regulatory contexts (e.g. the Waxman-Markey cap-and-trade proposal to reduce CO2 emissions) that electricity price increases could undermine the international competitiveness of energy-intensive, trade-exposed (EITE) sectors.[4]

Data on state RPSs make it apparent that there is substantial variation across programs (e.g. when they took effect, which renewables are included in the program, whether the goals are expressed as magnitudes or fractions of total electricity generation, whether they are voluntary or mandatory). In this paper, we focus only on the potential impacts of mandatory RPSs. In our main analysis, we include a continuous variable that measures the RPS stringency as the fraction of total electricity generation that is required from renewables, adjusted for how much of the requirement has actually been met or complied with. We hope to utilize other potentially important differences (e.g. types of renewables included, whether it applies only to new renewable generation or existing renewables can also be used to meet the

[4] The Effects of H.R. 2454 on International Competitiveness and Emission Leakage in Energy-Intensive Trade-Exposed Industries (2009). This report defines an energy-intensive sector as having energy-expenditures of at least 5% of domestic production and trade-exposed if its trade intensity (ratio of combined exports and imports to domestic production and imports) is at least 15%. We use this definition in our analyses.

standard, whether energy efficiency can be used to meet the standard) in RPSs across states in subsequent versions of the paper.

As mentioned above, our analysis in this paper does not simply focus on whether and how an RPS requirement impacts manufacturing activity. We are also interested in the pathway by which an RPS would affect manufacturing activity because RPSs do not directly stipulate specific policies for manufacturing activities. Rather, we expect that any impact of RPSs on manufacturing activities would operate through an electricity price pathway. Therefore, we explicitly model the impact of an RPS on electricity prices faced by manufacturing plants. This complicates our analysis by adding an additional estimation stage for the electricity price pathway.

Before we can model the effect an RPS requirement has on electricity prices, we must first model the state RPS requirement decision. Lyon and Yin (2010) have shown that RPS adoption is not random, but is a function of both political and economic factors. Furthermore, if states with higher (lower) electricity prices are less (more) likely to adopt an RPS than others, then an instrumental variable approach may be warranted. Moreover, plant-level electricity prices are, in theory, simultaneously determined with local manufacturing activity. Thus, directly including electricity price in an OLS regression for manufacturing activity and employment is potentially problematic since it may be determined simultaneously with employment; the same unobserved factors that drive a large sector to expand employment may also increase electricity demand and affect its price. This leads us to a three-stage estimation procedure. In the first stage we predict RPS stringency (adjusted for compliance), by state, using political and economic factors along the lines of Lyon and Yin (2010). In stage 2, we use predicted RPS stringency from stage 1 as an instrument to estimate plant-level electricity prices.[5] Finally, in the third stage we examine how the predicted plant-level electricity prices from stage 2, which vary across space and time, affect a plant's employment and production decisions.

Section 2 provides background information on renewable portfolio standards. Section 3 reviews the relevant literature on electricity prices and labor demand. Section 4 outlines a brief conceptual framework of the impact of regulation on employment. Section 5 discusses the data and empirical methodology. Section 6 presents the results, followed by concluding remarks and next steps in section 7.

2. Renewable Portfolio Standards

Conceptually, a renewable portfolio standard is quite simple: it requires that a certain amount of electricity within a particular year be generated using renewable sources such as wind

[5] Using predicted values as IVs is not unprecedented. Predicted values can be used in a 2SLS model with a non-linear first stage [see Angrist and Pischke(2009) and Wooldridge (2002)].

or solar. However, the specifics of any given RPS vary widely across states. For instance, they may vary in stringency, whether the goal is expressed as a share of total electricity generation or as a certain number of megawatt hours, the date by which a goal must be reached, whether the standard applies to wholesale or retail energy suppliers, the degree to which all renewable sources are allowed (i.e., hydropower), whether it applies only to new renewable generation or existing renewables can also be used to meet the standard, whether non-renewables can be used to meet the standard (e.g. energy efficiency improvements), how electricity generated outside the state is treated, and whether trading of credits across generators or banking and borrowing is allowed (Jaccard 2004; Wiser et al. 2007; Schmalansee 2011). Many states also have different requirements for investor-owned utilities (IOUs) and municipal utilities or cooperatives.

Not surprisingly, studies also vary widely in their predictions of the effect of RPSs on electricity prices. To the extent that an RPS is binding and encourages the market to generate higher cost electricity than it would have otherwise done on its own, electricity prices may rise (Palmer and Burtraw 2005, EIA 2003). Palmer and Burtraw (2005) find that a RPS has little effect on electricity prices at relatively low levels of stringency (5-10 percent), but that at high levels of stringency (20 percent) electricity prices rise due to additional wind generation that crowds out nonrenewable sources. However, it is also possible that renewables mainly displace peak sources of generation such as natural gas. As demand for natural gas falls, so too does its price, which may also reduce the overall price of electricity (Clemmer et al. 1999, Nogee et al. 2007, Wiser and Bollinger 2007).

Fischer (2009) attempts to identify the specific factors that could lead an RPS to lower electricity prices. Contrary to earlier studies that focus on the role of natural gas, Fischer finds that the relative responsiveness of renewable energy to electricity price changes compared to nonrenewable sources and the stringency of the RPS are the most important factors. More specifically, Fischer notes that an RPS essentially provides a subsidy to renewables in the form of the cost of credits that must be purchased by fossil fired generators to accompany their production, which in turn acts as an implicit tax on fossil fired generation. Fischer argues that if the supply curves of fossil-fuel fired generation are not perfectly elastic, the subsidy to renewables tends to lower electricity prices overall, whereas the tax on fossil-fuel fired generation tends to increase prices. Thus, a priori the price effect of an RPS is ambiguous and depends on whether the tax or subsidy effect dominates. On the other hand, Fischer's analytical and numerical modeling results suggest that negative price impacts are only likely for relatively less stringent RPS targets and that for higher RPS targets the implicit tax on fossil-fuel fired generation dominates and electricity prices increase quickly.

RPSs have also been viewed as potential avenues for job creation, particularly when renewable generation has to come from within the state. Lyon and Yin (2010) examine the reasons for RPS adoption and find that states with high renewable energy potential, a Democratic majority in the state legislature, an organized renewable energy industry in the state, low reliance on natural gas, and a restructured electricity market (i.e., not cost-of-service) are more likely to be early adopters of RPS policies. States with high unemployment rates are actually less likely to be early adopters, and the health of the labor market appears to play no role in whether a RPS imposes a within-state requirement on renewable sources. Yi (2013) analyzes clean energy policies and employment for U.S. metropolitan areas in 2006, to evaluate impacts on clean energy job growth. Implementing an additional state clean energy policy tool (renewable energy policies, GHG emissions policies, and energy efficiency polices such as energy efficiency resource standards, appliance or equipment energy efficiency standards, tax incentives, and public building energy efficiency standards) is associated with, on average, 1% more clean energy employment within a metropolitan area.

3. Electricity Prices and Labor Demand

The question of if and how environmental regulation affects economic outcomes in the U.S. manufacturing sector is not a new one. There is a wide-ranging literature that examines how the costs of complying with EPA regulations affects productivity (e.g., Färe, Grosskopf and Pasurka 1986, Boyd and McClelland 1999, Berman and Bui 2001b, Gray and Shadbegian 2002, Shadbegian and Gray 2005, Shadbegian and Gray 2006), investment (e.g., Gray and Shadbegian 1998), and environmental performance (e.g., Magat and Viscusi 1990, Laplante and Rilstone 1996, Shadbegian and Gray 2003, Shadbegian and Gray 2006). There is a much more limited set of studies that examine the impact of environmental regulations on employment (e.g., Berman and Bui 2001, Greenstone 2002, Morgenstern, Pizer and Shih 2002, and Cole and Elliott 2007). Nevertheless, given the relatively high unemployment rates during the recent economic downturn and policy-maker, industry and public concerns that more stringent environmental regulations may reduce employment, thereby exacerbating the unemployment problem, this literature has been growing in recent years (e.g., Walker 2011, Walker 2013, Gray and Shadbegian 2013, Curtis 2014, Gray, Shadbegian, Wang and Meral 2014, and Ferris, Shadbegian, and Wolverton 2014).

The literature that examines the impact of electricity prices on manufacturing employment is even smaller. The only papers we are aware of that study the effects of environmental policy and electricity prices on manufacturing employment are Kahn and Mansur (2013), Aldy and Pizer (2011, 2014), and Curtis (2014). Kahn and Mansur (2013) estimate the effect of electricity prices on manufacturing employment from 1998-2009, controlling for ozone and labor regulations. They find evidence that increases in electricity prices caused reduced employment, especially in energy-intensive industries. Aldy and Pizer (2011, 2014) estimate the historical relationship between changes in electricity prices and competitiveness and then assume environmental policy (in their case, a price on carbon) would increase electricity prices. Using this approach for more than 400 U.S. manufacturing sectors Aldy and Pizer find that increases in electricity prices have a small significant negative impact on net imports, particularly for energy intensive sectors. Curtis (2014) estimates the effect the NOx budget trading program had on employment in the manufacturing sector from 1998-2008. He links county-level manufacturing industries to electricity suppliers to identify the impact of generators' participation in the NOx trading program on labor demand for its customers but does not explicitly examine electricity prices or local environmental regulations. Curtis finds evidence suggesting that the NOx trading program caused highly energy-intensive manufacturing industries to hire fewer new employees relative to less energy-intensive industries.[6,7]

Similar to Kahn and Mansur (2013), we model the impact of electricity prices on manufacturing employment. Based on Curtis (2014), we also understand that regulations - in our case RPSs - which affect electricity providers (perhaps in another county or state) may indirectly affect manufacturing activity. This insight leads us to base our analysis on the RPS faced by the

[6] Deschênes (2012), using data from the Current Population Survey from 1976-2007, evaluates the effect state electricity prices have on employment in all sectors of the U.S. economy and finds a small significant negative relationship.

[7] Aldy and Pizer (2014) begin by estimating the historical relationship between changes in electricity prices and competitiveness and then assume environmental policy (in their case a price on carbon) would increase electricity prices. Using this approach for more than 400 U.S. manufacturing sectors Aldy and Pizer find that increase in electricity prices have a small significant negative impact on net imports, particularly for energy intensive sectors.

electricity generator, rather than simply using the RPS in the state where the manufacturing plant is located.

4. Conceptual Framework

As a conceptual framework for this analysis, we rely on the neoclassical theory of labor demand and follow the framework in Deschênes (2012). As described in Deschênes (2012), in a model with multiple factors, the cross-price elasticity of labor demand with respect to energy prices, η_{LE}, is given by:

(1) $\eta_{LE} = s_E\,[\sigma_{LE} - \rho/(\rho - \theta)]$

where s_E is the share of energy in total production costs, σ_{LE} is the partial elasticity of substitution between labor and energy, ρ is a measure of market power of the firm (= 1 if the firm is a price-taker in the product market, and > 1 if the firm is a price-maker), and θ measures the degree of homogeneity of the production function. . As Deschênes (2012) states, this formula has two key implications for his research (and both also apply to ours): (a) the cross-elasticity of labor demand with respect to energy prices is likely small since s_E is small for most industries, and (b) the sign of η_{LE} will depend on whether the substitution effect ($s_E\,\sigma_{LE}$) or the scale effect ($s_E\,\rho/(\rho - \theta)$) dominates.

5. Data and Empirical Methodology

The research for this paper was conducted at the Census Bureau's Boston Research Data Center, using confidential plant-level datasets developed by the Census Bureau's Center for Economic Studies. The primary information on plants comes from the Census of Manufactures (CMF) and Annual Survey of Manufactures (ASM), linked together in the Longitudinal Business Database (LBD) as described in Jarmin and Miranda (2002). Because we consider all manufacturing plants over a twenty-year period (1990-2009 - a huge sample even excluding administrative records, missing variables, and non-matching records - we have nearly 1.3 million observations. These Census data include the plant's total employment (EMP), production worker hours (PH), and total value of shipments (TVS), which are used in log form as the dependent variables in our analysis (the TVS value is deflated by an industry-specific price deflator from the NBER-CES manufacturing industry database). The Census data also include the cost and quantity of purchased electricity, from which we derive a plant-specific electricity price (ELEC). We also construct several explanatory variables from the Census data. There is an indicator of whether the plant is part of a multi-plant firm (MU). The LBD is used to identify the first year the plant was in the Census data, from which we derive plant age and construct two age dummies, AGE5 (0-4 years old) and AGE10 (5-9 years old).

Every 5 years, the CMF data provide a snapshot of all manufacturing plants in the country, which we use to develop additional plant characteristics. The CIWAGE is the average local wage (payroll/employees) paid in similar establishments nearby – in most cases this is an average wage of all other establishments in the same 6-digit NAICS (or 4-digit SIC) industry in the same county, although if there are fewer than 3 establishments in that category we expand to broader industry definitions within the same county. CIEMP is the total employment in the same industry and county, as a measure of local agglomeration effects. We also look at the national size distribution of TVS for plants in that industry and create dummies for this plant being in the top quartile (SIZE75) or the next-lower quartile (SIZE50) of its industry's distribution as possible measures of market power. To avoid simultaneity issues, we use the CMF data from 3-7 years in the past (if the plant was not present in that CMF year, we deflate its current TVS value to the earlier year to create its SIZE dummies, and we could get a zero value for CIEMP if no other establishments existed at the time in that industry and county).[8]

Our key explanatory variable, RPS, is calculated at the county level, although the actual regulations are adopted at the state level. We assumed that an RPS affects the cost of electricity based on where that electricity is generated; the activities of some electric utilities span multiple states, so that electricity generated in one state may be sold in another state. We linked utilities to the counties in which they sell electricity (using the EIA 861 database). We then identified the generating plants connected to each utility (using the EIA 767 database) and checked whether that generating plant was in a state with an RPS requirement. We rely on Lawrence Berkeley National Laboratory's RPS Compliance Database (LNBL) and augmented with data from the Quantitative RPS Data Project at the Database of State Incentives for Renewables and

[8] One complication with using the annual Census data is the need to have different lag-lengths on the past CMF data – unlike papers using only CMF-year data such as Greenstone (2002), which can consistently use 5-year lags.

Efficiency(DSIRE)[9]. This enabled us to calculate what fraction of the electricity generated for each utility was covered by an RPS and apply that number to each county serviced by that utility. In cases where multiple utilities were selling electricity in a given county, we averaged their RPS values to get a single number for each county-year.

While this approach could in principle give us variation across counties within a state, and could cause an RPS requirement in one state to spill over into another state, we see in Figures 1-3 that while these county-level numbers are expanding across the country between 2000 and 2010, they do not spill across state boundaries very much. Comparing Figure 3 to Figure 4, both showing 2010 RPS measures, we see that the county-level RPS measure is similar to what would have been obtained by using a dummy variable based on the state's own RPS requirements. One feature of RPS requirements that differs across states is that some states set their goals with higher percentages of electricity generated from renewable sources (these goal percentages can also vary over time within a state) and some states are closer to meeting their goals. To reflect this, we construct RPSPCT, which is calculated in a similar manner to the RPS variable described above, but instead of being based on a state RPS dummy it is based on the fraction of the electricity generated in the state that is required to come from renewable sources based on the state's RPS regulation in that year and an assessment of how close the state is to meeting its requirement.

Measures of regulatory intensity besides RPS are also available. From EPA's Green Book data we obtain indicators of county non-attainment with federal ambient air quality regulations for particulates (NAPM), ozone (NAOZ) and sulfur dioxide (NASO2), since the stricter regulations that often accompany non-attainment status may affect both manufacturing plants in the county and the cost of generating electricity there. We also characterize each plant based on whether its industry is a major emitter of that pollutant (using information from Greenstone 2002), and create interaction dummies (DNAPM, DNAOZ and DNASO2) for cases where a plant is in a non-attainment county for a pollutant it is likely to emit, since those plants are especially likely to face stricter regulations. The League of Conservation Voters compiles an annual scorecard of pro-environment voting by each Congressional delegation (we use the

[9] For quantitative information about state RPS programs, which we used to construct our variables, see http://emp.lbl.gov/rps and http://www.dsireusa.org/rpsdata/RPSspread031813.xlsx.

average score for the state's House delegation, LCVOTE), which we use as a proxy for a state's desire for more stringent environmental regulations.

We link additional information from external data sources, based on the plant's industry or county location. We measure the annual import penetration ratio (IMPRAT) for each industry, using trade datasets organized by Peter Schott (2008). We obtain various county-level characteristics from the USA Counties database, including the percent of college graduates (COLGRD), percent speaking a language other than English at home (NONENG), percent voting for the Democratic candidate in the most recent presidential election (PCTDEM) and land area. The Regional Data web page from the Bureau of Economic Analysis provides per-capita income (PCINC), population (which we combined with land area to create population density, POPDEN), and fraction of county employment in manufacturing (PCTMAN).

Empirical Framework

Our analysis in this paper focuses on whether and how an RPS requirement impacts manufacturing employment and production by explicitly modeling the impact of an RPS on electricity prices faced by manufacturing plants. However, before we can model the effect an RPS requirement has on electricity prices, we must first model the state RPS requirement decision due to the possibility that RPS adoption is not exogenous (Lyon and Yin 2010). This leads us to a three stage estimation procedure. In stage 1 we predict RPS stringency (adjusted for compliance), by state, using political and economic factors along the lines of Lyon and Yin (2010). In stage 2, we use predicted RPS stringency from stage 1 as an instrument to estimate plant-level electricity prices. Finally, in the third stage we examine how the predicted plant-level electricity prices from stage 2, which vary across space and time, affect a plant's employment and production decisions.

Stage 1: *Endogeneity of RPS Stringency*

An open question is whether RPS adoption is exogenous. If states with higher (lower) electricity prices are less (more) likely to adopt a RPS than others, then an instrumental approach may be warranted. Lyon and Yin (2010) find evidence that certain political and economic factors significantly affect the likelihood and timing of RPS adoption at the state level, several of which directly relate to the electricity market. In particular, they find that states with higher unemployment rates (UNEMP) or a higher proportion of electricity generated from natural gas (NGCAP) – which is sometimes displaced by renewables – are slower to adopt RPS policies, while states with more active in-state renewable (RENCAP) interests, a restructured electricity market (DEREG), or a relatively high technical potential for solar (CSP and UTILITY_SOLAR) or wind generation (ONSHORE_WIND and OFFSHORE_WIND) drive early RPS adoption.

To instrument for RPS requirements in state s at time t, we first run a Tobit regression. We use a Tobit specification because many states do not adopt a RPS; only states with a RPS have specified renewable requirements over time. We use the predicted value for RPS from the Tobit in our second stage electricity price regression model. Our Tobit model is:

$$(2)\quad RPSPCT_{st} = \alpha_0 + \alpha_1 UNEMP_{st} + \alpha_2 DEREG_{st} + \alpha_3 ASES_{st} + \alpha_4 RENCAP_{st} + \alpha_5 NGCAP_{st} + \alpha_6\, ONSHORE\_WIND_{st} + \alpha_7 (ONSHORE\_WIND)^2_{st} + \alpha_8\, OFFSHORE\_WIND_{st} + \alpha_9 (OFFSHORE\_WIND)^2_{st} + \alpha_{10} CSP_{st} + \alpha_{11} (CSP)^2_{st} + \alpha_{12} UTILITY\_SOLAR_{st} + \alpha_{13} (UTILITY\_SOLAR)^2_{st} + \alpha_{14} BIOGAS_{st} + \alpha 15 (BIOGAS)^2_{st} + t + t^2 + \varepsilon_{st}$$

where the dependent variable, $RPSPCT_{st}$, is the RPS requirement in state s at time t in percentage terms adjusted for actual compliance rates.[10]

The independent variables are defined as follows: $UNEMP_{st}$ is the unemployment rate in state s, at time t, lagged one year; $DEREG_{st}$ is a dummy variable indicating whether a state had a restructured electricity market at the time of RPS adoption; ASESs is a dummy variable that indicates whether a state has a staffed American Solar Energy Society office; $RENCAP_{st}$ is the proportion of total electricity generation from renewables in state s, lagged five years from the initial RPS year; $NGCAP_{st}$ is the proportion of total electricity generation from natural gas in state s, lagged five years form the initial RPS year; and $ONSHORE\_WIND_s$, $OFFSHORE\_WIND_s$, CSP_s, $UTILITY\_SOLAR_s$, and $BIOGAS_s$ are measures of a state's technical potential - based on "system performance, topographic limitations, environmental, and land-use constraints" (Lopez et al. 2012) - to support various types renewable generation (wind,

[10] Note in the next version of this paper this Tobit model will be expanded to capture more variables related to RPS requirements including League of Conservation Voters scorecard, political preferences, and emissions from EGUs. We also plan to explore alternative specifications that potentially parse the decision of whether to adopt an RPS from the stringency of the requirement in states that have such requirements.

solar and biogas).[11] We also include a quadratic time trend to control for general macroeconomic factors that affect all plants (or utilities) over time.

Stage 2: *Endogeneity of Electricty Prices*

We use the predicted RPS requirements (from Stage 1) faced by the electricity generator as an instrument for plant-level electricity prices which are, in theory, simultaneously determined with local manufacturing activity. Including price in an OLS regression is problematic since it may be determined simultaneously with employment; the same unobserved factors that drive a large sector to expand employment, for example, may also increase electricity demand and affect its price.

To address this simultaneity issue, we estimate the relationship between manufacturing employment, RPS policies, and electricity prices using instrumental variables. The ideal instrument would be correlated with electricity price, while also being uncorrelated with any unobserved factors that influence both labor demand and electricity prices at that plant. Fortunately, the geographic heterogeneity of RPS adoption and stringency, combined with the geographic dispersion of electricity generation provides us with just such an instrument.

Our main specification follows, where the unit of analysis is by manufacturing plant *i* and year *t.* Summary statistics for these data are provided in Table 2. We use an IV approach to estimate the employment impacts of electricity price and RPSs. Our second stage is a regression explaining electricity prices which will then be used in the third stage regression explaining manufacturing employment and shipments.

$$(3)\ \ln(\mathrm{ELEC})_{it} = \beta_0 + \beta_1 RPSPRD_{st} + \beta_x X_{ct} + \beta_t + \varepsilon_{ct}$$

ELEC is our plant-specific electricity price derived from Census data on the cost and quantity of purchased electricity. In our preferred specification, the *RPSPRD* is the predicted RPS

[11] Unemployment rates and ASES staffing were gathered from the same sources used by Lyon and Yin (2010): the U.S. Department of Labor, and the ASES website (http://www.ases.org/local/). We obtained information on the timing and status of electricity restructuring from the Energy Information Administration's website (http://www.eia.gov/electricity/policies/restructuring/restructure_elect.html). Note that we did not use its current status, but instead looked at the data underlying the U.S. map to identify the timing of electricity deregulation. Renewable, natural gas, and total electricity generation by year and state is measured in gigawatt hours and also from EIA. Finally, the assessment of a state's technical potential for various renewables is from a National Renewable Energy Laboratory (NREL) spreadsheet (http://www.nrel.gov/gis/re_potential.html).

requirement in percentage terms adjusted for actual compliance rates from stage 1. *X* designates other control variables: county-level nonattainment status (NAPM, NAOZ, NASO2), voting record variables (LCVOTE, PCTDEM), per-capita income (PCINC), population density (POPDEN), manufacturing intensity (PCTMAN), whether the plant is part of a multi-plant firm (MU), plant-age dummies (AGE5, AGE10), and dummies for where the plant is in its industry's size distribution (SIZE75, SIZE50). We also include state and year dummies.

Stage 3: *Impact of Electricity Prices on Manufacturing Activity*

The third stage regresses manufacturing employment at plant *i* in year *t* on predicted electricity price (from stage one), and other control variables. We tested various combinations of the control variables, and also took advantage of the panel nature of plant-level data to estimate both fixed- and random-effects models (though with our large sample size it is no surprise that we always reject equality of the coefficients between FE and RE models, indicating that the FE model is preferred, so that's what we report in our results).

$$(4)\ \ln Y_{it} = \beta_0 + \beta_1\, \mathrm{PRLELEC}_{it} + \beta_x X_{it} + \beta_{\mathrm{industry}} + \beta_t + \varepsilon_{it}$$

Y is one of: the manufacturing plant's total employment (EMP), production worker hours (PH)[12], or total value of shipments (TVS; the TVS value is deflated by an industry-specific price deflator from the NBER-CES manufacturing industry database). PRLELEC is the predicted value of the log plant-level electricity price from the second stage. Control variables, *X,* are: county-level nonattainment status (NAPM, NAOZ, NASO2), interaction dummies with indicators for polluting industries when a plant is in a non-attainment county for a pollutant it is likely to emit (DNAPM, DNAOZ and DNASO2), voting record variables (LCVOTE, PCTDEM), demographic characteristics (PCINC, POPDEN, COLGRAD, NONENG), county manufacturing intensity (PCTMAN), and plant-level characteristics (CIWAGE, CIEMP, MU, IMPRAT, AGE5, AGE10, SIZE75, and SIZE50). As with the second-stage model of electricity prices, we explored various combinations of control variables; we also included industry or plant fixed effects, in addition to year fixed effects.

[12] In earlier versions of the analysis, we also estimated models using the number of production workers as the dependent variable, with results very similar to those for production worker hours.

6. **Results**

We begin with a discussion of our Stage 1 analysis, predicting RPS stringency levels adjusted for compliance rates, based on state characteristics. Table 1 contains the summary statistics for the state-level dataset. We see that only about one-eighth of the observations have an RPS requirement in place – not surprising since our dataset covers 1990-2009 while hardly any RPS programs pre-date 2000. Recognizing that the RPSPCT value is zero for most of the observations, the average RPS requires that about 4.5% of electricity generation come from renewable sources.

The results of our model predicted RPS stringency are reported in Table 2. Similar to Lyon and Yin (2010), we find that states with higher unemployment rates are significantly less likely to adopt an RPS (or a less stringent RPS). While we also find that having a staffed ASES chapter is positively associated with RPS adoption, in our case it is not significant. We find that states that restructured their electricity market are less likely to adopt an RPS, which is contrary to expectations since one way to compete in a new marketplace could be through renewables, but this variable is also not significant.

We also find that the more a state already derives electricity from renewables, the more likely it adopts a RPS. Lyon and Yin find this variable is not significant. However, we differ from their regression both in terms of our dependent variable and the number of lags employed (five versus one). States that already relied on natural gas more heavily as a source of electricity generation are also significantly more likely to adopt a RPS, which is opposite in sign from Lyon and Yin (2010). They posited that since natural gas is often displaced by renewables the natural gas industry would likely oppose RPS adoption. It is important to note, however, that their measure for natural gas influence in the state was not significant.

Finally, we find that several of the technical potential variables are significant. Lyon and Yin (2010) only included dummies for wind, solar, and biomass, while we employ continuous variables for a more disaggregated set of renewables. Technical potential in wind – whether on or offshore, appears to have no effect on the likelihood of RPS adoption. The only renewable for which technical potential is positively associated with adopting an RPS of increasing stringency is utility-scale photovoltaic solar, though the squared term is negative and significant. On average, concentrated solar and biogas are both negatively associated with RPS adoption, though the squared terms are positive and significant. In other words, while states with average technical potential for concentrated solar or biogas are less likely to adopt an RPS, those with particularly high technical potential are more likely to do so than the average.

Table 3 displays the summary statistics and variable definitions of all the variables used in the Stage 2 and Stage 3 analysis, based on plant-level Census data. The dataset used for our analysis is an unbalanced panel, with 1,275,800 plant-year observations on 327,200 plants over the 1990-2009 time-period. The average plant in our sample has 150 workers and real (1997$) annual shipments of almost $50 million. The average electricity price faced by a plant is about 7 cents per kilowatt-hour. Approximately one-fifth of our plant-year observations purchase electricity from a utility covered by an RPS, somewhat higher than the average in the state-year dataset used in the first stage, indicating that RPS states are larger or more manufacturing-intensive than others. The average RPSPCT is 0.57 percent in the full sample; adjusting for those states without an RPS, the average RPS requires about 3% of electricity to come from renewable sources (RPSPCT/RPS). Nearly half our plants are operating in ozone non-attainment areas, whereas 17% and 3% operate in PM and SO2 non-attainment areas, respectively. We first present and discuss results for the full sample of manufacturing industries. Then we present and discuss results for a subsample of energy-intensive, trade-exposed industries where we might expect to find more significant effects.

Table 4 shows the results of our stage 2 regression model. All specifications include state and year fixed effects, while models 2 and 5 include a set of control variables, and models 3 and 6 add plant fixed effects. The OLS models with state fixed effects explain about 40% of the variation of electricity prices in our sample. The impact of the RPS stringency faced by the utility from which the plant purchases electricity, our key coefficient, is positive and significant across all six specifications. The coefficient magnitudes are similar between those using the actual level of RPS stringency (RPSPCT) and the ones using the predicted RPS stringency from the first stage (RPSPRD). Using the RPSPCT results, a plant purchasing electricity from utilities under a typical RPS requirement (3% renewables) would face approximately 6% higher electricity prices, which is statistically significant; using the RPSPRD results would result in about 5% higher electricity prices. This implies that electricity prices would rise by $0.003 - $0.004/KWh. These effects are consistent with the work of Palmer and Burtraw (2005) who find that an RPS has only a small effect on electricity prices at relatively low levels of stringency.

Our preferred second-stage specification, which we use to predict electricity prices for our third stage, is model 5 in table 4. We don't want to include plant-specific fixed-effects (model 6) in order to avoid possible plant-level endogeneity in the predicted price. The three dummy variables indicating if a plant purchases electricity from a plant located in a non-attainment county – NAPM, NAOZ, and NASO2 – have the expected positive impact on electricity prices, while LCVOTE, a measure of the state's U.S. Congressional delegation for environmental legislation, has an unexpected negative effect on electricity prices. The county-level demographic variables – PCTDEM, POPDEN, and PCINC – all have the expected positive impact on electricity prices, but the percent of the county employed in manufacturing has an unexpected negative effect on electricity prices. It is possible that the unexpected negative effect could be due to reverse causality – counties with higher electricity prices have less manufacturing activity. Finally, plant size has a positive impact on electricity prices.

Table 6 presents our third stage results, where we estimate the impact of predicted electricity prices from the second stage on employment, production worker hours and output. The models alternate between including year and industry fixed effects (models 1, 3, and 5) and including plant-level dummies (models 2, 4, and 6). Control variables in these models include the average local wage (payroll/employees) paid in similar nearby establishments, a measure of local agglomeration effects, plant-level controls and the annual import penetration ratio as well as year and industry fixed effects. In Table 5, the local wage and measure of agglomeration effects have the expected impacts in most cases – negative for wages and positive for agglomeration. Multi-unit plants, as expected, have higher employment (as well as production worker hours) and produce more output. Older plants tend to be larger in terms of employment and output.

For Table 6, in the OLS models with year and industry controls, we find the expected negative impact of predicted electricity prices on shipments, employment, and hours. However, when we include plant fixed effects (models 2, 4, and 6) the impact of predicted electricity prices changes sign and we find that higher electricity prices are associated with higher employment. This is surprising, though theoretically possible, as Deschênes (2012) notes that standard microeconomic theory cannot predict whether increases in electricity prices will increase or decrease labor demand. If the two inputs are highly substitutable, labor demand may increase with an increase in electricity prices, otherwise it may decrease. However, it is harder to explain why increases in electricity prices would also increase output. In any case, the effects of electricity prices on employment and output are very small. For example, for the full sample in our preferred specification in table 4 (model 5) we find that electricity prices faced by plants which purchase electricity from a utility that needs to meet an RPS requirement of 3% are approximately 5% higher than plants which do not. A 5% increase in electricity prices would cause total employment, production hours and shipments to increase by approximately 1-2%.

As noted earlier, most manufacturing plants use relatively little electricity as a share in their total cost, so we now explore the impact of electricity prices on output, employment, and hours for plants in those industries for whom such effects might be expected to be larger. These are the "EITE" industries – energy intensive and trade exposed – as listed in the report from the Interagency Competitiveness Analysis Team (2009). The EITE dataset includes only 63,600 observations, about 5% of the original sample. Table 5 shows the second stage model predicting log electricity prices for this subsample of EITE industries. As seen for the full sample earlier, plants whose supplying utility faces greater RPS stringency tend to pay higher prices for their electricity. Using the RPSPCT results, plants purchasing electricity from utilities facing a 3% RPS requirement face approximately 3% higher electricity prices than a plant facing no RPS requirement; using the RPSPRD results yields 6% higher electricity prices; both are statistically significant. This implies that electricity prices would rise by $0.002 - $0.004 /KWh.

Our preferred second-stage specification, which we use to predict electricity prices for our third stage, is model 5 in table 5 (again avoiding potential endogenity from the plant-specific fixed-effects). The three dummy variables indicating if a plant purchases electricity from a plant located in a non-attainment county – NAPM, NAOZ, and NASO2 – have the expected positive impact on electricity prices, while LCVOTE, a measure of the state's U.S. Congressional delegation for environmental legislation, now has the expected positive effect on electricity prices. The county-level demographic variables – PCTDEM, POPDEN, and PCINC – all have the expected positive impact on electricity prices, as does the percent of the county employed in manufacturing has an unexpected negative effect on electricity prices. Finally, plant size has a negative impact on electricity prices.

We then examine the impact of predicted electricity prices (taken from model 5 in table 5) on output, employment, and hours, shown in Table 7. For these EITE plants, we find that all six models show significant negative impacts of electricity prices – both for the OLS models with year and industry dummies (models 1, 3, 5) and the fixed effect analysis (models 2, 4, 6).

For comparison purposes, Tables 8 and 9 present results for the full sample and the EITE subsample, using the actual log electricity price (LELEC) rather than the predicted value (PRLELEC). The results show similar signs to those in Tables 6 and 7 – negative impacts of electricity prices in all models except for the full-sample fixed-effect ones. Focusing on the EITE results in Table 9, we see that the estimated impacts are slightly smaller for the OLS models, possibly driven by the somewhat smaller variance in PRLELEC compared to LELEC. For the fixed-effect models the results are dramatically smaller – on the order of one-eighth of the Table 7 results.

7. Concluding Remarks and Next Steps

Renewable portfolio standards (RPSs) are a relatively recent but increasingly popular phenomena in the United States. The majority of U.S. states had enacted RPSs by the end of our sample period, in order to encourage cleaner sources of power. In this paper we estimate the impact of RPS adoption on U.S. manufacturing activity, and in particular, labor demand, via its effect on electricity prices faced by manufacturing facilities. Using a large plant-level dataset covering the entire U.S. manufacturing sector from 1990 – 2009, as well as a smaller set of energy-intensive trade-exposed (EITE) industries, we find that plants purchasing electricity from utilities under an RPS requirement face approximately 3% - 6% significantly higher electricity prices. This implies that electricity prices would rise by $0.002 - $0.004/KWh. These RPS induced electricity price increases have an impact on manufacturing employment and output. The direction of the impact varies across specifications. In particular, the models including plant-specific fixed-effects for the full sample of industries show unexpectedly positive impacts of higher electricity prices on output, employment, and hours. However, when we focus on the EITE subsample, all models show the expected negative impacts of electricity prices on output, employment, and hours. In the EITE subsample using our preferred specification we find that electricity prices faced by plants which purchase electricity from a utility facing a 3% RPS requirement (the average requirement in our sample) are approximately 6% higher than at plants using non-RPS utilities. This 6% increase in electricity prices is associated with decreases in total employment, production worker hours and output of approximately 2-3%. Alternative estimates that use the actual electricity price rather than a predicted electricity price also find negative impacts, but much smaller, with all impacts less than 1%.

In the next version of this paper we plan to add more details about the RPS requirements faced by electric utilities. As noted earlier, we are planning to include additional state characteristics in the first-stage model predicting RPS stringency. In addition, we are interested in potential differences in the effective stringency of the RPS. For instance, the achieved percent renewables, which we currently utilize in our analysis, may be a poor reflection of actual stringency in states where hydropower, non-renewable, or existing sources are allowed to count towards the goal. Fischer (2009) also points out that the responsiveness of renewables relative to non-renewables in the state could be an important factor in predicting the direction of the RPS effect on electricity price. To control for this, we plan to explore including variables such as the amount of pre-existing renewable capacity in the state and whether a state relies on non-renewables that are easier or harder to ramp up or down as indicators of relative responsiveness. We will also explore including an indicator for having any RPS program in addition to a measure of the program's stringency.

In the next version of the paper we also, following Kahn and Mansur (2013), plan to include measures of electricity input prices based on annual fuel price and utility capacity fuel shares in our first stage electricity price model. We will explore further the differences in the results between the full sample and the plants in energy-intensive trade-exposed industries, including more detailed (quartile) measures of energy-intensity. We will also experiment with alternative sets of control variables and hope to expand the time period covered to 2011.

References:

Aldy, J., and W. Pizer. 2013. The Employment and Competitiveness Impacts of Power-Sector Regulations, in *Does Regulation Kill Jobs?*, eds., C. Coglianese, C. Carrigan, and A. Finkel. University of Pennsylvania Press.

Clemmer, S., A. Nogee, and M. Brower. 1999. *A Powerful Opportunity: Making Renewable Electricity the Standard*. Cambridge: Union of Concerned Scientists.

Cox, Michael, Andreas Peichl, Nico Pestel, Sebastian Siegloch (2013), "Labor Demand Effects of Rising Electricity Prices: Evidence for Germany", IZA Policy Paper No. 74.

Curtis, M. 2014. Who Loses Under Power Plant Cap-and-Trade Programs? Estimating the Impact of the NOx Budget Trading Program on Manufacturing Employment, Georgia State working paper.

Davis, S., C. Grim, John Haltiwanger, and M. Streitwieser. 2013. Electricity Unit Value Prices and Purchase Quantities: U.S. Manufacturing Plants, 1963–2000, *Review of Economics and Statistics*, 95(4): 1150-1165.

Deschênes, Olivier (2012) "Climate Policy and Labor Markets" in The Design and Implementation of U.S. Climate Policy, Don Fullerton and Catherine Wolfram, eds. University of Chicago Press, p. 37 – 49.

EIA (Energy Information Administration). 2014. *Levelized Cost and Levelized Avoided Cost of New Generation Resources in the Annual Energy Outlook 2014*. Washington, DC: EIA. http://www.eia.gov/forecasts/aeo/electricity_generation.cfm.

EIA (Energy Information Administration). 2003. *Impacts of a 10 Percent Renewable Portfolio Standard*. SR/OIA/F/2003-01. Washington, DC: EIA.

Ferris, Ann E., Ronald J. Shadbegian and Ann Wolverton (2014) "The Effect of Environmental Regulation on Power Sector Employment: Phase I of the Title IV SO2 Trading Program" (with Ann Ferris and Ann Wolverton). *Journal of the Association of Environmental and Resource Economists* 1: 521-553.

Fischer, C. 2009. Renewable Portfolio Standards; When Do They Lower Energy Prices? *The Energy Journal* 30, 4: 81-98.

Gray, Wayne B., Ronald J. Shadbegian, Chunbei Wang, and Merve Meral. (2014) "Do EPA regulations affect labor demand? Evidence from the pulp and paper industry." *Journal of Environmental Economics and Management* 68:188–202.

Gray, W., and R. Shadbegian. 2014. Do the Job Effects of Regulation Differ with the Competitive Environment? in *Does Regulation Kill Jobs?,* eds., C. Coglianese, C. Carrigan, and A. Finkel, eds. University of Pennsylvania Press.

Greenstone, M. 2002. The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures. *Journal of Political Economy*, 110: 1175-1219.

Interagency Competitiveness Analysis Team. 2009. The Effects of H.R. 2454 on International Competitiveness and Emission Leakage in Energy-Intensive, Trade-Exposed Industries. An interagency report responding to a request from Senators Bayh, Spector, Stabenow, McCaskill, and Brown. Washington, DC: U.S. Government. http://www.epa.gov/climatechange/economics/pdfs/InteragencyReport_Competitiveness-EmissionLeakage.pdf

Jaccard, M. 2004. Renewable Portfolio Standard in *Encyclopedia of Energy*. Volume 5: 413-421.

Jarmin, R., and J. Miranda. 2002. The Longitudinal Business Database. Center for Economic Studies Discussion Paper CES-WP-02-17

Kahn, M. 2012. Comment on "Climate Policy and Labor Markets", in The Design and Implementation of U.S. Climate Policy, Don Fullerton and Catherine Wolfram, eds. University of Chicago Press, p. 49-51.

Kahn, M., and E. Mansur. 2013. Do Local Energy Prices and Regulation Affect the Geographic Concentration of Employment? *Journal of Public Economics*, 101: 105–114.

Lopez, A., B. Roberts, D. Heimiller, N. Blair, and G. Porro (2012). U.S. Renewable Energy Technical Potentials: A GIS-Based Analysis. NREL Technical Report. NREL/TP-6A20-51946.

Lyon, T., and H. Yin. 2010. Why Do States Adopt Renewable Portfolio Standards: An Empirical Investigation. *The Energy Journal* 31, 3.

Nogee, A., J. Deyette, and S. Clemmer. 2007. The Projected Impacts of a National Renewable Portfolio Standard. *The Energy Journal* 20, 4: 33-47.

Palmer, K.,and D. Burtraw. 2005. Cost-Effectiveness of Renewable Electricity Policies *Energy Economics* 27(6): 873-894.

Schmalansee, R. 2011. Evaluating Policies to Increase Electricity Generation from renewable Energy. *Review of Environmental Economics and Policy* 6: 1: 45-64.

Schott, Peter K. 2008. The relative sophistication of Chinese exports. *Economic Policy Journal*: 5-49.

Walker, W. Reed (2011). "Environmental Regulation and Labor Reallocation: Evidence from the Clean Air Act." American Economic Review Papers and Proceedings 101 (3):442–447.

Walker, W Reed. (2013). "The Transitional Costs of Sectoral Reallocation: Evidence from the Clean Air Act and the Workforce." Quarterly Journal of Economics: 1787–1835.

Wiser, R., and M. Bolinger. 2007. Can Deployment of Renewable Energy Put Downward Pressure on Natural Gas Prices? *Energy Policy*. 35: 295–306

Wiser, R., C. Namovicz, M. Gielecki, and R. Smith. 2007. The Experience with Renewable Portfolio Standards in the United States. *The Electricity Journal* 20, 4: 8-20.

Yi, H. 2013. “Clean Energy Policies and Green Jobs: An Evaluation of Green Jobs in U.S. Metropolitan Areas.” *Energy Policy*, 56: 644-65.

Data Sources:
NBER-CES industry data (www.nber.org/data/nbercesS5809.html)

Peter Schott trade data from NAICS-based industry file provided 1990 to 2005 data - http://faculty.som.yale.edu/peterschott/files/research/data/xm_naics_89_105_20120424.zip

Supplemented from the Peter Schott trade data with year-by-year imports and exports for 2006-2011 (sample links for the 2006 data below – years 2007-2011 use file names "107n"-"111n")
http://faculty.som.yale.edu/peterschott/files/research/data/imp_detl_yearly_106n.zip
http://faculty.som.yale.edu/peterschott/files/research/data/exp_detl_yearly_106n.zip

BEA - Regional Data web page, http://www.bea.gov/itable/iTable.cfm?ReqID=70&step=1
Local Area Personal Income and Employment category, mostly from Economic Profiles table (CA30). Percent of jobs in manufacturing calculated from total and manufacturing employment found in table of Total Full-Time and Part-Time Employment by Industry (CA25, CA25N)

The USA Counties database provides data through 2010 from a variety of sources (including Population Census and Annual Community Survey).
http://www.census.gov/support/USACdataDownloads.html
Updated information for more recent years was taken from Census QuickFacts for Counties at http://quickfacts.census.gov/qfd/index.html

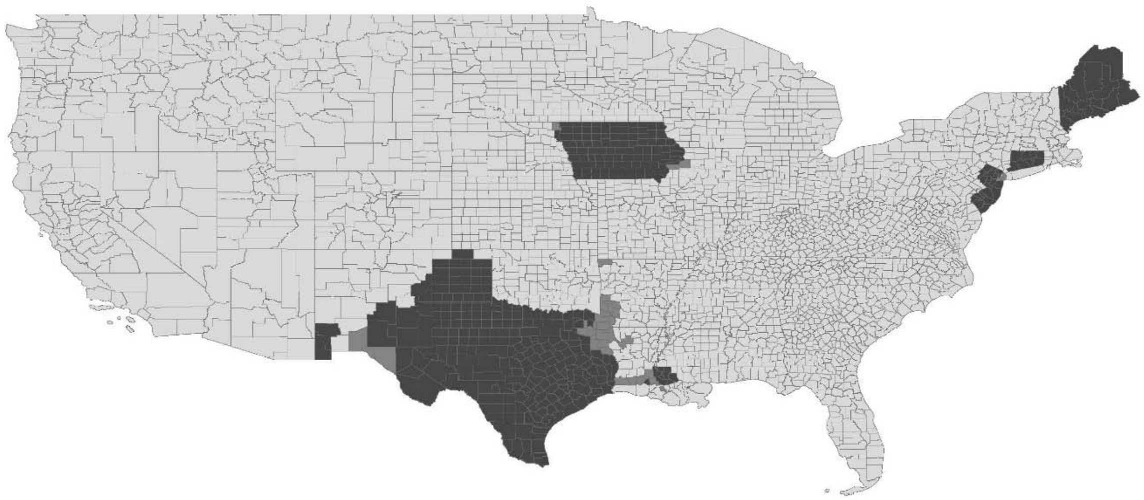
League of Conservation Voters – annual scorecard of pro-environment voting by county's Congressional delegation (average score for House delegation used here)
http://scorecard.lcv.org/scorecard/archive

County non-attainment status for criteria pollutants (these data used PM10, ozone, and SO2). Taken from EPA Green Book data:
http://www.epa.gov/airquality/greenbook/data_download.html

Electricity generation data:
http://www.epa.gov/cleanenergy/documents/egridzips/eGRID_9th_edition_V1-0_year_2010_Data.xls

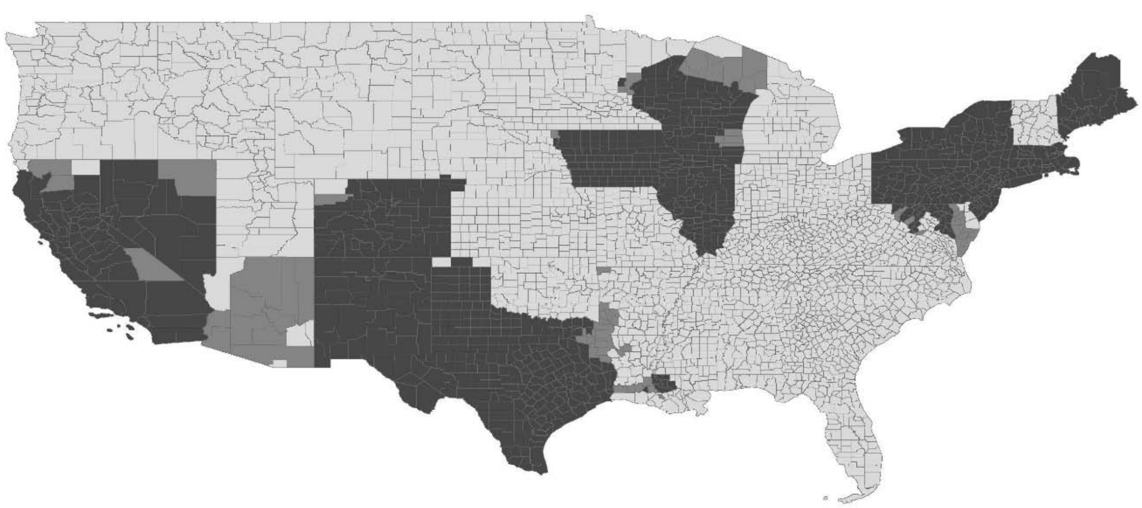
RPS data: DSIRE (Database of State Incentives for Renewable Energy). 2013. *Renewable Portfolio Standard Database*. March. http://www.dsireusa.org/rpsdata/RPSspread031813.xlsx

Figure 1
RPS – County-level measure for 2000



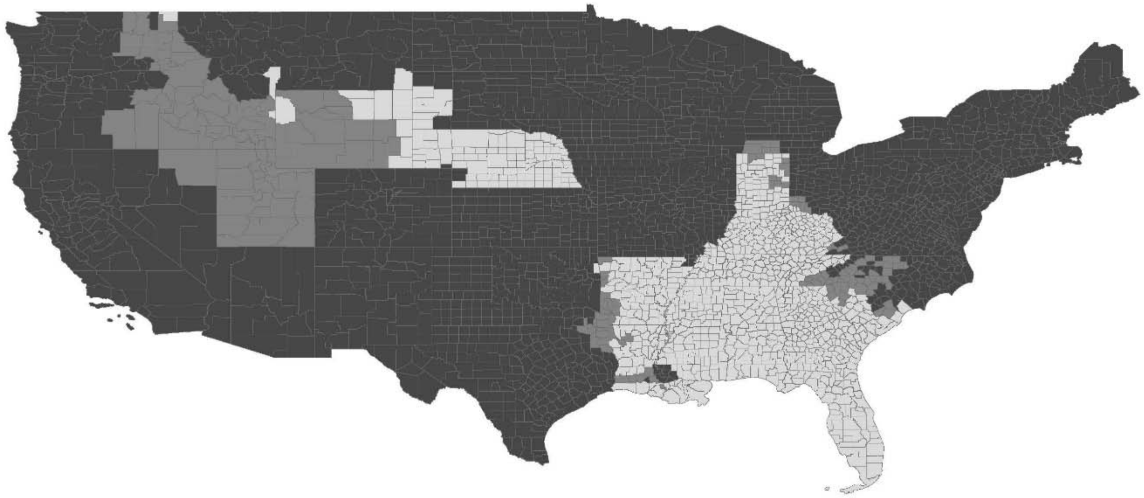
(light=RPS<0.1, shaded=RPS between 0.1 and 0.9, black=RPS>0.9)

Figure 2
RPS – County-level measure for 2005



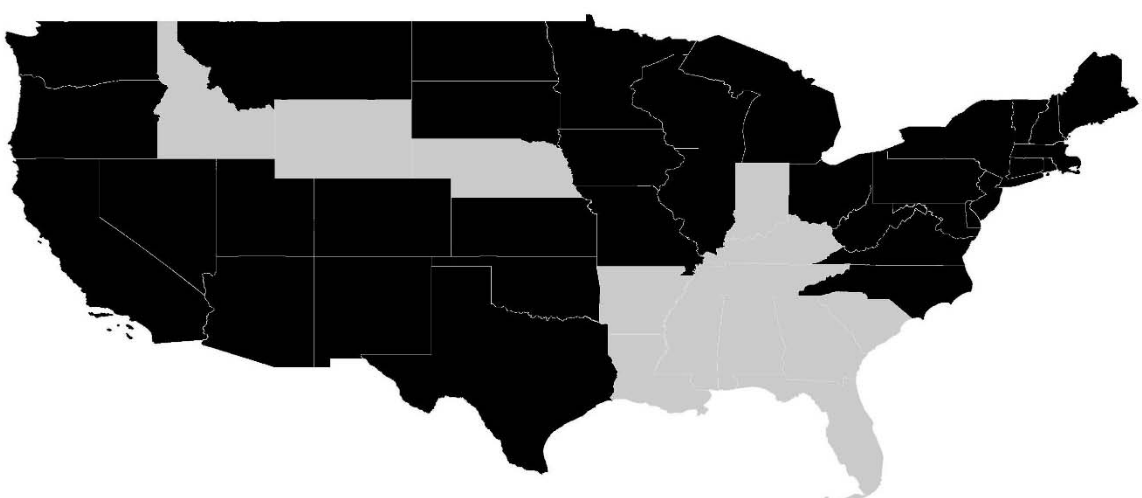
(light=RPS<0.1, shaded=RPS between 0.1 and 0.9, black=RPS>0.9)

Figure 3
RPS – County-level measure for 2010



(light=RPS<0.1, shaded=RPS between 0.1 and 0.9, black=RPS>0.9)

Figure 4
RPS – State-level measure for 2010



(light=RPS<0.1, shaded=RPS between 0.1 and 0.9, black=RPS>0.9)

Table 1 – Summary Statistics for State-Level Dataset

RPSPCT (N=960)

Variable	**Mean (Standard Deviation)**
*RPS (**RPS**)* *(0-1 dummy)*	0.129 (0.098)
*RPS Stringency (**RPSPCT**)* (percentage)	0.572 (2.472)
*Unemployment Rate **(UNEMP**)* (percentage)	5.078 (1.354)
*Electricity Deregulation **(DEREG)***	0.313 (0.464)
*ASES Staff **(ASES)***	0.313 (0.464)
*Renewables capacity **(RENCAP)*** (percentage)	12.958 (21.572)
*Natural gas capacity **(NGCAP)*** (percentage)	11.679 (18.242)
*Onshore wind technical potential **(ONSHORE_WIND)*** (TWh)	654.24 (1171.11)
*Offshore wind technical potential **(OFFSHORE_WIND)*** (TWh)	294.57 (533.65)
*Concentrated solar technical potential **(CSP)*** (TWh)	2419.40 (4780.73)
*Utility-scale photovoltaic solar technical potential **(UTILITY_SOLAR)*** (TWh)	5719.18 (6339.98)
*Biogas technical potential **(BIOGAS)*** (TWh)	1.85 (2.49)

Table 2: Tobit model predicting RPSPCT

Variable	**Coefficient (Standard Error)**
Unemployment Rate ***(UNEMP)***	-0.84* (0.44)
Electricity Deregulation ***(DEREG)***	-0.62 (1.52)
ASES Staff ***(ASES)***	0.82 (1.19)
Renewables capacity ***(RENCAP)***	0.11*** (0.04)
Natural gas capacity ***(NGCAP)***	0.12*** (0.03)
Onshore wind technical potential ***(ONSHORE_WIND)***	1.32 (0.91)
Onshore wind technical potential - squared	-0.03 (0.05)
Offshore wind technical potential ***(OFFSHORE_WIND)***	1.55 (0.95)
Offshore wind technical potential – squared	-0.66 (0.06)
Concentrated solar technical potential ***(CSP)***	-15.00*** (2.41)
Concentrated solar technical potential - squared	0.79*** (0.13)
Utility-scale photovoltaic solar technical potential ***(UTILITY_SOLAR)***	15.04*** (2.41)
Utility-scale photovoltaic solar technical potential - squared	-0.56** (0.20)
Biogas technical potential ***(BIOGAS)***	-11.31*** (3.59)
Biogas technical potential - squared	0.65** (0.26)
Adjusted R-Squared	0.28

Table 3
Summary Statistics (1,275,800 obs from 327,200 plants)

Variable	Mean	S.D.	Description	Sources
ELEC	0.072	.031	Plant electricity price, $/kwh	ASM
LELEC	-2.711	.374	Log of plant electricity price, $/kwh	ASM
PRLELEC	-2.711	.235	Predicted log plant elec. price, $/kwh	ASM
TVS	47255.1	269561.1	Total value of shipments, $000 (1997$)	ASM
TE	150.952	430.320	Plant total employment	ASM
PH	216.66	551.816	Production worker hours, hours (000)	ASM
LSHIP	8.982	1.895	Log total value of shipments, $000	ASM
LEMP	3.973	1.430	Log plant total employment	ASM
LPH	4.255	1.531	Log production worker hours, hours (000)	ASM
RPS	.211	.402	Pct. of county elec. under RPS	RPS, EPA
RPSPCT	.0057	.021	RPS goal, renewable pct generation adjusted for compliance rate, averaged across suppliers	RPS, EPA
RPSPRD	.0030	.013	Predicted RPSPCT (from Stage 1, Table 2)	RPS
NAPM	.169	.374	0/1, County non-attainment, particulates	EPA
DNAPM	.022	.148	0/1, Particulate polluter in non-att cty	EPA
NAOZ	.487	.500	0/1, County non-attainment, ozone	EPA
DNAOZ	.197	.398	0/1, Ozone polluter in non-att cty	EPA
NASO2	.031	.174	0/1, County non-attainment, sulfur oxide	EPA
DNASO2	.004	.062	0/1, Sulfur oxide polluter in non-att cty	EPA
LCVOTE	.487	.191	State pro-environment voting score	LCV
PCTDEM	.47	.120	Pct. of county that voted Democrat	USACTY
POPDEN	6.131	1.659	Log county pop. density (pop/land area)	BEA
PCINC	10.237	.324	Log county per capita income	BEA
PCTMAN	.138	.078	Pct. county employed in manufacturing	BEA
COLGRD	.237	.093	Pct. of county that graduated college	USACTY
NONENG	.155	.144	Pct. of cty speaking non-english language.	USACTY
CIWAGE	2.891	.883	Log of avg. local wage, similar establishments	CMF
CIEMP	6.27	1.488	Log, total emp. in same ind and cty	CMF
MU	.455	.498	0/1, part of multi-plant firm.	ASM
AGE5	.101	.301	0/1, Plant 0-4 years old	LBD
AGE10	.145	.352	0/1, Plant 5-9 years old	LBD
SIZE50	.243	.429	0/1, Plant in third quartile of tvs	CMF
SIZE75	.562	.496	0/1, Plant in top quartile of tvs	CMF
IMPRAT	.003	.008	Import penetration ratio	SCHOTT

Table 4

Impact of RPS on Electricity Prices

	(1) **LELEC**	**(2)** **LELEC**	**(3)** **LELEC**	**(4)** **LELEC**	**(5)** **LELEC**	**(6)** **LELEC**
RPSPCT	1.8467*** (117.60)	1.8276*** (116.39)	1.8611*** (115.16)			
RPSPRD				1.68*** (67.39)	1.62*** (64.93)	1.67*** (66.91)
NAPM		0.0219*** (22.61)	0.0228*** (14.72)		0.0202*** (20.81)	0.0248*** (15.91)
NAOZ		-0.0003 (-0.43)	-0.0245*** (-22.39)		0.00179* (2.21)	-0.0222*** (-20.19)
NASO2		0.0273*** (16.29)	-0.00213 (0.85)		0.0222*** (13.20)	-0.00705** (-2.79)
LCVOTE		-0.0349*** (-9.65)	0.0133*** (3.84)		-0.00849* (-2.33)	0.0252*** (7.20)
PCTDEM		0.0546*** (17.72)	-0.2172*** (-31.07)		0.0846*** (27.48)	-0.1*** (-14.43)
POPDEN		0.0106*** (34.43)	0.0391*** (31.26)		0.00830*** (27.03)	0.0292*** (23.32)
PCINC		0.0481*** (28.27)	0.0437*** (8.59)		0.0569*** (33.32)	0.0730*** (14.28)
PCTMAN		-0.0281*** (-6.40)	0.2097*** (15.86)		-0.0259*** (-5.89)	0.1997*** (14.99)
MU		-0.0307*** (-53.69)			-0.0307*** (-53.59)	
AGE5		-0.0105*** (-10.59)	0.0212*** (12.51)		-0.0110*** (-11.01)	0.0206*** (12.11)
AGE10		-0.00601*** (-8.00)	0.00593*** (5.85)		-0.00595*** (-7.89)	0.00571*** (5.61)
SIZE50		0.00689*** (8.22)	-0.01004*** (-8.69)		0.00701*** (8.34)	-0.00989*** (-8.51)
SIZE75		0.00921*** (11.52)	-0.001799 (-1.37)		0.00965*** (12.03)	-0.00120 (-0.91)
Year	X	X	X	X	X	X
State	X	X		X	X	
Plant			X			X
R-sq	0.391	0.399		0.387	0.395	

N=1,275,800; t statistics in parentheses; *p<0.05, **p<0.01, ***p<0.001

Table 5 (EITE=1)

Impact of RPS on Electricity Prices

	(1) **LELEC**	**(2)** **LELEC**	**(3)** **LELEC**	**(4)** **LELEC**	**(5)** **LELEC**	**(6)** **LELEC**
RPSPCT	1.0966*** (13.28)	1.0939*** (13.60)	1.082*** (15.23)			
RPSPRD				2.15*** (20.02)	2.09*** (20.08)	2.00*** (22.58)
NAPM		0.0260*** (5.05)	0.0097 (1.57)		0.0235*** (4.57)	0.0085 (1.39)
NAOZ		0.0168 (4.52)	0.0009 (0.19)		0.0176*** (4.73)	0.0004 (0.09)
NASO2		0.0701*** (9.40)	0.0661*** (6.38)		0.0657*** (8.82)	0.0556*** (5.38)
LCVOTE		0.0293 (1.75)	0.0349* (2.55)		0.0714*** (4.27)	0.0723*** (5.27)
PCTDEM		0.0742*** (5.11)	-0.2407*** (-9.02)		0.0927*** (6.42)	-0.1529*** (-5.83)
POPDEN		0.0119*** (8.06)	0.0142* (2.49)		0.0114*** (7.76)	0.0107 (1.88)
PCINC		0.1036*** (10.49)	0.1613*** (6.96)		0.0984*** (9.98)	0.1034*** (4.42)
PCTMAN		0.0473* (2.52)	0.3036*** (6.70)		0.0339 (1.81)	0.2188*** (4.82)
MU		-0.1097*** (-33.56)			-0.1098*** (-33.64)	
AGE5		0.0255*** (4.85)	0.0293*** (3.72)		0.0258*** (4.91)	0.0293*** (3.74)
AGE10		0.0221*** (5.54)	0.0103* (2.23)		0.0226*** (5.67)	0.0111* (2.41)
SIZE50		-0.0429*** (-11.88)	-0.0160** (-3.36)		-0.0429*** (-11.91)	-0.0158** (-3.32)
SIZE75		-0.0985*** (-29.02)	-0.0220*** (-3.95)		-0.0983*** (-29.01)	-0.0202*** (-3.65)
Year	X	X	X	X	X	X
State	X	X		X	X	
Plant			X			X
R-sq	0.365	0.408		0.367	0.410	

N=63,600; t statistics in parentheses; *p<0.05, **p<0.01, ***p<0.001

Table 6

Impact of Electricity Prices on Shipments/Employment/Hours (Full Sample)

	(1) LSHIP	(2) LSHIP	(3) LEMP	(4) LEMP	(5) LPH	(6) LPH
PRLELEC	-0.0231**	0.515***	-0.230***	0.291***	-0.0605***	0.295***
	(-2.93)	(20.16)	(-3.72)	(14.81)	(-8.82)	(11.74)
NAPM	-0.0866***	0.0008	-0.0903***	0.0011	-0.0969***	0.0006
	(-22.67)	(0.23)	(-30.15)	(0.42)	(-29.15)	(0.18)
DNAPM	0.141***	-0.0116	0.134***	0.0034	0.130***	0.0145*
	(16.63)	(-1.57)	(20.23)	(0.59)	(17.65)	(1.99)
NAOZ	0.0366***	-0.0198***	0.0266***	-0.0082***	0.0318***	-0.0124***
	(10.15)	(-7.28)	(9.42)	(-3.93)	(10.14)	(-4.65)
DNAOZ	-0.0402***	0.0089**	-0.0269***	0.0009	-0.0175***	0.0020
	(-8.85)	(2.64)	(-7.55)	(0.33)	(-4.41)	(0.61)
NASO2	0.0245***	-0.0277***	0.0386***	-0.0259***	0.0276***	-0.0194***
	(3.53)	(-4.92)	(7.09)	(-5.98)	(4.58)	(-3.50)
DNASO2	0.0454*	-0.0874***	0.0633***	0.0310**	0.0784***	0.0117
	(2.39)	(-5.99)	(4.24)	(2.76)	(4.74)	(0.82)
LCVOTE	0.0227**	-0.0443***	0.0670***	-0.0251***	0.0517***	-0.0198**
	(3.03)	(-6.04)	(11.38)	(-4.44)	(7.92)	(-2.74)
PCTDEM	-0.174***	-0.138***	-0.148***	-0.0177	-0.180***	-0.0451**
	(-14.42)	(-9.08)	(-15.62)	(-1.52)	(-17.20)	(-3.02)
POPDEN	0.0214***	-0.0151***	0.0122***	-0.0272***	0.0115***	-0.0229***
	(18.08)	(-5.22)	(13.16)	(-12.24)	(11.21)	(-8.05)
PCINC	0.115***	0.420***	-0.0778***	0.217***	-0.100***	0.286***
	(11.47)	(31.32)	(-9.91)	(21.07)	(-11.50)	(21.64)
COLGRD	-0.0034	-1.048***	0.0932***	-0.437***	-0.142***	-0.732***
	(-0.14)	(-26.63)	(5.01)	(-14.43)	(-6.90)	(-18.91)
NONENG	-0.503***	0.152***	-0.476***	0.357***	-0.454***	0.375***
	(-42.11)	(5.01)	(-50.73)	(15.34)	(-43.70)	(11.62)
CIWAGE	-0.529***	0.0316***	-0.554***	-0.0373***	-0.555***	-0.0347***
	(-348.95)	(27.76)	(-465.63)	(-42.61)	(-420.66)	(-31.01)
CIEMP	0.304***	-0.00182*	0.288***	0.0216***	0.298***	0.0224***
	(343.03)	(-2.32)	(415.27)	(35.74)	(387.28)	(29.04)
MU	1.0194***		0.653***		0.687***	
	(388.20)		(316.89)		(294.02)	
AGE5	-1.171***	-0.237***	-0.966***	-0.247***	-0.994***	-0.243***
	(-301.39)	(-67.81)	(-316.86)	(-91.69)	(-294.02)	(-70.46)

Table 6 (Cont.)

Impact of Electricity Prices on Shipments/Employment/Hours (Full Sample)

	(1) **LSHIP**	**(2)** **LSHIP**	**(3)** **LEMP**	**(4)** **LEMP**	**(5)** **LPH**	**(6)** **LPH**
AGE10	-0.232***	-0.0542***	-0.252***	-0.0737***	-0.265***	-0.0696***
	(-73.96)	(-25.27)	(-102.08)	(-44.66)	(-96.81)	(-32.99)
IMPRAT	4.233***	0.846***	2.169***	0.0161	2.847***	0.113
	(21.86)	(8.04)	(14.27)	(0.20)	(16.90)	(1.09)
Year	X	X	X	X	X	X
Industry	X		X		X	
Plant		X		X		X
R-sq	0.591		0.557		0.526	

N=1,275,836; t statistics in parentheses; *p<0.05, **p<0.01, ***p<0.001

Table 7
(EITE=1)
Impact of Electricity Prices on Shipments/Employment/Hours

	(1) LSHIP	(2) LSHIP	(3) LEMP	(4) LEMP	(5) LPH	(6) LPH
PRLELEC	-1.092***	-0.186**	-0.769***	-0.502***	-0.793***	-0.545***
	(-32.35)	(-2.68)	(-30.17)	(-10.21)	(-28.64)	(-8.68)
NAPM	-0.280***	0.0215	-0.176***	0.0452**	-0.205***	0.0210
	(-10.95)	(1.17)	(-9.14)	(3.47)	(-9.79)	(1.27)
DNAPM	0.215***	-0.0159	0.170***	-0.0260	0.192***	0.0126
	(6.63)	(-0.68)	(6.94)	(-1.56)	(7.21)	(0.59)
NAOZ	0.369**	-0.0494***	0.259***	-0.0257*	0.248***	-0.0227
	(18.77)	(-3.53)	(17.45)	(-2.59)	(15.38)	(-1.79)
DNAOZ	-0.163***	0.0816***	-0.133***	0.0450***	-0.111***	0.0268
	(-7.39)	(4.94)	(-7.99)	(3.84)	(-6.13)	(1.79)
NASO2	0.0721	-0.111**	0.0818*	-0.102***	0.125**	-0.0501
	(1.34)	(-2.84)	(2.01)	(-3.69)	(2.82)	(-1.41)
DNASO2	0.0559	0.131**	0.0911	0.128***	0.0714	0.0722
	(0.89)	(2.87)	(1.93)	(3.97)	(1.39)	(1.76)
LCVOTE	-0.320***	-0.123***	0.0139	-0.0087	-0.0627*	-0.0274
	(-9.52)	(-4.12)	(0.55)	(-0.41)	(2.28)	(-1.02)
PCTDEM	0.635***	-0.0198	0.392***	-0.0980*	0.433***	-0.0751
	(11.42)	(-0.34)	(9.34)	(-2.36)	(9.48)	(-1.42)
POPDEN	-0.0302***	-0.0363**	-0.0086*	0.0113	-0.0210***	0.0223
	(-7.20)	(-2.66)	(-2.09)	(1.17)	(-4.70)	(1.81)
PCINC	0.576***	0.573***	0.313***	0.256***	0.317***	0.273***
	(11.14)	(10.12)	(8.01)	(6.38)	(7.46)	(5.31)
COLGRD	-1.458***	-1.108***	-0.853***	-0.443***	-1.079 ***	-0.911***
	(-12.35)	(-6.31)	(-9.57)	(-3.35)	(-11.14)	(-5.72)
NONENG	0.392***	1.028***	-0.0895*	0.416***	-0.111*	0.455***
	(6.77)	(8.55)	(-2.05)	(4.31)	(-2.34)	(3.69)
CIWAGE	-0.458***	0.0396***	-0.532***	-0.0356***	-0.534***	-0.0358***
	(-71.23)	(8.55)	(-109.50)	(-10.83)	(-101.19)	(-8.53)
CIEMP	0.392***	-0.0045	0.382***	0.0280***	0.396***	0.0301***
	(87.31)	(-1.19)	(112.53)	(10.37)	(107.23)	(8.74)
MU	1.083***		0.597***		0.675***	
	(73.78)		(53.86)		(56.08)	
AGE5	-1.549***	-0.192***	-1.280***	-0.184***	-1.313***	-0.212***
	(-71.48)	(-11.24)	(-78.24)	(-15.19)	(-73.81)	(-13.67)

Table 7 (Cont.)

Impact of Electricity Prices on Shipments/Employment/Hours (EITE=1)

	(1) **LSHIP**	**(2)** **LSHIP**	**(3)** **LEMP**	**(4)** **LEMP**	**(5)** **LPH**	**(6)** **LPH**
AGE10	-0.195***	-0.0517***	-0.272***	-0.0757***	-0.297***	-0.0903***
	(-11.87)	(-5.09)	(-21.89)	(-10.51)	(-22.05)	(-9.83)
IMPRAT	4.452**	-2.190**	2.407	-1.096*	3.317*	-0.733
	(2.69)	(-3.38)	(1.89)	(-2.38)	(2.40)	(-1.25)
Year	X	X	X	X	X	X
Industry	X		X		X	
Plant		X		X		X
R-sq	0.552		0.546		0.544	
N=63,600; t statistics in parentheses; *p<0.05, **p<0.01, ***p<0.001						

Table 8

Impact of Electricity Prices on Shipments/Employment/Hours (Full Sample)

	(1) LSHIP	(2) LSHIP	(3) LEMP	(4) LEMP	(5) LPH	(6) LPH
LELEC	-0.176**	0.0240***	-0.128***	0.0077***	-0.156***	-0.0017
	(-51.38)	(11.13)	(47.62)	(4.62)	(-52.46)	(-0.81)
NAPM	-0.050***	0.0134	-0.0893***	0.0084**	-0.0961***	0.0083*
	(-22.30)	(3.90)	(-29.86)	(3.18)	(-28.98)	(2.43)
DNAPM	0.138***	-0.0123	0.132***	0.0029	0.127***	0.0138
	(16.26)	(-1.65)	(19.90)	(0.50)	(17.33)	(1.90)
NAOZ	0.0530***	-0.0164***	0.0278***	-0.0065***	0.0416***	-0.0109***
	(15.16)	(-6.05)	(13.80)	(-3.10)	(13.69)	(-4.07)
DNAOZ	-0.0387***	0.0086**	-0.0258***	0.0007	-0.0158***	0.0019
	(-8.53)	(2.55)	(-7.23)	(0.27)	(-4.01)	(0.57)
NASO2	0.0217***	-0.0147**	0.0367***	-0.0186***	0.0263***	-0.012**
	(3.13)	(-2.63)	(6.75)	(-4.32)	(4.35)	(-2.19)
DNASO2	0.0464*	-0.0872***	0.0639***	0.0311**	0.0785***	0.0119
	(2.44)	(-5.98)	(4.28)	(2.77)	(4.75)	(0.83)
LCVOTE	0.0802***	-0.0520***	0.106***	-0.0294***	0.0873***	-0.0242***
	(11.52)	(-5.98)	(19.46)	(-5.22)	(14.40)	(-3.35)
PCTDEM	-0.164***	-0.0962***	-0.141***	0.0051	-0.174***	-0.0231
	(-13.64)	(-6.38)	(-14.93)	(0.44)	(-16.60)	(-1.56)
POPDEN	0.0205***	-0.0111***	0.0114***	-0.0248***	0.0107***	-0.0203***
	(17.14)	(-3.83)	(12.32)	(-11.20)	(10.46)	(-7.16)
PCINC	0.146***	0.493***	-0.0561***	0.260***	-0.0783***	0.332***
	(14.65)	(38.42)	(-7.18)	(26.36)	(-16.60)	(26.27)
COLGRD	-0.0764**	-1.118***	0.0417*	-0.481***	-0.195***	-0.784***
	(-3.12)	(-28.54)	(2.35)	(-15.95)	(-9.47)	(-20.35)
NONENG	-0.393***	0.274***	-0.399***	0.429***	-0.382***	0.453***
	(-35.51)	(9.28)	(-45.99)	(18.89)	(-29.69)	(15.61)
CIWAGE	-0.527***	0.0315***	-0.552***	-0.0373***	-0.553***	-0.0347***
	(-347.38)	(27.71)	(-464.18)	(-42.65)	(-419.08)	(-31.06)
CIEMP	0.302***	-0.0019*	0.287***	0.0215***	0.297***	0.0224***
	(340.88)	(-2.41)	(413.23)	(35.70)	(385.15)	(29.05)
MU	1.018***		0.652***		0.687***	
	(390.01)		(318.37)		(302.05)	
AGE5	-1.174***	-0.245***	-0.968***	-0.251***	-0.996***	-0.247***
	(-302.62)	(-70.51)	(-317.97)	(-93.86)	(-295.05)	(-72.11)

Table 8 (Cont.)

Impact of Electricity Prices on Shipments/Employment/Hours (Full Sample)

	(1) LSHIP	(2) LSHIP	(3) LEMP	(4) LEMP	(5) LPH	(6) LPH
AGE10	-0.235***	-0.0576***	-0.253***	-0.0756***	-0.266***	-0.0715***
	(-74.78)	(-26.93)	(-102.84)	(-45.93)	(-97.54)	(-33.96)
IMPRAT	4.224***	0.833***	2.162***	0.0094	2.842***	0.107
	(21.84)	(7.92)	(14.24)	(0.12)	(16.88)	(1.04)
Year	X	X	X	X	X	X
Industry	X		X		X	
Plant		X		X		X
R-sq	0.592		0.558		0.527	

N=1,275,836; t statistics in parentheses; *p<0.05, **p<0.01, ***p<0.001

Table 9
(EITE=1)

Impact of Electricity Prices on Shipments/Employment/Hours

	(1) LSHIP	(2) LSHIP	(3) LEMP	(4) LEMP	(5) LPH	(6) LPH
LELEC	-0.818***	-0.0249**	-0.578***	-0.0545***	-0.652***	-0.0842***
	(-54.17)	(-2.62)	(-50.58)	(-8.08)	(-52.59)	(-9.78)
NAPM	-0.296***	0.0173	-0.188***	0.0339**	-0.216***	0.0088
	(-11.77)	(0.95)	(-9.87)	(3.47)	(-10.48)	(0.53)
DNAPM	0.215***	-0.0159	0.170***	-0.0262	0.190***	0.0129
	(6.73)	(-0.68)	(7.02)	(-1.57)	(7.25)	(0.60)
NAOZ	0.320**	-0.0527***	0.224***	-0.0344***	0.217***	-0.0324*
	(16.78)	(-3.78)	(15.57)	(-3.48)	(13.91)	(-2.57)
DNAOZ	-0.153***	0.0813***	-0.126***	0.0440***	-0.101***	0.0260
	(-7.03)	(4.93)	(-7.65)	(3.76)	(-5.70)	(1.74)
NASO2	0.0534	-0.124**	0.0687	-0.138***	0.114**	-0.0881*
	(1.01)	(-3.20)	(1.71)	(-5.02)	(2.62)	(-2.50)
DNASO2	0.0550	0.132**	0.0904	0.132***	0.0694	0.0781
	(0.89)	(2.92)	(1.94)	(4.11)	(1.37)	(1.90)
LCVOTE	-0.425***	-0.132***	-0.0593*	-0.0346	-0.117***	-0.0545*
	(-13.65)	(-4.47)	(-2.52)	(-1.65)	(-4.59)	(-2.04)
PCTDEM	0.615***	-0.0390	0.378***	-0.138***	0.423***	-0.134*
	(11.23)	(-0.67)	(9.14)	(-3.57)	(9.42)	(-2.53)
POPDEN	-0.0411***	-0.0383**	-0.0010*	0.0059	-0.0228***	0.0164
	(-7.67)	(-2.81)	(-2.45)	(0.61)	(-5.19)	(1.33)
PCINC	0.546***	0.533***	0.291***	0.144***	0.302***	0.158**
	(10.74)	(9.88)	(7.58)	(3.77)	(7.25)	(3.23)
COLGRD	-1.480***	-1.060***	-0.867***	-0.307*	-1.105 ***	-0.775***
	(-12.73)	(-6.08)	(-9.88)	(-2.48)	(-11.58)	(-4.91)
NONENG	0.313***	0.987***	-0.144***	0.299**	-0.125**	0.341**
	(5.77)	(7.33)	(-3.51)	(3.13)	(-2.82)	(2.79)
CIWAGE	-0.442***	0.0393***	-0.520***	-0.0365***	-0.521***	-0.0365***
	(-69.57)	(8.49)	(-108.30)	(-11.11)	(-99.92)	(-8.72)
CIEMP	0.372***	-0.0045	0.367***	0.0281***	0.378***	0.0303***
	(83.44)	(-1.18)	(108.98)	(10.40)	(103.49)	(8.80)
MU	1.152***		0.645***		0.720***	
	(83.40)		(61.87)		(63.56)	
AGE5	-1.563***	-0.200***	-1.290***	-0.205***	-1.319***	-0.233***
	(-73.42)	(-11.86)	(-80.11)	(-17.14)	(-75.55)	(-15.29)

Table 9 (Cont.)

Impact of Electricity Prices on Shipments/Employment/Hours (EITE=1)

	(1) **LSHIP**	**(2)** **LSHIP**	**(3)** **LEMP**	**(4)** **LEMP**	**(5)** **LPH**	**(6)** **LPH**
AGE10	-0.216***	-0.0566***	-0.286***	-0.0891***	-0.312***	-0.105***
	(-13.35)	(-5.68)	(-23.40)	(-12.61)	(-23.51)	(-11.60)
IMPRAT	3.684*	-2.229**	1.780	-1.205**	2.583	-0.839
	(2.22)	(-3.44)	(1.43)	(-2.62)	(1.89)	(-1.43)
Year	X	X	X	X	X	X
Industry	X		X		X	
Plant		X		X		X
R-sq	0.565		0.557		0.556	

N=63,600; t statistics in parentheses; *p<0.05, **p<0.01, ***p<0.001