NCEE Working Paper

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Working Paper 22-03
September, 2022

U.S. Environmental Protection Agency
National Center for Environmental Economics
https://www.epa.gov/environmental-economics

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The U.S. Manufacturing Sector's Response to Higher Electricity Prices: Evidence from State-Level Renewable Portfolio Standards

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Abstract: While several papers examine the effects of renewable portfolio standards (RPS) on electricity prices, they mainly rely on state-level data. Our analysis of RPS policies uses plant-level electricity prices. In addition, there has been little research on how RPS policies affect manufacturing activity via their effect on electricity prices. Using a plant-level dataset for the entire U.S. manufacturing sector and all electric utilities from 1992 – 2015, we jointly estimate the effect of RPS adoption and stringency on plant-level electricity prices and production decisions. To ensure our results are not sensitive to possible pre-existing differences across manufacturing plants in RPS and non-RPS states, we implement coarsened exact covariate matching. Results suggest that electricity prices for plants in RPS states averaged about 2% higher than in non-RPS states. This estimate is notably lower than prior estimates based on state-level data. In response to these higher electricity prices, we estimate that plant electricity usage declined by 1.2% for all plants and 1.8% for energy-intensive plants, on average, which is broadly consistent with published estimates of the elasticity of electricity demand for industrial users. We find smaller declines in output, employment, and hours worked (relative to the quantity of electricity). Finally, we find that several key RPS policy design features that vary substantially from state-to-state produce heterogeneous effects on plant-level electricity prices.

Key Words: Cost of regulation; employment impacts; renewable portfolio standards

JEL Codes: Q48, Q52

Acknowledgements: The authors thank Ann Ferris, Nadya Baryshnikova, Arik Levinson, Sarah West, Rachel Feldman, and workshop participants at the NBER, IZA, National University of Singapore, Keio University, Indiana University, and U.S. EPA for their helpful comments and suggestions. We also thank Brendan Casey, Tao Tao, and Yue Gao for their excellent research assistance.

1. Introduction

A wide-ranging literature has examined how the costs of complying with environmental regulations affects firm productivity (e.g., Berman and Bui 2001a, Gray and Shadbegian 2003, Shadbegian and Gray 2005), investment (e.g., Gray and Shadbegian 1998), environmental performance (e.g., Magat and Viscusi 1990, Shadbegian and Gray 2003, Shadbegian and Gray 2006), and employment (e.g., Berman and Bui 2001b; Greenstone 2002; Walker 2013; Gray, et al. 2014; Ferris, et al. 2014; Sheriff, et al. 2019). We add to this body of work by evaluating how changes in plant-level electricity prices associated with renewable portfolio standards (RPS) affect facility-level manufacturing decisions, including electricity use, labor and output.[1]

States have increasingly relied on RPSs to encourage cleaner power generation. RPSs require electric utilities to generate a certain amount or percentage of their electricity each year from renewable sources including wind and solar (Barbose 2019). While only a handful of states enacted RPSs in the late 1990s, 27 states (including DC) had mandatory RPSs by the end of 2015 (Figure 1) (DSIRE 2017). The popularity of RPSs stems from a desire to encourage the production of electricity from lower emitting renewable sources instead of greenhouse-gas-intensive fuels including coal and natural gas. In addition, proponents of RPSs argue that diversifying electricity generation reduces the risk of potential disruptions in fuel supplies and vulnerability to fuel price fluctuations (Jaccard 2004, Schmalansee 2011).

How have RPS policies affected electricity prices faced by manufacturing facilities? Until recently, renewable sources of electricity typically were far more expensive than fossil fuels.[2] Thus, we might expect that increasing renewable energy use would also increase the cost and therefore the price of electricity faced by manufacturing facilities (Palmer and Burtraw 2005; EIA 2003). However, some studies suggest that the additional renewable energy induced by RPS

[1] While manufacturing has declined in relative importance to the U.S. economy, it still accounted for 12% of real GDP and 9% of overall employment in 2015 (Chien and Morris 2017).

[2] In 2010, the levelized cost of electricity for new generation was predicted as $83/MWh to $100/MWh for conventional fuel sources (in 2010 dollars), and $150/MWh to $396/MWh for renewables in 2016 (EIA 2010). In 2018, the levelized cost of electricity for new generation was predicted to be about the same for natural gas combined cycle and onshore wind (~$48/MWh in 2017 dollars) in 2022, with photovoltaic solar slightly higher ($59/MWh) and no new conventional coal generation (EIA 2018).

policies could displace natural gas-fired generation – which was more expensive in the period prior to the shale gas boom - and lead to lower electricity prices (Clemmer, et al. 1999; Nogee, et al. 2007; Wiser and Bollinger 2007).[3] Others suggest that RPS stringency and differences in the responsiveness of renewable versus fossil-fuel generation to changes in electricity price are important for determining the effect of RPS policies on electricity prices (Fischer 2009). For instance, Palmer and Burtraw (2005) use an electricity sector model to show that an 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 as additional wind generation crowds out non-renewable sources.

Empirical results based on state-level panel data and difference-in-difference estimation strategies have estimated large retail electricity price increases in response to RPS adoption.[4] Wang (2016) found electricity prices for residential customers increased by 7 percent in the year in which an RPS was first binding. Upton and Snyder (2017) found that electricity prices for residential customers increased in RPS states by almost 11 percent and the quantity of electricity demanded decreased by about 6 percent compared to non-RPS states. Greenstone and Nath (2021) found that retail electricity prices were 11 percent higher seven years after passage.[5] The magnitude of their results is surprising given that they accounted for net renewable requirements (i.e., subtracting out existing generation means that stringency is 2.2% on average seven years after passage instead of 5.6%) as well as imports from other states.

Tra (2016) offers important insights into how use of state-level data may overestimate the effects of RPSs on the retail electricity market. Leveraging utility-specific electricity prices over

[3] Natural gas prices typically experience a fair amount of inter- and intra-annual volatility, but one can still discern a marked increasing trend in spot prices between 2001 and 2010 before they begin declining again. See https://www.macrotrends.net/2478/natural-gas-prices-historical-chart.

[4] Greenstone and Nath (2020) also find evidence that commercial and industrial electricity rates in RPS states were higher seven years after passage, though only the residential rate increase was statistically significant.

[5] Greenstone and Nath (2021) report even larger electricity price increases 12 years after passage, but this result is not easily comparable to the seven years after passage results because the subset of states that are included in the estimate is notably smaller. By our calculations, about 15 RPS states are dropped from the estimate since 12 years after passage would occur in a year not captured in the dataset.

time, he finds that accounting for utility-by-year and state-by-year fixed effects substantially reduces the estimated effects of RPSs on residential electricity prices (from about 8% to 3.5%). Tra (2016) also found that accounting for differences in stringency did not result in additional electricity price increases.

How have electricity price increases from renewable portfolio standards affected manufacturing plant production decisions? Theory alone cannot predict the effect of RPSs on manufacturing activity. For instance, how changes in electricity price impact labor demand in the manufacturing sector depends on substitutability between labor and energy (Deschênes, 2012). If labor and energy are highly substitutable, labor demand in the sector may rise with an increase in electricity price; if they are complements, it may decline (Pindyck and Rotemberg 1998). One needs to examine the effects empirically. The empirical literature that examines the impact of electricity price changes due to environmental mandates finds effects on manufacturing employment, output, and net imports are small and negative but mainly concentrated in energy-intensive manufacturing industries (Kahn and Mansur 2013; Aldy and Pizer 2013, 2015; Curtis 2018; Hille and Möbius 2019; Marin and Vona 2021). Most of these studies treat electricity prices as exogenous.[6] Marin and Vona (2021) improve on earlier papers by treating annual plant-level energy prices in France endogenously: they find that energy price increases over time - not associated with any particular environmental policy - result in small, negative effects on employment and productivity, and no significant effect on wages; as with earlier studies, negative effects are concentrated in energy-intensive, trade-exposed industries.

In this paper, we combine two highly disaggregated panel datasets, consisting of the entire U.S. manufacturing sector and all electric utilities from 1992 – 2015, to jointly estimate the effect of state-level RPS adoption and stringency on manufacturing plant-specific electricity prices and, in turn, on manufacturers' electricity use, output, and employment.[7] This is equivalent to

[6] Greenstone and Nath (2020) treat electricity prices as endogenous when estimating the impact of RPS policies on state-level average electricity prices. However, they do not incorporate these estimates into a second analysis of RPS' effect on state-level manufacturing employment (in which they find no statistically significant difference in manufacturing employment in RPS and non-RPS states seven years after RPS passage).

[7] Note that our focus is on effects in the manufacturing sector only via a change in electricity price. An increase in the price of electricity may also have general equilibrium effects that are not capture here.

estimating a difference-in-difference model to identify the effect of RPS policies on electricity prices at 'treated' manufacturing plants and then estimating how these price changes affect plant-level production decisions. To ensure greater balance between our treated and control groups, we also use a many-to-one coarsened exact matching algorithm to select a statistically comparable set of control plants, which reduces bias in our estimates arising from differences in plants in RPS and non-RPS states, allowing us to argue that our results are plausibly causal.

Our paper contributes to the literature in several important ways. To our knowledge, we are the first to examine how state-level renewable energy policies affect the manufacturing sector via changes in industrial electricity prices. Access to confidential data from the U.S. Census Bureau allows us to leverage annual plant-specific electricity prices instead of the state level averages used in much previous work. Davis, et al (2013) demonstrate that there is substantial within-state variation in the electricity prices faced by manufacturing facilities. Use of plant-specific data improves the precision of the estimates and allows us to include county, industry, and utility level fixed effects and to account for observed and unobserved differences at the plant level such as plant age and the potential for market power. Unlike most previous studies, we also treat electricity prices as potentially endogenous when examining how they affect the manufacturing sector.

Given previous research and policy concerns regarding higher electricity prices undermining the international competitiveness of U.S. firms, we separately analyze the effects of RPS policies on manufacturing plants in energy-intensive trade-exposed (EITE) sectors.[8] Finally, since there are substantial and potentially important differences in RPS policy design across states (e.g. stringency, timing of adoption, types of renewables included, whether the standard can be met using existing generation or energy efficiency improvements), we also examine the possibility of heterogeneous effects on electricity prices on manufacturing activity for several RPS features.

[8] The 2009 report, "The Effects of H.R. 2454 on International Competitiveness and Emission Leakage in Energy-Intensive Trade-Exposed Industries," designated a sector as energy-intensive and trade-exposed if it had energy-expenditures of at least 5% of domestic production and trade intensity (ratio of combined exports and imports to domestic production and imports) of at least 15%. We use this definition in our analysis.

The rest of the paper is organized as follows. Section 2 outlines a conceptual framework of the potential impact of regulation on employment via the electricity price pathway. Section 3 describes our empirical methodology. Section 4 summarize the data. Section 5 presents the results, followed by concluding remarks and next steps in section 6.

2. Conceptual Framework[9]

We assume that a manufacturing plant chooses its production level, *Y*, to maximize profits, *Π*:

(1) $\Pi(w^1, \ldots w^n, Y) = P(Y)Y - C(w^1, \ldots w^n, Y)$

where $w^1, \ldots w^n$ are the fixed unit costs of inputs to production and *C* is a twice differentiable cost function. Partially differentiating (1) with respect to Y and setting that expression equal to zero yields the following first order condition:

(2) $P(Y) = \rho\, C_y (w^1, \ldots w^n, Y)$

where ρ is defined as $1/(1+\eta^{PY})$. Note that η^{PY} is the elasticity of demand for good Y with respect to its own price. The variable ρ represents the degree of markup over marginal cost, C_Y, and is therefore a measure of market power. A firm operates in a perfectly competitive market when ρ = 1; if ρ is greater than one, it has some degree of market power.

Assuming that the production function is homogeneous of degree ϑ, Cahuc and Zylberberg (2004) show that the elasticity of production with respect to the cost of input *j*, η^{Yj}, is equal to:

(3) $\eta^{Yj} = s^j\, [\vartheta\rho\, /(\vartheta - \rho)]$

Since s^j, ρ, and ϑ are always positive and the second order condition of $\rho > \vartheta$, η^{Yj} is negative. Thus, when input *j* - in our case, electricity - becomes more expensive (or cheaper) due to a policy such as RPS, all else equal, we expect production of Y to decrease (increase) by $s^j\rho\vartheta/(\vartheta - \rho)]$. The magnitude of the decrease in production varies by industry based on its energy intensity (s^E), its ability to price above marginal cost due to market power (ρ) and returns to

[9] Note that our conceptual framework relies heavily on Cahuc and Zylberberg (2004).

scale (ϑ).[10] Since the share of energy in total production costs is small for most manufacturing industries (less than 1% for all of U.S. manufacturing, but up to 10-20% for cement and aluminium), we expect the output effect to be small in most cases.

The cross-elasticity of unconditional demand for any given factor *i* with respect to factor *j* is a function of the share of factor *j* in total cost, s^j, the partial elasticity of substitution between the two factors, σ^{ij},[11] and a scale effect that depends on the markup factor and the degree of homogeneity in production:

$$\eta^{ij} = s^j\,[\sigma^{ij} - \rho/(\rho - \vartheta)] \tag{4}$$

Overall, the sign on η^{ij} sign is ambiguous. For instance, whether labor and electricity are substitutes or complements depends on the sign of the partial elasticity of substitution (σ^{ij}), and on its magnitude relative to the scale effect, $[\rho/(\rho - \vartheta)]$.[12]

Thinking through how manufacturing plants respond to changes in electricity prices, equation (4) identifies four key sources of variation across industries: differences in energy intensity (s^E), market power (ρ), and production technology (ϑ and σ^{ij}). Given the share of energy in the total costs of manufacturing production is typically relatively small, η^{LE} also is likely small for most industries. However, there are some industries with large energy cost shares.[13] As discussed in the next section we, therefore, also separately analyze the effects of RPS policies on manufacturing plants in EITE industries.[14]

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[10] When ϑ is equal to one, a production function has constant returns to scale. If ϑ is less than one but greater than zero, production exhibits decreasing returns to scale; if ϑ is greater than one, production exhibits increasing returns to scale.

[11] The partial elasticity of substitution is conditional on output. In the short run, firms minimize costs to achieve a given level of production (i.e., there is no scale effect).

[12] Deschênes (2012) applies this formula in the context of the cross-price elasticity of labor demand with respect to energy prices: $\eta^{LE} = s^E\,[\sigma^{LE} - \rho/(\rho - \vartheta)]$.

[13] Electricity represents approximately 1 percent of total manufacturing costs as reported in the 2011 Annual Survey of Manufacturers. However, electricity expenditures represent 10 to 20 percent of total costs for specific energy-intensive manufacturing 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).

[14] In addition, because RPS requirements are imposed at the state level, with considerable flows of manufactured goods between states, industries located in RPS states may be at a competitive disadvantage due to higher

In this paper, we are specifically interested in changes in electricity prices that result from state-level RPS policies. As mentioned above, the effects of RPS policy on electricity prices may be positive or negative, depending on the types of fuels being displaced by renewables, the relative responsiveness of renewable energy to electricity price changes, and the stringency of the RPS (Fischer 2009). Thus, as a first step we need to estimate the effect of RPS policy on electricity prices before examining how this change in electricity price affects labor demand, electricity use, and output. Since RPS policies do not generally limit renewable energy generation to a single type, - utilities can use a mix of solar, wind, and other renewables to meet the RPS requirements - the electricity prices faced by manufacturing facilities reflect a weighted average across these different mixes of in different RPS states. We discuss our empirical approach in the next section.

3. Empirical Framework

Our empirical framework is directly informed by the conceptual model in section 2, outlining how changes in electricity prices are expected to affect manufacturing production, electricity use, and employment decisions. More specifically, we are interested in how the adoption of a mandatory RPS requirement affects manufacturing electricity use, employment and production via its effect on electricity prices.

To obtain the effect of RPS requirements on plant-specific electricity prices, we estimate:

$$(5) \qquad ln(ELECTRICITY\ PRICE)_{it} = \pi_0 + \pi_1 RPS\_Requirement_{st} + \delta X_{ist} + \lambda_z Z_{st} + \varepsilon_{it}$$

where *ELECTRICITY PRICE* is the electricity price for plant *i* in year *t*, *RPS_Requirement* is a measure of the RPS policy for state *s* in year *t*, *X* is a set of utility-, county-, or state-level control variables that vary over time, and Z is a set of exogeneous factors related to the likelihood of RPS adoption in a state *s* in year *t*. We describe the X and Z variables in more detail below.

We also estimate the effect of plant-specific electricity prices on plant production decisions:

$$(6) \qquad ln(Y)_{it} = \alpha_0 + \alpha_1 ln(ELECTRICITY\ PRICE)_{it} + \beta X_{it} + u_{it}$$

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electricity prices. Furthermore, it has been argued in other regulatory contexts that electricity price increases could undermine the international competitiveness of energy-intensive, trade-exposed sectors.

where *Y* is either the manufacturing plant's total employment (EMP), production worker hours (PH), total value of shipments (TVS), or the quantity of purchased electricity (QE).

We include plant and year fixed effects in both equations. In equation (5), this is equivalent to a difference-in-difference estimation strategy. As a result, only the interaction term between the post-policy period (i.e., when an RPS was first put in place, which varies by state) and treatment (i.e., in an RPS state) are identified in the regressions. Previous work conducted similar exercises but at the state-level and therefore were only able to include state-level fixed effects.

3.1 Estimation Challenges

To plausibly estimate the causal effect of RPS requirements on electricity prices in (5), we must address the possibility that a state's decision to adopt mandatory RPS requirements are endogenous (e.g., positively correlated with electricity prices). We also need to account for the omitted variables that affect both electricity prices faced by manufacturing plants and RPS adoption since they could bias our estimates. Because the same unobserved factors that drive expansions in employment and output may also increase electricity demand, potentially affecting its price, we also need to address the possibility that our estimated effect of electricity prices on manufacturing activity in (6) may be biased.

Addressing potential endogeneity and omitted variable bias in equation (5)

Several papers examining the effect of RPS polices on electricity prices attempt to control for endogeneity. Tra (2016) argues that use of disaggregated, utility-level electricity prices mitigates concerns regarding endogeneity that might occur at the state-level. Tra (2016) also includes utility size and degree of self-generation as control variables, and state-by-year and utility type-by-year fixed effects to help reduce any remaining bias. Upton and Snyder (2017) match each RPS state to a synthetic control that is a weighted average of similar non-RPS states with respect to political and economic factors as well as renewable energy potential to account for the potential endogeneity of RPS adoption.

Our approach combines aspects of Lyon and Yin (2010) and Tra (2016) to meet the assumption of conditional mean independence – $E[\varepsilon \mid RPS\_Adoption, Z] = E[\varepsilon \mid Z]$, which then allows us to interpret the effect of RPS adoption on electricity prices as plausibly causal. We include several exogeneous determinants of state-level RPS adoption (Z_{st}). Lyon and Yin (2010) find that states with a higher proportion of electricity generated from natural gas– which is sometimes displaced by renewables – are slower to adopt RPS policies, while states with more active in-state renewable interests, a competitive electricity market, or high technical potential for solar or wind generation drive early RPS adoption. Our Z variables are twice-lagged state natural gas generation as a percentage of generation capacity (NAT_GEN); twice-lagged renewable (non-hydro) generation as a percentage of generation capacity (RENEWABLE_GEN), and twice-lagged percentage of generation from independent power producers (COMP_ELEC_MKT).

To reduce the role of omitted factors that directly affect the electricity prices faced by manufacturing plants and RPS adoption, we use an approach consistent with Upton and Snyder (2017). We match treated manufacturing plants to untreated plants with similar observed characteristics that may affect electricity prices (other than the variable of interest, RPS adoption), thereby isolating the effect of RPS adoption from that of other characteristics which may, themselves, be correlated with RPS adoption. However, given the large number of observations in our data set, we do not need to construct a synthetic control group. Instead, we use a Coarsened Exact Matching (CEM) algorithm to construct the control group. CEM reduces the chances of significant omitted variable bias by controlling non-parametrically for observed pre-treatment differences between plants in the treated and control groups, while potentially also making them more comparable in terms of unobserved characteristics (Iacus et al., 2012).

Addressing potential bias in equation (6)

If we were only interested in estimating the effect of RPS adoption and stringency on annual electricity prices faced by the treated group (i.e., manufacturing plants in RPS states), we could just estimate equation (5) using the approach described above. However, since our goal is to examine the effect of the adoption of RPS mandates on manufacturing employment, electricity use, and production via their effect on the electricity prices faced by treated manufacturing plants, estimation of equation (6) is more challenging.

Plant-level electricity prices are, in theory, simultaneously determined with local manufacturing activity, therefore equation (6) cannot be estimated using OLS. The same unobserved factors that drive expansions in employment and output may also increase electricity demand, and thereby affect its price, which will bias the estimated effect of electricity prices on manufacturing activity. To address this simultaneity issue, we estimate the relationship between manufacturing activity and electricity prices jointly using an instrumental variables model. The ideal instrument is correlated with the electricity price faced by the manufacturing plant but uncorrelated with unobserved factors that influence both manufacturing activity and electricity prices at the plant. We use (twice) lagged plant-level electricity prices as an instrument for current electricity prices. Lagged plant-level electricity prices are highly correlated with current electricity prices (0.74) but not correlated with *current* unobserved factors affecting labor demand and output at the plant. This approach allows us to simultaneously estimate the effect of RPS requirements on the electricity prices faced by manufacturing plants and how these prices affect manufacturing activity. In the first stage, we use all the variables we would include if we were just estimating the effect of RPS adoption on electricity prices, plus twice lagged electricity price.

3.2 RPS Policy Variables

We measure our policy variable of interest, *RPS Requirement,* in two ways: 1) as a dummy variable equal to one in any year in which a state has mandatory RPS in place (RPS_{st}), and 2) as the state's RPS requirement in percentage terms adjusted for actual compliance rates over time ($\text{RPS Stringency}_{st}$).[15] In both cases, we define the first year of the RPS as the year in which an actual RPS requirement was in place. Others (e.g., Greenstone and Nath 2020; Upton and Snyder 2017) have defined the first year of an RPS as the year in which legislation was first passed to set requirements. The logic behind this approach is to allow for the possibility that utilities begin using renewables prior to a compliance year in anticipation of impending requirements. However, the lag between passage of legislation and the first year of an RPS

[15] The vast majority of manufacturing plants during our sample period purchased electricity from utilities within the same state in which they are located.

requirement is sometimes substantial. For example, in Connecticut legislation to establish an RPS was first passed in 1998 but the program did not begin until 2004. Our results are not sensitive to lagging RPS_{st} by one to two years.

The variable, RPS $Stringency_{st}$, is defined as the stated total state-level RPS requirement in a given year, expressed in percentage terms (relative to total generation) and adjusted for actual compliance in cases where the requirement was not met. Others have adjusted downward the stated requirement to account for in-state renewable capacity at the time legislation was passed (e.g., Greenstone and Nath 2020, Yin and Powers 2010). While we do not incorporate twice-lagged renewable capacity directly into our RPS stringency measure, as previously mentioned, it is included as a separate control variable (RENEWABLE_GEN) when estimating the effect of RPS policies on electricity prices (along with percentage natural gas generation (NAT_GEN) and percentage independent power producer generation (COMP_ELEC_MKT)).

3.3 Control Variables

Both equations (5) and (6) include X_{it}, a set of utility-, county-, state-level control variables. In equation (5) we include a utility-level fossil-fuel cost index (FF-COST-INDEX), which is the weighted average of the delivered cost of coal, natural gas, and oil. We also control for various types of environmental regulations faced by electric utilities that could affect the cost of electricity generation. First, we include county non-attainment status (NONATT) with one or more National Ambient Air Quality Standards (NAAQS). Electric power generators (and manufacturing plants) located in non-attainment areas often face stricter regulations than their counterparts in attainment areas, which can increase production costs. Second, we include two variables correlated with the likelihood of more stringent state-level environmental regulations, a state's Congressional environmental voting record (LCVOTE), compiled by the League of Conservation Voters, and the percent that voted Democrat (PCTDEM).[16] Finally, we include

[16] We have also tried other political variables highlighted in Lyon and Yin (2010) such as the percent of the state legislature that is Democrat or split, and whether the governor is a Democrat.

dummy variables beginning in the year that a state imposed a separate energy efficiency standard (EE) or participated in the Regional Greenhouse Gas Initiative (RGGI).[17]

Equation (6) includes county-level variables including population density (POPDEN), per-capita income (PCINC), and the fraction employed in manufacturing to control for electricity demand (PCTMAN). It also contains county-level controls to capture differences in the quality of the local labor market, including percent college graduates (COLGRAD); percent speaking a language other than English at home (NONENG); and the average local wage in the same industry (CIWAGE), as well as total county-level employment in the same industry (CIEMP) to measure local agglomeration effects. Finally, Equation (6) includes several unique control variables: an industry-level index of local demand growth for the plant's output (DEMAND GROWTH); annual import penetration ratio (IMPRAT) as a measure of the competition faced by manufacturing plants and dummies for plants that are younger than 10 years in age (AGE9) or belong to a multi-unit firm (MU).

Our conceptual model identifies production technology, market power, and the energy intensity of production as three factors affecting the responsiveness of plant-level behavior to electricity prices. Broadly speaking, plant age captures some differences in production technologies across plants, though precisely how this influences a plant's responsiveness to electricity prices is not clear. We expect that plants that are part of multi-unit firms are more likely to exhibit market power (e.g., by negotiating separate agreements with utilities). Plant fixed effects also capture time-invariant characteristics related to production technology and market power. Finally, we examine how energy intensity influences the response to electricity prices by separately analyzing the effects of RPS policies on manufacturing plants in EITE industries.

While not explicitly included as control variables because they do not vary over time, we explore the role of state-level heterogeneity in RPS policies by estimating electricity prices for different subsets of states. We first examine how the ability to purchase renewable energy

[17] Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey (2009-2011), New York, Rhode Island, and Vermont.

generated in non-RPS states to meet RPS requirements affects our estimates. We next explore the potential influence of variation in treatment timing by estimating effects for early adopting RPS states. Finally, we examine the role of specific RPS policy attributes: whether a specific solar or distributed generation mandate is nested within the overall RPS requirement; whether a policy allows demand or supply-side energy efficiency improvements and/or non-renewables states to count towards RPS requirements (e.g., installation of combined heat and power systems that use non-renewable energy sources, natural gas that displaces coal); and the use of cost containment mechanisms to guard against particularly large electricity price increases (capped at between 1 and 4% of a consumer's electricity bill).

4. Data

We use several confidential plant-level datasets from the U.S. Census Bureau.[18] Information on manufacturing plants comes from the Census of Manufactures (CMF) and the Annual Survey of Manufactures (ASM), linked together in the Longitudinal Business Database (LBD) as described in Jarmin and Miranda (2002). For our analysis we focus on plants in the ASM because they tend to have more accurate information on electricity prices. Because we consider all manufacturing plants for more than a twenty-year period (1992-2015), this gives us a very large sample, approximately 800,000 plant-year observations, even after we exclude administrative records, missing variables, and non-matching records. The ASM data include the plant's total employment (EMP), production worker hours (HOURS), quantity of purchased electricity (QE), expenditures on purchased electricity (PE), and total value of shipments (TVS), which are used in log form as dependent variables in our analysis (the TVS value is deflated by industry-specific price deflators from the NBER-CES manufacturing industry database. See Becker, et. al 2021).

A key explanatory variable is the annual average electricity price for each manufacturing plant, ELECTRICITY PRICE. To identify which plants purchased electricity from which electric utilities, Davis, et. al (2013), linked data from the U.S. Energy Information Administration's (EIA) Annual Electric Utility Reports (EIA-861), which contain information on which electric utilities sell

[18] Data assembly and econometric estimation for this paper was conducted at the Census Bureau's Boston Federal Statistical Research Data Center.

electricity to which counties, to manufacturing plant-level data from the ASM, which includes information on plant location. When there was only one electric utility serving a specific county, Davis et. al obtained an exact match. In cases where more than one electric utility served a county, Davis, et. al used supplemental data sources including GIS and maps of electric utility service areas to produce the most likely match. Once these linkages were complete, they calculated plant-specific average electricity prices as the ratio of electricity expenditures and quantity of purchase electricity (i.e., the ratio of PE to QE). These prices are included in the Prices and Quantities of Electricity in Manufacturing (PQEM) database. [19]

The original PQEM dataset was based on the single year of EIA data that was available at the time (2000). However, after 2000 EIA made the utility-level data available annually. We used the EIA data for 2000-2015 to extend the PQEM data following a similar methodology, which allows us to control for changes in utility supply patterns over time. To our knowledge, this is the first study to use plant-specific electricity prices to study the effect of renewable portfolio standards on manufacturing output, electricity use, and employment. Other studies of RPSs have relied on state-level average electricity prices, but as Davis et al (2013) show, there is substantial variation in the electricity prices faced by manufacturing facilities. We exploit this variation in plant-level electricity prices to improve the precision of our estimates. Moreover, the use of plant-level instead of state-level electricity prices reduces measurement error that would otherwise bias coefficient estimates.[20]

From EIA, we obtain a state's natural gas generation as a percentage of generation capacity (NATGEN), renewable (non-hydro) generation as a percentage of generation capacity (RENEWABLE GEN), and the percentage of generation produced by independent power

[19]Davis, et al. (2013) note the key limitation of a plant-specific electricity price measure is that it is the average of the ratio of annual expenditures on purchased electricity to annual quantity purchased and not the marginal price. However, Davis, et al. also note that many well-known studies (e.g., Joskow 1974, 2000, 2006; Besley and Coate 2003) also employ similar measures of unit electricity prices.

[20] Another possible measure is levelized cost of electricity (LCOE): "the average revenue per unit of electricity generated that would be required to recover the cost of building and operating a generating plant over an assumed financial lifetime and duty cycle" (EIA 2019). LCOE has been criticized as an indicator of the cost of electricity from renewables since it does not account for the additional costs of transmission to the total energy system, or of supplying electricity when intermittent sources are unavailable (Greenstone and Nath 2020).

producers (COMP-ELEC-MKT).[21,22] We also use data from EIA Forms 423 and 923 to construct a fossil fuel cost index (FF-COST-INDEX), a weighted average of the delivered cost of coal, natural gas, and oil costs at the utility from which the manufacturing plant purchases its electricity. These variables are all lagged by for two years to avoid potential endogeneity concerns.

We construct several explanatory variables from the Census data. We use the LBD to determine if a plant is part of a multi-plant firm (MU) and the first year the plant appeared in the data to construct a plant age dummy (AGE9). Every 5 years, the CMF data provide a snapshot of all manufacturing plants in the country, which we use to develop plant characteristics CIWAGE and CIEMP. CIWAGE is the average wage (payroll/employees) of all other establishments in the same 6-digit NAICS (or 4-digit SIC) industry in the same county; if there are fewer than three establishments in the category, we expand to broader industry definitions within the same county. CIEMP is total employment in the same industry and county. We get a zero value for CIEMP if no other establishments existed at the time in the same industry and county. To avoid simultaneity issues, we use CMF data lagged three to seven years.[23]

Information about the timing, stringency and ability to meet RPS requirements in a given year come from Lawrence Berkeley National Laboratory's (LNBL) RPS Compliance Database, augmented with data from the Quantitative RPS Data Project at the Database of State Incentives for Renewables and Efficiency (DSIRE).[24] The DSIRE database also includes information on when a state adopted separate demand-side energy efficiency (EE) standards and characteristics of each state's RPS policy including whether solar or distributed generation mandates are nested within the overall RPS requirement, which states allow demand or supply-side energy efficiency improvements and/or non-renewables to count toward RPS goals, and which states use cost containment mechanisms. See Table A.1 in the Appendix for a summary of state RPS policy characteristics.

[21] https://www.eia.gov/electricity/data/state/.
[22] See Borenstein and Bushnell (2015).
[23] 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.
[24] 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/.

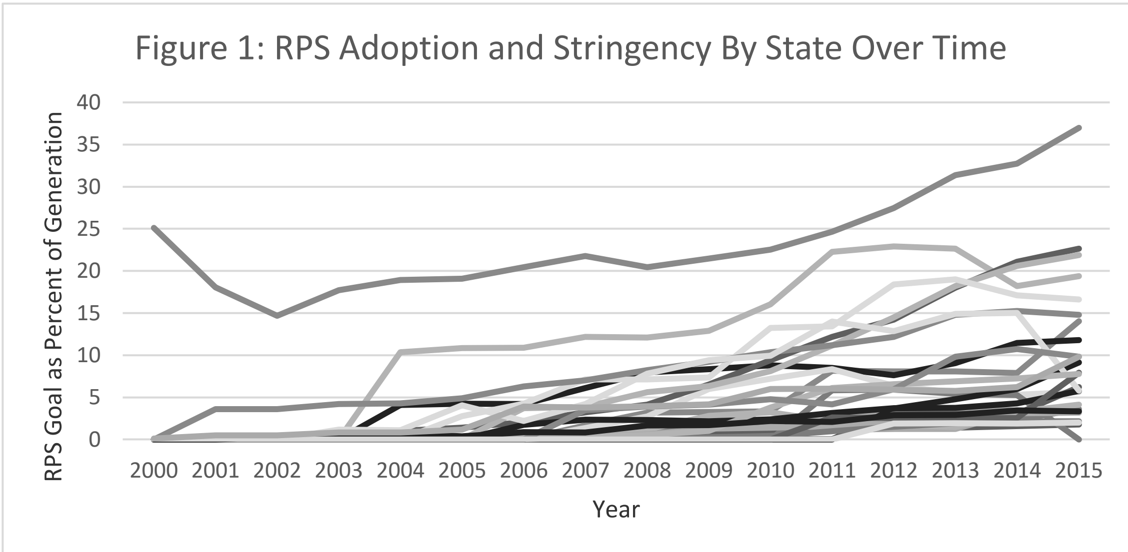
Many electricity utilities own multiple power plants. To measure the degree of regulatory scrutiny faced by an electric utility across multiple power plants, we construct a weighted value based on the share of each power plant's 1990 electricity generating capacity relative to the operating utility's total 1990 generating capacity for the NON_ATT, LCVOTE and PCTDEM variables. From EPA's Green Book we construct NONATT to indicate county non-attainment status with one or more of the national ambient air quality standards for particulates, ozone, and/or sulfur dioxide.[25] LCVOTE is the average score for a state's House delegation of pro-environment voting and PCTDEM is the percent of a county that voted for the Democratic candidate in the most recent presidential election. We lagged these variables by two years.

Based on the manufacturing plant's industry or county location, we merge in additional information to capture potentially important aspects of the labor and manufacturing markets. We obtain county-level characteristics from the USA Counties database, including the percent of college graduates (COLGRD), and percent speaking a language other than English at home (NONENG). The Bureau of Economic Analysis Regional Data web page 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). We develop an index of local demand growth for a plant's output (DEMAND_GROWTH) based on input-output tables and the growth rates of industries in nearby states. We measure the annual import penetration ratio (IMPRAT) for each industry using trade datasets from Schott (2008).

4.1 Summary Statistics

Both RPS adoption and stringency ramped up over our sample period. Between 2000 and 2005, ten states had adopted an RPS with an average stringency of less than 2% of electricity generation. By 2015, 27 states had adopted an RPS and required about 9% of electricity generation come from renewable sources, on average.[26]

[25] NON_ATT equals one if a county violates the NAAQS for one or more of three pollutants; otherwise, it is zero.
[26] Washington, D.C. implemented an RPS in 2007, but because it is fundamentally different from a state, we omitted it from the sample. Iowa is also dropped because it is treated over the entire sample: it adopted an RPS in 1983.



Underlying these trends is a great deal of heterogeneity. In 2005, RPS stringency ranged from 0.1% to 19%; in 2015, it ranged from 2% to 37% (Figure 1). The state with the most stringent RPS is Maine. However, its effect on overall electricity prices and manufacturing production decisions is likely limited; it ranks 44th out of 50 states in terms of level of economic activity. In contrast, California ranks first in terms of level of manufacturing activity in the U.S. Its RPS required almost 11% of the state's electricity generation come from renewable sources in 2005, increasing to 19% by 2015. Ohio, which also ranks high in terms of manufacturing intensity, had an RPS with a stringency of only 2% by 2015.

Tables 1A and 1B present summary statistics prior to the application of our CEM algorithm for the full and EITE samples and for the full sample of manufacturing plants in RPS and non-RPS states. We have approximately 797,000 plant-year observations in the full sample and 54,000 plant-year observations in the EITE sample.[27] Approximately three-quarters of plant-year observations in the full sample are in states that enact an RPS at some point during the period of study, with the remainder of plant-year observations in states that never enact an RPS policy. The average RPS stringency rate for plants in the full and EITE samples are 6% and 5%,

[27] Numbers of observations and plants throughout the paper are all rounded to meet Census Bureau disclosure requirements.

respectively, between 2000 and 2015 (without accounting for where manufacturing activity occurs, average stringency would be about 4.1%).

Table 1A: Summary Statistics for Policy and Dependent Variables

Variables	Full Sample	EITE	RPS States	Non-RPS States
RPS DUMMY	0.278 (0.448)	0.236 (0.425)	--	--
RPS STRINGENCY	1.672 (4.54)	1.183 (3.833)	--	--
ELECTRICITY PRICE (cents/kWh)	0.075 (0.032)	0.060 (0.026)	0.079 (0.033)	0.063 (0.025)
QUANTITY ELECTRICITY (QE) [thousands of kWh]	17,760 (117,600)	108,700 (389,200)	15,210 (100,800)	24,460 (152,900)
VALUE OF SHIPMENTS (TVS)	$90,890 (987,900)	$131,800 (289,400)	$89,570 (995,100)	$94,360 (968,700)
EMPLOYMENT (EMP) [Number of workers)	224.2 (533.7)	272 (498.1)	217.2 (543.2)	242.4 (507.7)
PRODUCTION HOURS (HOURS) (thousands of hours)	325.1 (1,224)	435.4 (741.0)	305.4 (1353.0)	377.0 (790.0)

While plants in the full sample purchase 84% less electricity on average than EITE plants, the average plant-level electricity price is higher in the full sample than in the EITE sample ($0.075/kWh and $0.06/kWh respectively). On average, plant-level electricity prices in the full sample are about 25% higher in RPS states ($0.08/kWh) compared to in non-RPS states ($0.6/kWh), despite purchasing roughly similar quantities of electricity. Manufacturing plants in the full sample tend to have lower total employment, production hours, and total value of shipments, on average, than the EITE sample. Likewise, plants in RPS states have lower total employment, production hours, and total value of shipments compared to non-RPS states.

Table 1B: Summary Statistics for Control Variables

Variables	Full Sample	EITE	RPS States	Non-RPS States
NATGAS (t-2)	0.172 (0.193)	0.160 (0.189)	0.193 (0.200)	0.119 (0.161)
RENEWABLE GEN (t-2)	0.032 (0.040)	0.027 (0.038)	0.036 (0.045)	0.020 (0.019)
COMP-ELECT-MKT (t-2)	0.187 (0.281)	0.162 (0.262)	0.239 (0.308)	0.051 (0.104)
SEPARATE EE	0.182 (0.386)	0.156 (0.363)	0.234 (0.424)	0.045 (0.207)
RGGI	0.027 (0.161)	0.020 (0.139)	0.036 (0.186)	0.003 (0.058)
FF-COST-INDEX (t-2)	2.75 (2.28)	2.55 (2.01)	2.95 (2.52)	2.24 (1.37)
NONATT (t-2)	0.484 (0.415)	0.442 (0.410)	0.593 (0.402)	0.197 (0.298).
LCVOTE (t-2)	0.470 (0.192)	0.436 (0.191)	0.522 (0.180)	0.335 (0.156)
PCTDEM (t-2)	0.469 (0.084)	0.455 (0.079)	0.486 (0.083)	0.422 (0.070)
Ln(POPDEN)	5.983 (1.60)	5.471 (1.53)	6.241 (1.608)	5.308 (1.360)
Ln(PCINC)	10.34 (0.327)	10.25 (0.309)	10.39 (0.324)	10.22 (0.303)
PCTMAN	0.132 (0.078)	0.141 (0.082)	0.125 (0.068)	0.148 (0.099)
COLGRAD	0.242 (0.095)	0.208 (0.083)	0.257 (0.095)	0.204 (0.085)
NONENG	0.150 (0.141)	0.112 (0.118)	0.178 (0.150)	0.077 (0.075)
Ln(DEMAND GROWTH)	4.58 (0.482)	4.45 (0.984)	4.58 (0.478)	4.58 (0.490)
IMPRAT	0.002 (0.007)	0.003 (0.005)	0.002 (0.007)	0.002 (0.007)
AGE9	0.159 (0.365)	0.117 (0.322)	0.155 (0.362)	0.167 (0.373)
MU	0.726 (0.446)	0.929 (0.257)	0.700 (0.458)	0.796 (0.403)
Ln(CIWAGE)	3.096 (0.926)	3.097 (1.014)	3.151 (0.897)	2.953 (0.985)
Ln(CIEMP)	6.123 (1.529)	6.108 (1.486)	6.189 (1.538)	5.951 (1.491)
Number of observations	797,000	54,000	577,000	220,000
Number of plants	118,000	5,400	88,000	30,000

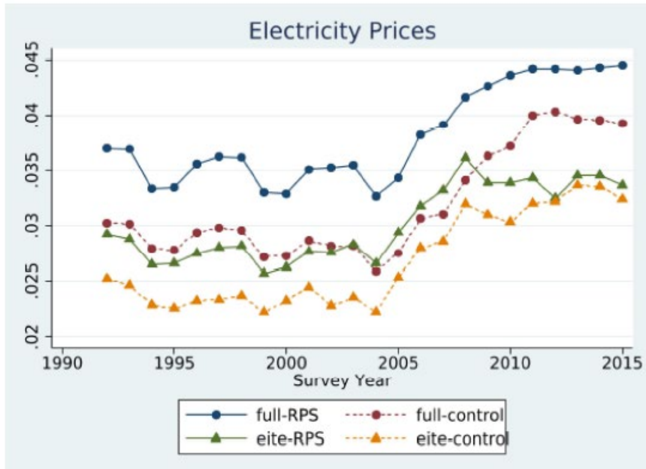
We observe several notable differences in characteristics that are potentially important predictors of the propensity to adopt an RPS, verifying our need to include them in the first stage regression. Natural gas and non-hydro renewables are a much larger percentage of generating capacity in RPS states than in non-RPS states (19% vs 12% and 3.6% vs. 2.0%, respectively). RPS states also have considerably more competitive electricity markets, with 24% of electricity generated by independent power producers in RPS states compared to just 5% in non-RPS states. As expected, states that adopt RPS policies are also much more likely to have separate energy efficiency standards and to join RGGI. Plants in RPS states are much more likely to purchase power from a utility whose generating units are located in counties out of NAAQS attainment (59% vs 20%), in states with a 'greener' environmental voting record and/or a greater propensity to vote Democratic. Plants in RPS states also tend to be located in counties with similar per capita incomes and that derive a similar percentage of their employment from manufacturing as those in non-RPS states, but they are located in counties that are more densely populated and have a higher percent college graduates and non-English speakers. Fossil fuels are notably more expensive for manufacturing plants in RPS states.

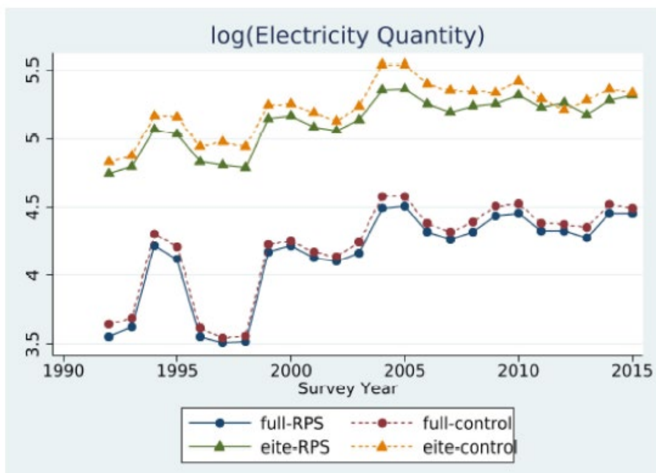
We see few differences in the average county- and plant-level characteristics related to the extent to which manufacturing plants may respond to changes in electricity prices across the full and EITE samples. However, there are some notable differences between the RPS and non-RPS samples. For example, manufacturing plants in RPS states, on average, tend to be slightly older and import slightly less. In addition, both wages and employment within the same industry as the manufacturing plant tend to be higher in RPS states.

4.2 Parallel Trends and CEM Matching

Figures 2a and 2b show average annual electricity prices and logged quantities of electricity purchased by treated vs. non-treated manufacturing plants from 1992 to 2015. While electricity prices are consistently higher for plants in RPS states in the pre- (1992- 1999) and post-treatment periods, they exhibit similar trends for the full and EITE samples. This is also the case for electricity purchases. Other outcome variables exhibit similar parallel trends pre-treatment (see Appendix A).

Figures 2a and 2b: Average Electricity Prices and Quantities 1990 - 2015





To ensure the plants in our treatment and control groups are as comparable as possible we use a many-to-one CEM algorithm. CEM pre-processes the data to limit the treatment and control groups to manufacturing plants that are exact matches based on a set of key pre-treatment observables up to the level of coarsening. The CEM algorithm first 'prunes' observations in both the treatment and control groups that cannot be matched and then uses weights to balance the number of observations in each stratum across groups.

The degree of multidimensional imbalance, L1, is bounded by 0 and 1, where an L1 value of 0 indicates perfect global balance, up to the level of "coarsening" or bin size, and an L1 value of 1 indicates complete separation.[28] Prior to matching, we find evidence of global imbalance in the covariate distributions between the manufacturing plants in the treated and control groups. The overall L1 statistic is 0.52 and 0.50 for the full and EITE samples, respectively, and is driven primarily by imbalance in county non-attainment status.

To minimize the imbalance between our treatment and control plants we match on all plant-level, pre-treatment, covariates: four-digit NAICS industry code, a dummy indicating when a plant is part of a multi-unit firm, a dummy indicating whether the plant is in a non-attainment county, plant size, measured by the total value of shipments coarsened into four bins, and plant age coarsened into three bins. We use the latest available year for each plant up to 1999, dropping plants lacking pre-2000 data. After CEM, the L1 parameter has a value of 0.31 and 0.34 for the full and EITE samples, respectively. Note that average RPS stringency after CEM is also slightly lower for both the full and EITE samples (5.5% and 4.7%, respectively).

5. Results

We begin by evaluating the effectiveness of our instrument in isolating exogenous variation in the endogenous variable, plant-specific electricity prices. In the first stage we find that twice lagged electricity prices, which we argued should not directly affect current employment and output, are positive and significantly associated with current electricity prices, indicating that our instrument passes the relevancy test. Moreover, the F-statistic on lagged electricity prices (i.e., the square of the t-statistic) is substantially greater than the Stock-Yogo critical value of 10, which indicates our instrumental variable passes the weak instrumental variable test.

First stage results (Table 2) based on our preferred CEM-matched sample indicate that adoption of RPS policies significantly increases the electricity prices faced by manufacturing plants. Purchasing electricity from a utility facing a typical RPS policy (average stringency of 5.5% renewables for the full sample) leads to a 1.8% increase in plant-specific electricity prices, on

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[28] The L1 parameter is calculated as the rectilinear distance between the k-dimensional histogram of all pretreatment covariates in the treated group and that in the control group, where k is the number of covariates used in the matching algorithm (Iacus et al., 2012).

average. This translates to an increase of about $0.0014/kWh, on average. Our results are consistent with Palmer and Burtraw's (2005) finding that RPS policies have a small, positive effect on electricity prices at relatively low levels of RPS stringency. As in Tra (2016), the increase in electricity price is mainly driven by RPS adoption; the level of stringency of the RPS policy either has a very small or statistically insignificant incremental effect on electricity prices.[29] For energy-intensive, trade-exposed (EITE) plants, we find that an RPS policy significantly increases electricity prices by 2.1%. Thus, manufacturing plants in EITE industries face an increase of about $0.0013/kWh in the price of electricity, on average.

Table 2: First Stage Logged Electricity Price Results with CEM Matching

Control Variables		Full Sample		EITE Sample	
RPS DUMMY		0.025*** (0.002)	0.018*** (0.002)	0.020*** (0.006)	0.021*** (0.006)
RPS STRINGENCY			0.002*** (0.0001)		-0.001 (0.001)
LN[ELECTRICITY PRICE] (t-2)		0.249*** (0.001)	0.248*** (0.001)	0.224*** (0.005)	0.224*** (0.005)
X Variables	FF-COST-INDEX	0.047*** (0.001)	0.048*** (0.001)	0.098*** (0.005)	0.098*** (0.005)
	NONATT	-0.0069*** (0.002)	-0.0041*** (0.002)	0.002 (0.005)	0.001 (0.005)
	POPDEN	0.013*** (0.002)	0.015*** (0.002)	0.027*** (0.007)	0.027*** (0.007)
	PCINC	0.104*** (0.007)	0.097*** (0.007)	0.012 (0.026)	0.013 (0.026)
	PCTMAN	0.068*** (0.018)	0.065*** (0.018)	0.071 (0.055)	0.070* (0.055)
	LCVOTE	0.0001*** (0.00004)	0.0001*** (0.00004)	0.0002 (0.00013)	0.0002 (0.00013)
	PCTDEM	-0.096*** (0.009)	-0.108*** (0.009)	-0.109*** (0.030)	-0.106*** (0.030)
	SEPARATE EE	0.022*** (0.002)	0.016*** (0.002)	0.052*** (0.006)	0.053*** (0.006)
	RGGI	-0.076*** (0.003)	-0.082*** (0.003)	-0.082*** (0.012)	-0.079*** (0.012)
Z Variables	NATGAS	0.165*** (0.008)	0.145*** (0.008)	0.189*** (0.028)	0.195*** (0.029)
	RENEWABLE GEN	0.259*** (0.023)	0.252*** (0.023)	-0.025 (0.084)	-0.020 (0.084)

[29] Greenstone and Nath (2020) also noted that industrial prices increased substantially in the first year after RPS passage, while prices in the commercial and residential sectors adjusted more gradually.

	COMP-ELECT-MKT	-0.079*** (0.002)	-0.075*** (0.002)	-0.064*** (0.009)	-0.064*** (0.009)
Second Stage Controls		X	X	X	X
Year Dummies		X	X	X	X
Plant FE		X	X	X	X
Plant-Year Obs		535,000	535,000	40,000	40,000

Variables included in the first stage to account for differences in the propensity of a state to adopt an RPS policy are all statistically significant and of the expected sign for the full sample. Manufacturing plants in states with more natural gas and (non-hydro) renewable capacity face higher electricity prices, while manufacturing plants in states with more competition in the electricity market face significantly lower electricity prices. For the EITE sample, however, the percentage of renewable generation is not statistically significant.

As expected, the first stage results indicate that increases in the cost of fossil fuels lead to a small but significant increase in electricity prices. County-level demographic variables are all positive but vary in significance between the two samples. Plants located in RGGI states also have lower electricity prices, though most states that belong to RGGI also adopt RPS policies. Plants in states with separate energy efficiency standards have electricity prices that are 1.6% and 0.5% higher in the full and EITE sample, on average, respectively.

The second stage results indicate that electricity prices have a statistically significant effect on manufacturing production decisions (Table 3). For example, a typical RPS policy that increases electricity prices by 1.8% and 2.1% in the full and EITE samples, respectively significantly reduces the quantity of electricity used by 1.2% and 1.8%. These estimates are broadly consistent with what others in the literature have found for industrial users.[30] With regard to the effect of electricity prices on output and employment, estimated coefficients are relatively small but significant: elasticities range from -0.07 for total number of employees to -0.08 for output to -0.095 for hours worked for the full sample of manufacturing plants. These elasticities imply the typical RPS policy reduces total number of employees, number of hours worked and

[30] Using utility-level data for 1972-2009, Ros (2017) found a long run price elasticity of demand of -0.6 for U.S. industrial users. For 2003-2015, Burke and Abayasekara (2017) found a long run elasticity of around -1.2.

output by 0.13%, 0.14% and 0.17%, respectively in the full sample. We find similar, though slightly larger impacts for EITE industries, with elasticities of around -0.09.

Older (AGE9=0) and multi-unit plants (MU) use more electricity, hire more workers, and have a higher value of shipments, on average, in both samples. Plants reduce output in the full sample but increase it in EITE industries in response to greater import competition (IMPRAT). Note that import competition increases electricity use, employment and hours in the full sample but is statistically insignificant for EITE plants. In the full sample, plants in states with higher local growth in demand for the plant's output also tend to use more electricity, hire more workers, and have a higher value of shipments. This is not always the case for the EITE sample. For both the full and EITE sample, plants in counties with higher industrial wages or lower industrial employment tend to be smaller on average, though they are not always statistically significant.[31]

[31] Tables A.2 and A.3 compare results with and without CEM matching. The estimated effects of RPS polices on electricity prices in the first stage are larger when we control non-parametrically for observed pre-treatment differences between manufacturing plants in the treated and control groups. In the second stage, we find relatively similar effects in the matched and unmatched specifications, though it is worth noting that the negative coefficient on quantity of electricity is noticeably larger in the matched sample for EITE plants.

Table 3: Production Decision Results with CEM Matched Sample

Control Variables	Full Sample				EITE Sample			
	LN(QE)	LN(EMP)	LN (HOURS)	LN(TVS)	LN(QE)	LN(EMP)	LN (HOURS)	LN(TVS)
Predicted LN[ELECTRICITY PRICE] (t-2)	-0.693*** (0.025)	-0.067*** (0.009)	-0.095*** (0.011)	-0.081*** (0.012)	-0.837*** (0.072)	-0.085*** (0.028)	-0.083** (0.033)	-0.089** (0.036)
DEMAND_GROWTH	0.018*** (0.005)	0.006*** (0.002)	0.009*** (0.002)	0.014*** (0.002)	-0.001 (0.008)	-0.019*** (0.003)	-0.016*** (0.004)	0.006 (0.004)
IMPRAT	0.278 (0.367)	0.673*** (0.132)	0.958*** (0.158)	-0.775*** (0.173)	-0.678 (1.790)	0.725 (0.693)	1.316 (0.812)	1.542* (0.904)
COLGRAD	0.166 (0.116)	-0.222*** (0.042)	-0.487*** (0.050)	-0.472*** (0.055)	0.238 (0.354)	-0.319** (0.137)	-0.682*** (0.161)	-0.948*** (0.179)
NONENG	0.926*** (0.094)	0.138*** (0.034)	0.088** (0.040)	0.608*** (0.044)	1.128*** (0.285)	-0.299*** (0.111)	-0.129 (0.130)	-0.578*** (0.144)
CIWAGE	-0.002 (0.002)	-0.007*** (0.001)	-0.005*** (0.001)	-0.001 (0.001)	-0.009 (0.006)	-0.002 (0.002)	-0.002 (0.003)	-0.001 (0.003)
CIEMP	0.011*** (0.001)	0.013*** (0.0004)	0.013*** (0.001)	0.014*** (0.001)	0.006* (0.004)	0.012*** (0.001)	0.013*** (0.002)	0.015*** (0.002)
AGE9	-0.176*** (0.008)	-0.149*** (0.003)	-0.141*** (0.004)	-0.124*** (0.004)	-0.260*** (0.028)	-0.190*** (0.011)	-0.178*** (0.013)	-0.161*** (0.014)
MU	0.141*** (0.012)	0.070*** (0.004)	0.074*** (0.005)	0.098*** (0.005)	0.0642 (0.050)	0.135*** (0.019)	0.134*** (0.023)	0.157*** (0.025)
First Stage Controls	X	X	X	X	X	X	X	X
Year Dummies	X	X	X	X	X	X	X	X
Plant FE	X	X	X	X	X	X	X	X
Plant-Year Obs	535,000	535,000	535,000	535,000	40,000	40,000	40,000	40,000

5.1 Accounting for Out-of-State REC Purchases

One factor that may prevent electricity prices in RPS states from rising as much as they otherwise would have is the ability of electric utilities to purchase renewable energy generated in other states via tradable renewable energy credits (RECs). If out-of-state renewable energy can be produced at a lower cost than in-state renewable energy, then absent constraints on the geographic origin of REC purchases and absent other market imperfections, we expect that electric utilities will rely on these sources of RECs to meet some of their RPS requirements. There is evidence to suggest that RPS requirements spurred growth in renewable electricity in other states: Barbose (2017) reports than more than 10 percent of additional RPS capacity was built in non-RPS states between 2000 and 2016.[32]

To the extent that electric utilities in RPS states mainly purchase renewable energy from other RPS states, the estimates in Section 5.1 already capture their effect on electricity prices. However, if electric utilities in RPS states meet requirements by purchasing renewable energy from non-RPS states, electricity prices faced by manufacturing plants in both the treated (RPS) and control (non-RPS) groups may be affected. This would contaminate our control group leading to an underestimate of the effect of RPS policies on electricity prices.

The ability to purchase out-of-state RECs varies by state. Some states specify that a certain percentage of RECs must be generated within state. Others limit REC purchases to a specific region (i.e., within state and from neighboring states). Compatibility between REC tracking systems may also limit which states can trade (Hollingsworth and Rudik 2019). Because information on out-of-state REC trading is difficult to confirm and often contradictory across sources, we mainly rely on information on 2012 cross-state REC transactions from Heeter, et al. (2015) to identify non-RPS states that contribute a substantial number of RECs to meet RPS requirements. Since 2012 is near the end of our sample, we view these data as a potential upper bound on the extent of REC trading between RPS and non-RPS states for the entire sample period, as RPS policies have tended to increase in stringency over time.

[32] Hollingsworth and Rudik (2019) find statistically significant effects of out-of-state renewable purchases on overall fossil fuel generation (negative) and wind generation (positive).

Since Heeter, et. al (2015) do not include detailed data on California, Nevada, Arizona, or North Carolina, we, to the extent possible, supplement from other sources to understand REC trading in these states. Based on information collected by the Western Electricity Coordinating Council (WECC 2015), Arizona and Nevada rely on a very small amount of out-of-state renewables. [33] Data on the contracts secured by individual utilities for renewable resources in California suggests that about 37% of the renewable contracts between 2004 – the year California's RPS was put in place - and 2012 were from out of state.[34] While Heeter, et al (2015) suggest that 43 percent of North Carolina renewable generation came from outside the state, disaggregated information on the origins of REC purchases is not available from other sources.

Evidence suggests that the extent to which RPS states relied on out-of-state RECs to meet renewable requirements varied widely.[35] Nine RPS states relied on zero or very small amounts of out-of-state renewable energy in 2012.[36] Six states purchased more than 10 percent of their renewable generation from non-RPS states.[37] Of these, two states (Maryland and New Jersey) had relatively stringent RPS requirements in 2012, increasing the possibility of cross-state effects on electricity prices.

For states that mainly purchased out-of-state renewable generation from other RPS states, we find they purchased more than 10 percent of their out-of-state RECs from three states that did not have an RPS in place until more than a year after the purchasing state (Rhode Island, New Hampshire and Washington). Finally, we find that one state supplied substantial amounts of renewables to meet RPS requirements in multiple states (Wyoming). As a sensitivity test, we

[33] The report shows that, combined, Arizona and New Mexico imported less than 10% of their electricity from other regions in 2014, the majority of which came from Colorado and Kansas - both RPS states. The electricity sub-region containing Nevada only imported 2% of its total electricity from other states in 2014 (WECC 2015).
[34] Data on out-of-state renewable purchases are from the California Power Source Disclosure Program: https://www.energy.ca.gov/2008publications/CEC-300-2008-005/index.html.
[35] The ability to trade across REC tracking systems also varies to some extent. For instance, mid-Atlantic states purchased from both other mid-Atlantic states and Midwestern states (Heeter, et al 2012).
[36] The nine states that rely on very little or no out-of-state RECS are Arizona, Colorado, Kansas, Michigan, Montana, Nevada, New Mexico, New York, and Texas. Iowa is excluded since its RPS began prior to the first year of our sample, but it also would fall into this category.
[37] The non-RPS states from which these states bought a substantial proportion of renewables were Indiana, Vermont, Virginia, and West Virginia.

treat these eight states (five non-RPS states and three RPS states) as though they had an RPS beginning in the earliest year of RPS adoption in the purchasing state.[38]

Table 4 indicates that including REC-supplying states in the treatment group results in slightly higher estimates of plant-specific electricity prices for the full sample (2.1% vs. 1.8% previously), but somewhat lower electricity prices for the EITE sample (1.3% vs. 2.1% previously), on average. This latter result may suggest that manufacturing plants in EITE industries were able to partially mitigate electricity price increases from RPSs by negotiating with out-of-state renewable suppliers. Based on state-level data, Greenstone and Nath (2020) also found fairly modest impacts of cross-state spillovers from REC trading on electricity prices.

Table 4: Log Electricity Price Results with Out-of-State REC Purchases (CEM Matching)

	Full Sample		EITE Sample	
	Treated are Only in RPS States	Treated Includes Non-RPS States	Treated are Only in RPS States	Treated Includes Non-RPS States
RPS DUMMY	0.018*** (0.002)	0.021*** (0.002)	0.021*** (0.006)	0.013** (0.005)
RPS STRINGENCY	0.002*** (0.0001)	0.002*** (0.0001)	-0.001 (0.001)	-0.001 (0.001)
LN[ELECTRICITY PRICE] (t-2)	0.248*** (0.001)	0.251*** (0.001)	0.224*** (0.005)	0.238*** (0.005)
X Controls	X	X	X	X
Z Controls	X	X	X	X
Year Dummies	X	X	X	X
Plant FE	X	X	X	X
Plant-Year Obs	535,000	528,000	40,000	40,000

The second stage coefficients – the effect of these electricity price changes on production decisions - are similar to what were previously reported (see Table A.4 in the Appendix).

[38] The RPS dummy is set equal to one beginning in 2001 for Indiana and West Virginia, 2003 for Rhode Island and New Hampshire, 2004 for Washington, 2006 for Virginia, and 2007 for Vermont and Wyoming.

5.2 Heterogeneity in Timing of RPS Adoption and RPS Design

Most RPSs include elements designed to enhance a state's ability to monitor compliance – for instance, the use of renewable energy certificates (RECs) to track compliance and penalties for noncompliance – but RPS policies vary widely in many other dimensions as well (Barbose 2019). For instance, RPSs differ in how the goal is expressed (e.g., share of total electricity generation or megawatt hours), the types of energy suppliers covered (e.g., investor-owned utilities, municipalities), which renewable sources are allowed (i.e., hydropower), and the extent to which existing renewables or non-renewables can be used to meet the standard. RPS policies also differ in terms of how electricity generated outside the state is treated, the use of carveouts or multipliers to encourage specific types of renewables, whether trading, banking and/or borrowing of RECs is allowed, and reliance on cost containment mechanisms to prevent large increases in electricity prices (Jaccard 2004; Wiser, et al. 2007; Schmalansee 2011; Barbose 2019). While studies of the effect of RPSs on electricity prices often examine differences in stringency and coverage (Yin and Powers 2010, Maguire and Munasib 2016, Tra 2016, Upton and Snyder 2017), none has attempted to capture these other potentially important differences using plant level data.

We explore how heterogeneity in treatment timing and in RPS design attributes for various subsets of treated states affect electricity prices.[39] First, we examine effects of RPS policies on electricity prices in early adopting states.[40] Early adopters are defined as states that both passed early legislation (prior to 2000) and had mandated RPS goals in place prior to 2004 (i.e., AZ, MA, ME, NJ, NV, TX, WI). We find much larger electricity price increases in early adopting RPS states compared to the overall sample (Table 6). Specifically, we find that electricity prices

[39] Average treatment effects may be biased in cases where there is heterogeneity in treatment timing. This stems from the fact that difference-in-difference estimation uses group sizes and treatment variances as weights. Observations with low treatment variance receive greater weight as controls. Whether variation in treatment timing biases the average treatment effect depends on how much weight an observation receives in the treatment versus control group (Goodman-Bacon 2018).

[40] RPS policies in early adopting states may differ in ways that are hard to measure, reflecting the greener preferences of their constituents and being a first mover with more limited opportunities to learn from others.

for plants in early adopting RPS states increased by 6.1% (vs. 1.8% previously) in the full sample and 4.5% in the EITE sample (vs. 2.1% previously). As with the main results, these results are driven by RPS adoption; while the coefficient on RPS stringency is often statistically significant, it is very small relative to the average RPS stringency.

Table 6: Log Electricity Price Results for Early Adopters (CEM Matching)

	Full Sample		EITE Sample	
	All	Early Adopters	All	Early Adopters
RPS DUMMY	0.018*** (0.002)	0.061*** (0.002)	0.021*** (0.006)	0.045*** (0.009)
RPS STRINGENCY	0.002*** (0.0001)	-0.002*** (0.0002)	-0.001 (0.001)	-0.004*** (0.001)
LN[ELECTRICITY PRICE] (t-2)	0.248*** (0.001)	0.221*** (0.002)	0.224*** (0.005)	0.204*** (0.006)
X Controls	X	X	X	X
Z Controls	X	X	X	X
Year Dummies	X	X	X	X
Plant FE	X	X	X	X
Plant-Year Obs	535,000	411,000	40,000	29,000

We next explore whether RPS policies with specific design characteristics have heterogeneous effects on electricity prices. Specifically, we examine effects of three characteristics, which provide less flexibility in meeting the RPS requirements: 1) mandating that a portion of the overall RPS requirement be met with solar or distributed generation (NO_SOLAR); 2) not allowing demand or supply-side energy efficiency improvements or non-renewables to count towards their RPS requirements (NO_EFF_NONRENEW); and 3) not having a cost containment mechanism that prevents electricity prices from rising above a certain threshold (NO_COST_CONT). We expect that less flexibility in how RPS requirements can be met or lack of a cost containment mechanism may result in higher electricity prices. Table 7 shows the effect of RPS policies with specific design features on electricity prices for manufacturing plants purchasing from utilities in those states.

If RPS states that already have a propensity to use solar or distributed generation are also the ones that specify a separate requirement, then the effect on electricity price might be negligible or even negative. If instead the solar and distributed generation requirements spur additional investment in more expensive renewable energy options than would have occurred with the RPS requirement alone, then electricity prices may be pushed higher in these states. Summary statistics suggest that the proportion of a state's RPS requirement that need to be met by solar and distributed generation tend to be much higher in the three Western states (AZ, NV, and NM) compared to other states with these carve-outs (for example, almost 13% versus 3% in 2012), which broadly supports the first possibility. However, Barbose, et al. (2016) reported that solar and distributed generation carve-outs are a key driver of RPS costs in states such as Massachusetts and New Jersey, which supports the second possibility. We find that electricity prices in states without solar or distributed generation carveouts as part of their RPS mandates are notably higher than for the overall sample (6.3% vs. 1.8% for the overall sample; 5.9% vs. 2.1% for EITE plants).[41]

Table 7: Log Electricity Price Results for Heterogeneous RPS Samples (CEM Matching)

	Full Sample				EITE Sample			
	All	No Solar/DG Carveouts	No EE/ Non-renew	No Cost Contain	All	No Solar/DG Carveouts	No EE/ Non-renew	No Cost Contain
RPS DUMMY	0.018*** (0.002)	0.063*** (0.002)	0.053*** (0.002)	0.023*** (0.002)	0.021*** (0.006)	0.059*** (0.008)	0.042*** (0.008)	0.018** (0.008)
RPS STRINGENCY	0.002*** (0.0001)	-0.001*** (0.0002)	-0.0005** (0.0002)	0.003*** (0.0003)	-0.001 (0.001)	-0.003*** (0.001)	-0.001 (0.001)	0.0003 (0.001)
X Controls	X	X	X	X	X	X	X	X
Z Controls	X	X	X	X	X	X	X	X
Year Dummies	X	X	X	X	X	X	X	X
Plant FE	X	X	X	X	X	X	X	X
Plant-Year Obs	535,000	417,000	421,000	441,000	40,000	30,000	29,000	29,000

Manufacturing plants in states that do not allow energy efficiency or non-renewables to count towards their RPS requirements also experience noticeably larger electricity prices on average compared to a plant in a typical RPS state. Electricity prices are estimated to increase by 5.3% for these plants, on average, compared to a 1.8% increase for all RPS plants. For the EITE sample, electricity prices also increase by more (4.2%) compared to the full sample (2.1%). This

[41] In contrast, Greenstone and Nath (2020) find evidence of higher electricity prices, on average, in states with solar set asides. However, they note that examining price effects for subsets of RPS states may overtax the data.

result suggests that one mechanism for keeping electricity prices low is the ability to allow demand or supply-side energy efficiency improvements or less carbon-intensive non-renewables to count towards RPS goals.

Cost containment mechanisms are another way to prevent large increases in electricity prices. For the overall sample, we find electricity price increases that are higher in magnitude for plants in RPS states that do not have a cost containment mechanism (2.3% vs. 1.8%). While this result unexpectedly flips for EITE plants, the difference between the no cost containment and all EITE sample is slightly smaller in magnitude (1.8% vs. 2.1%).[42]

6. Conclusion

In this paper we estimate the impact of state RPS adoption on U.S. manufacturing activity via its effect on plant-specific electricity prices. Our paper is the first to jointly estimate how state-level RPS policies affect manufacturing activity via their effect on industrial electricity prices using plant-level data. We address the potential endogeneity of electricity prices when examining how they affect activity in the manufacturing sector. We also minimize the imbalance between our treatment and control using a many-to-one CEM algorithm, which reduces bias in our estimates arising from differences in plants in RPS and non-RPS states, allowing us to argue that our results are plausibly causal.

Many previous attempts to understand how RPS policies affect electricity prices used state level average electricity prices. However, research has shown there is substantial variation in the electricity prices faced by manufacturing facilities. We use a large plant-level dataset covering the entire U.S. manufacturing sector and all electric utilities from 1992 – 2015 to study the effect of RPS policies on electricity prices and subsequent production decisions. Our access to plant-level Census data allows us to leverage this inter-firm electricity price variation, which improves the precision of our estimates and reduces measurement error from using state-level electricity prices. Use of plant-level data also allows us to account for important observed and

[42] Compliance costs in 2014 were high enough in only one state, Colorado, to trigger a cost containment mechanism, though Barbose (2016) reports that they were binding in several states. Cost containment mechanisms were triggered several times in New Mexico and Missouri in previous years (Heeter, et al. 2014).

unobserved county, industry, and utility level characteristics when examining the effect of RPSs on electricity prices. We also account for observed and unobserved differences at the plant level, including production technology and market power, which are two factors our conceptual model identifies as affecting how plants react to electricity prices.

We find that RPS policies have a relatively small effect on industrial electricity prices and economic activity in the manufacturing sector. More specifically, we find that manufacturing plants in RPS states face approximately 1.8% significantly higher electricity prices for an RPS of average stringency in the full sample and about 2.1% in the EITE sample. This result is in contrast to findings based on state-level data of much larger effects on electricity prices from RPS policies. On the other hand, similar to other papers in the literature, we find that RPS adoption is the primary driver of subsequent electricity prices increases, not changes in stringency over time.

We find that the electricity prices from a typical RPS policy decreased electricity use by 1.2% and 1.8%, which is broadly in line with available elasticities from the literature. The responses of plant-specific output, employment, and hours are notably smaller, declining by roughly 0.15% and 0.2% for the EITE and full samples, respectively, in response to increased electricity prices. When we account for the potential use of electricity produced in non-RPS states to meet RPS requirements, we find somewhat higher estimated electricity prices (2.1% vs. 1.8% previously) in the full sample, but little difference in manufacturing plant production decisions. On the other hand, we find the increased flexibility of purchasing electricity from non-RPS states somewhat lowers electricity prices for the EITE sample (1.3% vs. 2.1% previously), on average. But, again, we find little difference in manufacturing plant production decisions.

RPS requirements vary significantly in stringency, timing, and other policy design features from state-to-state, therefore we also examine the extent to which various attributes of RPS policies produce heterogeneous effects on the electricity prices faced by manufacturing plants. Our results indicate that manufacturing plants (including EITE plants) in states that impose an RPS prior to 2004 (i.e., early adopting states) experience significantly larger increases in electricity prices. Manufacturing plants in states that do not allow energy efficiency or non-renewables to count towards their RPS requirements also experienced noticeably larger electricity prices on average compared to a plant in a typical RPS state. In contrast, we find that manufacturing plants in RPS states with separate solar or distributed generation requirements experienced decreases in electricity prices, on average. Plants in states with RPS policies that did not have a cost containment mechanism in place faced electricity price increases similar to those estimated for all plants in both the full and EITE sample.

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Data Sources:

NBER-CES industry data: www.nber.org/data/nberces5809.html

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

Supplemented Peter Schott trade data with year-by-year imports and exports for 2006-2011 (sample links for 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: http://www.bea.gov/itable/iTable.cfm?ReqID=70&step=1 . We construct variables using the Economic Profiles (CA30) and Total Full-Time and Part-Time Employment by Industry (CA25, CA25N) tables.

USA Counties database through 2010 (including Population Census and Annual Community Survey): http://www.census.gov/support/USACdataDownloads.html . More recent years is from Census QuickFacts for Counties: http://quickfacts.census.gov/qfd/index.html

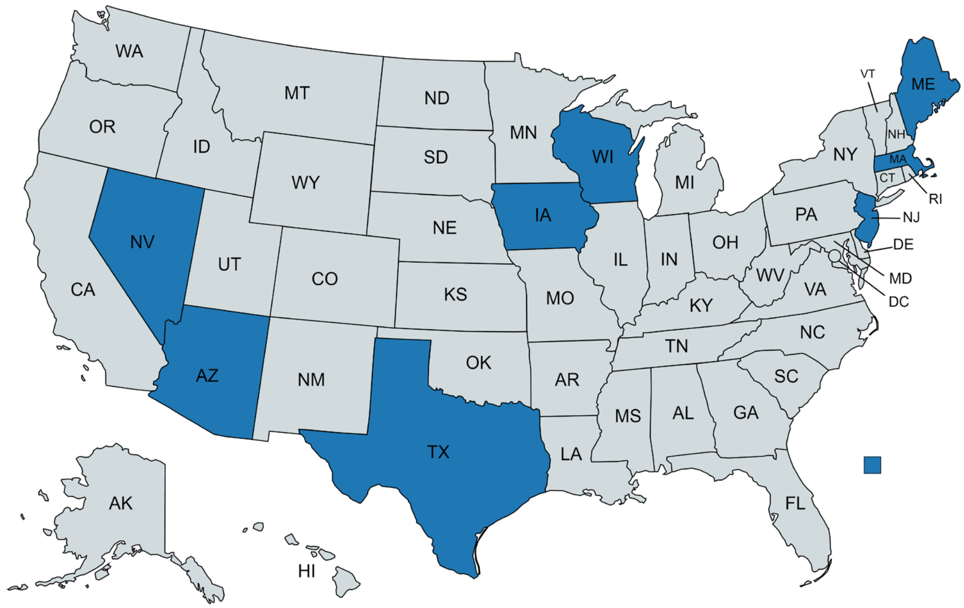
League of Conservation Voters annual scorecard of pro-environment voting by county Congressional delegation (use average score for House delegation):
http://scorecard.lcv.org/scorecard/archive

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

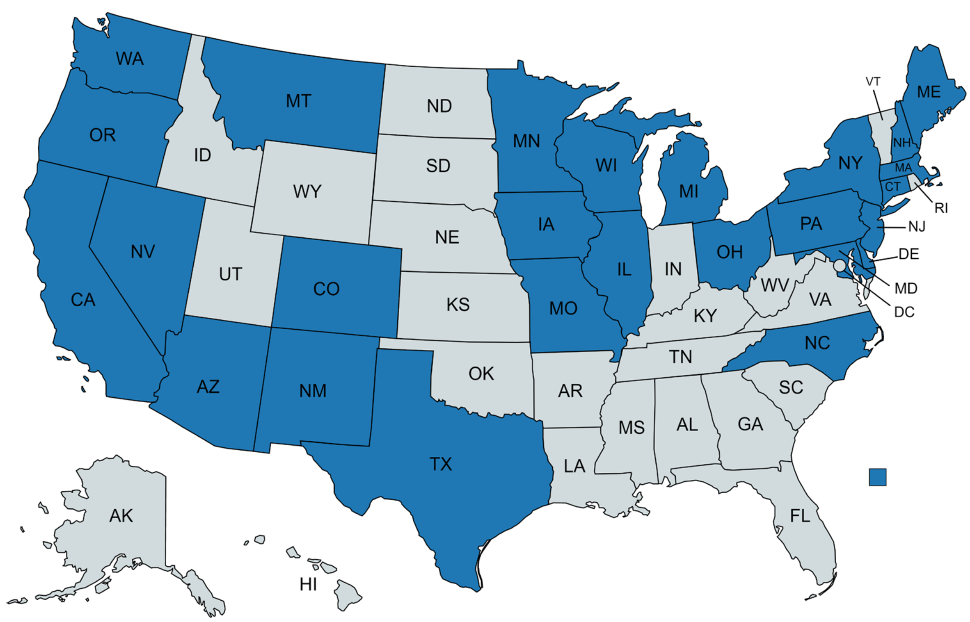
Electricity generation data from eGRID:
http://www.epa.gov/cleanenergy/documents/egridzips/eGRID_9th_edition_V1-0_year_2010_Data.xls

RPS data: DSIRE (Database of State Incentives for Renewable Energy). *Renewable Portfolio Standard Database*: http://www.dsireusa.org/resources/database-archives/

Figure 1: Mandatory RPS policies in Continental U.S. States 2003 and 2015



2003: 8 states had RPSs



2015: 27 states (including DC) had RPSs

Appendix

Figure A.1 Log Shipments for Full and EITE Samples in RPS and Non-RPS States: 1992 – 2015

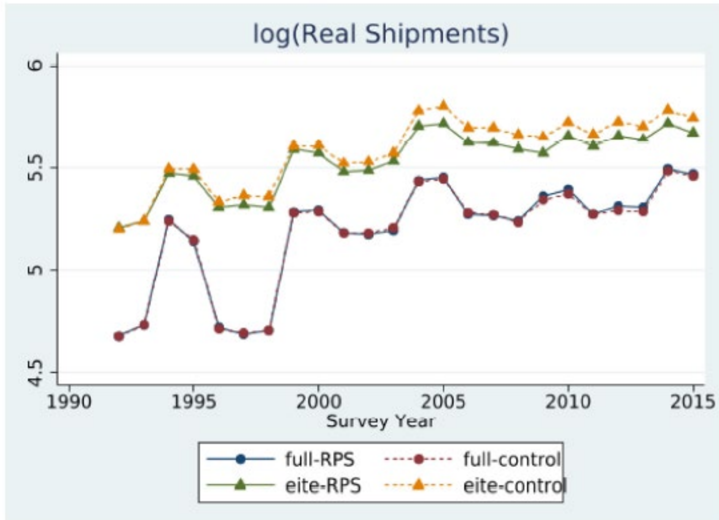


Figure A.2 Log Employment for Full and EITE Samples in RPS and Non-RPS States: 1992 – 2015

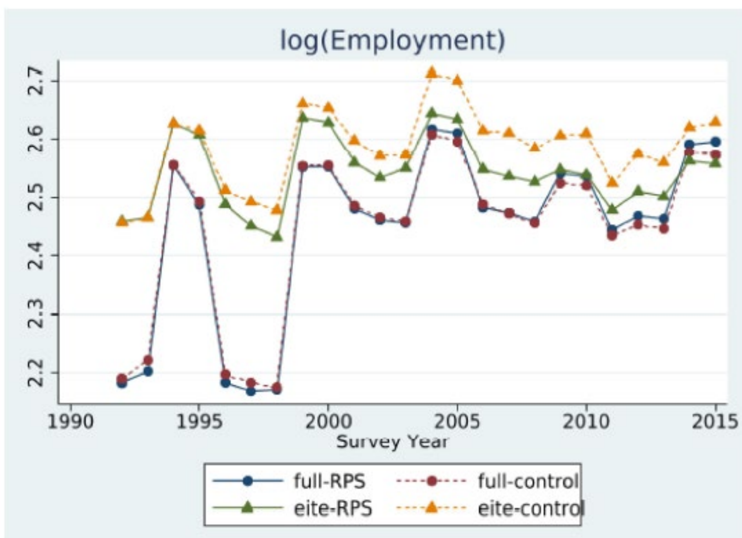


Figure A.3 Log Worker Production Hours for Full and EITE Samples in RPS and Non-RPS States: 1992 – 2015

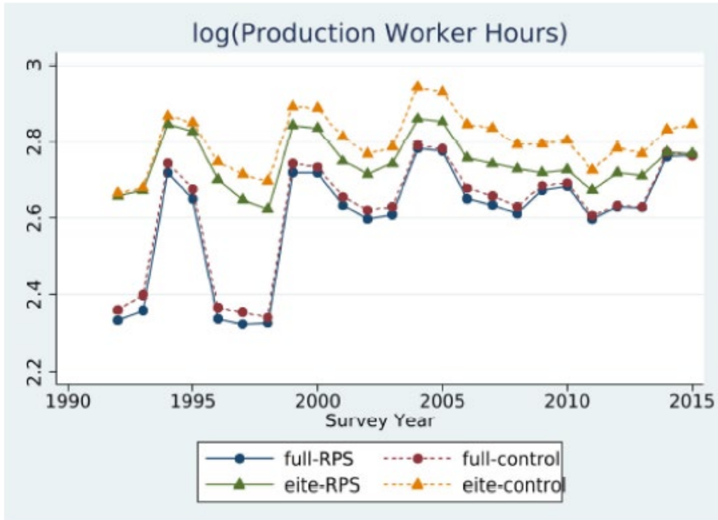


Table A.1. Key Characteristics of RPS Policies for States in Our Sample

State	Year of first mandated RPS goal	Solar carveouts	Energy efficiency or renewables allowed	Cost containment mechanisms	RGGI	Year separate energy efficiency standards began
AZ	2001	√				2011
CA	2004					2004
CO	2007	√	√	√		2011
CT	2004		√		√	
DE	2007	√		√	√	2015
IL	2008	√	√	√		2008
KS	2011					
MA	2003	√			√	2010
MD	2006	√			√	2011
ME	2000		√		√	2010
MI	2012		√	√		2009
MN	2005		√			2010
MO	2011	√				
MT	2008			√		
NC	2010	√	√	√		
NH	2008	√			√	
NJ	2001	√			√	
NM	2006	√		√		2010
NV	2003	√	√			
NY	2006	√	√			2008
OH	2009	√	√	√		2009
OR	2011		√	√		
PA	2006	√	√			2010
RI	2007				√	2008
TX	2002			√		2002
WA	2012			√		2010
WI	2000					2010

Source: DSIRE database.
Notes: DC and IA are not included in our sample. IA implemented an RPS in 1983; DC in 2007. AR, IN, and VT do not have an RPS in place during our period of study but adopted separate energy efficiency standards in 2011, 2010, and 2000, respectively, which we control for in the regressions. KS converted their RPS to a voluntary one in 2015.

Table A.2. First Stage – CEM vs. Non-CEM Matching Results

		Full Sample		EITE Sample	
Control Variables		CEM	Non-CEM	CEM	Non-CEM
RPS DUMMY		0.018*** (0.002)	0.007*** (0.001)	0.021*** (0.006)	0.017*** (0.005)
RPS STRINGENCY		0.002*** (0.0001)	0.002*** (0.0001)	-0.001 (0.001)	-0.0008 (0.0005)
LN[ELECTRICITY PRICE] (t-2)		0.248*** (0.001)	0.182*** (0.001)	0.224*** (0.005)	0.207*** (0.004)
X Variables	FF-COST-INDEX	0.048*** (0.001)	0.041*** (0.001)	0.098*** (0.005)	0.082*** (0.004)
	NONATT	-0.0041*** (0.002)	-0.001 (0.001)	0.001 (0.005)	0.010** (0.005)
	POPDEN	0.015*** (0.002)	0.010*** (0.002)	0.027*** (0.007)	0.015** (0.006)
	PCINC	0.097*** (0.007)	0.124*** (0.006)	0.013 (0.026)	0.070*** (0.023)
	PCTMAN	0.065*** (0.018)	0.048*** (0.016)	0.070* (0.055)	0.080* (0.048)
	LCVOTE	0.0001*** (0.00004)	0.0001*** (0.00004)	0.0002 (0.00013)	0.0002 (0.00013)
	PCTDEM	-0.108*** (0.009)	-0.085*** (0.007)	-0.106*** (0.030)	-0.076*** (0.026)
	SEPARATE EE	0.016*** (0.002)	0.029*** (0.001)	0.053*** (0.006)	0.043*** (0.005)
	RGGI	-0.082*** (0.003)	-0.073*** (0.002)	-0.079*** (0.012)	-0.085*** (0.009)
Z Variables	NATGAS	0.145*** (0.008)	0.176*** (0.007)	0.195*** (0.029)	0.156*** (0.024)
	RENEWABLE GEN	0.252*** (0.023)	0.241*** (0.020)	-0.020 (0.084)	-0.138* (0.075)
	COMP-ELECT-MKT	-0.075*** (0.002)	-0.087*** (0.002)	-0.064*** (0.009)	-0.078*** (0.008)
Second Stage Controls		X	X	X	X
Year Dummies		X	X	X	X
Plant FE		X	X	X	X
Plant-Year Obs		535,000	786,000	40,000	54,000

Table A.3. Effect of RPS on Production, With vs. Without CEM Matching

Panel (a): Value of Shipments and Quantity of Electricity

Control Variables	Full Sample				EITE Sample			
	LN(TVS)		LN(QE)		LN(TVS)		LN(QE)	
	No Match	CEM Match	No Match	CEM Match	No Match	CEM Match	No Match	CEM Match
Predicted LN[ELECTRICITY PRICE] (t-2)	-0.035*** (0.012)	-0.081*** (0.011)	-0.668*** (0.026)	-0.693*** (0.025)	-0.152*** (0.036)	-0.158*** (0.036)	-0.692*** (0.070)	-0.837*** (0.072)
First and Second Stage Controls	X	X	X	X	X	X	X	X
Year Dummies	X	X	X	X	X	X	X	X
Plant FE	X	X	X	X	X	X	X	X
Plant-Year Obs	786,000	535,000	786,000	535,000	54,000	40,000	54,000	40,000

Panel (b): Employment and Hours

Control Variables	Full Sample				EITE Sample			
	LN(EMP)		LN (HOURS)		LN(EMP)		LN (HOURS)	
	No Match	CEM Match	No Match	CEM Match	No Match	CEM Match	No Match	CEM Match
Predicted LN[ELECTRICITY PRICE] (t-2)	-0.064*** (0.009)	-0.065*** (0.009)	-0.084*** (0.011)	-0.095*** (0.011)	-0.127*** (0.027)	-0.083** (0.033)	-0.140*** (0.033)	-0.096*** (0.033)
First and Second Stage Controls	X	X	X	X	X	X	X	X
Year Dummies	X	X	X	X	X	X	X	X
Plant FE	X	X	X	X	X	X	X	X
Plant-Year Obs	786,000	535,000	786,000	535,000	54,000	40,000	54,000	40,000

Table A.4: Production Decision Results with Out-of-State REC Purchases (CEM Matching)

Panel (a): Value of Shipments and Quantity of Electricity

Control Variables	Full Sample				EITE Sample			
	LN(TVS)		LN(QE)		LN(TVS)		LN(QE)	
	RPS Only	Non-RPS in Treated	RPS Only	Non-RPS in Treated	RPS Only	Non-RPS in Treated	RPS Only	Non-RPS in Treated
Predicted LN[ELECTRICITY PRICE] (t-2)	-0.081*** (0.012)	-0.072*** (0.012)	-0.693*** (0.025)	-0.680*** (0.025)	-0.089** (0.036)	-0.093** (0.037)	-0.837*** (0.072)	-0.861*** (0.071)
First and Second Stage Controls	X	X	X	X	X	X	X	X
Year Dummies	X	X	X	X	X	X	X	X
Plant FE	X	X	X	X	X	X	X	X
Plant-Year Obs	535,000	528,000	535,000	528,000	40,000	40,000	40,000	40,000

Panel (b): Employment and Hours

Control Variables	Full Sample				EITE Sample			
	LN(EMP)		LN (HOURS)		LN(EMP)		LN (HOURS)	
	RPS Only	Non-RPS in Treated	RPS Only	Non-RPS in Treated	RPS Only	Non-RPS in Treated	RPS Only	Non-RPS in Treated
Predicted LN[ELECTRICITY PRICE] (t-2)	-0.067*** (0.009)	-0.057*** (0.009)	-0.095*** (0.011)	-0.083*** (0.011)	-0.085*** (0.028)	-0.104*** (0.028)	-0.083** (0.033)	-0.090*** (0.033)
First and Second Stage Controls	X	X	X	X	X	X	X	X
Year Dummies	X	X	X	X	X	X	X	X
Plant FE	X	X	X	X	X	X	X	X
Plant-Year Obs	535,000	528,000	535,000	528,000	40,000	40,000	40,000	40,000