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

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Abstract

Renewable portfolio standards (RPSs) are a relatively recent but increasingly popular phenomena in the United States. The majority of U.S. states have recently enacted RPSs, in order to encourage cleaner sources of power. To date there has not been any research on how the adoption of an RPS affects manufacturing activity. 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 plant-level dataset for the entire U.S. manufacturing sector from 1990 – 2009, we use the RPS faced by the electricity generator as an instrument for plant-level electricity prices. We then use the predicted price to test the impact of electricity prices on manufacturing activity. The estimated effects of an RPS on electricity prices and manufacturing employment and output are very small. For example, in our preferred specification we find that electricity prices faced by plants which purchase electricity from a utility that needs to meet an RPS requirement are approximately 4% higher than at plants purchasing from a non-RPS utility. A 4% increase in electricity prices would cause total employment, production hours and output to all increase by approximately 1%.

1. Introduction

Renewable portfolio standards (RPSs) are a relatively recent but increasingly popular phenomena in the United States. 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 have enacted mandatory renewable portfolio standards. Eight others have voluntary RPSs in place (DSIRE 2013). Their popularity stems from a desire to encourage sources of electricity other than coal and natural gas, which are generally viewed as being cleaner, lower in greenhouse gas emissions associated with climate change, and safer – compared to the other “clean’ alternative, nuclear. In addition, diversifying electricity generation is thought to make states more energy secure, reducing the risk of potential disruptions in fuel supplies and vulnerability to fluctuations in fuel prices (Jaccard 2004; Schmalansee 2011). Given that most renewable sources of electricity are more expensive than burning fossil fuels, we would expect that increasing the use of renewable energy will increase the cost of electricity (Palmer and Burtraw 2005). However, some studies suggest that the additional renewable energy use induced by RPSs could displace gas-fired generation and hence the demand for natural gas, lowering both its price and electricity prices (Wiser and Bollinger 2007).

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. However, given the conflicting results in the literature and to the best of our knowledge, the lack of peer-reviewed papers that examine the effect of RPSs on industrial sector electricity prices or subsequent impacts on manufacturing activity, this remains an important empirical question of keen interest to policymakers. Note, however, that several recent papers examine how increased electricity prices faced by manufacturing facilities due to other environmental regulations affect manufacturing activity (e.g., Kahn and Mansur 2012, Aldy and Pizer 2011, and Curtis 2013).

How reasonable is it to expect that RPS requirements will have a substantial 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 overall total manufacturing costs - approximately 1 percent as reported in the 2011 Annual Survey of Manufacturers (ASM). However, electricity represents 10-20 percent of total costs for some energy-intensive industries such as aluminum (NAICS 331312), industrial gases (NAICS 325120), and cement (NAICS 327310). Electricity represents 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, there could be some competitive disadvantage for industries in RPS states, particularly in states that see a rise in electricity prices The electricity-intensity of an industry provides one possible indication of how much a particular sub-sector may be affected by electricity price changes resulting from an RPS.

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). For our main analysis, we include both an RPS dummy for whether a county is being served by utilities whose generating facilities are covered by an RPS and a continuous variable that measures the RPS stringency as the fraction of total electricity generation that is required from renewables. We hope to utilize other potentially important differences in RPSs across states in subsequent versions of the paper.

We use maps of electric utility service territories, combined with the location of the corresponding power plants, to construct the RPS requirements for each utility and identify in which counties their electricity is being sold. We link the RPS requirements to manufacturing plants by their state and county. There are some cases of multiple utilities servicing the same county; in those cases, we use weighted averages of the utilities' RPS requirements for the RPS stringency measure. To provide some before-RPS variation, our analysis includes data from 1990-2009.

We begin the analysis by testing for an impact of RPS requirements on electricity prices faced by manufacturing plants. Using the Census data, we examine how the electricity prices paid by individual facilities vary across space and over time, based on the RPS coverage and RPS intensity faced by the utility(s) serving the county where that facility is located. We then use our first-stage results to consider the responsiveness of the plant's employment and production to the plant's own electricity prices, using predicted electricity prices from the first stage in place of the plant's own electricity price. Neoclassical microeconomic theory cannot predict the direction of the electricity price impact 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 (see Pindyck and Rotemberg 1998).

Using a plant-level dataset for the entire U.S. manufacturing sector from 1990 – 2009, we find that plants purchasing electricity from utilities under an RPS requirement face approximately 3% - 4.5% significantly higher electricity prices. This implies that electricity prices would rise by \$0.002 - \$0.003/KWh. The estimated effects of these electricity price increases on manufacturing employment and output are very small. For example, in our preferred specification we find that electricity prices faced by plants which purchase electricity from a utility that needs to meet an RPS requirement are approximately 4% higher than plants which do not. A 4% increase in electricity prices would cause total employment, production hours and output to all increase by approximately 1%.

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 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, other renewable sources allowed (i.e., some allow hydropower, some do not), whether it applies only to new renewable generation or existing renewables can also be used to meet the standard, whether some 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 level 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 to lower electricity prices. Contrary to earlier studies that focus on the role of natural gas, she 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. Furthermore Fischer argues that if the supply curves of fossil-fired are not perfectly elastic, the subsidy to renewables tends to lower electricity prices overall, whereas the tax on fossil-fired sources tends to increase prices. Thus, a priori the price effect of an RPS is theoretically 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-fired generation quickly 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.

3. Electricity Prices and Labor Demand

The question of if and how environmental regulation affects economic outcomes in U.S. manufacturing sector is not a new one. There is an 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 concern 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, Gray and Shadbegian 2013, Curtis 2014, Gray, et al. 2014, and Ferris, Shadbegian, and Wolverton 2014).

The literature that examines the impact of electricity prices on manufacturing employment is even smaller. The only two papers we are aware of that study the effects of electricity prices on manufacturing employment are Kahn and Mansur (2013) and Curtis (2014). Kahn and Mansur (2013) estimate the effect electricity prices had 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. 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.[2,3]

Similar to Kahn and Mansur (2013), we model the impact of electricity prices on manufacturing employment. On the other hand, like Curtis (2014), we also understand that regulation, or 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 the analysis on the RPS faced by the electricity generator, rather than simply using the RPS in the state where the manufacturing plant is located.

[2] Deschenes (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.

[3] Aldy and Pizer (2013) 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.

4. Conceptual Framework

As a conceptual framework for this analysis, we describe the static model of labor demand with multiple factor inputs. Following Hamermesh (1986) and Deschenes (2012), in a model with several factors, the cross-price elasticity of labor demand with respect to energy prices, η_{LE},, can be derived as follows:

With *N* factors of production and input prices *w*, define the production function Y = f(X_1,…, X_N) and cost function C=g(w_1,…, w_N,Y). The partial elasticity of substitution, σ_{ij} , the percentage effect of a change in w_i/ w_j on X_i/ X_j holding output and other input prices constant, is

$$\sigma_{ij} = C\, g_{ij} / g_i\, g_j$$

Then the cross-price elasticity of demand for X_i with respect to w_j is

$$\eta_{ij} = \partial \ln X_i / \partial \ln w_j = (f_j\, X_j / Y)\, \sigma_{ij} = s_j\, \sigma_{ij}$$

With output held constant, this expression only contains the substitution effect, which can be positive or negative. If output is allowed to vary, the scale effect enters the equation, and the cross-price elasticity becomes:

$$\eta_{ij} = s_j\, [\sigma_{ij} - \rho/(\rho - \theta)]$$

where 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 (Deschenes 2012). The overall sign of the cross-price elasticity will depend on whether the substitution or scale effect dominates. Inputs *i* and *j* are said to be *p*-substitutes if $\eta_{ij} > 0$, and *p*-complements if $\eta_{ij} < 0$. Cox et. al. (2013) further derive reduced form equations to estimate the cross-price elasticity both conditional on holding output constant (substitution effect only) and when output is allowed to vary.

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 are considering all manufacturing plants over a twenty-year period (1990-2009), this is 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. 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).[4]

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 being generated, and the activities of some electric utilities span multiple states, so that electricity generated in one state may be sold in another state. We started with maps of electricity service territories, indicating which utilities sell electricity in each county. We then identified the generating plants connected to each utility and checked whether

[4] One complication with using the annual Census data is this 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.

that generating plant was in a state with an RPS requirement. We rely on the Quantitative RPS Data Project at the Database of State Incentives for Renewables and Efficiency (DSIRE - http://www.dsireusa.org/) for quantitative information about state RPS programs. see http://www.dsireusa.org/rpsdata/RPSspread031813.xlsx). This enabled us to calculate what fraction of the electricity being generated for each utility was covered by an RPS. In cases where multiple utilities were selling 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 can see in Figures 1-3 that while these county-level numbers are expanding across the country between 2000 and 2010, they don't 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. In our analyses we use RPSDUM for ease of interpretation, a variant of RPS that is set to 1 if the RPS value is greater than 0.1 (virtually all of those counties have RPS values above 0.95, and the two variables give very similar results when we tested them in the analysis). 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). 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.

Measures of regulatory intensity besides RPS are also available. From EPA's Green Book data we obtain indicators of county non-attainment with 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 average score for the state's House delegation, LCVOTE).

We link in 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 get 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

We use the RPS 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*. We use an IV approach to estimate the employment impacts of electricity price and RPSs. The first stage is a regression of electricity price on RPS and other instruments which will be used in the second stage regression of manufacturing employment.

1st stage:

$$\ln(ELEC)_{it} = \beta_0 + \beta_1 RPS + \beta_x X_{ct} + \beta_t + \varepsilon_{ct}$$

ELEC is our plant-specific electricity price derived from Census data on the cost and quantity of purchased electricity. In our preferred specification, the *RPS* measure is a dummy variable (RPSDUM) that equals one if the electricity being sold in the plant's county is coming from generating units covered by an RPS. *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. In Table 2, we explore different model specifications including adding the percent of generation required to be from renewables (RPSPCT) and plant fixed effects.

The second 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's 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).

2nd stage:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln(ELEC)\text{-hat}_{it} + \beta_x X_{it} + \beta_{industry} + \beta_t + \varepsilon_{it}$$

Y is one of: the manufacturing plant's total employment (EMP), production worker hours (PH)[5], or total value of shipments (TVS; the TVS value is deflated by an industry-specific price deflator from the NBER-CES manufacturing industry database). Ln(ELEC)-hat is the predicted value of the plant-level electricity price. Control variables, *X,* are: county-level nonattainment status (NAPM, NAOZ, NASO2), interaction dummies with indicators for polluting industries when a

[5] We also tested the impact on the number of production workers, with results very similar to those for production worker hours.

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 first-stage model, we explored various combinations of control variables; we also estimated industry or plant fixed effects, in addition to year fixed effects.

6. Results

Table 1 displays the summary statistics and variable definitions of all the variables used in this study. The dataset used for our analysis is an unbalanced panel, with 1,275,836 plant-year observations on 327,236 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 (RPSDUM) and the average RPS requires about 5% of electricity to come from renewable sources (RPSPCT/RPSDUM). Nearly half our plants are operating in ozone non-attainment areas, whereas 17% and 3% operate in PM and SO_2 non-attainment areas, respectively.

Table 2 shows the results of our first stage regression model. All specifications include year fixed effects, while models 2 and 4 include state fixed effects, and models 3 and 6 control for 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 purchasing electricity from a utility that faces an RPS, our key instrument, is remarkably similar across all six specifications. Plants purchasing electricity from utilities under an RPS requirement face approximately 3% - 4.5% higher electricity prices, which is statistically significant. This implies that electricity prices would rise by $0.002 - $0.003/KWh, which is 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. The results in models 4-6 when we add RPSPCT to the equation imply that plants purchasing electricity from utilities which face more a stringent RPS (requiring a higher percentage of electricity to be generated from renewable sources) face lower electricity prices. At first this result may seem counterintuitive, but Fischer (2009) shows that at relatively less stringent RPS targets (arguably the situation prevailing in our sample) the renewable subsidy effect could dominate the fossil-fuel tax effect. In any case, this effect is quite small. For example, increasing the RPS requirement by five percentage points (roughly doubling the typical requirement in our sample) would reduce electricity prices by $0.005 - $0.010/KWh.

Our preferred first-stage specification, which we use to predict electricity prices for our second stage, is model 2 in table 2. The three dummy variables indicating if a plant is purchasing 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.

Tables 3 and 4 present our second stage results where we estimate the impact of predicted electricity prices from the first-stage on employment, production worker hours and output. In table 3 we present OLS models that include the average local wage (payroll/employees) paid in similar nearby establishments, a measure of local agglomeration effects, plant-level controls, the annual import penetration ratio as well as year and industry fixed effects. In all of these model specifications electricity prices have a negative and statistically significant impact on employment, production worker hours, and output. The impact is relatively large (-0.5 to -0.6) in the models that only include year and industry fixed effects (models 1, 3, and 5) but falls dramatically (to -0.1 to -0.3) when plant-level characteristics are added (models 2, 4, and 6). Both the local wage and measure of agglomeration effects have the expected impacts on all three outcomes – 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. On the other hand, older plants are unexpectedly smaller in terms of employment and output. Moreover, our measure of import competition has an unexpectedly positive effect on employment and output.

In table 4 we expand the model specifications, adding our county-level regulatory and demographic variables to the plant characteristics in table 3 and (in models 2, 4, and 6) adding plant fixed effects. Adding the county-level variables reduces the estimated negative impacts of electricity prices on output and employment still further, relative to the results in table 3 (models 1, 3, and 5).[6] On the other hand, once we include plant fixed effects (models 2, 4, and 6) the impact of predicted electricity prices changes sign and now 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, in our preferred specification in table 2 (model 2) we find that electricity prices faced by plants which purchase electricity from a utility that needs to meet an RPS requirement are approximately 4% higher than plants which do not. A 4% increase in electricity prices would cause total employment, production hours and output to all increase by approximately 1%.

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 have recently enacted RPSs, 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, we find that plants purchasing electricity from utilities under an RPS requirement face approximately 3% - 4.5% significantly higher electricity prices. This implies that electricity prices would rise by \$0.002 - \$0.003/KWh. These RPS induced electricity price increases have a very small impact on manufacturing employment and output, with the direction of the impact varying across specifications. In our preferred specification we find that electricity prices faced by plants which purchase electricity from a utility that needs to meet an RPS requirement are approximately 4% higher than plants which do not. This 4%

[6] In separate models in which we include the county variables but not the plant variables, the estimated impact of electricity prices on output and employment is smaller than the results in table 3 for the dummy-only models (1, 3, and 5) but larger than the results for the models which include plant variables (2, 4, and 6).

increase in electricity prices is associated with increases in total employment, production worker hours and output of approximately 1%.

In the next version of this paper we plan to add more details about the RPS requirements faced by electric utilities, including variations in the requirements faced by different utilities and the range of renewable sources allowed. We will also experiment with alternative sets of control variables, and hope to expand the time period covered to 2011.

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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 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

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Table 1
Summary Statistics (1,275,836 obs from 327,236 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
RPSDUM	.221	.415	0/1, county under RPS (rps>0.1)	RPS, EPA
RPSPCT	.011	.039	RPS goal, renewable pct generation averaged across suppliers	RPS, EPA
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 2

Impact of RPS on Electricity Prices

	(1) **LELEC**	**(2)** **LELEC**	**(3)** **LELEC**	**(4)** **LELEC**	**(5)** **LELEC**	**(6)** **LELEC**
RPSDUM	0.0376*** (39.23)	0.0380*** (38.88)	0.0299*** (30.72)	0.0454*** (44.82)	0.0454*** (44.21)	0.0333*** (32.83)
RPSPCT				-0.223*** (-23.84)	-0.219*** (-23.42)	-0.113*** (-11.92)
NAPM		0.0231*** (23.74)	0.0296*** (19.01)		0.0239*** (24.57)	0.0306*** (19.63)
NAOZ		0.000917 (1.14)	-0.0244*** (-20.34)		0.00140 (1.73)	-0.0222*** (-20.11)
NASO2		0.0247*** (14.64)	-0.00174 (-0.69)		0.0260*** (15.45)	-0.000349 (-0.14)
LCVOTE		-0.0552*** (-14.85)	-0.0157*** (-4.45)		-0.0528*** (-14.21)	-0.0158*** (-4.47)
PCTDEM		0.0784*** (25.36)	-0.119*** (-16.92)		0.0806*** (26.07)	-0.112*** (-15.90)
POPDEN		0.00809*** (26.31)	0.0302*** (23.98)		0.00759*** (24.63)	0.0292*** (23.15)
PCINC		0.0606*** (35.51)	0.0974*** (19.06)		0.0623*** (36.47)	0.103*** (20.09)
PCTMAN		-0.0203*** (-4.60)	0.256*** (19.25)		-0.0183*** (-4.16)	0.262*** (19.64)
MU		-0.0306*** (-53.43)			-0.0306*** (-53.43)	
AGE5		-0.0119*** (-11.94)	0.0188*** (11.03)		-0.0123*** (-12.31)	0.0187*** (10.97)
AGE10		-0.00590*** (-7.81)	0.00522*** (5.11)		-0.00589*** (-7.81)	0.00522*** (5.12)
SIZE50		0.00722*** (8.57)	-0.00924*** (-7.94)		0.00734*** (8.72)	-0.00911*** (-7.83)
SIZE75		0.00986*** (12.28)	-0.0000573 (-0.04)		0.0101*** (12.52)	0.000157 (0.12)
Year	X	X	X	X	X	X
State	X	X		X	X	
Plant			X			X
R-sq	0.386	0.394		0.386	0.394	

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

Table 3

Impact of Electricity Prices on Shipments/Employment/Hours (Basic Models)

	(1) LSHIP	(2) LSHIP	(3) LEMP	(4) LEMP	(5) LPH	(6) LPH
PRLELEC	-0.551***	-0.139***	-0.525***	-0.203***	-0.606***	-0.277***
	(-93.01)	(-27.24)	(-110.28)	(-50.84)	(-117.50)	(-62.62)
CIWAGE		-0.522***		-0.555***		-0.559***
		(-347.29)		(-469.73)		(-427.26)
CIEMP		0.295***		0.279***		0.289***
		(339.93)		(209.28)		(382.85)
MU		1.020***		0.657***		0.693***
		(388.35)		(318.70)		(303.10)
AGE5		-1.180***		-0.974***		-1.001***
		(-303.81)		(-319.20)		(-296.06)
AGE10		-0.241***		-0.258***		-0.269***
		(-76.61)		(-104.53)		(-98.55)
IMPRAT		4.233***		2.222***		2.925***
		(21.82)		(14.59)		(17.32)
Year	X	X	X	X	X	X
Industry	X	X	X	X	X	X
R-sq	0.413	0.590	0.322	0.556	0.317	0.524

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

Table 4

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

	(1) LSHIP	(2) LSHIP	(3) LEMP	(4) LEMP	(5) LPH	(6) LPH
PRLELEC	-0.0288***	0.256***	-0.0241***	0.300***	-0.0639***	0.234***
	(-3.63)	(8.05)	(-3.88)	(12.28)	(-9.27)	(7.50)
NAPM	-0.0865***	0.00760*	-0.0903***	0.00103	-0.0968***	0.00227
	(-22.65)	(2.14)	(-30.15)	(0.38)	(-29.14)	(0.65)
DNAPM	0.141***	-0.0121	0.134***	0.00348	0.130***	0.0145*
	(16.62)	(-1.63)	(20.23)	(0.61)	(17.65)	(1.98)
NAOZ	0.0372***	-0.0183***	0.0268***	-0.00820***	0.0322***	-0.0120***
	(10.33)	(-6.74)	(9.47)	(-3.92)	(10.26)	(-4.50)
DNAOZ	-0.0403***	0.00886**	-0.0269***	0.000959	-0.0175***	0.00207
	(-8.86)	(2.64)	(-7.55)	(0.37)	(-4.42)	(0.63)
NASO2	0.0244***	-0.0211***	0.0386***	-0.0260***	0.0275***	-0.0178**
	(3.51)	(-3.74)	(7.08)	(-5.98)	(4.56)	(-3.20)
DNASO2	0.0456*	-0.0873***	0.0634***	0.0310**	0.0785***	0.0117
	(2.39)	(-5.98)	(4.24)	(2.76)	(4.74)	(0.82)
LCVOTE	0.0249***	-0.0478***	0.0674***	-0.0245***	0.0530***	-0.0203**
	(3.32)	(-6.51)	(11.44)	(-4.33)	(8.11)	(-2.81)
PCTDEM	-0.174***	-0.124***	-0.148***	-0.0250*	-0.180***	-0.0456**
	(-14.40)	(-8.06)	(-15.61)	(-2.11)	(-17.19)	(-3.02)
POPDEN	0.0214***	-0.0124***	0.0122***	-0.0268***	0.0155***	-0.0220***
	(18.05)	(-4.28)	(13.15)	(-12.03)	(11.18)	(-7.72)
PCINC	0.115***	0.473***	-0.0778***	0.231***	-0.100***	0.307***
	(11.54)	(35.74)	(-9.91)	(22.71)	(-11.49)	(23.56)
COLGRD	-0.00432	-1.139***	0.0934***	-0.490***	-0.142***	-0.785***
	(-0.18)	(-29.11)	(5.02)	(-16.28)	(-6.89)	(-20.40)
NONENG	-0.499***	0.233***	-0.475***	0.370***	-0.452***	0.404***
	(-41.78)	(7.71)	(-50.62)	(15.93)	(-43.46)	13.58
CIWAGE	-0.529***	0.0315***	-0.554***	-0.0372***	-0.555***	-0.0347***
	(-348.95)	(27.73)	(-465.63)	(-42.59)	(-420.65)	(-31.01)
CIEMP	0.304***	-0.00182*	0.288***	0.0214***	0.298***	0.0224***
	(343.03)	(-2.32)	(415.27)	(35.72)	(387.28)	(29.03)
MU	1.019***		0.653***		0.687***	
	(388.12)		(316.87)		(300.58)	
AGE5	-1.171***	-0.241***	-0.966***	-0.247***	-0.994***	-0.244***
	(-301.41)	(-68.81)	(-316.87)	(-91.54)	(-294.04)	(-70.63)

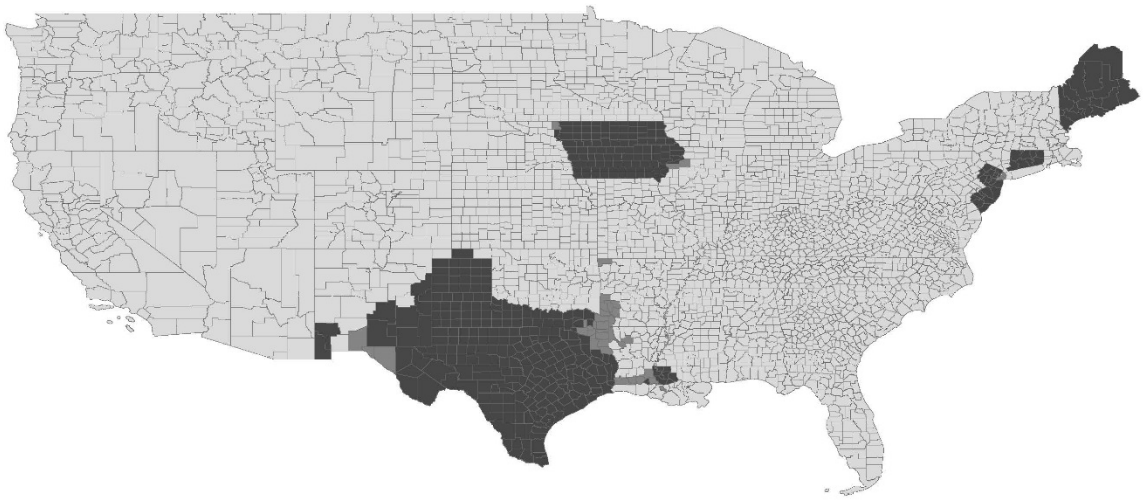
Table 4 (Cont.)

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

	(1) LSHIP	(2) LSHIP	(3) LEMP	(4) LEMP	(5) LPH	(6) LPH
AGE10	-0.232***	-0.0560***	-0.252***	-0.0738***	-0.265***	-0.0701***
	(-73.98)	(-26.07)	(-102.09)	(-44.69)	(-96.82)	(-33.20)
IMPRAT	4.233***	0.841***	2.169***	0.0156	2.847***	0.111
	(21.86)	(7.99)	(14.27)	(0.19)	(16.90)	(1.07)
Year	X	X	X	X	X	X
Industry	X		X		X	
Plant		X		X		X
R-sq	0.591		0.558		0.526	

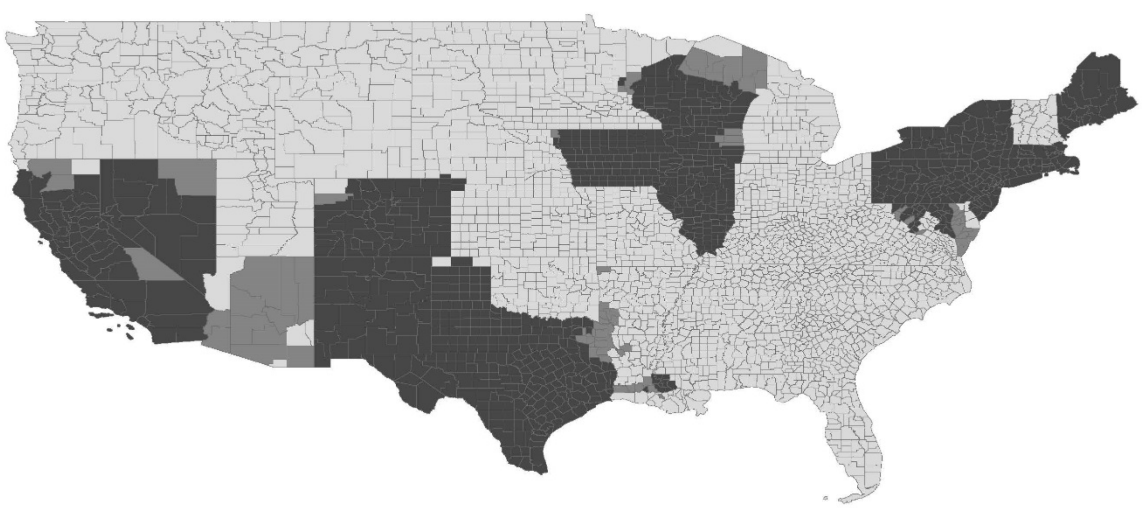
N=1,275,836; t statistics in parentheses; *p<0.05, **p<0.01, ***p<0.001

Figure 1
RPS – County-level measure for 2000



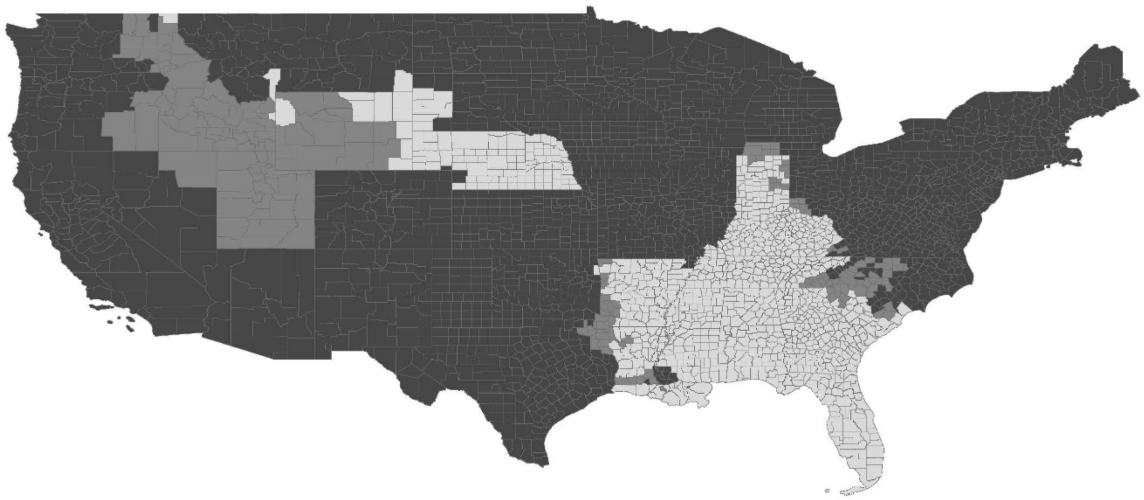
(light=RPS<0.1, shaded=RPS between 0.1 and 0.9, black=RPS>0.9)

Figure 2
RPS – County-level measure for 2005



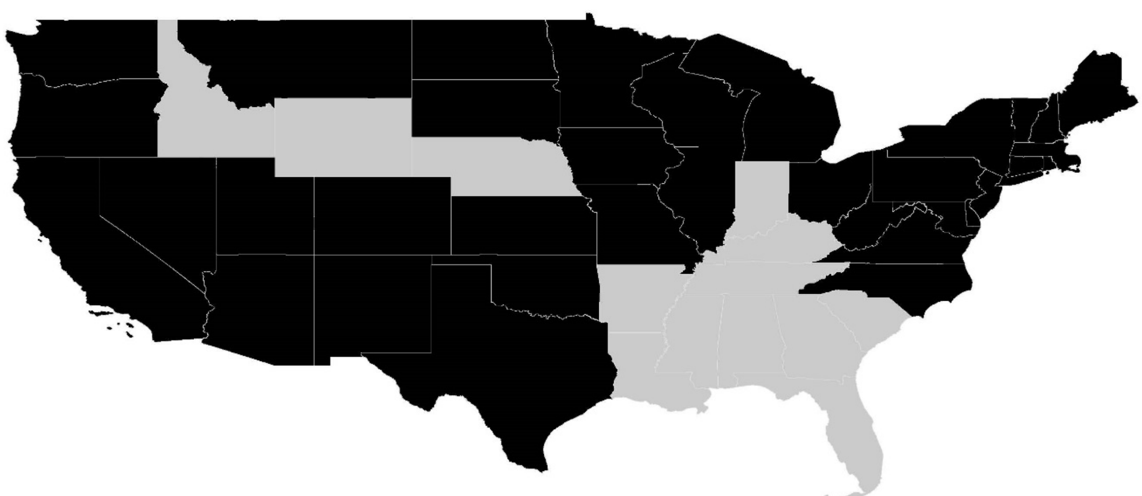
(light=RPS<0.1, shaded=RPS between 0.1 and 0.9, black=RPS>0.9)

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)