Do Renewable Portfolio Standards Reduce Carbon Emissions from Electricity Generation?

Jordan Fox and Simran Mehrotra
The University of Texas at Austin

Abstract

Carbon emissions have become a worldwide concern. In 2018 alone, over 40 billion metric tons of CO2 was released into the atmosphere; of these, an estimated 13 billion can be attributed to electricity generation. One of the most notable policies that states have enacted to incentivize the deployment of renewable energy are Renewable Portfolio Standards (RPS), which set minimum requirements for electricity providers to get a portion of their energy from renewable sources. We use a difference-in-differences approach to gauge the impact of RPS on carbon emissions from electricity. We find that states who have adopted RPS policies see decreases in carbon emissions as high as 17% and as low as 15%.

I. Introduction

Since 1983, more than thirty states have adopted Renewable Portfolio Standards with the aim of diversifying their respective energy supplies. These vary by mechanism, targeted sector, targeted energy source, and percentage of renewable energy requirement.[2] As a result, no two RPS regimes are the same, making direct comparisons as well as judgements of their overall effectiveness difficult. For example, one RPS may have a requirement for investor-owned utilities (IOU) to source a percentage of their energy from wind; another might have renewable requirements for municipalities or local governments, while offering incentives to invest in a specific energy source instead of direct mandates.

To measure the impacts of RPS, we use carbon emissions from electricity, modeling it as a function of state policy. This variable allows us to control for variations in emissions as a direct result of renewable energy deployment: because these technologies have the lowest carbon footprint, increases in their deployment should correspond to decreases in the levels of carbon dioxide from electricity generation while controlling for the generation capacities of non-renewable sources. Our results suggest that RPS have a moderate and statistically significant impact on electricity-related carbon emissions, while the strength of the policy and number of neighboring states with similar policies have no effect.

Our analysis follows this outline: First, we briefly summarize how RPS have been implemented in the US, reviewing their mechanisms, targeted sectors, targeted energy type, and minimum renewable requirements. Next, we cover the literature on the impacts and efficacy of RPS policies, comparing different studies with one another and contrasting them with our own. After that, we describe the data we collected to model carbon emissions. Then, after considering different modeling frameworks, we specify our baseline model and report our results. Lastly, we test if these results are robust to specification tests.

II. Literature Review

While there have been many studies on the impacts of RPS on renewable energy deployment, thorough treatments of their impacts on carbon emissions are somewhat infrequent given their popularity as a policy at the state-level. Currently, research has suggested a positive relationship between RPS adoption and renewable energy use. Sekar and Sohngen (2014) found that by 2010, RPS had already led to a 4% decrease in the carbon intensity of the energy supply of the US.[5] In a 2012 synthetic control study, Shrimali et al. (2012) found that RPS have a positive effect on renewable energy deployment. This effect was even larger for states which coupled their RPS with renewable energy credit (REC) unbundling, which allows such credits to be traded separately from energy generation.[6] Yin and Powers (2010) find that on top of having a positive and statistically significant impact on renewables and in-state renewable generation using a novel measure for RPS stringency, but REC unbundling has a negative impact on renewable deployment.[7] In a similar framework that controls for political climate, Kneifel (2008) finds that even voluntary standards, whereby the option to purchase green energy is encouraged but not mandated by the state, have positive and significant impacts on the deployment of certain renewable sources.[3]

Our paper complements existing research by controlling for variables that are featured across these studies, but not necessarily found in each one. By controlling for voluntary goals, the strength of minimum requirements specified by RPS, and the number of neighboring states which have adopted RPS and RPS-like policies, we're able to specify a model that is a synthesis of previous attempts at modeling their impacts.

III. Mechanisms, Targets, and Diversity in Policy

As previously mentioned, there is a great deal of heterogeneity among such policies. However, a common thread exists among all of these: all RPS are established alongside carbon markets, which are used to enforce compliance with minimum renewable requirements. RECs can then be traded among producers and consumers of electricity. As a result, one of the most popular mechanisms featured in RPS are credit multipliers, which award additional credits for different types of energy. So far, 38 credit multipliers have been adopted across 15 states [4], with roughly half being focused on solar and photovoltaics. Some aren't focused on specific technologies at all, and instead include provisions for community-run generation of electricity or electricity that is produced in-state [2].

Because over 70% of US electricity customers are served by providers that are investor-owned, the vast majority of RPS target investor-owned utilities. However, several states also target retail suppliers, municipalities and local governments, and cooperative utilities. Often, these sectors will face different requirements under the same RPS. For example, Illinois requires IOUs to get 75% of their annual requirement from wind sources, but retail suppliers only face a mandate of 60% [2].

For targeted energy sources, the majority of RPS focus on the deployment of photovoltaics, although many also include provisions for wind, hydro, and biomass technologies, and often feature more than one target. For example, Maryland's targets photovoltaics and wind, Delaware's focuses on solar and offshore wind, and Arizona's targets photovoltaics, in-state manufacturing, and other distributed renewables [4].

IV. RESEARCH DESIGN AND EMPIRICAL MODEL

The research design one chooses hinges on how comprehensive the control variables are for that particular variable being modeled. If there is no unobserved heterogeneity, that is, if each relevant confounding variable is included in the analysis, then a pooled OLS approach can deliver consistent, efficient results. However, if one believes unobserved heterogeneity to be present, then a panel framework such as a fixed or random effects model may be more appropriate, depending on the assumptions one makes. If the unobserved heterogeneity is believed to be time-invariant, then a fixed effects model is preferable as it can difference away from these unit-specific effects. If on the other hand this heterogeneity is believed to be determined by a random process, then a random effects model may be necessary.

Because we don't believe our set of controls can account for all of the variance observed in electricity-related carbon emissions, we cannot use pooled OLS for our analysis and instead prefer to use either a fixed effects or random effects framework. However, one of our control variables–renewable energy potential–is fixed over time. We believe this variable to be crucial for our analysis, as states with higher renewables potential (i.e., the space for photovoltaic panels or wind turbines) may more readily adopt an RPS; this presents a problem for a fixed effects model, which would essentially omit this variable during the process. At the same time, we also believe there are time-invariant, structural differences between states when it comes to electricity use and generation, and as a result, we're uncertain of which approach to use. We defer to a Hausman test, which tests the null hypothesis that there are no systematic differences between the two frameworks when applied to a particular problem. In the case that there are significant differences, the fixed effects model is favored. We test the following baseline models:

$$Y_{it} = \alpha_i + \beta_t + \delta RPS_{it} + \gamma X_{it} + \epsilon_{it} \tag{1}$$

$$Y_{it} = \delta RPS_{it} + \theta Potent_i + \gamma X_{it} + \epsilon_{it} \tag{2}$$

The first models electricity emissions as a function of state policy, population, per-capita income, average electricity price, fuel and coal costs for electricity generation, as well as time and state fixed effects. The second models electricity emissions almost identically, with the differences that renewable energy potential is included as a covariate and fixed effects are omitted. The results from our Hausman test show that there is a significant difference between the two models, indicating that a fixed effects framework is preferable to random effects, even if a relevant variable for RPS success is omitted.

Within the context of a fixed effects framework, the coefficient on δ can be interpreted as the difference-in-differences estimator, which in our case would represent the average treatment effect of going from RPS = 0 to RPS = 1. It can be represented mathematically as:

$$[Y(RPS_{i,t} = 1) - Y(RPS_{i,t-1} = 0)] - [Y(RPS_{j,t} = 0) - Y(RPS_{j,t-1} = 0)]$$

where $[Y(RPS_{i,t} = 1) - Y(RPS_{i,t-1} = 0)]$ represents the difference in carbon emissions for state i that adopted an RPS regime in time t. $[Y(RPS_{j,t} = 0) - Y(rps_{j,t-1} = 0)]$ would then represent the effect of state j not adopting a similar policy.

Next, it may be possible that states that adopted RPS did so in response to market conditions. For example, a state might adopt an RPS in response to the trend of carbon emissions, or even in response to fluctuations in the prices of fuels for generating electricity. This would imply these covariates are correlated with the unobservables and bias our estimates on the impacts of RPS. We estimate the following models to test for these:

$$Y_{it} = \theta RPS_{it} + \beta_t + \delta(RPS_{it} * t) + \gamma X_{it} + \epsilon_{it} \tag{3}$$

$$Y_{it} = \theta RPS_{it} + \beta_t + \delta(RPS_{it} * Coal_{it}) + \gamma X_{it} + \epsilon_{it} \tag{4}$$

$$Y_{it} = \theta RPS_{it} + \beta_t + \delta(RPS_{it} * Fuel_{it}) + \gamma X_{it} + \epsilon_{it} \tag{5}$$

If the coefficients for delta in any of these three are significant, it would suggest that we have an endogeneity problem with our model, and in the case of the first model, that there were significant differences in the trends of carbon emissions between states who did and did not adopt RPS. This would call into question our research design: the coefficient on delta can be interpreted as the difference-in-difference estimate, and the identifying assumption for any difference-in-difference analysis is that the trend of the outcome variable for treatment and control groups is the same in the pre-treatment period. We can see from Table 2, Table 3, and Table 4 that none of the coefficients for delta are significant in any specification. Most notably, the interaction between RPS and t in (1) is insignificant, which tells us that our fixed effects framework is appropriate.

V. Data

We use state-level data on carbon emissions (measured in millions of metric tons) from electricity between 1990 and 2017. We believe this gets us around two problems when trying to model the impacts of RPS: First, by focusing on a variable that will be impacted by any type of renewable deployment, we're able to gauge the effects of RPS as a whole without having to consider whether they focus on promoting the use of specific types of renewable sources. Second, by focusing on electricity emissions generated in each state, we're able to control for the fact that many states buy and sell electricity across state lines. Data on total carbon emissions isn't likely to show the impacts of RPS because these do not target emissions from industry and transportation, which together account for over 50% of carbon emissions in the United States.[1]

Our control variables are meant to capture economic conditions that might impact the amount of electricity generated at any time. The variables to capture supply-side characteristics include state carbon intensity of the energy supply, average price of electricity, fuel and coal costs for electricity generation,and renewable energy potential. We expect emissions to fluctuate based on these, in particular to changes in fuel and coal costs. For demand-side factors, we include data on population and per capita incomes. All of these were sourced from the EIA's website, and all data on prices and incomes are in 2019 dollars.

After running our baseline model, we run two additional specifications (Model 2 and Model 3, respectively), each with an additional covariate that we believe may remove upward bias on our estimated treatment effect. In the first of these we include our variable which measures the strength of each RPS, categorizing them as “weak, moderate, or strong” depending on the minimum renewable requirements mandated by policy. It's possible that lower-requirement policies have less of an effect, and that much of the variation in emissions for RPS-adopting states is being driven by those with aggressive requirements, such as California, Hawaii, Maryland, and New Jersey. Additionally, our variable on the number of states which have adopted RPS will account for the variation in carbon emissions that can be attributed to interstate electricity sales. This variable takes on values between 0 and 5, and tells us the number of states which have adopted RPS that a given state shares a contiguous border with.

VI. Results

Following Bertrand et al. (2004), we use clustered standard errors which correct for any serial correlation between the outcome variable and our controls. The results from our baseline, log-level estimate show that the effect of enacting an RPS results in, on average, a decrease in carbon emissions by about 11 percent. When we controlled for RPS strength, this effect grew to a 17% decrease, an effect that remained when we included the number of neighboring states in the third model. The estimate on RPS strength is difficult to interpret, but might not necessarily be a causal one: it's possible that states that adopted more aggressive RPS policies had higher levels of carbon emissions. The number of neighboring states with RPS has a slight negative impact, although this effect is statistically insignificant.

VII. Specification Tests

To test the robustness of our results, we run two additional models, each with an additional covariate that we believe may remove upward bias on the estimates in our baseline model. In the first of these, we include our variable which measures the aggression of each RPS, categorizing them as "weak, moderate, or strong" depending on the minimum renewable requirements mandated by policy. It's possible that lower-requirement policies have less of an effect, and that much of the variation in emissions for RPS-adopting states is being driven by those with aggressive requirements, such as California, Hawaii, Maryland, and New Jersey. Additionally, our variable on the number of states which have adopted RPS will account for the variation in carbon emissions that can be attributed to interstate electricity sales. This variable takes on values between 0 and 5, and tells us the number of states that a given state shares a contiguous border with.

We can see from Table 5 that when we control for voluntary goals, our estimate for the effects of RPS decreases by about 3 percentage points to only 8% in the baseline model. When we control for RPS strength, this effect grows to a 15% decrease, which remains even when we control for the number of neighboring states which have an active RPS. All of these effects are significant at the 99% level. Meanwhile, voluntary goals do not appear to have any effect on carbon emissions from electricity generation.

Next, we drop observations for the states of Vermont, Maine, and DC and rerun the model from Table 5. We believe that because these states have exceptionally low levels of carbon emissions from electricity generation–and all three have adopted RPS–that it's possible that the average treatment effect is being overstated. Table 6 shows the results from this specification. Here, we can see that RPS adoption results in an 11% decrease in carbon emissions in the baseline model. When we control for RPS strength, this effect grows to a near-17% decrease. All of the effects of RPS are significant at the 99% level. However, neither RPS strength nor the number of neighbors are found to be significant.

VIII. Conclusion

While our findings suggest that RPS have a moderate and statistically significant effect on carbon emissions at the state level, our controls are hardly comprehensive enough to call our study definitive.

Instead, we prefer to conclude that our results provide modest evidence in favor of RPS as an effective environmental policy, and that the strength of RPS–as well as environmental policies of neighboring states–have little to no role in determining state-level carbon emissions from electricity. Further investigation is needed if state lawmakers plan to continue adopting these policies, and additional mechanisms beyond what are currently being used may be necessary to promote renewable energy deployment at the state level.

REFERENCES

[1] Sources of Greenhouse Gases, US EPA. https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions. (Accessed on 12/13/2020).
[2] State Renewable Portfolio Standards and Goals. https://www.ncsl.org/research/energy/renewable-portfolio-standards.aspx. (Accessed on 12/13/2020).
[3] Joshua Kneifel. Effects Of State Government Policies on Electricity Capacity from Non-Hydropower Renewable sources. 2008.
[4] Lips, Brian. Credit Multipliers in Renewable Portfolio Standards. (Accessed on 12/13/2020).
[5] Samantha Sekar and Brent Sohngen. The Effects of Renewable Portfolio Standards on Carbon Intensity in the United States. *Resources for the Future Discussion Paper*, (14-10), 2014.
[6] Gireesh Shrimali, Steffen Jenner, Felix Groba, Gabriel Chan, and Joe Indvik. Have State Renewable Portfolio Standards Really Worked? Synthesizing Past Policy Assessments to Build an Integrated Econometric Analysis of RPS Effectiveness in the US. 2012.
[7] Haitao Yin and Nicholas Powers. Do State Renewable Portfolio Standards Promote In-State Renewable Generation? *Energy Policy*, 38(2):1140–1149, 2010.

TABLE I
LOG-LEVEL SPECIFICATION

Coefficients	**Model 1**	**Model 2**	**Model 3**
RPS	-0.114*** (-0.0167)	-0.174*** (-0.0224)	-0.174*** (-0.0224)
RPS Strength		0.0529*** (-0.0132)	0.0538*** (-0.0132)
Neighbor			-0.00665 (-0.00673)
Cons	-0.234 (-0.222)	-0.098 (-0.224)	-0.0914 (-0.224)
Standard errors in parentheses	="* p¡0.05	** p¡0.01	*** p¡0.001"

TABLE II
ENDOGENEITY TEST 1

Coefficients	**Model 1**	**Model 2**	**Model 3**
RPS	156 (-131.6)	140.1 (-315.7)	-10.17 (-326.6)
RPS*t	-0.0789 (-0.0655)	-0.0716 (0.157)	0.00325 (-0.163)
RPS strength		1.138 (-1.271)	1.358 (-1.153)
Neighbor			-1.951** (-0.568)
Cons	31.62*** (-5.495)	33.18*** (-7)	28.47*** (-5.783)
N	1344	1344	1344
Standard errors in parentheses	="* p¡0.05	** p¡0.01	*** p¡0.001"

TABLE III
ENDOGENEITY TEST 2

Coefficients	**Model 1**	**Model 2**	**Model 3**
RPS	-0.748 (-3.797)	-2.338 (-4.422)	-4.017 (-4.529)
Coal*RPS	-0.864 (-2.207)	-0.706 (-2.208)	0.202 (-2.256)
RPS strength		1.137 (-1.272)	1.364 (-1.157)
Neighbor			-1.951** (-0.565)
Cons	31.88*** (-6.495)	33.45*** (-6.935)	28.52*** (-5.711)
N	1344	1344	1344
Standard errors in parentheses	="* p¡0.05	** p¡0.01	*** p¡0.001"

TABLE IV
ENDOGENEITY TEST 3

Coefficients	Model 1	Model 2	Model 3
RPS	-1.897 (-1.543)	-3.294 (-2.595)	-3.924 (-2.435)
Fuel*RPS	-0.046 (-0.136)	-0.0371 (-0.136)	0.0282 (-0.139)
RPS strength		1.147 (-1.271)	1.367 (-1.156)
Neighbor			-1.959** (-0.565)
Cons	32.48*** (-6.051)	33.95*** (-6.479)	28.27*** (-5.114)
N	1344	1344	1344
Standard errors in parentheses	="* p¡0.05	** p¡0.01	*** p¡0.001"

TABLE V
RPG SPECIFICATION MODEL

Coefficients	Model 1	Model 2	Model 3
RPS	-0.085 (-0.0502)	-0.152** (-0.0522)	-0.151** (-0.0542)
RPG	0.0726 (-0.0685)	0.0699 (-0.0679)	0.071 (-0.0714)
RPS strength		0.0534* (-0.0264)	0.0533* (-0.0264)
Neighbor			-0.00331 (0.0242)
Cons	-0.416 (-0.804)	-0.266 (-0.777)	-0.246 (0.788)
N	1389	1389	1389
Standard errors in parentheses	="* p¡0.05	** p¡0.01	*** p¡0.001"

TABLE VI
RPG SPECIFICATION MODEL, WITHOUT DC, VERMONT, OR MAINE

Coefficients	Model 1	Model 2	Model 3
RPS	-0.107*** (-0.0173)	-0.167*** (-0.0228)	-0.167*** (-0.0228)
RPG	0.0501 (-0.0298)	0.0469 (-0.0296)	0.0491 (-0.0297)
RPS strength		0.0523*** (-0.0132)	0.0533*** (-0.0132)
Neighbor			-0.00741 (0.00674)
Cons	-0.247 (-0.222)	-0.112 (-0.224)	-0.105 (0.224)
N	1337	1337	1337
Standard errors in parentheses	="* p¡0.05	** p¡0.01	*** p¡0.001"