12-2018

Renewable Portfolio Standards and Environmental Goals

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RENEWABLE PORTFOLIO STANDARDS AND ENVIRONMENTAL GOALS

by

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A thesis submitted in partial fulfillment
of the requirements for the degree

of

MASTERS OF SCIENCE

in

Economics

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UTAH STATE UNIVERSITY
Logan, Utah

2018

ABSTRACT

Renewable Portfolio Standards and Environmental Goals

by

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Utah State University, 2018

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Renewable portfolio standards (RPS) are one of the most common state-level policies meant to encourage low-carbon energy development. RPS require that utilities purchase electricity from certain qualifying electricity generators, usually with no reference to the cost of that electricity. Though RPS are often pushed as a means to clean up electricity generation, they also provide rents to the industries that are included in the RPS by protecting them from market competition with other generators. I explore the association between RPS and carbon emissions. I collect data from 1960 to 2017 on factors related to environmental quality, energy production, and state economic factors. The data's availability varies, however, so the most expansive variables are from 1960 to 2015 while many others fall into a shorter timeframe. The dataset relies heavily on the State Energy Data System (SEDS) that the Department of Energy's Energy Information Administration (EIA) maintains, but also draws from a variety of other academic sources. Other variables, such as the dates of electricity market restructuring, I collect myself from primary sources. After accounting for existing linear trends in the data there appears to be no statistically significant relationship with RPS and carbon emissions.

(60 pages)

PUBLIC ABSTRACT

Renewable Portfolio Standards and Environmental Goals

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Renewable portfolio standards (RPS) are one of the most common state policies meant to encourage clean energy use. They require that utilities purchase electricity from certain qualifying electricity generators, usually with no reference to the cost of that electricity. Although RPS are meant to clean up electricity generation through using clean energy sources instead of fossil fuels, they may not do so effectively. Further, some energy companies may lobby state legislators to include their energy sources regardless of their actual environmental benefit. The actual relationship between enacting an RPS and a state's emissions from energy production is unclear. I explore RPS associations with carbon emissions. I collect data from 1960 to 2017 on factors related to environmental quality, energy production, and state economic factors. The data availability varies, however, so the most expansive variables are from 1960 to 2017 while many others fall into a shorter timeframe. The dataset relies heavily on the State Energy Data System (SEDS) that the Department of Energy's Energy Information Administration (EIA) maintains, but also draws from a variety of other academic sources. Other variables, such as the dates of electricity market restructuring, I collect myself from primary sources. After accounting for existing linear trends in the data there appears to be no statistically significant relationship with RPS and carbon emissions.

ACKNOWLEDGMENTS

I owe many individuals an acknowledgment for their assistance on this project and throughout my graduate program. My committee who has put up with my careening from research question to research question and provided guidance on which are most promising. In particular, Bill Shughart, whose public choice theory class shaped my approach to the world and to policy questions more than any other class. Dr. Depew and Dr. Bosworth remained invaluable throughout in helping provide econometric guidance and serving as not just sounding boards, but strong critics of my work that ultimately improved this paper and my econometric skills.

I will claim all the remaining errors, but credit each of these individuals for the good ideas.

Josh T. Smith

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CHAPTER 1

RENEWABLE PORTFOLIO STANDARDS AND ENVIRONMENTAL GOALS

Renewable portfolio standards (RPS) are a common state-level policy that require electricity providers in a state to use certain sources of electricity as a percentage of their electricity-generating portfolio. The amount of required electricity from qualifying sources starts at a low level and then rises to a final ceiling. According to the Database of State Incentives for Renewables and Efficiency (DSIRE), 29 states and Washington DC have adopted binding RPS. Several other states, such as Utah and Kansas, have voluntary standards. Figure 1 from DSIRE shows a map of state RPS as of February of 2017.

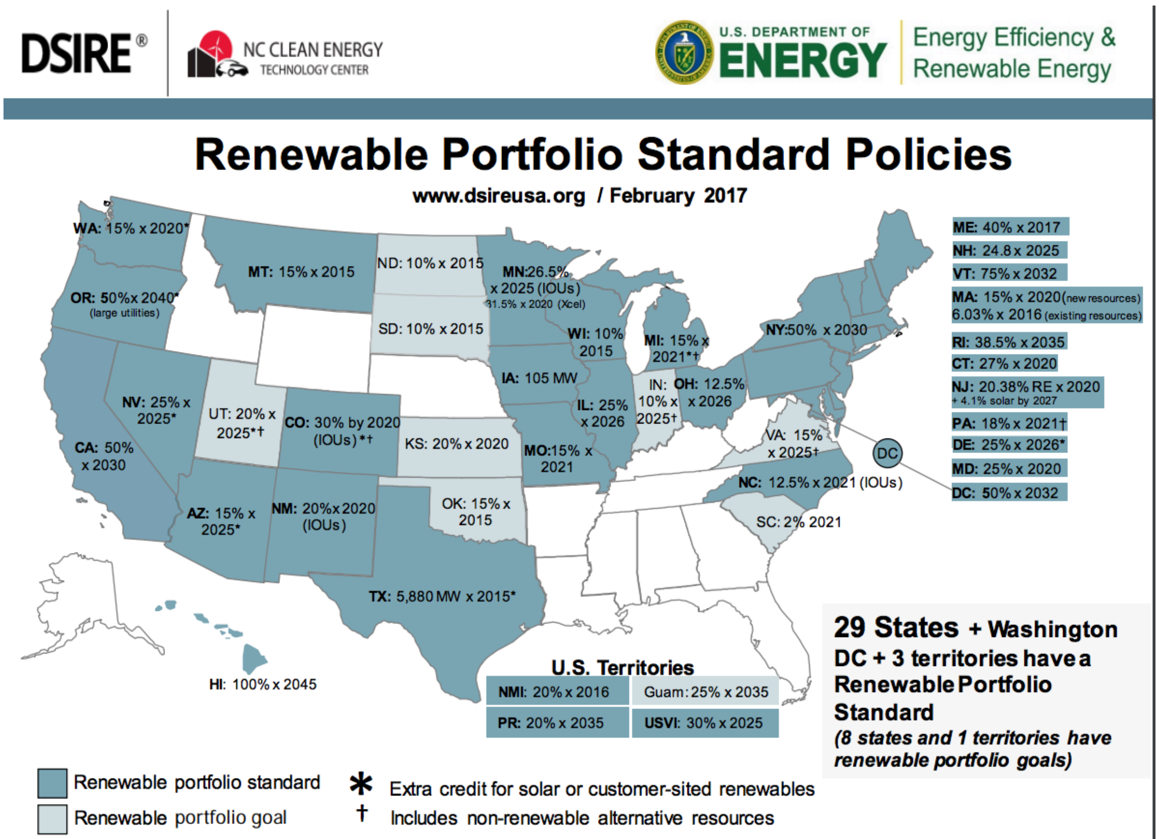

Figure 1. State RPS Map from the Database of State Incentives for Renewables and Efficiency.[1]

[1] http://ncsolarcen-prod.s3.amazonaws.com/wp-content/uploads/2017/03/Renewable-Portfolio-Standards.pdf

RPS Goals and History

RPS primarily were enacted to promote the use of low-carbon, or clean, energy sources. As one of many policies adopted to climate change, they are intended to reduce carbon emissions and prevent environmental pollution. Clean energy advocates claim that RPS will boost economic growth and create jobs, and some enacting legislation includes this as a goal of the policy, but economic goals are secondary goals to the environmental purposes of an RPS.

State requirements vary under RPS, as DSIRE's map makes clear. For example, New Hampshire's RPS requires that 25.2 percent of its electricity be generated from qualifying energy sources by 2025.[2] Texas, instead of requiring a percentage of the energy mix, requires that 10,000 megawatts (MWs) of electricity be produced from renewables by 2025.[3]

The timing of RPS enactments also varies widely. Iowa enacted the first RPS in 1983. Other states began adopting renewable portfolio standards in the following years. Table 1 displays the enactment dates updated from previous studies of RPS (Upton & Snyder 2017; Lyon, 2015). Kansas and West Virginia both repealed their RPS in early 2015. Kansas in May and West Virginia in February. Extending Upton & Snyder (2017), my timeline also includes Vermont's 2015 enactment of an RPS.

Table 1

RPS Enactment Dates Updated from Upton & Snyder (2017) and Lyon (2015)[4]

State	*Year RPS Enacted*

[2] http://programs.dsireusa.org/system/program/detail/2523
[3] http://programs.dsireusa.org/system/program/detail/182
[4] Blanks indicate that no RPS has been enacted in that state. These dates are updated from Upton and Snyder (2017) and Lyon (2015).

Alaska	No RPS
Alabama	No RPS
Arkansas	No RPS
Arizona	2001
California	2002
Colorado	2004
Connecticut	1999
Delaware	2005
Florida	No RPS
Georgia	No RPS
Hawaii	2004
Iowa	1983
Idaho	No RPS
Illinois	No RPS
Indiana	No RPS
Kansas	2009 (repealed 2015)
Kentucky	No RPS
Louisiana	No RPS
Massachusetts	1997
Maryland	2004
Maine	1999
Michigan	2008
Minnesota	1997
Missouri	2008

Mississippi	No RPS
Montana	2005
North Carolina	2007
North Dakota	No RPS
Nebraska	No RPS
New Hampshire	2007
New Jersey	2001
New Mexico	2002
Nevada	1997
New York	2004
Ohio	2008
Oklahoma	No RPS
Oregon	2007
Pennsylvania	2004
Rhode Island	2004
South Carolina	No RPS
South Dakota	No RPS
Tennessee	No RPS
Texas	1999
Utah	No RPS
Virginia	No RPS
Vermont	2015
Washington	2006
Wisconsin	1999

West Virginia	2009 (repealed 2015)
Wyoming	No RPS

Most RPS enactments occur through normal political means. State legislatures enact them after a period of discussion and debate. Arizona, however, originally created a solar only standard through the Arizona Corporation Commission, which is the state's public utility commission. Eventually the state expanded the RPS to include more than solar. When Iowa enacted its RPS, long legal disputes ensued, but those eventually were resolved and RPS went into effect.

There is extensive public debate in states with RPS revolving the appropriate levels to set. California and some other states, for example, raise their RPS goals occasionally from the initial levels set under the first bill. States without RPS often consider enacting them and two states, West Virginia and Kansas, have repealed their RPS in response to worries about RPS driving increases in electricity rates and concerns about economic costs.

The environmental goal of lowering carbon emissions is the primary aim of RPS. Figure 2 shows the carbon emissions for states that enacted an RPS.

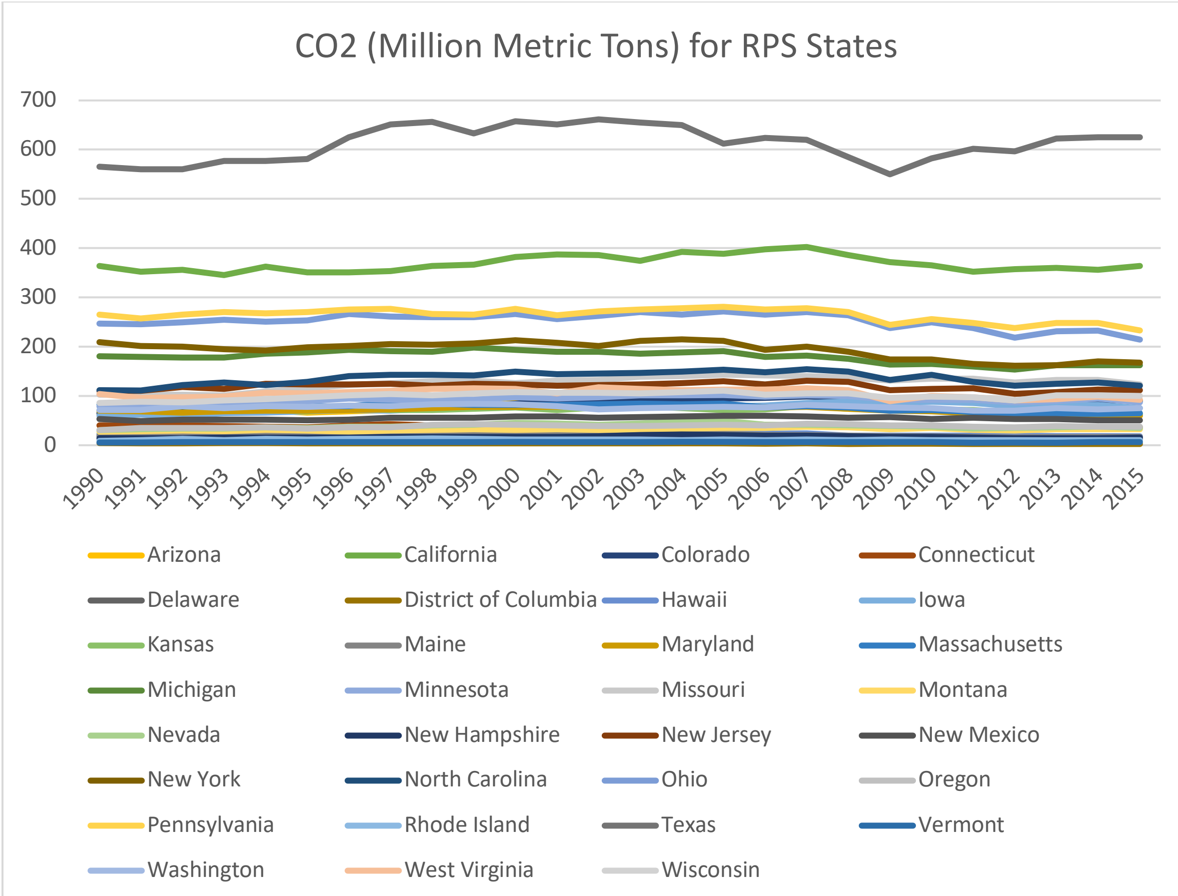

Figure 2. Carbon Emissions in RPS States (calculated from EIA Data)

Carbon emissions have been stable overall from 1990 to 2015 in RPS states. As Figure 3 shows, a similar trend holds for non-RPS states.

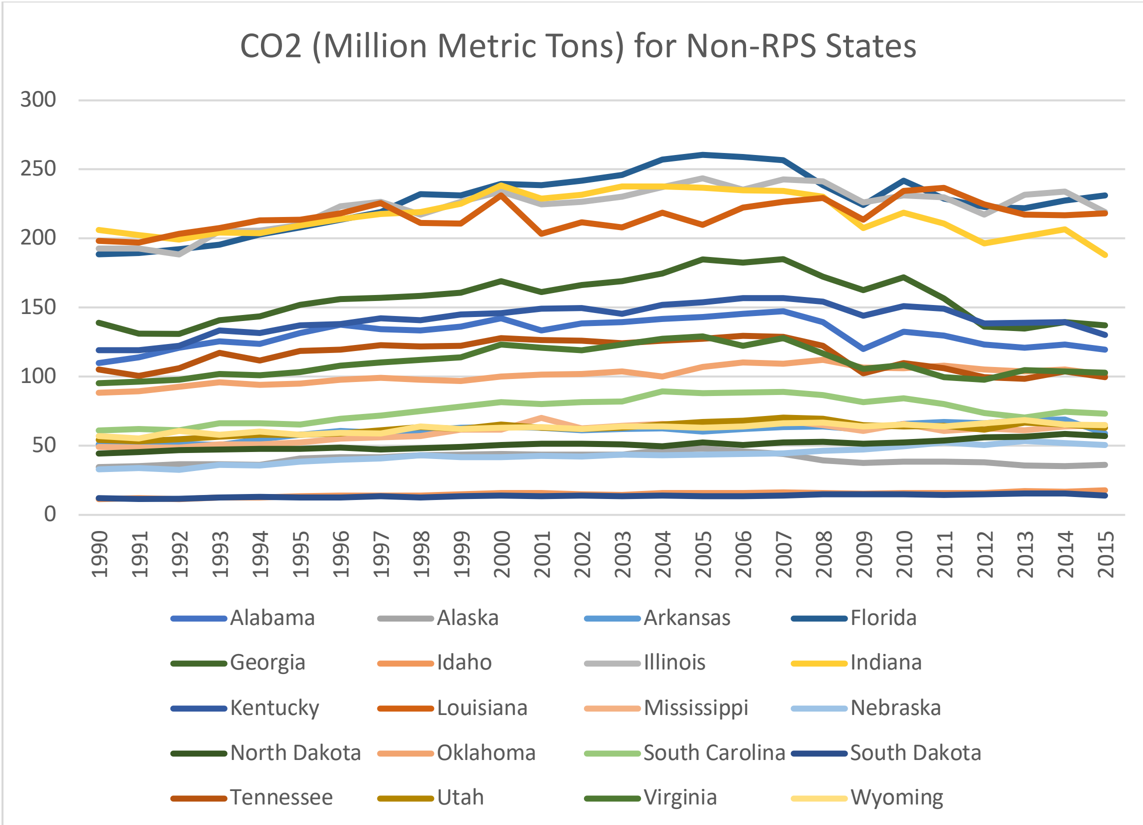

Figure 3. Carbon Emissions in Non-RPS States (calculated from EIA Data)

The average difference in CO_2 emissions between RPS states and non-RPS states is small. Figure 4 shows that the two groups of states are at relatively similar levels and appear to behave in similar manners on average.

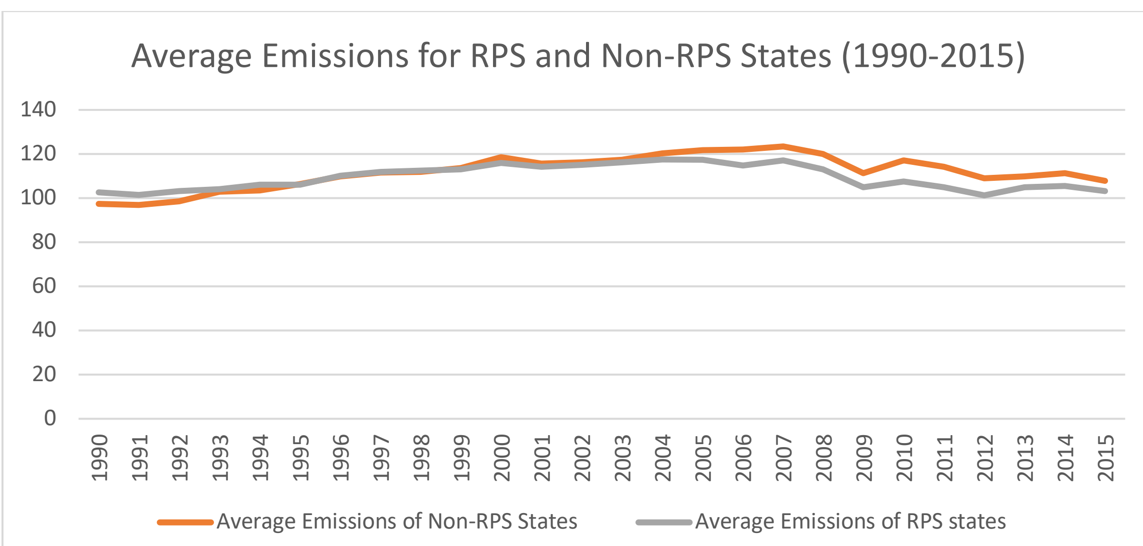

Figure 4: Average CO_2 Emissions for RPS and Non-RPS States (calculated from EIA Data)

Figures 2, 3, and 4 do not reveal an obvious relationship between an RPS and lower carbon emissions. This makes a more rigorous statistical analysis an interesting research question.

Overview of Methods, Findings, and Implications

To investigate the relationship between RPS and carbon dioxide (CO_2) emissions I estimate a simple difference-in-differences (DD) model that controls for state fixed effects and time fixed effects. Initial modeling reveals a statistically significant reduction in CO_2 of about five percent. This relationship is robust to several controls but fades out when a control for total energy consumption is added to the model. It appears an RPS decreases carbon emissions by lowering overall consumption of energy. This is in line with the findings of previous research that posits that an RPS may raise electricity prices and thus push down electricity consumption (Upton & Snyder 2017).

The model cannot attribute those emissions declines to the RPS, however, because of the pre-existing trends. Instead, what appears to be happening is that RPS states likely enact many environmental policies that target emissions. The cumulative effect of those regulations does appear to lower emissions. Accurately attributing the emissions reduction to any single policy is difficult to justify. States with an RPS, for example, likely have a powerful environmental lobbying sector responsible for originally passing the RPS. This lobby likely is interested in other environmental protections and so there is a fundamental difference between RPS states and non-RPS states that a DD model cannot adequately address. This relationship may drive the results found in other work on RPS employing the DD method as well.

The state fixed effects and the time fixed effects control for time invariant factors such as the qualities of renewable energy resources in a state or the culture of a state. Yet the fixed effects for states and years may not properly account for the existing trends in states before the enactment of an RPS. Although a DD model mimics an experimental design by creating treated and untreated groups for comparison, the enactment of RPS is unlikely to be random and so does not meet all of the standards for interpreting the research design as a true natural experiment. As I ultimately show, there are preexisting trends in states that enact RPS that do not exist in non-RPS states. So RPS states may not be on a parallel trend, sometimes called a parallel path, with non-RPS states, thereby rendering any DD model's findings as spurious and unreliable.

After accounting for the pre-existing policy state-specific policy heterogeneity by introducing trend variables, the model predicts no statistically significant relationship between RPS and lower emissions of CO2. These results extend past findings (Upton & Snyder 2017), which did not account for the state trends that existed before the RPS was enacted. These state trends, however vary by state and if not accounted for, lead to spurious results in statistical models.

The inclusion of linear trends is a unique contribution to the study of RPS and emissions as well as possibly a unique contribution to the growing number of studies exploring the impacts of RPS.

CHAPTER 2

PREVIOUS WORK ON RPS

There are several common strands in the previous academic literature on RPS. Individual studies rarely silo themselves neatly into a single branch. Three areas in particular stand out as involving most of the academic work on RPS. First, one of the largest branches of research on RPS examines the factors contributing to the enactment of an RPS. Broadly, it finds that political factors such as ideology, party affiliation, and voter preferences are important predictors of RPS enactment in addition to renewable resource potential in the state. Second, as a primarily environmental policy, researchers regularly examine the environmental benefits of RPS such as projected carbon abatement and increased renewable energy capacity built. Finally, perhaps one of the most controversial areas of research in political circles is the effect RPS have on electricity prices. Most research here finds that RPS increase electricity prices (Tra 2016; Upton & Snyder 2017).

I fit into all three of these veins of research. The dataset I ultimately develop will be used in projects that directly contribute to each of these strands in future work. For example, other studies of RPS enactment have not accounted for whether or not a state restructured its electricity market. There are important questions with this question alone for all three research areas. Restructuring may have a differential influence on whether an RPS is enacted, how well it achieves its environmental goals, and how costly the policy is. For example, do more competitive electricity markets lower or enhance the environmental benefits created by an RPS? Or similarly for the economic costs area, do restructured markets make RPS more or less economically costly? And finally, are states that enact an RPS also more likely to pursue restructuring? Perhaps because of an underlying desire to promote innovative energy policies? Each of these questions merit their own investigation and study, but my novel dataset is a step towards answering each of them.

Why do States Enact RPS?

The enactment of an RPS is meant to serve multiple goals. As such, previous literature on why states adopt RPS examines the influence of: environmental interest groups, fossil fuel interest groups, political ideology, neighboring states' policies, and renewable energy resource quality.

Research on RPS adoption has long shown the importance of political factors such as the size and relative powers of competing interest groups (Chupp 2011; Lyon & Yin 2010; Matisoff 2008; Fowler 2013). Fowler (2013) concludes that the political factors like partisanship and political culture are most important in RPS adoption.

Lyon and Yin (2010) provide an exhaustive test of multiple hypotheses and find a variety of interesting results. For example, Lyon and Yin hypothesize that states with lower air quality may be more likely to enact RPS so that they can improve their state's air quality, but they ultimately reject this hypothesis even when examining the adoption of in-state requirements. They find that having a greater number of Democrats in the state legislature increases the likelihood that states will adopt an RPS, but also that the governor's party is inconsequential. Two primary results of interest that fit into the interest-group theory of regulation from Olson (1960) are that Lyon and Yin find that the presence of well-organized renewable energy interest groups is associated with a 19 times increase in the likelihood of a state adopting an RPS. Similarly, a heavy reliance on natural gas decreases the likelihood that a state will adopt an RPS.

Huang, Alavalapati, Carter, and Langholtz (2007) investigate whether the adoption of an RPS by states is random. They find that education levels and the political party in power are two of the most important predictors. Matisoff (2008) investigates a similar question on whether or not neighboring states' policies push states to adopt an RPS and finds that citizen demands for an RPS are better explanations than is diffusion from one state to another. Chandler (2009) by contrast, concludes that neighbor diffusion variables are important. Chandler's findings, however, use a broader definition of RPS that includes energy efficiency standards as well as the RPS that Matisoff investigates. That may still pick up the influence of neighboring states since it is not necessarily true that the diffusion must be for exactly the same policy. More recent work by Carley Nicholson-Crotty, and Miller (2017) shows geographical peers are most important in diffusion, but that ideological peers are most important in terms of reinventing policies.

Renewable energy resources are another common predictor of whether or not a state adopts an RPS. Lyon and Yin (2010) find that biomass resources are not related to adoption, but that wind and solar resources are. This finding has been verified in other works as well (Upton & Snyder 2015).

Carley and Miller (2012) investigate why states may adopt a more or less stringent RPS. They find that there is stratification between the contributing factors by stringency factors. More stringent standards are driven by different factors than are less stringent factors. State-level citizen ideology is a significant predictor for voluntary and weaker RPS. Stronger policy designs are more affected by the government level ideology than citizen ideology.

What Environmental Effects do RPS Have?

RPS incentivize the use of renewable energy and deter the use of fossil fuels. Ultimately, this is meant to lower carbon emissions and the emissions of other pollutants (Wiser et al. 2017). Using the Regional Energy Development System to project several scenarios, researchers at the Lawrence Berkeley National Laboratory estimated that RPS create between $97 billion and $161 billion worth of benefits, most of which come from reduced pollution and the corresponding health effects (Wiser et al. 2017). These benefit estimates follow from the more conservative assumptions based on existing RPS policies and far outstrip their cost estimates. Other work using similar modeling techniques like the National Energy Modeling System have made similar projections (Kydes 2007).

One worry about these estimates, however, is that RPS may not actually contribute to expanded renewable energy generation capacity. A contentious point in the literature concerns the effect RPS have on the development of additional renewable energy capacity. Some early work found increasing renewable energy capacity in the states that enacted RPS (Kydes 2007; Carley 2009; Yin & Powers 2010; Eastin 2014). Yin and Powers (2010) develops a measure of RPS stringency for its analysis and finds that RPS are associated with higher levels of in-state renewable energy development but note that it is sensitive to when renewable energy credits (RECs) trading is allowed. RECs are the compliance mechanism for states with RPS. Electricity generators earn RECs by generating electricity from the qualifying sources in the RPS and can either retire them against their own obligation to produce renewable energy or sell them. Some states allow REC trading across state borders while others do not.

Some studies of RPS enactment and renewable energy deployment show mixed results. Even Carley (2009), though she finds that an RPS is associated with increased capacity, does not find evidence of increased electricity generation from renewable energy sources. Kniefel and Shrimali (2011) find that an RPS increases deployment of geothermal and solar while decreasing the use of other renewable sources like wind and biomass. Maguire (2016) finds that the enactment of an RPS seems to be unrelated to the growth of wind power within states. Maguire and Munasib (2016), by contrast, employ a synthetic control model and find strong evidence of the effect of RPS on renewable energy deployment only in Texas. Texas is unique. It met its RPS obligation several years ahead of schedule and even though the RPS is legally binding, it may not have been an economically binding constraint on electricity providers in the state. Maguire and Munasib contend that a synthetic control method (SCM) is a more appropriate method than previous studies employed because state RPS vary widely. Another paper employed a difference-in-differences (DD) method and a SCM for comparison and found no evidence of increased renewable energy capacity associated with the enactment of an RPS (Upton and Snyder 2017). Although they are not specific to the effect of an RPS, analyses of incentive programs for specific energy sources such as wind and solar consistently find that they increase deployment of the supported energy source even though the effect of the RPS is not always statistically significant (Hitaj 2012; Lasco & Chernyakhovskiy, 2016).

If RPS are not associated with increased renewable energy development in states that enact them, there is good reason to doubt they will achieve their environmental goals. Yet only a few estimates of the relationship between emissions and RPS exist. Upton and Snyder (2017) do characterize their evidence of an emissions reduction as weak and attribute it to the increase in prices associated with an RPS and the resulting lower total demand and not to increased reliance on renewable energy. Eastin (2014) finds evidence of cleaner air at the 0.05 level and lower carbon emissions, but only at the 0.1 level. Eastin also caveats that these findings may not be only because of the RPS, but rather the full suite of policy options that states, municipalities, and federal groups offer to the renewable energy industry. In an unpublished working paper, Sekar and Sohngen (2014) investigate state-level carbon intensities after the implementation of an RPS and find a statistically significant decrease. They estimate the adoption of an RPS reduced total carbon emissions in the United States by about four percent in 2010. They do not attribute this decline to increasing renewable energy generation, but instead to the increase in prices associated with RPS adoption that results in lower electricity consumption.

Even if RPS do lower carbon emissions, some research suggests it is not a cost-effective means to reach lower emissions. Modeling comparing a cap-and-trade policy to RPS shows that an RPS is more expensive, but less expensive than a renewable energy production tax credit (Palmer & Burtraw 2005).

What Economic Costs do RPS Have?

Early advocates and analyses of the likely effect of RPS argued that they would provide environmental benefits in addition to lowering electricity prices. Although speaking of an analysis of a federal RPS, Sovacool and Cooper (2007) summarize work by the Union of Concerned Scientists, the Network for New Energy Choices, the U.S. Energy Information Administration, and the Lawrence Berkeley National Laboratory which all concluded that an RPS would lower electricity prices through economies of scale. Advocates of renewable energy contest almost any link between RPS and higher electricity prices (American Wind Energy Association 2013; Shahan 2014).

The academic literature is generally clear that adopting an RPS is associated with higher electricity prices (Palmer and Burtraw 2005; Fischer 2009; Tra 2015; Upton and Snyder 2015; Wang 2016; Upton and Snyder 2017). These results hold across a variety of empirical methods and when including a variety of controls. Maguire and Munasib (2018) appear to be unique in finding no price increase associated with the enactment of Texas's RPS. This is, however, likely a result that cannot be generalized outside of

Texas.

Fischer (2009) models the conditions required for an RPS to lower electricity prices. She finds that an RPS can lower electricity prices only when an RPS is set between three and 7.5 percent. These are far smaller levels than those that states commonly set as their ultimate standards. The price declines originally because decreased demand for natural gas lowers electricity prices. Then prices rise as the implicit tax on energy production from non-qualifying sources overwhelms the decline in natural gas prices.

In addition to RPS's association with electricity prices, researchers also often investigate the effect of RPS on employment. Advocates of RPS generally claim that the policy can both decrease carbon emissions and create jobs (Rabe 2007). Empirical investigations of this claim, however, have found little relationship. In a working paper, Boampong, Knapp, and Phillips (2016) find no evidence of a change in total employment. Bowen (2013) however, finds no total job growth but does observe an increase in green businesses associated with RPS adoption.

Importantly, however, some research contests the ability of RPS to serve both economic and environmental goals simultaneously. A working paper by Bento, Garg, and Kaffine (2017) finds that increasing RPS likely results in either large emissions savings or large job growth in the renewable energy industry, but not both. They decompose the effect of an RPS increase into three parts: a substitution effect, an output-tax, and an output effect. The substitution effect is movement of capital from fossil fuel resources and into renewable energy investment because of the pull of the subsidy. This effect can create resource growth in the renewable energy industry. The output-tax occurs for a similar reason when capital leaves the electricity industry, either fossil fuel or renewable, and is used in a composite sector instead. Together, the substitution and output-tax effect, according to the researchers, are the two means for RPS compliance. That is, a standard can be met by either increasing renewable energy generation or by lowering fossil fuel energy production. The third and final effect the researchers discuss is the output effect, which is caused by changes in prices because of the change in the RPS. As the price of electricity rises, the composite good becomes relatively cheaper and consumers naturally purchase less electricity and more of the composite.

My Contribution to the Literature

The existing literature on RPS and carbon emissions so far has assumed that the DD models employed meet the background assumptions of parallel trends. Chapter 5 provides evidence that this assumption may not hold. There appears to be a difference between RPS and non-RPS states that must be accounted for that previous work has ignored.

CHAPTER 3

DATA SOURCES AND EXPLANATIONS

I collect the majority of data employed in the empirical testing from the State Energy Database System (SEDS), which is run by the United States Department of Energy's Energy Information Administration (EIA).[5] Broadly, SEDS includes the production and use of energy sources from 1960 to 2015 and the prices of energy resources from 1970 to 2015. The EIA also provides data on emissions from 1990 to 2015 in a separate dataset.[6] The separate dataset calculates emissions based on the SEDS data by multiplying certain fuel sources by "carbon coefficients" that represent how much carbon is generated from using each fuel source. One note about this data, however, is that it excludes carbon emissions from biomass by assuming that biomass emissions will be a lifecycle net zero since new biomass will be planted to replace the burned biomass. Energy from biomass is only a small portion of total energy consumption and so is unlikely to affect the results.

For robustness checks I also collected data provided by the Institute for Public Policy and Social Research (IPPSR) at Michigan State University and the University of Kentucky Center for Poverty Research (UKCPR) on political and economic factors that may also influence RPS emissions.[7] The IPPSR (2017) data is from a project to combine datasets involving state policy factors for use by other researchers and ultimately foster further research. Its data's timeline varies widely based on the original study that it is pulled from, but the variables I use generally run from 1980 to 2015.

The UKCPR's (2017) data is a state-level dataset maintained for use in policy

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[5] U.S. Energy Information Administration. State Energy Data System (SEDS): 1960-2015. June 30, 2017. Retrieved from https://www.eia.gov/state/seds/seds-data-complete.php?sid=US

[6] U.S. Energy Information Administration. State Carbon Dioxide Emissions Data. Energy Information Administration. January 22, 2018. https://www.eia.gov/environment/emissions/state/ /

[7] Jordan, Marty P. and Matt Grossmann. 2016. *The Correlates of State Policy Project v1.14.* East Lansing, MI: Institute for Public Policy and Social Research (IPPSR).; University of Kentucky Center for Poverty Research. 2017. "UKCPR National Welfare Data, 1980-2016." Gatton College of Business and Economics, University of Kentucky, Lexington, KY. Retrieved January 4, 2018 from http://www.ukcpr.org/data.

analysis and academic work, particularly as it relates to questions of poverty. It generally runs from 1980 to 2015. My preferred model's results generally are robust to the inclusion of these variables and since they are not the central factor in my research question, I do not include them in the baseline model.

I also constructed a binary variable for whether or not a state's electricity market is a restructured or a vertically integrated market. A vertically integrated electricity market is a state-granted natural monopoly on electricity generation, transmission, and distribution. Generation is the creation of electricity that is then transmitted along high voltage power lines and eventually distributed along lower voltage lines for use by electricity consumers. A restructured electricity market, by contrast, breaks up the monopoly and allows competition in the generation market (Lien 2008).[8]

To be clear, restructuring electricity markets is too diverse a policy change to be represented accurately by a binary variable. Although many states restructured their electricity markets, the extent and type of restructuring does not collapse to a binary factor and retain much of its meaning. Not only do states begin restructuring processes and then halt them, as in the cases of states like California, Montana, and New Mexico, but they restructure in fundamentally different ways. The adoption and acceptance of restructuring by electricity customers varies widely. Texas follows a retail choice model that creates a market for electricity similar to markets for any other good or service that covers most of the state. Consumers within the competitive electricity markets in Texas may enter their zip code on powertochoose.org and browse the plans, sometimes the

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[8] Lien, Jeff. "Electricity Restructuring: What Has Worked, What Has Not, and What is Next." Economic Analysis Group Discussion Paper. April 2008. Retrieved from https://www.justice.gov/sites/default/files/atr/legacy/2008/04/30/232692.pdf

hundreds of plans. Another confounding factor is that Texas's model is facilitated by the Electric Reliability Council of Texas (ERCOT), which lies entirely within Texas and therefore is state-controlled. State-control grants ERCOT much more latitude than other electricity markets receive. By contrast, Virginia allows only a small portion of its electricity consumers to participate in the restructured market.

The EIA maintained a map of restructured electricity markets but discontinued the updates in 2003 (EIA 2003).[9] Other sources do not provide clear and consistent definitions of restructured in their own data. Electricchoice.com, for example, maintains a small database of the current restructuring trends at the state-level and counts Virginia as a restructured state.[10] The implications of restructuring electricity markets on emissions and electricity prices deserves its own investigation in future projects.

None of these datasets timelines match perfectly with each other. Since I am primarily interested in the relationship of RPS with CO2 emissions I limit the data used in my empirical modeling to only the 26 years contained in the emissions data, 1990 to 2015. This is the timeline I have complete data for each of my variables. Ultimately, the dataset I create can serve as a basis for future projects on RPS and related environmental or energy questions.

[9] U.S. Energy Information Administration (EIA). "Status of State Electric Industry Restructuring Activity." February 2003.

[10] Electric Choice. "Map of Deregulated Energy States and Markets." 2017. Retrieved from https://www.electricchoice.com/map-deregulated-energy-markets/

CHAPTER 4

EMPIRICAL METHODS: SIMPLE DD MODEL

I estimate two primary difference-in-differences (DD) models. First, a simple DD model with state and year fixed effects to examine the association of an RPS with emissions. The second more complicated model, explained in chapter 5, includes the first model, but importantly also includes controls for pre-existing trends that allows for state heterogeneity in trends before an RPS is ever enacted. I find some evidence that quadratic and cubic trends may be necessary, but the linear trend is likely justified. I present the results from those models as well in the next chapter. This second model's insight into how state-specific trends affect the results of DD models is a unique contribution to the study of RPS.

A DD model will show the total effect of the policy and later controls can be included in order to investigate the channels that an RPS may work through. In the case of an RPS, controls can be added to the model to reveal if an RPS is working as it is intended. That is, does an RPS work by increasing investment in renewable energy technologies, or if there are other channels an RPS is associated with emissions through.

Even though an RPS is meant to reduce carbons by encouraging the use of lower carbon sources of energy, it may reduce carbon in other ways. For example, an RPS could raise electricity prices and thereby lower the amount of electricity demanded by consumers. This lower electricity demand would in turn lower emissions from utilities. Another mechanism that is likely lowering carbon emissions is the switch from coal to natural gas. Natural gas is less carbon intensive than coal, meaning it produces greater amounts of electricity for each unit of carbon emissions. Given that the fracking boom occurs during the data's timeline, this is a possible confounding factor. The theory of the environmental Kuznets curve (EKC) may also play a factor in any statistical estimate of reduced emissions associated with an RPS. The EKC argues that the demand for environmental quality is not a linear function. Poor people are less concerned with their environmental quality and the environment's cleanliness. Economic development thus originally contributes to declining environmental quality as individuals create pollutants. At some level of wealth, however, an inversion point is reached, and the richer individuals begin demanding cleaner environments. As individuals become wealthier they may invest in environmental policies, including the RPS but not limited to it, that improve environmental quality.

Each of these factors relates to the channels through which an RPS may improve environmental health and prevent climate change. They all complicate the theoretical story of how an RPS works (inducing additional use of clean energy sources) because they may be causing other actions that lower carbon emissions. By adding in control variables, however, the original and simple model can be expanded to investigate a more nuanced relationship between an RPS and carbon emissions.

Simple DD Model and Assumptions

I use a simple difference-in-differences (DD) model that controls for state fixed effects and time fixed effects to investigate the relationship between RPS and carbon dioxide (CO2). The state fixed effects and the time fixed effects control for time invariant factors such as the quality of renewable energy resources in a state or the culture of a state.

DD models mimic an experimental design by creating treated and untreated groups for comparison. Importantly, DD models assume that the treated and untreated states have parallel trends before the treatment. The assumption is simply that if the treated group had gone untreated, then it would have behaved the same as the untreated group. That is, states cannot be moving in opposite directions prior to the treatment or trending at different rates prior to the treatment. If states are not on parallel trends, then the DD will incorrectly estimate the coefficient on the DD variable. It can overestimate or underestimate the coefficient depending on the trend. The parallel trends assumption requires that the factors affecting the control and the treatment groups were the same before the treatment, and only after the treatment is applied do the states change. As I go on to show in chapter 5, the fundamental problem with this simple DD model is that it cannot examine a true "counterfactual" because the parallel trends assumption is violated.

Each model of emissions and RPS can be understood using the following equation:

$$Emissions_{s,t} = RPS_{s,t} + stateFE_s + yearFE_t + v_{s,t} + \varepsilon_{s,t}. \qquad (1)$$

The left-hand side simply is the emissions of CO2 in metric tons. The first independent variable on the right-hand side is the DD estimator, a binary variable indicating whether or not an RPS exists in that state in that year. The next two variables are state and year fixed effects that account for time-invariant unobserved variables. The controls are represented by $v_{s,t}$. Controls vary in the models I present but include natural gas use and total energy use. The final variable is simply the unobserved factors.

I estimate three variants of equation one to examine the relationship between carbon emissions and RPS. The first only includes the RPS and fixed effects for states and years. This is the baseline model and in then include controls in the second and third models. Splitting the models like this serves as a robustness check for the first model's results. It allows researchers to examine the channels that an RPS, or other policy instrument, works through. The controls can provide a more nuanced view of how the

RPS affects emissions. For example, in the second model I control for the total consumption of natural gas because carbon emissions are falling in part because of the switch from coal to natural gas. In particular, previous research shows that as the amount of renewable energy generation grows in an area, more natural gas is consumed because natural gas plants are less expensive backups for variable renewable energy sources (Verdolini et. al, 2016).

In the case of RPS and CO2 emissions, I want to estimate the decrease in CO2 associated with an increase in the use of the qualifying energy sources and not because of greater reliance on natural gas. So, the second model includes the log of total natural gas consumption for each state. Similarly, in the third model I also control for total energy consumption in the third variation of the CO2 model. The same natural gas theory holds for total energy consumption. I am primarily interested in the decrease in emissions from the increased use of renewable energy technologies and not because energy consumption decreases in response to an RPS. Including total energy consumption also serves as a robustness check for the RPS variable. I predict that as total energy consumption increases, carbon emissions will similarly increase.[11]

Table 2 displays results from three variations of the model estimating the

[11] In addition to these three models, I also investigated other theories on CO2 emissions from the literature, but they do not affect the model's primary results and are not presented. First, per capita income in 2016 dollars to account for any confounding effects that wealth may have. Income should be positively related to carbon emissions as wealthier people will likely consume more energy. I also included a squared term for the per capita income variable. This can be understood as a control for the Environmental Kuznets Curve as well. The U.S. in 1990, when the emissions data begins, was likely already on the downward sloping portion of the curve so it is unlikely this a major factor in emissions. Second, I controlled for whether or not the Governor of the state is a Democrat as a high-level proxy for how many other environmental programs the state has enacted and how environmentally conscious the state's citizens residents are. Having a Democratic governor is likely negatively related to emissions. None of these inclusions, however, meaningfully changed the direction or size of the coefficient of interest and likely introduce some amount of endogeneity and so are excluded. The party affiliation variable is also likely changing too slowly to have a large influence considering the fixed effects included in the base model.

relationship between RPS and carbon emissions.[12]

Table 2

CO2 and RPS Regression

	(1)	(2)	(3)	(4)
VARIABLES	Simple DD	DD w/ Controls 1	DD w/ Controls 2	DD w/ Controls 3
RPS	-0.0494**	-0.0539***	-0.0144	-0.0178
	(0.0204)	(0.0191)	(0.0148)	(0.0143)
Log(Natural Gas Consumption)		0.0721*		0.0335***
		(0.0397)		(0.0130)
Log(Total Energy Consumption)			0.659***	0.634***
			(0.0731)	(0.0739)
Constant	3.569***	2.661***	-5.876***	-5.944***
	(0.0140)	(0.503)	(1.048)	(1.089)
Observations	1,300	1,300	1,300	1,300
R-squared	0.99	0.99	0.99	0.99
Number of States	50	50	50	50
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
F Stat (p-value)		3.30 (0.0692)	81.26 (0.000)	76.43 (0.000)

Notes. Standard errors clustered by states in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Models 1 and 2 show a statistically significant decrease in carbon emissions of

[12] Lags and leads of three years had no meaningful influence on these results and were not statistically significant. Including the state's governor's party, logged population, and real per capita income (in 2016 dollars) did not alter the results.

about five percent. The significance, however, is sensitive to the inclusion of total energy demand in model 3. This suggests that an RPS may work through decreasing total energy demand. Model 4 simply includes both controls to demonstrate robustness. Controlling for both total energy consumption and natural gas consumption means that an increase or decrease in natural gas now cannot change the total amount of energy consumed in a state in that year. Any increase in natural gas must now result in a decrease in the use of other energy sources. How this affects carbon emissions will depend on the energy generation portfolio of sources. From 1990 to 2015, much of the energy was generated by coal.

CHAPTER 5

INCLUDING STATE-SPECIFIC TRENDS IN THE DD MODEL

Introducing Trends to the Simple DD Model

In chapter 5, I demonstrate the influence of the linear trend on the variable and further discuss the parallel trends assumption and how it is violated. The data employed in the earlier DD model does not satisfy the technical assumption of "parallel paths" for DD models. The assumption's violation is likely responsible for the statistical significance of the estimated relationship between RPS enactment and CO2 emissions since including controls for the trend eliminates the significance. In this chapter I show how the parallel paths assumption is not met and that there are likely state linear trends and possibly higher order trends that must be accounted for to make the predictions from the DD model accurate. Even after accounting for these trends, skepticism is justified.

The Parallel Trends Assumption is Likely Violated

Parallel trends, or sometimes called common trends or parallel paths, is a bedrock assumption of DD models that is often simply taken as given. It holds that before the treatment, both the untreated and treated groups were following parallel paths. The parallel paths assumption guarantees that the differences tested before and after treatment are due to the treatment and not to underlying trends. Without it, there is no guarantee that the results are accurate, reliable, or unbiased.

The trends that the parallel paths assumption prohibits are separate trends than simple time trends that the time fixed effects variables control for. Instead, they represent the key to DD's identification strategy. Regressions using differences-in-differences assumes that without the treatment the treated group and the untreated group would continue along a common trend. It then exploits a treatment of a subset of the group to formally consider the counter-factual of what would have happened without the treatment. If the two groups were not on a common trend before the treatment, however, then the treatment variable will not be correctly estimated. The effect may be overestimated or underestimated depending on the trend. For example, Figure 5 graphically shows the theory of a DD model.

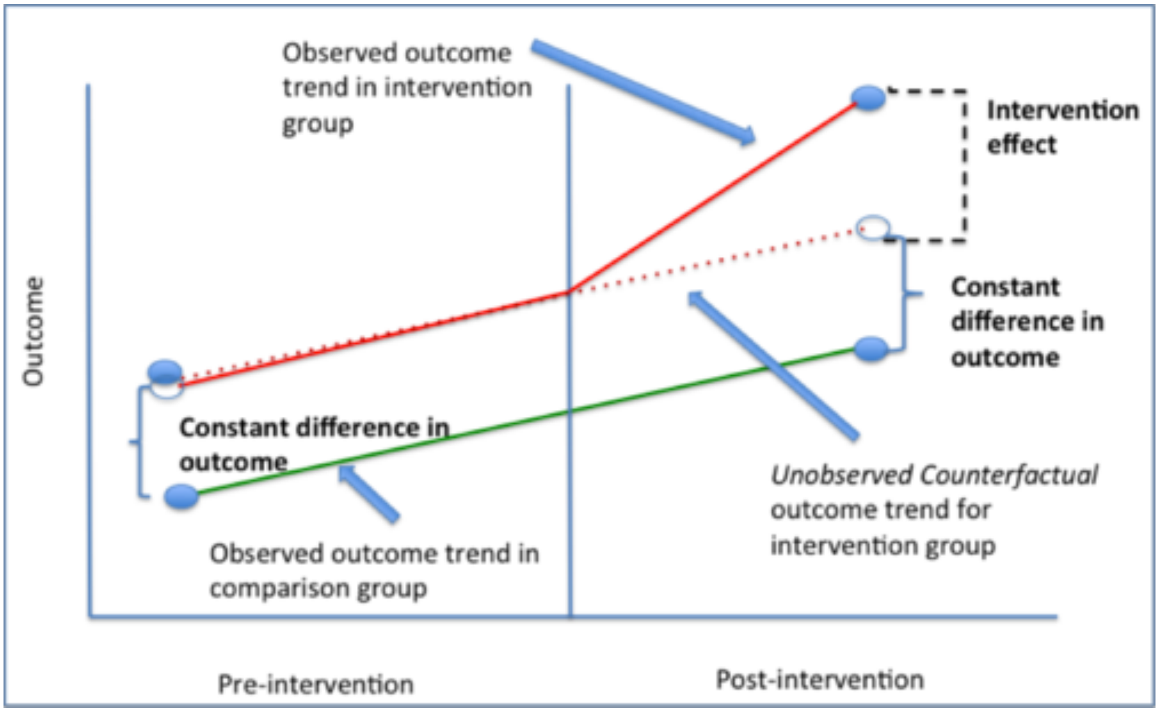

Figure 5. Graphical Representation of the DD Model[13]

Even though the two groups shown in Figure 2 are not on the exact same path, the distance between them is constant until the treatment is applied. This allows researchers to exploit the difference between the treated and untreated groups to consider what could have happened without the treatment and thus establish the treatment's effect.

The use of parallel is important because the assumption does not require that the two groups be on the same path, but rather simply that the paths head in generally the same direction. If RPS states have consistently higher emissions, for example, but it is by approximately constant levels before the RPS was enacted, this would not violate the

[13] This figure is taken from Columbia University's Mailman School of Public Health's website: https://www.mailman.columbia.edu/research/population-health-methods/difference-difference-estimation

parallel paths requirement.

A violation of the parallel paths assumption is when the treated and untreated groups are not simply at different levels of the variable of interest, but rather when they are traveling in different directions. Parallel lines never cross, diverge, or converge. If the data before RPS enactment shows divergence, for example, then this assumption is likely violated and the results of any DD analysis using the data will be spurious. Figure 6 does not clearly demonstrate that divergence, however. Note that the data is limited to 1990-1996 because the first RPS enactments in my data begin to appear in 1997 and 1999 (although Iowa enacted in 1983).

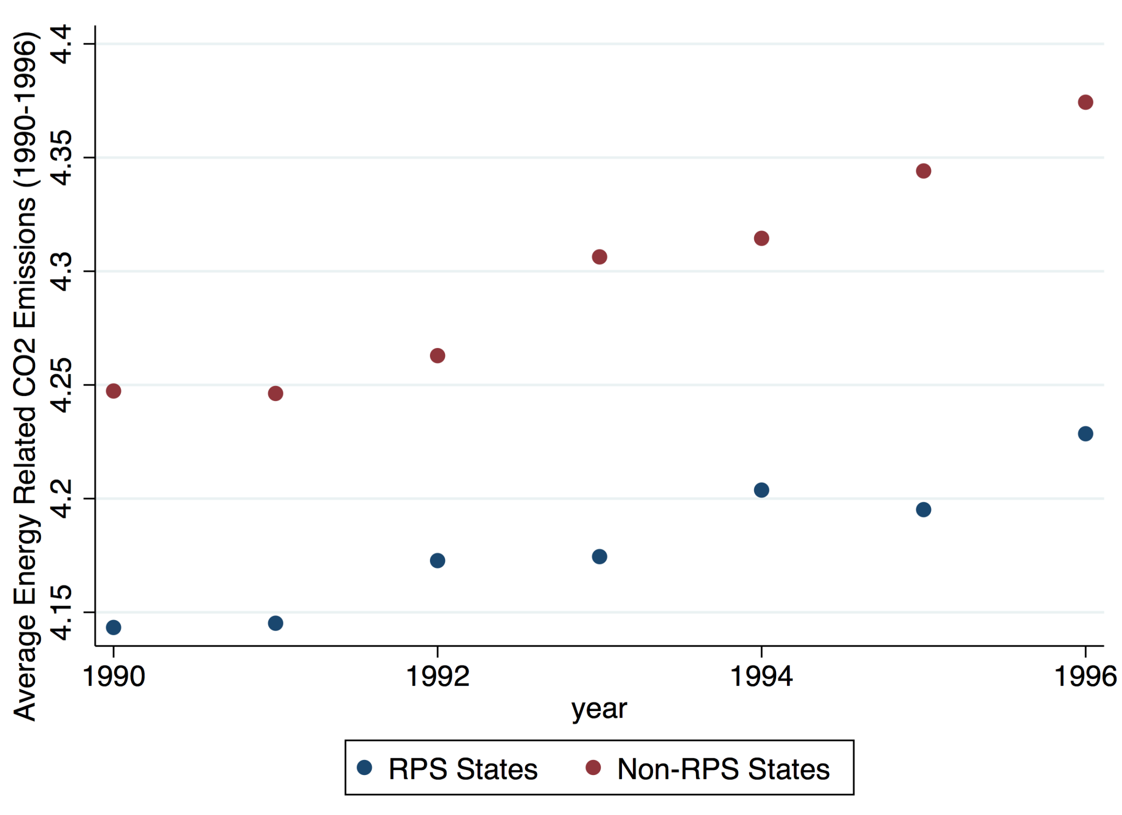

Figure 6. CO2 Emissions Before the Majority of RPS Enactments (1990-1996)

Figure 7 contains the full range of data from 1990 to 2015 to provide a picture of the overall trend. It shows that carbon emissions from RPS states are declining more quickly.

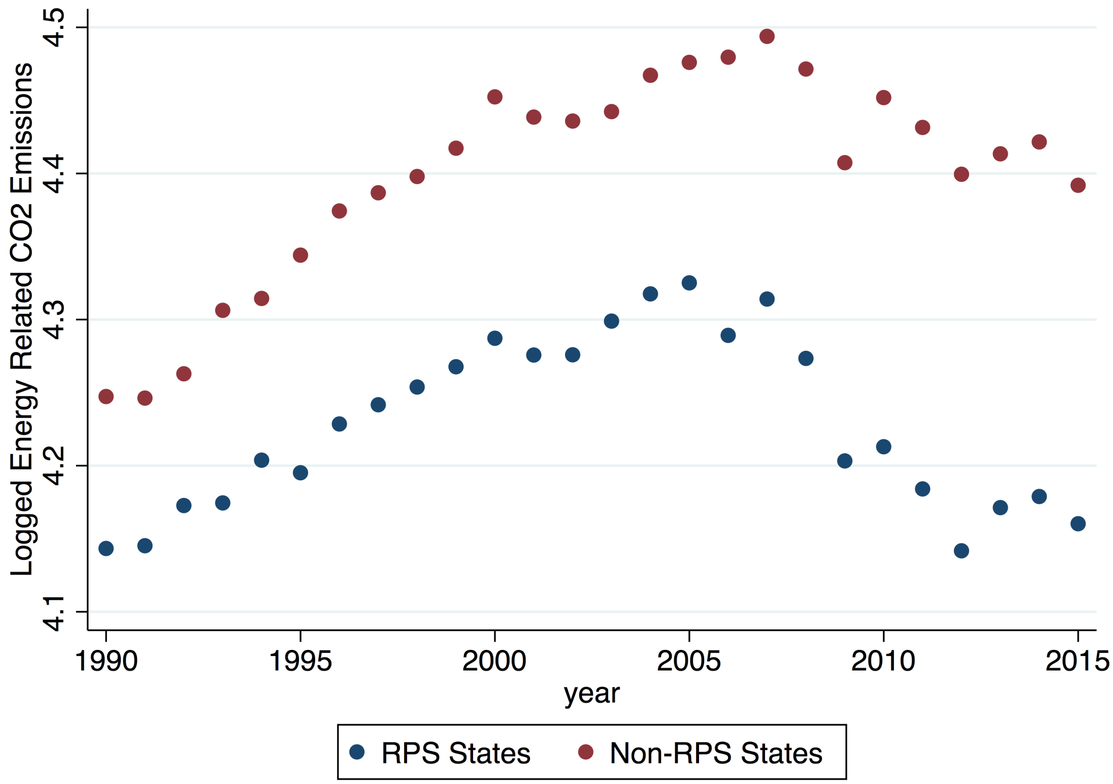

Figure 7. Average Logged CO2 Emissions by Year (1990-2015)

As depicted, although the CO2 emissions in 1990 are relatively close, the gap between RPS and non-RPS states grows throughout time. It is clear that the emissions of RPS states, shown in blue, are on a diverging path from the states without an RPS, shown in red. It is not clear from these graphs, however, if the parallel trends assumption is violated. From 1990 to 1996 there appears to be little to no divergence before the treatment, RPS enactment, is applied to the states. Figures 3 and 4 show that RPS states have lower emissions before they even enact an RPS. This is not a problem for the assumptions undergirding DD analyses. The growing gap between the two types of states does suggest that the parallel trends assumption should be investigated statistically. The gap could indicate that there is a trend that distinguishes RPS and non-RPS states that should be accounted for.

Demonstrating the Trend

Demonstrating the trend is a difficult endeavor, but the simplest way is to create a linear variable to feed into the regression, then create a policy variable, and finally to interact the two and consider if the trend is merely linear or quadratic or an even higher order relationship. The most straightforward test is then an F test to compare a restricted model to an unrestricted model. The results indicate that at least a linear trend is needed. These tests will estimate whether states that enacted a policy were trending differently than states that did not enact a policy.

Equation one can be modified to represent these tests:

$$Emissions_{s,t} = RPS_{s,t} + \theta_s + \delta_t + \tau_s Trend_t + \varepsilon_{s,t}. \qquad (2)$$

Additional trends, quadratic and cubic, can be included in the regression model. Table 3 includes the trend, the policy variable, and the interaction term between the two. I also restrict the regression so that when a state drops out once it enacts an RPS. The negative and significant interaction terms indicate there is at least a linear trend related to states enacting an RPS and verifies the divergence prior to treatment that renders the simple DD model's findings spurious. If the RPS coefficient in the DD model was negative, but the interaction was positive, then that would provide evidence that the original results were correct. Because it would work against the argument that RPS states are on a divergent path from non-RPS states where their emissions decline at a faster rate because of a preexisting trend. It would still be difficult to know the actual effect of an RPS, but it would support the original findings direction.

To check the existence of the trend, I restrict the regression to data before 1997. This is because only Iowa, since it enacted in 1983, has an RPS in this timeframe. This tests the trends pre-treatment. Table 3 contains these results. It shows only a significant linear trend. Note that this regression only contains 350 observations, seven years with 50 states in each year. This indicates that states that enact an RPS are on different trends before an RPS is enacted that must be accounted for to accurately employ a DD model.

Table 3

Check for Trends (1990 through 1996 Test)[14]

	(1)	(2)	(3)
VARIABLES	Policy*Trend	Policy*Trend Quadratic	Policy*Trend Cubic
Policy	0.0799***		0.0362
	(0.0143)		(0.0361)
Linear Trend	0.0222***	0.00766	
	(0.00208)	(0.00665)	
Policy * Linear Trend	-0.00863**	0.00270	0.0331
	(0.00356)	(0.0103)	(0.0305)
Quadratic Trend		0.00181**	0.00466***
		(0.000873)	(0.000886)
Policy * Quadratic Trend		-0.00142	-0.0103
		(0.00119)	(0.00767)
Cubic Trend			-0.000281**
			(0.000129)
Policy * Cubic Trend			0.000741

[14] Running this same regression with data through 1999, which only includes a few RPS enactments, shows similar results.

			(0.000596)
Constant	3.541***	3.558***	3.566***
	(0.00890)	(0.0101)	(0.00661)
Observations	350	350	350
R-squared	0.999	0.999	0.999
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Linear Trend	Yes	Yes	Yes
Quadratic Trend	No	Yes	Yes
Cubic Trend	No	No	Yes
F Stat (p-value)	5.87 (0.0191)	3.72 (0.0315)	3.54 (0.0211)

Notes. Standard errors clustered by states in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

The results in Table 3 suggest that the interaction between the policy variable and the linear trend is significant. This verifies the existence of the trend that could not earlier be verified visually from the data. The F tests restrict each interaction term to zero and provide statistical evidence that the trends should be included.

As a robustness check for the existence of a linear trend I run the same regression as above, but as an unbalanced panel. States are in the regression until they enact an RPS. Again, the linear trend and policy variable interaction term are significant and suggest a linear trend. The quadratic and cubic trends, however, are not. The inclusion of the interaction term is further verified by an F test.

Table 4

Robustness Check Using an Unbalanced Panel Test for Interactions

	(1)	(2)	(3)
VARIABLES	Policy*Trend	Policy*Trend Quadratic	Policy*Trend Cubic
Policy	0.836***	0.830***	0.852***

	(0.0146)	(0.0197)	(0.0231)
Linear Trend	0.00572***	0.0319***	0.0261***
	(0.00126)	(0.00333)	(0.00413)
Policy * Linear Trend	-0.00649***	-0.00483	-0.0147*
	(0.00187)	(0.00458)	(0.00779)
Quadratic Trend		-0.000970***	-0.000485
		(0.000136)	(0.000371)
Policy* Quadratic Trend		-7.88e-05	0.000936
		(0.000162)	(0.000794)
Cubic Trend			-9.81e-06
			(9.75e-06)
Policy*Cubic Trend			-2.76e-05
			(2.18e-05)
Constant	3.534***	3.511***	3.509***
	(0.0155)	(0.0160)	(0.0162)
Observations	923	923	923
R-squared	0.997	0.997	0.997
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Linear Trend	Yes	Yes	Yes
Quadratic Trend	No	Yes	Yes
Cubic Trend	No	No	Yes
F Stat (p-value)	12.04 (0.0011)	9.01 (0.0005)	12.04 (0.0000)

Notes. Standard errors clustered by states in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

The F tests in these models are also significant. The first F test restricting the interaction term between the linear trend and the policy variable to zero returns an F statistic of 12.04 and a p-value of less than 0.01. This indicates the interaction term likely cannot be legitimately restricted to zero by removing it from the model. The second and third F tests are significant at similar levels providing some evidence of quadratic trends and possibly cubic trends as well.

Accounting for the Trends

Now that the trends have been statistically verified they can be included in the regression from the previous chapter to examine the association between RPS and carbon emissions while controlling for the trend. The full results are excluded from the table so that they fit on the page.

Table 5

Results When Accounting for Linear, Quadratic, and Cubic Trends

	(1)	(2)	(3)
VARIABLES	Policy*Trend	Policy*Trend Quadratic	Policy*Trend Cubic
RPS	0.0210	0.0254*	0.0224*
	(0.0157)	(0.0134)	(0.0123)
Constant	3.615***	3.500***	3.486***
	(0.00882)	(0.00870)	(0.00569)
Observations	1,300	1,300	1,300
R-squared	0.998	0.999	0.999
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Linear Trend	Yes	Yes	Yes
Quadratic Trend	No	Yes	Yes
Cubic Trend	No	No	Yes

Notes. Standard errors clustered by states in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$)

The results in Table 5 show no statistically significant relationship between carbon emissions and RPS at the traditional 0.05 level. The models with more than a linear trend show a statistically significant increase in CO_2 emissions, but below the usual levels.

To examine the mechanisms that an RPS may work through I now include the logged total natural gas consumption and logged total electricity consumption with a linear trend. The results are in Table 6 below. These tests provide a more nuanced view an RPS's relationship with carbon emissions by controlling for potential channels an RPS may affect carbon emissions through.

Table 6

CO2 and RPS Accounting for a Linear Trend and Controls[15]

VARIABLES	(1) Base Model	(2) NG	(3) Total Consumption	(4) NG and Total Consumption
RPS	0.0210	0.0113	0.00687	0.00120
	(0.0157)	(0.0129)	(0.0137)	(0.0104)
Logged Total Natural Gas Consumption		0.124***		0.0894***
		(0.0353)		(0.0190)
Logged Total Energy Consumption			0.721***	0.654***
			(0.0550)	(0.0566)
Constant	3.615***	2.083***	-6.761***	-6.898***
	(0.00882)	(0.435)	(0.792)	(0.803)
Observations	1,300	1,300	1,300	1,300
R-squared	0.998	0.998	0.999	0.999
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustered by State	Yes	Yes	Yes	Yes
Linear Trend	Yes	Yes	Yes	Yes
Quadratic Trend	No	No	No	No
Cubic Trend	No	No	No	No
F Stat	1.79 (0.1877)	12.42 (0.0009)	171.83 (0.0000)	91.68 (0.0000)

Notes. Standard errors clustered by states in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

[15] Including residential electricity prices produces similar results.

The results in Table 6 show no statistically significant relationship between CO2 and RPS enactment. Natural gas consumption and total energy consumption are both positively related to carbon emissions. F tests restricting the inclusion of the controls provide statistical evidence in favor of their inclusion in the model.

Graphical Verification of the Results

Figure 8 graphically displays the results from the previous regressions. It places RPS enactment in event time and shows no coherent relationship between CO2 emissions and RPS enactment at time zero.

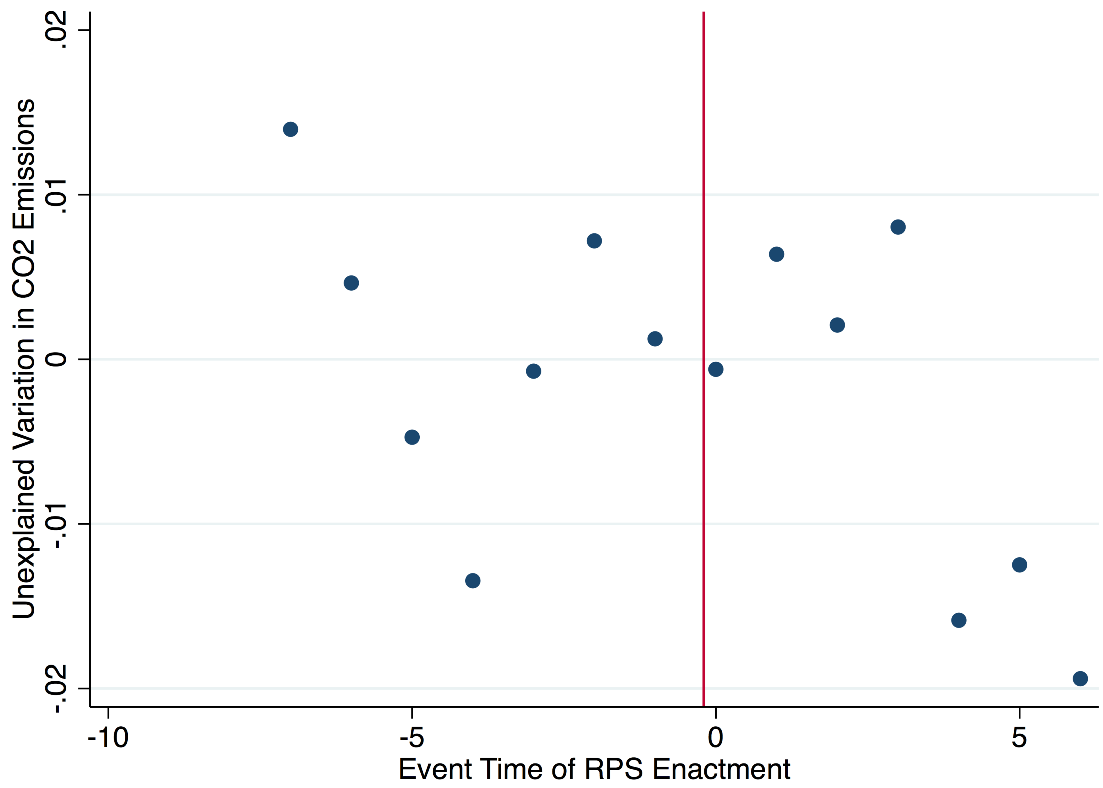

Figure 8. Event Time Graphical Investigation of the Results: Seven years before and after enactment.

There are many reasons an RPS may not have a statistically detectable relationship with carbon emissions. The answer likely lies in how RPS states differ from non-RPS states. A state with an RPS is likely to have a powerful environmental lobby that played an instrumental role in providing the political interest group to pass the RPS. This lobby is unlikely to care only about enacting the RPS. Instead, it likely pushes for many environmental rules and regulations and the RPS is simply one of many measures pushing carbon emissions down in the state. The methods I employ may not be able to isolate the effect of the RPS. Some previous literature has suggested that there is significant interplay between policy instruments (Yi & Feiock 2012; Park 2015).

CHAPTER 6

FUTURE WORK ON RPS AND IMPLICATIONS

Summary of Results

The model of CO_2 emissions and the enactment of renewable portfolio standards (RPS) I develop and estimate is the first to account for state-level heterogeneity by entering trend variables. The simple DD model that does not account for the preexisting state emissions trends shows that RPS reduces carbon emissions by about five percent, but those results may be unreliable. Instead, what is occurring is that the DD model overestimates the effect of renewable portfolio standards because RPS states follow a path distinct from non-RPS states. That divergence violates the parallel paths assumption that DD models rely on. Once the pre-existing trends are accounted for, the DD models provide no statistically significant evidence that a renewable portfolio standard has any relationship with carbon emissions. Importantly, this study cannot definitively determine if RPS achieve the environmental goals they aim to meet, but there are other econometric techniques that may be better suited for similar research questions.

Future Projects

There are multiple avenues for future work on RPS. Chief among them is the need for other statistical investigations with different tools. For example, other statistical methods could be employed that may be more appropriate for the data's limitations and nature of the research question. Future researchers could examine cases where random assignment or RPS enactment is a more robust assumption, but that approach likely is impossible. Regulatory standards do not emerge randomly. Some states, however, may better match this assumption than others (states with close elections, for example) and thus better approximate the background assumptions of DD estimations. Another method might be to match states with similar characteristics and examine the influence of an RPS on those states instead of all treated states. This could investigate the effect of an RPS by providing a theoretical justification for ignoring certain confounding effects. Synthetic control (SC) methods, however, are likely to be the most promising forward step in researching the effects of RPS. Synthetics increasingly are common in empirical analyses and could be applied to RPS.[16] A chief advantage of SC methods is that they account for the nonrandom treatment problem that DD methods cannot.

Theoretical modeling work could also examine the effects of different RPS designs. For example, it could model the effects of an environmental performance standard in place of a technology standard for RPS. Current standards include potentially dirty energy sources while excluding some viable low carbon sources. There are several commonly included energy sources on which environmental advocates disagree on. For example, Mark Jacobson of the Stanford Solutions Project, the leader of a group of academics that modeled how the United States and other countries could run on 100 percent renewable energy sources, excludes biomass because of concerns about its environmental effects. In Pennsylvania, coal ash is included as a qualifying power-generating resource. Nuclear is commonly identified as a strange energy source to exclude from RPS mandates since it produces zero carbon energy. Perhaps even more absurd, hydroelectric likewise is also often excluded (Stori 2013; The Hydropower Reform Coalition 2014). The political economy of the design of these standards is also an important question.

Another theoretical question for future examination is the effect of trading the Renewable Energy Credits (RECs) that are used to monitor compliance with the RPS between states. Each unit of electricity generated from a qualifying energy source creates a REC that, in some states, can be traded across state lines (Berry & Jaccard 2001).

[16] See Upton & Snyder (2017), Maguire & Mumasib (2018), and Maguire & Munasib (2016) for examples.

Texas, by contrast, requires that all electricity used to meet its goal be generated in the state and retired within the state (Center for Energy Economics 2009).

If the goal of an RPS is to lower emissions and ultimately prevent climate change, then it should not matter where the carbon is abated. Climate change is a global problem and if the RPS induces consumption of electricity from low carbon sources in place of consumption of electricity from high carbon sources, portfolio standards could be seen as successful. Some RPS legislation, however, prohibits or limits trading RECs from outside of the state. These are, again, likely political economy questions about state-based energy groups attempting to capture the rents RPS creates. Yet from a policy perspective, restricting REC trading seems unlikely to facilitate lower emissions. This is especially true considering that renewable energy resources vary widely by state. These variations in energy resource quality simply represent the possibility for gains from trade.

Apart from the economic and environmental effects of an RPS, researchers could also more closely examine the factors contributing to RPS adoption and the enactment of certain quirks of RPS design. For example, state policies differ on the amount and type of hydroelectric power that counts towards the RPS's mandate. The restriction of certain types of low-carbon energy sources, despite their ability to serve the environmental goals of the RPS, present interesting political economy questions about the influence of interest groups on RPS design.

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