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Funding renewable energy: An analysis of renewable portfolio standards

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ABSTRACT

Thirty states have adopted renewable portfolio standards (RPSs) that set targets for renewable energy generation by mandating that electric power utilities obtain a minimum percentage of their power from renewable sources. Our synthetic control (SC) model finds that states with RPSs have experienced increases in electricity prices and decreases in electricity demand relative to non-RPS states with similar economic, political and renewable natural resource characteristics. While both RPS and non-RPS SCs experienced increases in renewable energy generation over the sample time period, we do not find evidence that RPS states have experienced increases in renewable energy generation relative to SCs and weak evidence of emissions reductions.

1. Introduction

Over the past two decades, the federal government and many state governments have implemented a wide array of policies aimed at reducing the CO_2 intensity of the electricity sector by increasing the market penetration of renewable energy technologies. These policies take a wide variety of forms from direct subsidies, such as production tax credits which pay for each kilowatt-hour of renewable electricity produced, to more indirect financial incentives such as favorable tax accounting.[1]

Renewable energy policies may be implemented directly through state legislatures or may be indirectly stimulated through the regulatory action of state regulators (Public Service Commissions, Public Utility Commissions, etc). For example, California has more than 200 state and federal policies aimed at increasing adoption of renewable energy (DSIRE, 2015) but this does not include the myriad of actions undertaken by the California Public Utilities Commission through its normal regulatory authority to approve and disapprove construction of new power generation. This paper will focus on one particular state level policy, renewable portfolio standards (RPSs), that have had widespread implementation across the U.S. and examine how RPSs have impacted state electricity markets. We test the impact of RPSs on four outcomes of interest: in-state renewable energy generation, electricity prices, CO_2 emissions associated with electricity generation and electricity demand.

RPSs are state-level policies in the U.S. that require a proportion of state electrical demand be supplied by specified renewable sources by a specified date. RPSs target utilities and other electricity providers and require that they comply with the regulatory mandate, typically including a system of renewable energy credits (RECs) in which renewable energy providers generate one REC for every MW h of renewable electricity produced. RECs can be bought and sold independently of the electricity to help electricity providers meet their RPS obligations (Mack et al., 2011). States may implement RPSs for a number of reasons: they may seek to diversify their electricity portfolio, to encourage investment in the renewable energy sector, to improve state air quality, or to reduce CO_2 emissions. This paper evaluates the effectiveness of RPSs at achieving these outcomes, as well as other outcomes that are not directly targeted by

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[1] For example, it is estimated that over the 2004–2018 period, the U.S. federal government will spend approximately \$1.9 billion per year for the production tax credit (Sherlock, 2015), but this makes up just a small fraction (< 10%) of total federal spending on renewable energy subsidies (Dinan and Webre, 2012).

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the policy, by examining renewable energy generation, electricity prices, CO_2 emissions and electricity demand in RPS states relative to similarly situated non-RPS states. More specifically, we analyze the impact of RPSs on in-state renewable energy generation, electricity prices, CO_2 emissions associated with electricity generation and electricity demand.

The first RPS was implemented in Iowa in 1983 and was referred to as the *Alternative Energy Production* law. This RPS required Iowa's two investor-owned utilities to create more than 100 megawatts (MW) of renewable generating capacity. On face value, this RPS has been very successful, as Iowa today is home to more than 5000 MW of wind capacity and more than a quarter of Iowa's electricity generation comes from wind. Other states were not quick to follow suit though, as the next RPS was not passed until 1997. Today there are a total of thirty states with RPS policies (Eastin, 2014; Carley, 2009). Table 1 lists each RPS state and the year that the policy was passed. As shown in Fig. 1, these policies are prevalent throughout all regions in the United States with noticeable holes in the southeastern states and several rural western states.

While these policies have become prevalent, it is still uncertain how they have impacted electricity markets. As illustrated in Fig. 2, both renewable energy generation and electricity prices have seen substantial increases over the past decade, at the same time that RPSs were becoming widespread, but it is unknown whether RPSs have played a role in these changes.

There are three potential hypotheses on the impact of RPSs on renewable energy generation and electricity prices. The first hypothesis is based on the assumption that renewable energy generation is more expensive than traditional alternatives, such as fossil fuel and nuclear generation, and therefore increases in renewable energy generation spurred by an RPS will lead to increases in electricity prices. Thus, the first hypothesis is that RPSs will lead to increases in both renewable energy generation and electricity prices. Both proponents (Nogee et al., 1999) and opponents (Bryce, 2012) of RPSs have acknowledged that higher electricity prices are a likely side effect.

The second hypothesis is that RPSs will neither lead to increases in electricity rates nor renewable energy generation relative to similarly situated non-RPS states. RPSs are just one mechanism that allow state utility commissions to approve utility scale renewable energy projects. While an RPS legislatively puts a very specific renewable energy target in place, the normal regulatory framework in most states already allows state utility commissions to approve relatively expensive renewable projects and pass these costs onto ratepayers in the form of higher electricity prices. Therefore, both RPS and non-RPS states might experience increases in renewable energy generation and electricity prices due to the implementation of renewable energy projects, and no change in RPS states relative to similarly situated non-RPS states may be observed for either outcome.

Table 1
Overview of renewable portfolio standards.

State	Year	State	Year
Arizona	2001	Montana	2005
California	2002	Nevada	1997
Colorado	2004	New Hampshire	2007
Connecticut	1999	New Jersey	2001
Delaware	2005	New Mexico	2002
Hawaii	2004	New York	2004
Illinois	2005	North Carolina	2007
Iowa	1983	Ohio	2008
Kansas	2009	Oregon	2007
Maine	1999	Pennsylvania	2004
Maryland	2004	Rhode Island	2004
Massachusetts	1997	Texas	1999
Michigan	2008	Washington	2006
Minnesota	1997	West Virginia	2009
Missouri	2008	Wisconsin	1999

Source: Upton and Snyder (2015). Notes: West Virginia's RPS was repealed in 2015. Vermont passed an RPS in 2015, but was not included in the analysis due to its passage occurring beyond the time frame in this study.

The third hypothesis is that RPSs lead to increases in electricity prices, but do not increase renewable energy generation relative to comparable non-RPS states. There are two explanations for why this is plausible.

First, the mechanism through which RPSs spur renewable energy generation is through renewable energy credit (REC) markets. When a renewable energy source produces a MW h of renewable energy it receives a REC. Because RPSs set a consumption based mandate – not a generation based mandate – utilities have the choice to either produce enough renewable energy themselves to meet the RPS requirement and retire the RECs at the end of the year or purchase the needed RECs from the market. While some states have attempted to limit RECs such that they can only be produced in-state, this practice has been challenged legally (Elefant and Holt, 2011) and utilities have been known to import RECs from out of state (Mack et al., 2011), thus subsidizing renewable generation in surrounding states while passing the cost onto in-state ratepayers.[2]

The second potential explanation for increases in electricity prices without an increase in renewable energy generation relative to non-RPS states is that there are multiple potential funding sources for renewable energy, only one of which is higher electricity prices. When a utility builds more expensive renewable capacity, or purchases RECs from the market, this cost is passed onto ratepayers in the form of higher electricity prices. But this is not the only mechanism that a state can use to incent renewable energy generation; the obvious alternative being direct taxing and spending. For instance, many states without RPS policies have implemented other financial incentives such as property tax exemptions for utility scale renewable energy projects (Nebraska, Tennessee), sales tax exemptions for expenditures associated with renewable energy projects (Georgia, Utah),[3] and state renewable production tax credits (Nebraska, Oklahoma, South Carolina, Utah) that serve as direct subsidies to renewable projects. These states might still experience increases in renewable energy generation and still have to pay a premium for this generation, but the cost passes through to taxpayers in the form of increased taxes or decreased spending on other government services — not increased electricity rates. Thus, both RPS and non-RPS states may experience a similar increase in more costly renewable generation, but in RPS states this may increase electricity prices while in non-RPS states the generation may be paid for via other channels.

It is also unknown whether RPSs have impacted CO_2 emissions associated with electricity generation. Hereafter "emissions" will refer specifically to CO_2 emissions associated with electricity generation. Fig. 2 shows that RPS states have had lower emissions per capita for the last two decades, even before RPSs were implemented. But both RPS states and non-RPS states have seen declines in emissions in recent years, likely due to increases in awareness about potential harms of emissions on global climate (Tiefenbeck et al., 2013; Jacobsen et al., 2012), but also due to income shocks associated with the Great Recession of 2009 (Burnett et al., 2013; Branch, 1993) and the displacement of coal power generation with available and inexpensive natural gas.

Finally, we test the impact of RPSs on electricity demand. This serves two purposes. First, if an electricity price increase is observed, then we will expect to also see a decrease in electricity demand. Because the estimated shock to electricity price is induced by the RPS, the subsequent change in electricity demand also induced by this shock can provide insight into the long run price elasticity of

[2] RECs can be transferred both from RPS states to other RPS states, as well as from non-RPS states to RPS states (Holt, 2014).

[3] Georgia's sales tax exemption is limited to the purchase of biomass.

Fig. 1. State level RPS policies.

electricity demand that has been estimated in a number of empirical studies (Narayan et al., 2007; Nakajima and Hamori, 2010; Alberini and Filippini, 2011). Second, if we do observe a decrease in CO_2 emissions, the impact on electricity demand will inform us on the potential channel through which these reductions are achieved. Emissions reductions are potentially achieved through the supply side (i.e. new renewable generation) but emissions reductions could also be achieved through the demand side (i.e. reductions in electricity consumption associated with response to increased electricity prices). The channel through which emissions are plausibly reduced is of pertinence to policymakers interested in emissions reductions.

We estimate that RPSs are associated with increases in electricity prices of approximately 0.86¢ to 0.90 ¢/kW h (or about 10.9–11.4%) and that electricity demand decreases after RPS implementation by 0.71 to 0.92 MW h per person (or about 5.6 to 7.2%) likely due to the increase in price. This implies a long run price elasticity of approximately −0.5 to −0.6, which is consistent with prior estimates (Narayan et al., 2007; Nakajima and Hamori, 2010; Alberini and Filippini, 2011).[4] We find no evidence that renewable energy generation increases in RPS states relative to similar non-RPS states and weak evidence of emissions reductions.

1.1. Review of literature

Menz and Vachon (2006) test for the impact of RPSs on wind energy capacity, finding that RPS states have higher wind generating capacity, on average, than non-RPS states. Carley (2009) extends this analysis and estimates that RPSs have had a statistically significant and positive effect on state-wide renewable generation even after controlling for a number of covariates.[5] Yin and Powers (2010) expand on this literature by taking into account the heterogeneity in stringency across states' policies and finds increases in renewable energy development in states with relatively ambitious generation goals. While the statistical strength of these studies have varied, the overwhelming conclusion from this literature has been that RPS states have more renewable capacity than non-RPS states. Notably, Shrimali and Kniefel (2011) present a contrarian finding that RPSs have a *negative* impact on renewable capacity.[6]

There has been limited academic research on the impact of RPSs on electricity prices, and these prior studies have presented large ranges of estimated costs of RPS compliance. For instance, Palmer and Burtraw (2005) estimate that a hypothetical 20 percent RPS could lead to an 8 percent increase in electricity prices, with significantly lower costs for less ambitious (lower percent RPS) policies. Similarly, Kydes (2006) estimates that electricity prices would rise by about 3% in response to a theoretical 20 percent federal RPS being implemented. Most recently, Barbose et al. (2015) find that RPS

[4] These estimates likely imply a *long-run* elasticity, as the average treatment effect estimated is over the entire post-RPS adoption period.

[5] Carley (2009) also tests for the impact of RPS policies on renewable generation as a percent of total generation, but does not find evidence to support this result.

[6] There is a distinction between renewable capacity, a stock, and renewable energy generation, a flow. Most of the previous literature focuses on the impact of RPSs on renewable capacity — not renewable generation. Because RPSs target generation goals, not capacity goals, all empirical estimates presented in this paper are for generation. Results for the impact of RPS on capacity are presented in Online Appendix Table A.16, but do not differ qualitatively from the results on renewable generation.

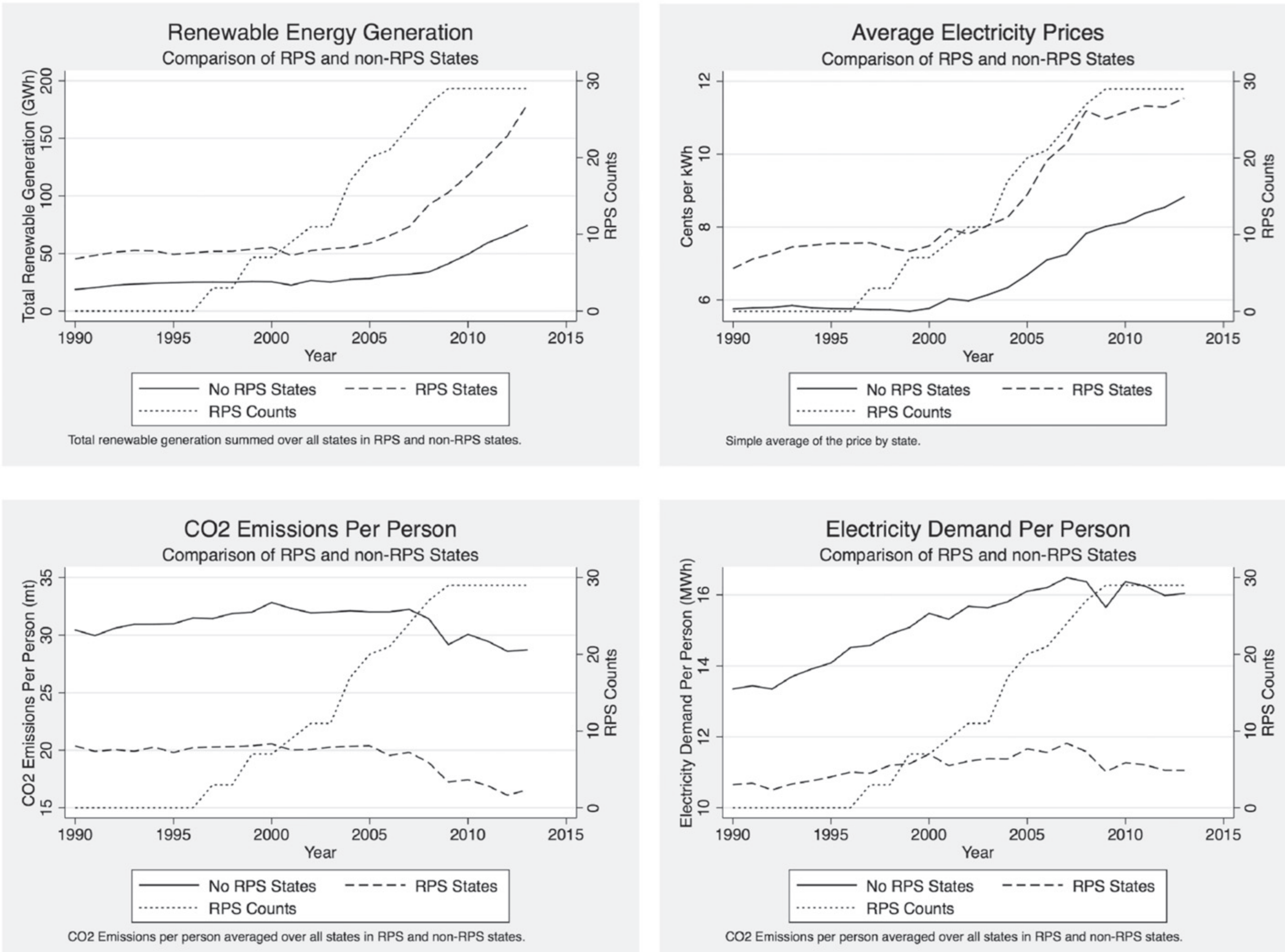

Fig. 2. Trends in renewable energy generation, electricity prices, CO_2 emissions, and electricity demand. Comparison of RPS and non-RPS states.

compliance costs constituted < 2% of average retail rates in most U.S. states over the 2010–2013 period. This analysis uses a bottom's up approach, accounting for total costs and savings associated with the implementation of the policy. No study to date has found an impact of RPSs on electricity prices using an ex-post econometric analysis.

Sekar and Sohngen (2014) test the effect of RPSs on carbon intensity and find that RPS states have 30% less carbon intensity on average than states that did not implement a RPS.[7] Most recently Eastin (2014) finds that RPSs are negatively associated with CO_2 emissions and coal powered electricity generation. Thus, previous evidence suggests that RPSs are effective at decreasing CO_2 emissions, but none of these studies have explored the possible mechanisms for the decrease in emissions. Furthermore, there have been no studies that have empirically estimated the impact of RPSs on electricity demand that could also be driving declines in CO_2 emissions.

While these studies examining a number of outcomes have compared RPS states to non-RPS states, taking into account both variation over time and between states, only one study to date has taken into account the likely endogenous selection into the policy. Hitaj (2013) tests the impact of a number of policies (including RPSs, corporate tax credits, property tax credits, production incentives, among others) on county level wind development using an IV approach where political factors and pollution levels are used to predict policy adoption. While a number of policies are found to be significant predictors of investment in wind power, RPSs are found to have a negative impact on wind capacity additions in one specification, and positive impacts in another.[8]

2. Data

We utilize data from a panel of forty-nine states from 1990 to 2013.[9] Outcome variables include state level renewable energy generation, electricity prices, emissions associated with electricity production and electricity demand. Wind and solar resources, the number of Democrats and Republicans in the state house and senate, the political party of the governor, gross state product, and mining and manufacturing gross state product are utilized to create synthetic control groups. Cooling degree days (CDDs) and motor gasoline consumption per day are used as outcome variables in falsification tests. State level population is used to normalize many of these variables for appropriate across state comparisons. Table 2 shows the summary statistics for each variable.

7 Carbon intensity is defined as carbon emissions per dollar of GSP.

8 In addition to the inconclusive results of this study with regard to RPSs, Hitaj (2013) self admittedly makes a number of strong assumptions that might threaten the identification strategy. For instance, electricity prices are assumed to be exogenous and not impact by RPS adoption.

9 Alaska was excluded due to the fact that solar and wind capacity in Alaska are simply not comparable to the other U.S. states due to the abnormal size and location of Alaska.

Table 2
Summary statistics.

	Sample average	Std. Dev.	N
Outcome variables			
Renewable energy generation (kW h) per person	475.5	835.4	1176
Average electricity price (¢/kW h)	7.87¢	3.06¢	1176
CO_2 emissions (tons) per person	24.16	18.89	1176
Electricity demand (MW h) per person	12.79	3.83	1176
Synthetic control construction variables			
Percent legislature democrat[a]	53.4%	15.7%	1078
Democratic governor	43.3%	49.2%	1176
GSP per person	$39,036	$10,926	1176
Mining GSP per person	$1000	$2470	1176
Manufacturing GSP per person	$5099	$2272	1176
Wind resource potential (GW h/yr)[b]	753,713	1,380,380	49
Solar resource potential (kW h/m^2 day)[b]	4.64	1.02	49
Falsification test outcome variables			
Cooling degree days (CDD)	1166	919	1176
Gasoline consumption (gallons/day) per person	1.30	0.21	1176

[a] Nebraska's state legislature is unique in that it is non-partisan. Therefore data is not available on the political affiliation of its legislators.
[b] Wind and solar resource potential vary across states but not across years. State legislature political party data only available until 2011.

The four dependent variables of interest are provided by the U.S. Energy Information Administration (EIA). EIA provides estimates of renewable energy generation (kW h) and includes all electric power producers including electric utilities, independent power producers, and commercial power as well as all major renewable energy sources including geothermal, biomass, solar thermal and photovoltaic, wind, and wood derived fuels (EIA, 2014a). Average electricity price is provided by EIA's Questionnaire 826 which collects information on retail sales of electricity and associated revenues from a statistically chose sample of electric utilities (EIA, 2014c). EIA's State Energy Data System provides estimates of state level CO_2 emissions associated with electricity power production (EIA, 2014e). CO_2 emissions include all emissions associated with the consumption of energy and are based on consumption data for three categories of coal, natural gas, and ten petroleum products.[10] CO_2 emission does not include emissions due to agriculture and land use change but does include emissions associated with electrical generation and transportation. Electricity demand (MW h) is sales of electricity to all end users and includes all customer classes; residential, commercial and industrial customers (EIA, 2014b).

The eight variables used to construct synthetic controls were collected from three sources. Political data on the number of democrats and republicans in each chamber of each state's legislature and the party of the governor were collected from Klarner (2013).[11] For all statistical results, the total Democratic members of both the house and the senate as a percent of the total members of both bodies are used.

Data on the gross state product and the mining and manufacturing gross state products were collected from the U.S. Bureau of Economic Analysis (2016). Data from 1997–2013 are in chained 2009 dollars while data from 1990–1996 are in chained 1997 dollars and inflation adjusted to 2009 values.

Data on the potential wind and solar resources by state were collected from the U.S. Department of Energy's National Renewable Energy Laboratory (NREL). The solar resource is defined as the average irradiance received per day by the average m^2 of area in the state. The irradiance is then averaged over the year to give irradiance in kW h/m^2/day. Direct normal irradiance (DNI) is used as an indicator of the solar resource; DNI is a measure of the irradiance received by a unit of area that is always normal (perpendicular) to the sun's rays and is the standard measure used in choosing utility scale project locations (NREL, 2010). Data on the potential wind resource by state is based on their analysis of the maximum potential wind generation by state. NREL's study defined "windy" areas as those areas with wind speeds above 6.5 m/s at an 80 m hub height, consistent with utility scale criteria. NREL then subtracts land area that is unsuitable for wind development to generate an estimate of the potential electricity generation if all commercial viable (windy) land area in a state was to be used to generate electricity, after excluding for incompatible land use. Data were on a GW h/yr basis.[12]

The two variables used for falsification tests are collected from two sources. Cooling degree days (CDDs) are computed by the National Weather Service's Climate Prediction Center. Cooling degree days are the positive differences in the mean temperature above a 65 °F base. For example, if a mean temperature of 68 °F is recorded on a given day, that day would be recorded as 3 CDDs. The annual number of CDDs is simply the summation of daily values over the course of the year. Mean temperatures are based on observations from individual weather station located across the country. CDDs serve as an appropriate falsification test because they are predictive of electricity demand (higher CDDs are associated with higher electricity demand), but should not be impacted by RPSs.

Demand for motor gasoline was taken from EIA's Prime Suppliers Sales Volumes. Prime suppliers are defined as a firm that produces, imports, or transports selected petroleum products and sells the product to local distributors, local retailers, or end users. Data are based on Form EIA-782C (EIA, 2014d). Motor gasoline demand also serves as an appropriate falsification test as it is a measure of energy demand that should not be impacted by RPSs.

[10] This only includes CO_2 that is actually emitted at a power plant located within the state. For instance, if a State A burns coal to generate electricity and exports that electricity to State B, these emissions will be counted in State A.

[11] While the names of state legislatures vary, the larger legislative chamber in each state was considered the "house" while the smaller chamber was considered the "senate ". Nebraska's legislature is unique in that it is non-partisan. Therefore, the average weight of surrounding states' legislatures political affiliation was used as a proxy for Nebraska.

[12] The solar and wind resource potential are not directly comparable due to the fact that solar resources are provided in kW h/m^2/day while the wind resources are provided in total GW h/yr aggregated over the entire state. These reporting differences are due to the specifics and technicalities of the two very different renewable resources. Theoretically, the solar resource could be aggregated and compared to the wind resource through multiplying by total state land area and excluding incompatible land use, however, this requires significant assumptions about solar energy development and land use patterns which are unnecessary and unwarranted for the current purpose.

The population of each state in each year was used to normalize variables on a per capita basis where appropriate. Population data were collected from the U.S. Centers for Disease Control's (CDC) National Center for Health Statistics (U.S. Center for Disease Control, 2014) and are estimates of the population of each state as of July 1 of a given year. The data are estimated jointly by the CDC and the U.S. Census Bureau.

3. Empirical strategy

3.1. Difference-in-differences(DD) estimation

Eq. (1) illustrates the commonly used DD estimation strategy that will be used to test for the impact of RPS programs on state electricity markets.

$$y_{st} = \alpha + \delta(S_{RPS} \times RPS_{st}) + \gamma_1 D_s + \gamma_2 D_t + \varepsilon_{st} \tag{1}$$

where y_{st} is the outcome of interest – renewable energy generation, electricity price, emissions or electricity demand – in state *s* in year *t*. S_{RPS} is an indicator variable corresponding to the treated states and is zero for the control states. RPS_{st} is an indicator variable that indicates the time periods after the RPS was implemented for a particular state. The treated states and the corresponding years of treatment are presented in Table 1.[13]

There are thirty states that have implemented an RPS, and these states are considered the "treatment group" in this analysis. D_s and D_t are state and year fixed effects that are included in all regressions. The coefficient of interest is δ, as it represents the estimated treatment effect of the RPS.

Three sets of empirical results are presented, all of which will utilize this DD framework. First, as a baseline, we simply use the nineteen states that do not have an RPS as a control group compared to the thirty states that have implemented an RPS as the treatment group. The estimated δ simply provides us with the change in these four outcomes of interest in RPS states relative to non-RPS states after policy adoption, but does not address endogenous adoption of policies. Thus, this baseline specification is a descriptive analysis that simply shows the actual change in outcomes of interest in RPS states before and after policy implementation relative to non-RPS states. A graphical representation of this baseline DD analysis is illustrated in Fig. 2. A comparison of these baseline point estimates to the estimates discussed below will provide insight as to the importance of addressing the endogeneity of RPS adoption.

Given that selection into RPSs is likely not random, for the next two empirical tests we will utilize synthetic control (SC) groups. First, we create a synthetic control state for each state that implemented an RPS. SC analysis is unique in that it enables the researcher to create a specific synthetic control for each treated state. Following (Abadie et al., 2010) synthetic control groups are made by choosing a weighted average of non-RPS states that are most similar to the RPS state with respect to politics, economic characteristics and renewable energy generation potential.[14] Thus, this approach allows us to compare the change in the four outcomes of interest after RPS implementation to a "synthetic" state that is similar among observables in the pre-RPS time period. The "synthetic controls" are created by taking a weighted average of non treated units, so in this application each synthetic state will be constructed as a weighted average of the nineteen non-RPS states that have similar pre-treatment characteristics to the treated state.[15]

RPS adoption is not random. It has consistently been shown that political and economic factors can impact a state's decision to implement an RPS (Upton and Snyder, 2015; Fowler and Breen, 2013; Chandler, 2009; Ming-Yuan et al., 2007; Lyon and Yin, 2010). In addition, some studies have tested whether states with significant renewable potential have been more likely to adopt RPS policies (Upton and Snyder, 2015; Matisoff, 2008; Chandler, 2009; Lyon and Yin, 2010). Therefore political, economic and natural resource endowment variables shown in Table 2 are used to construct the vector of pre-intervention characteristics for purposes of creating synthetic states. This will account for differences in observable factors that can impact RPS adoption.

To illustrate this further consider the state of Massachusetts that implemented one of the first RPSs in 1997. Comparing the change in renewable energy generation in Massachusetts, a state with little potential for wind energy due to its size and population density, to a midwestern non-RPS state like Nebraska or Wyoming is likely not a reasonable comparison. Potentially Nebraska and Wyoming experienced large increases in wind generation *because* they have significant wind potential, despite the fact that Massachusetts implemented an RPS while Nebraska and Wyoming did not. Thus, we create a "synthetic state" that is a weighted average of other states that are most similar to Massachusetts along the observable characteristics in the pre-RPS time period listed in Table 2. The "synthetic Massachusetts" for purposes of analyzing renewable energy generation is comprised of 64.8% Virginia and 35.2% Louisiana. A similar synthetic state is created for each RPS state for each outcome of interest. Comparing outcomes of interest in RPS states relative to these synthetic states is a more plausible counterfactual than the baseline specification that simply pools all non-RPS states together as the control group.

The differences in outcomes in synthetic states compared to RPS states will provide an estimated treatment effect of RPSs on four outcomes of interest. Synthetic states corresponding to each RPS state for the four outcomes of interest are presented in A.18 to A.25 in the Online Appendix.

We will conduct two empirical tests using the SCs. First, we will pool all of the RPS states and synthetic states into one regression and estimate the treatment effect using the DD framework shown in Eq. (1). This will provide the average treatment effect of the RPS compared to synthetic non-RPS states for each outcome.

Next, we estimate a treatment effect for each RPS state compared to its synthetic state individually. A variation of Eq. (1) will be employed.

$$y_{st} = \alpha + \gamma_1 S_{RPS} + \gamma_2 PreRPS_t + \delta(S_{RPS} \times RPS_t) + \varepsilon_{st} \tag{2}$$

[13] For purposes of this research, we consider the date the RPS was made law in the state as the treatment date, as this is earliest time utilities could reasonably be expected to act to procure renewable energy resources in response to the RPS. While final RPS goals are commonly set in the distant future, virtually all states that have implemented RPS policies have mandated a schedule of intermediate goals that must be achieved in the near term, usually within two to five years of RPS adoption. Therefore, it is reasonable to expect utilities to respond rapidly to RPS passage. As a robustness check, results are also presented with lagged treatments (and years between passage and lagged treatment as null values) of differing time intervals from one to five years for both the baseline specification and synthetic control specification. Results are presented in the Online Appendix Table A.17. These results show that the treatment effects tend to increase as the treatment is lagged, thus indicating that empirical estimates presented are likely conservative.

[14] More specifically, synthetic control groups are made by choosing a W^* that minimizes $\sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)}$ where X_1 is a vector of pre-intervention characteristics for the exposed regions (or treatment group) and X_0 is a vector of pre-intervention characteristics of the non-exposed regions (or control group). Following Kaul et al. (2017), we use the *average* of pre-intervention outcomes and covariates in constructing the synthetic control group. W is a $(J \times 1)$ vector of positive weights that sum to one. V is some $(k \times k)$ symmetric and positive semidefinite matrix.

[15] While there are thirty states with an RPS, Iowa's RPS was passed in 1983 and therefore no pre-treatment observations are available. Therefore, Iowa is not included in the SC analysis. Weights contained in W^*, which are estimated econometrically, can be found in Online Appendix Tables A.18–A.29.

where S_{RPS} is an indicator for the RPS state and zero for the synthetic state. $PreRPS_t$ is an indicator variable that represents the pre-treatment time period and δ represents the estimated treatment effect of the RPS compared to the synthetic state. An estimated treatment effect will be obtained for each treated state individually compared to its synthetic control state. Using a simple t-test we will test whether the average of these estimated treatment effects is statistically significantly different than zero.

Next, three robustness checks are employed. First, a placebo test will be employed where synthetic states are constructed for the nineteen non-RPS states as a weighted average of other untreated states. A random placebo treatment year is assigned between 1997 and 2009 to each state.[16] We estimate both a pooled treatment effect using Eq. (1) as well as an estimated treatment effect for each state individually using Eq. (2). We expect that these treatment effects will be randomly distributed around zero.

Next we implement two falsification tests. We estimate a treatment effect on two outcomes that we do not expect to be impacted by RPSs. First, we estimate a treatment effect of RPSs on state level cooling degree days (CDDs). While CDDs are commonly used to predict electricity demand, CDDs are a function of the weather and therefore RPSs should have no impact. If we find that policy adoption leads to changes in the weather, we will have reason to be concerned.

While the SC approach can account for observable factors that impact non-random policy adoption, this approach is imperfect in that it does not control for unobservable factors that can simultaneously impact RPS adoption and outcomes of interest therefore potentially biasing results. While results in this research do find changes in outcomes in RPS states relative to non-RPS states with similar economic, political and renewable natural resource characteristics, the specification fails to account for potential unobservables that can also impact both policy adoption and outcomes of interest. For this reason, we implement a second falsification test to address the extent to which unobservable factors are plausibly driving results of the SC analysis. Specifically, the second falsification test outcome is state-wide demand for motor gasoline. This is chosen because it is an alternative form of energy demand that should not be impacted by an RPS but might be impacted by unobserved shocks that would simultaneously predict RPS adoption and the outcomes of interest.

As a final robustness check, we address the potential impact of heterogeneous RPS stringency on our results. If RPSs differ in terms of their stringency, and therefore their effectiveness, not accounting for heterogeneity between policies might induce a bias towards zero in average treatment effects, especially if some states pass policies that might be ineffective. Therefore, we test the sensitivity of our results to a measure of RPS stringency (Carley and Miller, 2012).

4. Results

First, we estimate the average differences in the change in the four outcomes of interest in RPS and non-RPS states using the standard DD framework. This specification does not take into account endogenous selection into the RPS policy, and therefore these estimates are simply a baseline illustration of the actual observed changes of the two groups relative to one another. The baseline estimates shown in Table 3 suggest that renewable energy generation actually decreased by 287 kW h per person per year (or approximately 60%) in RPS states relative to non-RPS states after policy adoption. This result is not statistically significant and the point estimate is not in the expected direction.

Electricity prices are shown to have increased by 0.91 ¢/kW h (or about 11.6%) in RPS states relative to non-RPS states. CO_2 emissions decreased by 0.897 MT per person (3.7%) [17] and electricity demand decreased by 0.954 MW h per person (7.5%). These baseline results are not an estimate of the effect of RPSs on these outcomes of interest, but instead are a simple comparison of what *actually occurred* in RPS states relative to non-RPS states after RPS implementation. These results show that RPS states have not experienced increases in renewable energy generation relative to non-RPS states, but have experienced increases in electricity prices. These results also show that CO_2 emissions have decreased in RPS states relative to non-RPS states likely due to decreases in demand associated with higher electricity prices, not renewable energy generation.

Next, Table 3 presents the results of the DD analysis utilizing the synthetic control states. Using the SCs, the estimated effect of RPSs on renewable energy generation is small and not statistically significant. While the baseline specification (also presented in Table 3) shows that RPS states experienced 60% *less* renewable energy generation growth than non-RPS states in general after implementation, this point estimate attenuates to $<2\%$ (or 7.4 kW h per person) when the synthetic control group is employed as the control group. Therefore, while both RPS states and non-RPS SCs experienced increases in renewable energy generation over the sample period (as illustrated in Fig. 2), we do not find evidence that RPS states have experienced a change in renewable energy generation relative to non-RPS states with similar renewable energy potential, political and economic conditions.

We again find a statistically significant and positive impact of RPSs on electricity prices. Using the SCs, we estimate that electricity prices increased by 0.86 ¢/kW h (10.9%) in RPS states relative to the synthetic states. This point estimate is very similar to the baseline specification.

Using SCs, the coefficient for CO_2 emissions attenuates relative to the baseline specification and is no longer statistically significant, but we still do find a strong statistically significant estimated impact of RPS on electricity demand. Specifically, we find that RPS states have experienced a 0.713 MW h (5.6%) per person decrease in electricity demand on average relative to synthetic states. This decline in electricity demand associated with the estimated increase in electricity price of 10.9% implies a long run price elasticity of demand of −0.51. Nakajima and Hamori (2010) provide a list of studies that estimate the long run price elasticity of residential electricity demand.[18] Estimates range from very inelastic (−0.04) to elastic (−1.56). The mid-point of these estimates is approximately −0.5 which is consistent with our estimate. It should be noted, that unlike these estimates, our estimate not only focuses on residential customers but includes commercial and industrial customers as well.

Table 4 presents the estimated treatment effect for each RPS state relative to its specific SC as illustrated in Eq. (2). The average treatment effect on renewable energy generation is −21.75 kW h per person (4.6%). This average treatment effect is not statistically significantly different than zero using a simple two-tailed t-test, thus we consistently do not find evidence that RPS states have achieved increases in renewable energy generation relative to states with similar renewable energy potential, political and economic conditions. Consistent with previous results, we estimate that RPSs are associated with a 0.90 ¢/kW h (11.4%) increase in electricity prices.

[16] This is the range of years in which RPS was actually implemented in other states as shown in Table 1.

[17] These emissions are associated with power plants that are actually located within a state. So if a state purchases a REC from out of state, the renewable energy production, and therefore decrease in emissions associated with that displaced production, will be accounted for in the state that the power is produced — not the state that purchases the power.

[18] Estimates presented in this research are interpreted as the average change in each outcome over the post treatment time period. Therefore, these are more reasonably compared to a long run elasticity estimate in response to a permanent change in price, not a short-run elasticity that measures changes in electricity demand in response to transitory shocks.

Table 3
Estimated impact of RPS: baseline specification.

	Renewable generation	Electricity price	CO_2 emissions	Electricity demand
	(1)	(2)	(3)	(4)
Baseline differences-in-differences				
RPS	−286.9	0.910**	−0.897*	−0.954***
	(203.6)	(0.379)	(0.513)	(0.284)
Observations	1176	1176	1176	1176
Synthetic control specification				
RPS	−7.424	0.860**	−0.256	−0.713***
	(84.02)	(0.387)	(0.390)	(0.166)
Observations	1392	1392	1392	1392
Placebo treatment				
Placebo RPS	−81.75	0.104	0.105	0.0583
	(96.26)	(0.0636)	(0.245)	(0.131)
Observations	912	912	912	912

Standard errors clustered at state level. State level fixed effects included in all regressions; full regression output can be found in online Appendix. Variable units are as follows: renewable energy generation — kW h per person; electricity price — cents per kW h; CO_2 emission — metric tons per person; electricity demand — MW h per person. Baseline differences in differences specification uses non-RPS states as control group. Synthetic control specification utilizes synthetic states as controls. Placebo treatment compares non-treated states to synthetic states using random placebo treatment year. Iowa was excluded from the SC analysis because its RPS was implemented before the first year of data available and therefore no pre-treatment characteristics are available.
*, **, and *** represent significance at the $p < .10$, $p < .05$, and $P < .01$ respectively.

We do not find statistically significant evidence of a decrease in CO_2 emissions but estimate that electricity demand decreased by 0.92 MW h per person (7.2%). Similar to the pooled results in Table 3, these results imply a price elasticity of 0.63. The estimated treatment effects for each state relative to its SC are presented in Appendix Table A.12.

4.1. Robustness checks

4.1.1. Placebo treatments

The first robustness check tests for the impact of a "placebo treatment" on non-RPS states relative to synthetic controls. The first step in conducting placebo tests is to create a synthetic state for each of the non-RPS states as a weighted average of other non-RPS states.[19] Once these synthetic states are created, a random placebo treatment year was chosen for each state between 1997 and 2009, the range of years when RPSs were implemented in treated states.

As a corollary to the main results we conduct placebo tests using both the pooled DD specification and a comparison of each state relative to its specific SC as illustrated in Eqs. (1) and (2), respectively. Table 3 presents the pooled placebo results utilizing all non-RPS states with the placebo treatment compared to the pooled SCs. The point estimates for renewable generation, electricity prices, CO_2 emissions and electricity demand are all statistically insignificant. In addition, the placebo coefficient estimates for the two variables that are found to be significantly impacted by RPSs – electricity price and electricity demand – are orders of magnitude smaller than the estimated effect in RPS states.

Next, we compare each non-treated state to its SC separately and obtain an estimated treatment effect as shown in Eq. (2). The results presented in Table 4 are similar to the pooled placebo test. The average placebo treatment effect for non-RPS states is not statistically significantly different than zero for any of the four outcomes of interest. In addition, the magnitude of the coefficients for electricity price and electricity demand is orders of magnitude smaller than the estimated treatment effect for RPS states.

4.1.2. Falsification outcomes

As a second robustness check we conduct falsification tests. We estimate the impact of RPSs on two outcomes that we do not expect to be impacted by an RPS; cooling degree days and end user gasoline consumption. Tables 5 and 6 show results for the falsification tests for both outcomes. These results are corollaries to the main empirical results presented in Tables 3 and 4 and we present results using (a) the pooled non-treated states as the control group, (b) pooled synthetic controls and (c) each state relative to its specific synthetic state. We also present placebo treatment tests where we treat each non-RPS state for each falsification outcome. If the main results of this research are valid, we should see no effect of RPSs on the outcomes of interest and should not see systematic differences in placebo treatment coefficients relative to estimated treatment effects for RPS states.

The first potential threat to identification that is addressed in these falsification tests is potentially changing weather patterns in RPS states relative to non-RPS states that could lead to systematic differences in electricity rates and demand. For instance, if the number

Table 4
Comparison of estimated treatment effects.

	Average treatment effect	Standard error	N
Renewable energy generation per person			
Actual treated	−21.75 kW h	54.25	29
Placebo treatment	−74.61 kW h	215.31	19
Electricity price			
Actual treated	0.90¢***	0.332	29
Placebo treatment	0.19¢	0.145	19
Emissions per person			
Actual treated	−0.276 tons	0.360	29
Placebo treatment	−0.347 tons	0.544	19
Electricity demand per person			
Actual treated	−0.923 MW h***	0.250	29
Placebo treatment	−0.201 MW h	0.318	19

Iowa was excluded from this analysis because its RPS was implemented before the first year of data available and therefore no pre-treatment characteristics are available.
*, **, and *** represent significance at the $p < .10$, $p < .05$, and $P < .01$ respectively. Statistical significance based on two tailed *t*-test.

[19] These weights can be found in Online Appendix Tables A.26–A.29

Table 5
Falsification test: baseline specification.

	CDD	Gasoline demand
	(1)	(2)
Baseline differences-in-differences		
RPS	−12.63	−0.0119
	(20.34)	(0.0282)
Observations	1176	1176
Synthetic control specification		
RPS	−21.19	−0.00490
	(19.09)	(0.0251)
Observations	1392	1392
Placebo treatment		
Placebo RPS	−7.475	−0.0130
	(15.77)	(0.0154)
Observations	912	912

Standard errors clustered at state level. State level fixed effects included in all regressions; full regression output can be found in online Appendix. Variable units are as follows: CDD — a measure for the number of days in which the average user in the state will use air conditioning due to the average temperature in that day exceeding 65 °F. Gasoline demand is prime supplier sales of motor gasoline sold for local consumption. Placebo treatment utilizes non-treated states to synthetic states using random placebo treatment year. Iowa was excluded from the SC analysis because its RPS was implemented before the first year of data available and therefore no pre-treatment characteristics are available.

Table 6
Falsification test: comparison of estimated treatment effects.

	Average treatment effect	Standard error	N
CDDs			
Actual treated	−45.33	28.95	29
Placebo treatment	4.58	15.02	19
Gasoline demand			
Actual treated	0.011 gal/day	0.023	29
Placebo treatment	0.011 gal/day	0.357	19

Iowa was excluded from this analysis because its RPS was implemented before the first year of data available and therefore no pre-treatment characteristics are available. Statistical significance based on two tailed *t*-test.

of CDDs declines in RPS states relative to non-RPS states, then electricity demand would also decrease which could then lead to higher electricity prices associated with the higher average cost needed to support the utility grid's infrastructure.[20] As shown in Table 5, using the baseline specification and SCs, we do not find a statistically significant effect of RPSs on CDDs (point estimates suggest a change of $< 1\%$). The placebo treatment is also statistically insignificant. Table 6 shows results for each treated state relative to its specific synthetic state. The average treatment effect for CDDs is −45.33 (or about 3.9%) and not statistically significant. The placebo treatment is also small and not statistically significant.

The second threat to identification is that RPS states might have experienced decreases in energy consumption in general relative to non-RPS states potentially due to concerns about climate change in RPS states relative to non-RPS states. This could lead to both lower electricity demand and therefore higher electricity prices (through the same mechanism discussed in the previous paragraph). While the SCs attempt to mitigate this concern by choosing a comparable synthetic state that is very similar along economic and political dimensions, if a decline in gasoline demand is observed in RPS states relative to SCs, this will cause concerns that the increase in electricity prices and decrease in electricity demand might not be due to the RPS, but instead these results might simply be picking up on decreases in energy demand in general within the state. Results in Tables 5 and 6 show no change in gasoline demand in RPS states relative to both the baseline control group and SCs. Placebo treatments are also not statistically significant and oscillate around zero.

Of the ten coefficient estimates presented in these falsification tests, none are statistically significant at 10%. Thus, these falsification test results do not reveal any concerns to our initial empirical findings.

4.1.3. Policy heterogeneity

Another potential threat to identification is that not accounting for RPS heterogeneity might induce a bias towards zero in the average treatment effect, especially if some states pass policies that are ineffective. Potentially, some states that passed stringent RPSs have indeed experienced significant increases in renewable generation due to the policy, but this effect is not picked up empirically due to the slue of other states with less stringent policies. To test whether this heterogeneity in policy stringency might be downward biasing our treatment effects, we incorporate stringency into our empirical estimates.

More specifically, Carley and Miller (2012) – hereafter referred to as CM – calculated the stringency of each state's RPS based on the initial renewable generation target, the final generation target, the time between RPS adoption and the final generation target, and the proportion of the state load covered by the RPS. CM calculated the initial RPS stringency at the time of policy adoption and incorporated stringency revisions through 2008. Because our analysis extends to 2013, we updated CM's stringency calculations to the end of our sample period.[21]

As a corollary to Eq. (1), Eq. (3) below incorporates the RPS stringency into the empirical specification.

$$y_{st} = \alpha + \delta(S_{RPS} \times RPS_{st} \times Stringency_{st}) + \gamma_1 D_s + \gamma_2 D_t + \varepsilon_{st} \tag{3}$$

where again y_{st} is the outcome of interest – renewable energy generation, electricity price, emissions or electricity demand – in state s in year t. S_{RPS} is an indicator variable corresponding to the treated states and is zero for the control states. RPS_{st} is an indicator variable that indicates the time periods after the RPS was implemented for a particular state. $Stringency_{st}$ is the stringency measure developed by CM. Appendix Table A.14 lists state level stringency and revisions over the sample time period.

Table 7 shows DD results incorporating policy stringency using both the baseline specification that uses all RPS states as the control group as well as the SC specification. Results are consistent with results presented in Table 3. We estimate a negative treatment effect associated with renewable generation in both the baseline and SC model, with neither coefficient being statistically significant. We again find that RPS states have experienced increases in electricity prices relative to both control groups. The baseline specification suggests that adoption of an RPS with average stringency (with a measure of 69.0) is associated with a 1.35 ¢/kW h increase in electricity prices, while adoption of the most stringent policy (with a measure of 105.1) is associated with an increase of 2.06 ¢/kW h. The SC specification suggests a more modest effect of a 0.67¢ increase associated with an average stringency policy and 1.03¢ increase associated with the most stringent policy. Using this stringency specification, we again find evidence of decreases in electricity demand, likely associated with electricity price increases, and no effect on CO_2 emissions. Thus, results are robust to the inclusion of this measure of policy stringency.

[20] Electric utilities are natural monopolies. Rates are set based on a revenue requirement which is the depreciated capital expenditure times some allowed rate of return. If electricity demand declines, this necessarily increases electricity rates, as the company still must meet its revenue requirement. Therefore, if changes in climate are impacting electricity demand, this will impact electricity rates as well.

[21] This updating was done based on DSIRE database, which provides changes through August of 2011. Author's independent research found no examples of further changes between August of 2011 and the end of our sample period in 2013.

Table 7
Stringency and RPS effectiveness.

	Renewable generation	Electricity price	CO_2 emissions	Electricity demand
	(1)	(2)	(3)	(4)
Baseline differences-in-differences				
RPS × stringency	−4.262	0.0196**	−0.0108	−0.0139***
	(3.443)	(0.00869)	(0.00789)	(0.00467)
Observations	1152	1152	1152	1152
Synthetic control specification				
RPS × stringency	−1.133	0.00978*	−0.00157	−0.00330**
	(0.707)	(0.00560)	(0.00505)	(0.00157)
Observations	1392	1392	1392	1392

Stringency measures are from Carley and Miller (2012) . Standard errors clustered at state level. State level fixed effects included in all regressions; full regression output can be found in online Appendix. Variable units are as follows: renewable energy generation — kW h per person; electricity price — cents per kW h; CO_2 emission — metric tons per person; electricity demand — MW h per person. Baseline differences in differences specification uses non-RPS states as control group. Synthetic control specification utilizes synthetic states as controls. Iowa was excluded from the SC analysis because its RPS was implemented before the first year of data available and therefore no pre-treatment characteristics are available. Iowa also excluded from baseline specification because stringency not available (see Carley and Miller, 2012).
*, **, and *** represent significance at the $p < .10$, $p < .05$, and $P < .01$ respectively.

It should be noted that, just as RPS adoption is not random, the policy stringency chosen is also likely not random. Not only might policy stringency be impacted by observables used in constructing the SC analysis, but also changes to stringency might be impacted by a state's success in reaching the policy goals set in prior years. Thus, a state that is having difficulty complying with its RPS target might be more likely to revise the policy to become less stringent, while a state with significant renewable energy growth might decide to strengthen its policy. If such endogenous policy changes exist, the SC analysis presented in this research will not be adequate in accounting for this potential bias. For this reason, these results should be interpreted as a test of robustness to the inclusion heterogenous policy stringency, not necessarily an unbiased treatment effect of policy stringency on these outcomes.

5. Discussion

5.1. Policy implications

Results of this research have a number of policy implications. The most notable result for policy makers is that RPS states have not experienced increases in renewable energy generation relative to non-RPS states. In fact, a simple descriptive analysis reveals the fact that RPS states have actually experienced less growth in renewables. But, on the other hand, RPS states have experienced increases in electricity prices relative to non-RPS states. Results of electricity price increases are consistent in the simple descriptive analysis (i.e. baseline specification) as well as in the SC analysis that attempts to account for non-random policy implementation by comparing RPS states to non-RPS states with similar economic and political conditions and similar renewable energy generation potential.

This main result has significant public finance implications, especially given the fact that electricity is one of the classic examples of a regressive good. While it is generally known that RPSs can lead to increases in electricity prices (Schmalensee, 2012; Kydes, 2006; Palmer and Burtraw, 2005), this is the first paper to econometrically find evidence of this increase from an ex-post difference-in-differences style approach. Similar to carbon tax policies that have been shown to be regressive (Hassett et al., 2009; Burtraw et al., 2009; Dinan and Rogers, 2002; Metcalf, 1999), these results provide suggestive evidence that RPSs may also be regressive in nature. Alternative policies, such as direct subsidies for renewable projects, might also achieve the goals of an RPS through progressive taxation instead of regressive electricity price increases.

This is also the first paper to specifically link renewable energy policies to decreases in electricity demand through the electricity price channel. RPSs can potentially lead to reductions in CO_2 emissions through two channels; the supply side (i.e. new renewable generation) and the demand side (i.e. reductions in electricity consumption associated with response to increased electricity prices). Results of this research find weak evidence that RPS states have experienced decreases in CO_2 emissions relative to non-RPS states, but that these reductions are likely due to reductions in electricity demand, not renewable energy generation. Thus, an electricity tax equivalent to the estimated price increase might yield a similar demand reduction, and therefore CO_2 emissions reduction, as the RPS policy. These tax revenues could then be spent on other programs aimed at reducing electricity demand and CO_2 emissions, such as energy efficiency for low-income rate payers. Such policies might be less regressive (or even progressive) in nature, and these investments can be kept in state (unlike investments in renewables that are moving across state lines).

Results of this research can also inform policymakers on how to address, and if they should address, RPSs potential to spur renewable energy generation into other states at the expense of in-state ratepayers. On the one hand, one might argue that states should restrict out of state REC purchases, to the extent that this is feasible and legal,[22] so that the economic benefits associated with the construction and operation of renewable energy projects are received by in-state ratepayers who also bear the cost of this generation. On the other hand, funding enough in-state renewables to meet the entirety of an RPS requirement might lead to further increases in electricity rates, as lower cost generation potential might be available across state lines. This might particularly be true for states with lower renewable energy generation potential, such as Delaware and Connecticut, but might not be as large of a concern for other states with abundant renewable energy potential, such as Texas and Kansas.

5.2. Extensions for future research

Different states have very different ways of determining rates for customers. In particular, there are two main categories of states: cost of service states (i.e. states that did not go through electricity market "restructuring") and competitive states (i.e. "restructured" states).

[22] While RPS states have made attempts to incentivize renewable projects to occur in state (Mack et al., 2011), in general restricting trade of RECs across state lines is a violation of the Commerce Clause of the U.S. Constitution (Elefant and Holt, 2011). In addition, the 7th Circuit Court of Appeals ruled that Michigan's in-state requirements for their RPS were in violation of the Commerce Clause of the U.S. Constitution.

How these different regulatory regimes might plausibly differ with relation to an RPS are discussed in Schmalensee (2012). In addition, Barbose et al. (2015) take restructuring into account when estimating RPS compliance costs. But no research to date has empirically compared the impact of RPSs on outcomes of interest in restructured and un-restructured states. There is room for future research on how market restructuring can augment, or diminish, the potential effectiveness of an RPS.[23]

While this is the first analysis to test the impact of RPSs on retail electricity prices faced by consumers using an ex-post differences in differences style approach, more research might explore why such a large range of estimates on costs more generally associated with RPSs exist in the literature (Barbose et al., 2015; Kydes, 2006; Palmer and Burtraw, 2005). A number of factors might contribute to these differences. Potentially not all costs associated with RPSs are directly related to renewable electricity procurement. For instance, Texas' CREZ project, a series of major transmission upgrades, was required in order to get wind energy to the market. How to allocate such costs as associated with an RPS compared to transmissions upgrades that would be made regardless of the RPS on a project by project basis is likely implausible. In addition, the effect of intermittent renewable sources on fossil fuel based plants is also difficult to quantify. For these reasons, and potentially other technical reasons, adding up plausible costs and benefits associated with an RPS might lead to over or underestimation of the actual net increase in electricity prices. Understanding the limits of different approaches in estimating costs and benefits of RPSs and how the approach chosen can inherently bias an estimate is important for policy makers who want a holistic understanding of these policies.

6. Conclusions

In this research we test the impact of state level renewable portfolio standard (RPS) implementation on four outcomes of interest; in-state renewable energy generation, electricity prices, CO_2 emissions associated with electricity generation and electricity demand. In contrast to a number of studies (Menz and Vachon, 2006; Carley, 2009; Yin and Powers, 2010), while both RPS states and non-RPS states experienced increases in renewable energy generation during the sample period, we find no evidence that RPS states have experienced increases in renewable energy relative to similarly situated non-RPS states. If anything, point estimates suggest that RPS states have actually seen less renewable energy generation growth than non-RPS states, more consistent to results found by Shrimali and Kniefel (2011).

However, we do find that RPSs are associated with a 10.9 to 11.4 percent increase in electricity prices compared to synthetic states with similar economic and political conditions and similar renewable energy generation potential. Prior studies have presented large ranges of estimated costs of RPS compliance. For instance, Palmer and Burtraw (2005) estimate that a hypothetical 20 percent RPS could lead to an 8 percent increase in electricity prices, with significantly lower costs for less ambitious (lower percent RPS) policies. Similarly, Kydes (2006) estimates that electricity prices would rise by about 3% in response to a theoretical 20 percent federal RPS being implemented. Most recently, Barbose et al. (2015) add up specific costs and benefits of RPSs and estimate compliance costs of $< 2\%$ of average retail rates in most U.S. states over the 2010–2013 period. Our results are on the high end of these estimates, but this is the first paper to analyze the impact of RPSs on electricity prices in an ex-post differences-in-differences framework.

We also find that RPSs are associated with a 7.2 to 7.5 percent decrease in electricity demand. This decrease in electricity demand is likely due to the increase in electricity price and therefore comparison of these results implies a long run price elasticity of approximately -0.51 to -0.63, which is in the mid-range of prior empirical estimates (Nakajima and Hamori, 2010).

While the specific implications of state level RPS policies as well as the potential for a federal RPS will likely be debated for years to come, research that analyzes the effect of RPSs on outcomes of interest must consider the non-random selection into these policies. Simple comparisons of the change in outcomes before and after policy implementation or comparisons of RPS and non-RPS states are not sufficient in order to holistically understand the effect of these policies on electricity markets. Furthermore, research should be concerned not only with the most visible outcomes of RPSs, namely increases in renewable generation and decreases in emissions, but should also focus on other effects such as increases in electricity prices and subsequent demand decreases. This is the first paper to take non-random adoption of RPSs into account in the empirical specification and is also the first empirical paper to examine electricity prices and demand. Understanding the intricacies of how effective RPSs are at achieving emissions reductions, and the channels through which these reductions are achieved relative to other potential policies, is a necessary step towards the goal of carbon emissions reductions.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2017.06.003.

References

Abadie, A., Diamond, A., Hainmueller, J., 2010. Synthetic control methods for comparative case studies: estimating the effect of California's tobacco control program. J. Am. Stat. Assoc. 105 (490), 493–505.

Alberini, A., Filippini, M., 2011. Response of residential electricity demand to price: the effect of measurement error. Energy Econ. 33 (5), 889–895.

Barbose, G., Bird, L., Heeter, J., Flores-Espino, F., Wiser, R., 2015. Costs and benefits of renewables portfolio standards in the United States. Renew. Sust. Energ. Rev. 52, 523–533.

Branch, E.R., 1993. Short run income elasticity demand for residential electricity using consumer expenditure survey data. Energy J. 14 (4), 111–121.

Bryce, R., 2012. The high cost of renewable-electricity mandates. Tech. Rep., Center for Energy Policy and the Environment at the Manhattan Institute.

U.S. Bureau of Economic Analysis 2016.

Burnett, J.W., Bergstrom, J.C., Dorfman, J.H., 2013. A spacial panel data approach to estimating, U.S. state-level energy emissions. Energy Econ. 40, 396–404.

Burtraw, D., Sweeney, R., Walls, M., 2009. The incidence of U.S. climate policy: alternative uses of revenues from a cap-and-trade auction. Natl. Tax J. 62 (3), 497–518.

Carley, S., Miller, C.J., 2012. Regulatory stringency and policy drivers: a reassessment of renewable portfolio standards. Policy Stud. J. 40 (4), 730–756.

Carley, S., 2009. State renewable energy electricity policies: an empirical evaluation of effectiveness. Energy Policy 37, 3071–3081.

U.S. Center for Disease Control, 2014.

Chandler, J., 2009. Trendy solutions: why do states adopt sustainable energy portfolio standards? Energy Policy 37, 3274–3281.

Database of State Incentives for Renewables and Efficiency (DSIRE), 2015. North Carolina Clean Energy Technology Center. Available at: http://www.dsire.org. Accessed 5 July, 2017.

Dinan, T., Rogers, D.L., 2002. Distributional effects of carbon allowance trading: how government decisions determine winners and losers. Natl. Tax J. 55 (2), 199–221.

Dinan, T., Webre, P., 2012. Federal financial support for the development and production of fuels and energy technologies. Tech. Rep., Congressional Budget Office.

Eastin, L.J., 2014. An assessment of the effectiveness of renewable portfolio standards in the United States. Electr. J. 27 (7), 126–137.

EIA, 2010. Status of electricity restructuring by state. Tech. Rep., Energy Information Administration.

EIA, 2014a. Electricity — detailed state data. Tech. Rep., U.S. Energy Information Administration.December.

[23] Of the 29 RPS states, 15 of these states are restructured, while the other 14 are not. Specifically, restructured RPS states include CT, DE, IL, ME, MD, MA, MI, NH, NJ, NY, OH, OR, PA, RI, and TX (EIA, 2010). While the structure of utility rate design with respect to RPS effectiveness is beyond the scope of this research, it should be noted that simply comparing state specific point estimates shown in Appendix Table A.12 across these four outcomes of interest for restructured vs. non-restructured states reveals no statistically significant difference.

EIA, 2014b. Form 861. Tech. Rep., U.S. Energy Information Administration.December.
EIA, 2014c. Form Eia-826. Tech. Rep., U.S. Energy Information Administration.December.
EIA, 2014d. Monthly report of prime supplier sales of petroleum products sold for local consumption. Tech. Rep., U.S. Energy Information Administration.December.
EIA, 2014e. State CO_2 emissions. Tech. Rep., U.S. Energy Information Administration.December.
Elefant, C., Holt, E.A., 2011. The Commerce Clause and Implications for State Renewable Portfolio Standard Programs. Clean Energy States Alliance State RPS Policy Report,
Fowler, L., Breen, J., 2013. The impact of political factors on states' adoption of renewable portfolio standards. Electr. J. 26 (2), 79–94.
Hassett, K.A., Mathur, A., Metcalf, G.E., 2009. The incidence of a U.S. carbon tax: a lifetime and regional analysis. Energy J. 30 (2), 155–177.
Hitaj, C., 2013. Wind power development in the United States. J. Environ. Econ. Manag. 65, 394–410.
Holt, E., 2014. Potential RPS Markets for Renewable Energy Generators. Clean Energy States Appliance,
Jacobsen, G.D., Kotchen, M.J., Vandenbergh, M.P., 2012. The behavioral response to voluntary provision of an environmental public good: evidence from residential electricity demand. Eur. Econ. Rev. 56, 946–960.
Klobner, S., Pfeifer, G., Scieler, M., 2017. Synthetic Control Methods: Never Use All Pre-intervention Outcomes as Economic Predictors. Working Paper.
Klarner, C., 2013. State Partisan Balance Data 1937–2011.
Kydes, A.S., 2006. Impacts of a renewable portfolio generation standard on US energy markets. Energy Policy 35, 809–814.
Lyon, T.P., Yin, H., 2010. Why do states adopt renewable portfolio standards?: an empirical investigation. Energy J. 31 (3), 133–157.
Mack, J.H., Gianvecchio, N., Campopiano, M.T., Logan, S.M., 2011. All RECs are local: how in-state generation requirements adversely affect development of a robust REC market. Electr. J. 24 (4), 8–25.
Matisoff, D.C., 2008. The adoption of state climate change policies and renewable portfolio standards: regional diffusion or internal determinants? Rev. Policy Res. 25 (6), 527–546.
Menz, F.C., Vachon, S., 2006. The effectiveness of different policy regimes for promoting wind power: experiences from the states. Energy Policy 34, 1786–1796.
Metcalf, G.E., 1999. A distributional analysis of green tax reforms. Natl. Tax J. 52 (4), 655–681.
Ming-Yuan, Alavalapati, J.R., Carter, D.R., Langholtz, M.H., 2007. Is the choice of renewable portfolio standards random? Energy Policy 35, 5571–5575.
Nakajima, T., Hamori, S., 2010. Change in consumer sensitivity to electricity prices in response to retail deregulation: a panel empirical analysis of the residential demand for electricity in the United States. Energy Policy 38 (5), 2470–2476.
Narayan, P.K., Smyth, R., Prasad, A., 2007. Electricity consumption in G7 countries: a panel cointegration analysis of residential demand elasticities. Energy Policy 35 (9), 4485–4494.
Nogee, A., Clemmer, S., Paulos, B., Haddad, B., 1999. Powerful solutions. 7 ways to switch America to renewable electricity. Tech. Rep., Union of Concerned Scientists.
NREL, 2010. Dynamic maps, GIS data and analysis tools—solar summaries. Tech. Rep., National Renewable Energy Laboratory.
Palmer, K., Burtraw, D., 2005. Cost-effectiveness of renewable electricity policies. Energy Econ. 27 (6), 873–894.
Sekar, S., Sohngen, B., 2014. The Effects of Renewable Portfolio Standards on Carbon Intensity in the United States. Resources for the Future Discussion Paper.
Schmalensee, R., 2012. Evaluating policies to increase electricity generation from renewable energy. Rev. Environ. Econ. Policy 6 (1), 45–64.
Sherlock, M.F., 2015. The renewable electricity production tax credit: in brief. Tech. Rep., Congressional Research Service.
Shrimali, G., Kniefel, J., 2011. Are government policies effective in promoting deployment of renewable electricity resources? Energy Policy 39, 4726–4741.
Tiefenbeck, V., Staake, T., Roth, K., Sachs, O., 2013. For better or for worse? Empirical evidence of moral licensing in a behavioral energy conservation campaign. Energy Policy 57, 160–171.
Upton, G.B., Snyder, B.F., 2015. Renewable energy potential and adoption of renewable portfolio standards. Util. Policy 26, 67–70.
Yin, H., Powers, N., 2010. Do states renewable portfolio standards promote in-state renewable generation? Energy Policy 38, 1140–1149.