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Karen Maguire
Assistant Professor
Department of Economics and Legal Studies
Oklahoma State University
Stillwater, OK

Abdul Munasib
Research Scientist
Department of Agricultural & Applied Economics
University of Georgia
213 Stuckey Building, 1109 Experiment Street, Griffin, GA 30223

Department of Economics
Oklahoma State
University
Stillwater, Oklahoma

339 BUS, Stillwater, OK 74078, Ph 405-744-5110, Fax 405-744-5180

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Karen Maguire
Assistant Professor
Department of Economics and Legal Studies
Oklahoma State University
327 Business Building, Stillwater, OK 74075
Phone: 405-744-5112
E-mail: karen.maguire@okstate.edu

Abdul Munasib
Research Scientist
Department of Agricultural & Applied Economics
University of Georgia
213 Stuckey Building, 1109 Experiment Street, Griffin, GA 30223
Phone (770) 229-3419
E-mail: munasib@uga.edu

Abstract

Several papers have used panel data analyses to examine the effectiveness of U.S. state-level Renewable Portfolio Standards (RPS) in promoting renewable capacity development, but the findings are inconclusive. Estimation of average treatment effects, however, can mask the fact that RPS policies across states are disparate and the treatment states are heterogeneous. We use the Synthetic Control Method (SCM) to conduct individual case studies of the early adopter states. Our findings indicate that the impact of RPS varied across states. We find Texas to be unique among these early adopters in that RPS in Texas has led to increased renewable capacity.

Keywords: Renewable portfolio standard (RPS), renewable energy, electricity, synthetic control method (SCM)
JEL classification: Q4, Q42, Q48, H7

I. Introduction

As of January 2012, 29 U.S. states and the District of Columbia had enacted a Renewable Portfolio Standards (RPS) or other mandated renewable energy policies. RPS require that electricity producers supply a portion of their electricity from designated renewable resources by a specified future date. The adoption of RPS is motivated by a complex set of political and economic factors, including increasing concerns over climate change and energy security (Yi and Feiock 2012). While several policies have been proposed to address these concerns, RPS is one of the most frequently advanced policies to promote renewable energy development for electricity generation (Fischer 2010). We examine whether RPS is having the intended effect of increasing renewable generation capacity.

Several papers have implemented panel data analyses to study the role of renewable energy policies in promoting renewables development.[1] They, however, do not provide any consensus. Yin and Powers (2010) find that RPS has a positive influence on the percentage of non-hydro renewable generating capacity, but the finding is predicated on the construction of an RPS stringency index. Shrimali and Kniefel (2011), on the other hand, found a negative impact of RPS on the ratio of non-hydro renewable capacity over total net generation. Carley (2009) focuses on generation and finds that in the years after RPS adoption an additional year of RPS has a positive effect, although RPS implementation has no predictive power. Delmas and Montes-Sancho (2011) analyzed capacity rather than generation and found that RPS led to declining renewable electricity capacity. Additionally, a number of studies on wind capacity found no impact of RPS. Hitaj (2013), for instance, provides a county-level analysis and finds that RPS did not have a significant influence on

[1] Carley (2009): 48-state 1998-2006 panel, Delmas and Montes-Sancho (2011): panel of 650 utilities from 48-states over 1998-2007, Hitaj (2013): county-level 1998-2007 panel, Maguire (2014): state-level 1994-2012 panel, Shrimali and Kniefel (2011): 50-state 1991-2007 panel, Yin and Powers (2010): 50-state 1993-2006 panel.

wind capacity, and Maguire's (2014) state-level analysis also concludes that RPS did not have a significant effect on wind capacity.

The empirical literature discussed above has generally failed to find conclusive evidence of an average treatment effect of RPS on renewables adoption across RPS states. This highlights the need for analyses that accommodate the possibility of treatment heterogeneity (Keele et al. 2013), particularly because RPS are unique state-level policies. Estimation of average effects can mask the fact that adopter states are heterogeneous and state RPS policies are disparate. The assumption of a uniform effect of RPS across states can be quite restrictive when the states differ in their policy environment, electricity market characteristics, renewable resource potential, likelihood of successful implementation of their RPS, and a host of observed and unobserved characteristics.

Treating disparate state level RPS as a uniform intervention is also inappropriate. RPS vary in the amount of electricity generation that must be supplied from renewables, the types of allowable renewables, the year of required implementation of the final mandate, and the magnitude and the timing of intermediate mandates. RPS also differ in the nature of the Renewable Energy Credit (REC) trading markets, and the degree and scope of restructuring requirements (see section II.3 for more details). We, therefore, adopt a case study approach to examine the effect of a state's RPS on its renewable capacity. We examine the period 1991-2008 and focus on the early adopter states (see Appendix A for a list of RPS states and final mandates).[2] Our set of treatment states are Nevada (1997), Connecticut (1998), New Jersey (1999), Maine (1999), Texas (1999) and Wisconsin

[2] The earliest available state-level data for generation capacity is 1990. Starting at the end of 2008, five additional states adopted RPS. Extending our analysis beyond 2008, therefore, would significantly shrink the size of the donor pool.

(1999), states that enacted RPS between 1997 and 2000.[3] Our outcome variable of interest is the generation capacity of the modern renewables: wind, solar, geothermal, and biomass.[4]

We employ the Synthetic Control Method (SCM) for comparative case studies (Abadie and Gardeazabal 2003, Abadie et al. 2010) to estimate the impact of RPS in each of these states. SCM constructs a unique counterfactual (or 'synthetic') for each RPS (treatment) state using a weighted average of the non-RPS (control) states based on a set of pre-intervention (pre-RPS) characteristics. By examining each state as a stand-alone case study we are able to allow for heterogeneous effects of RPS.

We focus only on early adopter states (i.e., states that enacted RPS between 1997 and 2000) in order to allow for sufficient post-intervention years to capture the effect of RPS. Unlike other policies such as changes in gun laws or driving restrictions, RPS does not become immediately binding on its effective date. The renewable mandates are implemented years after the RPS effective date through a series of intermediate goals and mandates leading up to the final mandate. For instance, Nevada enacted RPS in 1997, and updated the policy in 2001 to establish the minimum requirement that 2 percent of electricity be supplied from eligible renewable sources, increasing every two years and culminating in a 15 percent mandate by 2013.[5] In Texas, RPS, passed in 1999, had intermediate mandates in 2002 and 2007 with their final mandate initially binding in 2010 and then subsequently amended to 2015. A similar pattern is observed in the other RPS states where the final mandate is effective on a future date preceded by a series of intervening targets.

[3] Iowa is the only state that passed RPS before 1997. But it passed its RPS in 1983, which falls outside our data range.

[4] Hydroelectric generation capacity is not considered a *modern renewable* resource and is excluded. Although it constitutes 52% of renewable electricity generation in the U.S. in 2013, because most hydroelectric capacity was added prior to the mid-1970s it is not a newly developed resource. (http://www.eia.gov/energy_in_brief/article/renewable_electricity.cfm)

[5] Nevada RPS was significantly revised again in 2009, which falls beyond our study period.

Our SCM estimates show that the impact of RPS indeed varies across states. Texas is unique among the early adopter states in that we find a positive impact of RPS on renewable capacity in Texas. Within a decade after enacting RPS, Texas installed more wind generation capacity than any other state.[6] As we discuss in detail in sections II.2-II.4 the energy market characteristics of Texas are also quite unique: Texas is the only early adopter state with substantial modern renewable potential. Texas is also the only mainland state with its own grid, and its RPS, specified in terms of capacity and not generation, is atypical.

In what follows, we provide some background information on the U.S. electricity market and describe the RPS characteristics of the early adopter states in section II, present a brief description of the empirical methodology in section III, describe the data in section IV, and discuss the results in section V. Section VI concludes.

II. Renewable Generation, Electricity Markets, and Renewable Portfolio Standards

II.1. Renewable generation

Renewable energy sources provided 13 percent of total U.S. electricity generation in 2013, 49 percent of which is from modern renewables; wind, biomass, geothermal, and solar, i.e., non-hydroelectric sources. Today, the United States produces more electricity from non-hydroelectric renewable sources than any other country, China and Germany rank second and third.[7] The Energy Information Association (EIA) predicts that between 2013 and 2040, non-hydroelectric renewables will account for 24 percent of the overall growth in the United States electricity generation. Solar is expected to increase from 8 GW in 2012 to 48 GW by 2040, while wind is predicted to increase from

[6] In 2013, Texas accounted for 22percent of the 167 million MWh of total power generated from wind nationwide. If Texas were a country it would be sixth in the world in wind capacity following China, the United States, Germany, Spain, and India. See Hurlbut (2008), EIA-PTC: http://www.eia.gov/todayinenergy/detail.cfm?id=8870, EIA-Texas: http://www.eia.gov/todayinenergy/detail.cfm?id=15851, EIA: http://www.eia.gov/state/?sid=TX, ERCOT Time-line: http://www.ercot.com/about/profile/history, and Office of the Governor: www.TexasWideOpenForBusiness.com.

[7] http://www.eia.gov/todayinenergy/detail.cfm?id=16051

60 GW to 87 GW over the same period. In addition, geothermal capacity is predicted to triple and biomass capacity is predicted to double. Finally, modern renewable generation is predicted to exceed hydroelectric generation and comprise two-thirds of all renewable generation by 2040.[8]

II.2. Electricity Market

The electricity system in the United States consists of three regions: the Eastern Interconnection, the Western Interconnection, and the Texas Interconnection. Grid connectivity within an interconnection enables utilities to import and export generation across states.[9] Within the Interconnections, there are nine Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs) that coordinate the trading of electricity generation across states (See Figure 1). They provide the rates, terms and conditions for the wholesale market and transmission within the region.

Renewable Energy Credits (REC) markets allow for the trading of renewable energy between utilities within a particular region.[10] REC are designed to provide an accurate account of eligible renewable energy production, and to be tradable between producers and retailers. For example, in New England, the ISO New England RTO coordinates the trading of renewable generated electricity across states using REC.[11] Because in these states utilities are allowed to import and export renewable generation from other states, utilities may import rather than add additional renewable

[8] http://www.eia.gov/forecasts/aeo/MT_electric.cfm#cap_natgas

[9] http://www.un.org/esa/sustdev/publications/energy/chapter2.pdf.

[10] Arizona, Nevada, Texas and Wisconsin were the earliest states to allow for or require the use of tradable REC to meet RPS.

[11] Power generated from renewable resources is used to create REC, which are measured in energy units. For instance, one REC may represent 1 MWh of qualified renewable energy. The existing REC markets and tracking systems serve a distinct region: the NEPOOL Generation Information System (NEPOOL GIS) supports a six-state area in New England comprising the ISO New England control area, the PJM Generation Attribute Tracking System (GATS) supports the PJM control area, which covers 13 states and the District of Columbia, while the ERCOT REC program only operates in Texas. See (Doot, Belval, and Fountain 2007) for more details. The New England ISO was established by the Federal Energy Regulatory Commission (FERC) in 1997 and was designated as an RTO in 2005, giving the organization additional authority over the regional grid (http://www.iso-ne.com/about/what-we-do/in-depth/industry-standards-structure-and-relationships).

capacity if importing is a low-cost alternative to meet their RPS mandates. Conversely, it may also be more cost effective for a utility to become an exporter of renewable generation. According to the National Renewable Energy Laboratory (NREL), "The primary regional markets for REC exist in New England and the Mid-Atlantic states" (Heeter and Bird, 2010, p.6). The NEPOOL_GIS REC trading market for the New England region began in 2002, while the PJM-GATS REC trading market serving the Mid-Atlantic states began in 2005 (Heeter and Bird, 2010, p.9).[12]

One unique state in terms of interconnectivity is Texas. The Texas Interconnection is separated from the rest of the nation, making Texas the only mainland state with its own grid. Also, the Texas REC trading program was unusual in that it requires the REC generated electricity to be produced in Texas (Hurlbut 2008).[13] Nevada is the only other early adopter state that limits renewable generation to within state producers, but they do allow limited out of state production.

II.3. Renewable Potential

The renewable energy potential for each state varies significantly. Texas is the only early adopter state with substantial modern renewable potential.[14] According to the NREL's renewable potential data, Texas ranks first in onshore wind and solar photovoltaic potential, fifth in biopower (solid) potential, and eighteenth in geothermal-hydrothermal potential.[15] Other states with significant renewables potential that have enacted RPS include Washington, California, Oregon and

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[12] The NEPOOL_GIS REC trading activity included imports of 20,163 GWh and exports of approximately 10,861 GWh in 2008. This represents approximately 6 percent and 3 percent of total U.S. renewable generation (modern renewables and hydroelectric generation) in 2008.

[13] The Electric Reliability Council of Texas (ERCOT) which manages the Texas Interconnection manages electric power for approximately 85% of the state's total electric load. For more details, see Office of the Governor (www.TexasWideOpenForBusiness.com), ERCOT(http://www.ercot.com/about, http://www.ercot.com/content/news/mediakit/maps/NERC_Interconnections_color.jpg), and DSIRE (http://www.dsireusa.org/incentives/incentive.cfm?Incentive_Code=TX03R).

[14] http://www.nrel.gov/gis/re_potential.html

[15] None of the other early adopter states has a top 10 ranking in any category, except Nevada which ranks second in geothermal-hydrothermal potential. NREL biopower estimates include crop, forest, primary/secondary mill residues, and urban wood waste from Milbrandt (2005). See NREL 2012 for more information on the calculation of each renewable energy potential measure.

New York, but they passed their RPS on or after 2003. In addition, in these four states, hydroelectricity constitutes the largest share of renewable generation and most of the hydroelectric capacity existed in these states before their respective RPS were enacted.

II.4. Heterogeneity of RPS across States

RPS are state-adopted policies and there is significant variation in the characteristics of RPS across states, which is one of the rationales for our case study approach. Our SCM estimates allow us to determine the effect of a state's unique RPS policy in the context of its distinct political and market characteristics.

RPS vary not only in the magnitude and timing of the final renewables mandate but also the magnitude and timing of intermediate mandates (Appendix A details the current targets for all the RPS states). For instance, Wisconsin's RPS (passed in 1999) requires 10 percent renewable generation by 2015 while Maine's RPS (also passed in 1999) requires 40 percent by 2017, one of the most stringent in the nation. The Texas RPS mandate is set in terms of capacity and not in terms of the percentage of generation requiring 10,000 MW by 2025. Kneifel (2007) identifies this as an important feature vis-à-vis the effectiveness of RPS.[16]

In addition to the final mandate, states vary in their definitions of 'renewable resources'. This variation is a function of their unique resources, political conditions, and economic standing in the regional economy. The mandated renewable sources can include wind, solar, geothermal, biomass, some types of hydroelectricity, and other resources such as landfill gas, municipal solid waste, and tidal energy. For some states modern renewables are largely categorized as Class 1 and make up an increasing portion of the renewable requirements over time. For instance, Connecticut

[16] The only other state that set its RPS based on capacity was Iowa, but their mandate was small. Iowa's RPS mandated 105 MW of renewable capacity.
(http://twww.dsireusa.org/incentives/incentive.cfm?Incentive_Code=IA01R&re=1&ee=1)

and New Jersey mandated three categories of renewables each with their own generation requirements. The early adopter states included modern renewables in their set of allowable renewables.

There is also variation in the coverage of the policy in different states. In some states only specific types of utilities, investor owned utilities (IOUs), municipal, or rural electric cooperatives (Coops) are required to meet RPS. For example, In Wisconsin the initial RPS mandate applied only to IOUs and Coops. The Texas RPS applied to both IOUs and retail suppliers while municipal utilities and Coops could opt in. The legislative path of the passing of RPS also varied across states. Wisconsin was the first state to implement RPS without restructuring its electricity market, while in the rest of the early adopter states, RPS passed as part of legislation that included restructuring of the electricity market.

III. Synthetic Control Method (SCM) for Comparative Case Study

There are a number of advantages to using SCM in this study. First, in program evaluation, researchers often select comparisons on the basis of subjective measures of similarity between the affected and the unaffected regions or states. But, neither the set of all non-RPS states nor a single non-RPS state likely approximates the most relevant characteristics of a treatment (or RPS) state. SCM provides a comparison state (or synthetic) that is a combination of the control states, a data-driven procedure that calculates 'optimal' weights to be assigned to each state in the control group based on *pre-intervention* characteristics, thus making explicit the relative contribution of each control unit to the counterfactual of interest (Abadie and Gardeazabal 2003; Abadie et al., 2010). With reduced discretion in the choice of the comparison control units, the researcher is forced to demonstrate the affinities between the affected and unaffected units.

Secondly, even when aggregate data are employed, as the case is in this paper, there is uncertainty about the ability of the control group to reproduce the counterfactual outcome that the affected state would have exhibited in the absence of the intervention. As Buchmueller, DiNardo, and Valleta (2011) explain, in a 'clustering' framework, inference is based on the asymptotic assumption, i.e., the number of states grows large. The comparison of a single state against all other states in the control group collapses the degrees of freedom and results in much larger sample variance compared to the one typically obtained under the conventional asymptotic framework and can seriously overstate the significance of the policy intervention (Donald and Lang 2007; Buchmueller, DiNardo, and Valletta 2011; Bertrand et al. 2004). We, therefore, apply the permutations or randomization test that SCM readily provides (Bertrand, Duflo, and Mullainathan 2004; Buchmueller, DiNardo, and Valletta 2011; Abadie, Diamond, and Hainmueller 2010; Bohn, Lofstrom, and Raphael 2014).

Thirdly, because the construction of the optimal weights does not require access to post-intervention information, SCM allows us to decide on a study design without knowing its bearing on the findings (Abadie, Diamond, and Hainmueller 2010). The ability to make decisions on research design while remaining blind to how a particular decision affects the conclusions of the study is a safeguard against actions motivated by a 'desired' finding (Rubin 2001).

Finally, Abadie, Diamond, and Hainmueller (2010) argue that unlike the traditional regression-based difference-in-difference model that restricts the effects of the unobservable confounders to be time-invariant so that they can be eliminated by taking time differences, SCM allows such unobservables to vary with time. In particular, Abadie, Diamond, and Hainmueller

(2010) show that with a long pre-intervention matching on outcomes and characteristics a synthetic control also matches on time-varying unobservables.[17]

III.1. The Synthetic Control

A typical SCM analysis is feasible when one or more states exposed to an intervention can be compared to other states that were not exposed to the same intervention. In this paper, the intervention is RPS, the outcome is renewable capacity, and the set of exposed states are the early RPS adopter states. The donor pool (unexposed/control states) consists of states that did not have the policy for the observed period.

To obtain the synthetic control we follow Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010). For states $i = 1,\ldots,J+1$ and periods $t = 1,\ldots,T$, suppose state $i = 1$ is exposed to the intervention at $T_0 \in (1,T)$. The observed outcome for any state i at time t is,

(1) $$Y_{it} = Y_{it}^{N} + \alpha_{it} S_{it},$$

where Y_{it}^{N} is the outcome for state i at time t in the absence of the intervention, the binary indicator variable S_{it} denotes the intervention taking the value 1 if $i=1$ and $t > T_0$, and α_{it} is the effect of the intervention for state i at time t.

We want to estimate $(\alpha_{1T_0+1},\ldots,\alpha_{1T})$. Abadie, Diamond, and Hainmueller (2010) show that, under standard conditions, there exist $\mathbf{W}^{*} = (w_2^{*},\ldots,w_{J+1}^{*})'$ such that pre-intervention matching is achieved with respect to the outcome variable as well as characteristics (or predictors), and we can use,

[17] As Abadie et al. (2014) explains the intuition as, "… only units that are alike in both observed and unobserved determinants of the outcome variable as well as in the effect of those determinants on the outcome variable should produce similar trajectories of the outcome variable over extended periods of time."

(2) $$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}, \qquad t \in \{T_0 + 1, \ldots, T\},$$

as an estimator for α_{1t}. The term $\sum_{j=2}^{J+1} w_j^* Y_{jt}$ on the right-hand-side of (2) is simply the weighted average of the observed outcome of the control states for $t \in \{T_0 + 1, \ldots, T\}$ with weights $\mathbf{W}^*$. The procedure to obtain $\mathbf{W}^*$ is in Appendix B.

III.2. Inference

Once an optimal weighting vector $\mathbf{W}^*$ is obtained, the "synthetic" is constructed by calculating the weighted average outcome of the donor pool. The post-intervention values of the synthetic control serve as our counterfactual outcome for the treatment state. The post-intervention gap between the actual outcome and the synthetic outcome, therefore, captures the impact of the intervention.

To begin, we calculate a difference-in-difference estimate for the treatment state (Bohn, Lofstrom, and Raphael 2014, Munasib and Rickman 2015),

(4) $$\Delta_{TR} = \left| \overline{Y}_{TR,actual}^{post} - \overline{Y}_{TR,synthetic}^{post} \right| - \left| \overline{Y}_{TR,actual}^{pre} - \overline{Y}_{TR,synthetic}^{pre} \right|,$$

where $\overline{Y}_{TR,actual}^{post}$ is the average of the post-intervention actual outcome of the treatment state, $\overline{Y}_{TR,synthetic}^{post}$ is the average of the post-intervention outcome of the counterfactual. Similarly, $\overline{Y}_{TR,actual}^{pre}$ is the average of the pre-intervention actual outcome of treatment state, and $\overline{Y}_{TR,synthetic}^{pre}$ is the average of the pre-intervention outcome of the counterfactual. If the outcome changed in response to the intervention in time T_0 we would expect $\Delta_{TR} > 0$.

To formally test the significance of this estimate, we apply the permutations or randomization test, as suggested by Bertrand et al. (2004), Buchmueller et al. (2011), Abadie et al. (2010) and Bohn et al. (2014), on this difference-in-difference estimator. Specifically, for each state in the donor pool, we estimate the difference-in-difference as specified in equation (4) as if it was exposed to RPS at time T_0 (i.e., apply a fictitious intervention). The distribution of these "placebo" difference-in-difference estimates then provides the equivalent of a sampling distribution for Δ_{TR}. To be specific, if the cumulative density function of the complete set of Δ estimates is given by $F(\Delta)$, the p-value from a one-tailed test of the hypothesis that $\Delta_{TR} > 0$ is given by $F(\Delta_{TR})$ (Bohn et al. 2014). Note that this answers the question, how often would we obtain an effect of RPS of a magnitude as large as that of the treatment state if we had chosen a state at random, which is the fundamental question of inference (Bertrand et al., 2004, Buchmueller et al. 2011, Abadie et al. 2010).

We carry out a second test where we calculate what we call the DID rank. It is the ranking of the absolute value of the magnitude of the difference-in-difference of the treatment state against all the placebo difference-in-difference magnitudes (Bohn et al. 2014, Munasib and Rickman 2015). For example, if DID rank is 1 then the estimated impact of the intervention in the treatment state is greater than any of the estimated placebo impacts.

IV. Data

We collected the data for the outcome variable, renewable capacity, from the EIA. The information on state RPS is collected from the Database of State Incentives for Renewables & Efficiency (DSIRE) database (see Appendix A). Figure 2 demonstrates that states that have adopted RPS are largely the states that have renewable generation capacity additions. This, of course, is confounded by various aggregate factors such as the Federal Production Tax Credit (PTC). One of the rationales behind our case study approach is that we can purge out these aggregate effects, factors such as the PTC apply to both control and treatment states.

Much of the remaining energy data, including electricity generation and price, generating capacity, number of customers, etc., were also collected from the EIA. We used information on geographical features such as sunlight and natural amenities from the Economic Research Service (ERS) of the U.S. Department of Agriculture (USDA) and temperatures from National Oceanic and Atmospheric Administration (NOAA). Population as well as economic indicators such as per capita personal income and manufacturing earnings share were obtained from the Bureau of Economic Analysis (BEA). Poverty rates are from the Census.

In addition, we collected data on technical renewable potentials from Pacific Northwest National Laboratory (PNNL) and NREL. There are two wind potential measures. The first measure is derived from wind potential estimates produced by the PNNL in 1991 (Elliott, Wendell, and Glower 1991, p. B-1). Wind potential calculations indicate the amount of wind that a state or region is theoretically capable of producing under a specific set of technological and land use assumptions, excluding transmission limitations.[18] The second measure is an updated 2010 wind potential measurements constructed by NREL.[19] Similarly, the photovoltaic potential, biopower (solids) potential, and geothermal-hydrothermal potential measures are also 2010 estimates from NREL (NREL 2012). Table 1 presents a summary description for all the variables used in the analysis.

[18] For instance, the installed capacity calculations are based on an assumption of 5 MW/km2 of installed capacity.

[19] The two measures differ based on technological and land use assumptions. For instance, the 1991 measure was constructed with an assumed turbine height of 50m due to the availability of wind technology at the time, while the 2010 measure was constructed using an 80m turbine height (NREL 2010).

V. Results

V.1. SCM Estimates of the Impact of RPS on Renewable Capacity

We construct the counterfactual (or synthetic) renewable capacity for each of our early adopter states (as discussed in Section III). Our donor pool consists of 26 states that did not pass a law similar to mandatory RPS as of 2008.

Figure 3 is a graphical representation of the SCM estimates of the impact of RPS on renewable capacity for the six exposed states. In each panel, the picture on the left shows the actual and the synthetic renewable capacities for the period 1990-2008. The picture on the right presents the permutations/randomization or the placebo tests: the dark line is the gap between actual and synthetic for the treatment state, whereas each grey line is the gap between actual and synthetic of a placebo. The details of the estimation are reported in Table 2.

The left picture in panel A (Nevada) shows that the synthetic renewable capacity coincides well with the actual renewable capacity over 1990-1996. On the right picture of panel A, we find that Nevada (the dark line) does not stand out from the placebos (the grey lines). As explained in section III.2, we examine the comparison of the post-pre difference ratios from the placebo tests. Along the first column of Table 2, we find that the DID rank is 25 and the p-value of the DID measure does not have a significant p-value. We, thus, conclude that RPS did not have a significant impact on renewable capacity in Nevada.

We observe the same pattern for Connecticut (panel B of Figure 3 and column 2 of Table 2), Maine (panel C of Figure 3 and column 3 of Table 2), New Jersey (panel D of Figure 3 and column 4 of Table 2) and Wisconsin (panel F of Figure 3 and column 6 of Table 2). In each of these cases we find that the DID rank is high and not statistically significant.

For Texas, however, we find that RPS had a significant impact on renewable capacity addition. On the left picture of panel E of Figure 3, we see that the actual capacity starts to deviate from the synthetic in the post-intervention period (i.e., 1999, the year of RPS) and keeps diverging. On the right picture of Panel E, we see that the gap between actual and synthetic for Texas stands out in the midst of all the placebo gaps. In column 5 of Table 2, we find that Texas's DID rank is 1, and it is significant at 1 percent. The main constituents of Texas's synthetic as indicated by the w-weights are (in order of importance): Indiana, Illinois and Virginia. The strongest predictors of renewable capacity for Texas's synthetic are (not shown): coal and natural gas generation shares, per capita income, growth of customers and per capita income, and share of manufacturing income.

V.2. Alternative Set of Predictors

To test if our estimates are robust to changes in the set of predictors (for pre-intervention matching) we carry out robustness checks with an alternative set of predictors. We include the 1991 wind potential measure and geographic and weather variables: January sunlight, summer cooling degree days, summer heating degree days. Alaska is dropped from the donor pool because the 1991 wind potential measure and the geographic variables are not available for this state. Table 3 presents these results. Based on the DID ranks as well as the p-values of the DID measures, we conclude that only in case of Texas, RPS had a significant impact on renewable capacity.

V.3. Additional Robustness Checks for Texas

In each SCM reported in Tables 2 and 3, for each treatment state, the state's pre-intervention outcome (renewable capacity) is included with a common set of predictors. Then, the matching is done to calculate the optimal w-weight. In the case of Texas, therefore, matching is done on the common set of predictors as well as the outcome variable (renewable capacity) for the period 1990-

1998.[20] However, Texas's renewable electricity market did not exist prior to 1998. So, we have conducted a robustness check, reported in column 1 of Table 4, where the matching is done on the set of predictors that includes renewable capacity for 1998 only. We find that our inference remains unchanged. The main constituents of Texas's synthetic as indicated by the w-weights are (in order of importance): Oklahoma, Illinois, and South Dakota.

Another issue is that the Texas RPS includes some degree of restructuring in the electricity market. To determine if the effect of restructuring is confounding the findings, in column 2 of Table 4 we present the SCM results where we have excluded states that had any kind of deregulation (i.e., the donor pool has only non-RPS and non-deregulated states). The set of predictors remains the same as that in Table 2. Again, we arrive at the same conclusion that RPS had a significant impact on renewable capacity.

V.4. Discussion: Heterogeneity of RPS Impacts

We find that of the six early RPS adopters, Texas is the only state where RPS had an impact on modern renewable capacity. It is important to point out that Texas stands out among these states in a number different ways. First, Texas is an exception in specifying RPS in terms of capacity. All other states, with the exception of Iowa, specify RPS as a percentage of total generation. Kneifel (2007) argues that the type of mandate influences its effectiveness.

Second, the five early adopter states where we do not find an effect are also among the smallest energy producing states; New Jersey, which is the largest producer of these five states, had only a 0.5 percent share of the total U.S. generation in 2012. Texas, on the other hand, was the

[20] This is the standard procedure followed in SCM due to Abadie et al. (2010) and Bohn et al. (2014).

largest energy producing state for every year between 1990 and 2012.[21] The size of the Texas electricity market may have given Texas an edge in adding renewable capacity.

Third, in addition to size, grid interconnectivity has important implications for the expansion of renewable capacity. In New England, the ISO New England RTO coordinates the trading of renewable generated electricity across states using REC. This may have influenced the pace of within state renewable capacity additions in Connecticut and Maine, both in the ISO New England region.[22] New Jersey, which is in the PJM RTO, promotes within state development, particularly for solar generation. However, if approved by the New Jersey Board of Public Utilities, renewable generation can also be generated from regional capacity (Daniel et al, 2014, p. 7). In Wisconsin tradable credits are created only when an electric utility or cooperative provides total renewable energy to its retail electric customers in excess of the RPS requirements (See Berry 2002 for details). Texas, on the other hand, is the only mainland state with its own grid and unlike other REC programs, the ERCOT REC program only operates in Texas; to generate a unit of REC the electricity has to be generated (from renewables) and metered in Texas.

In Nevada, utilities are required to meet a minimum of 5 percent of the required renewables mandate through solar generated electricity. Nevada did not meet 100 percent of their RPS obligation until 2008.[23] In New Jersey, in 2005, the mandate was revised whereby the share that must come from Class 1 renewables was set to be 17 percent by 2021. Until 2005, however, the

[21] http://www.eia.gov/electricity/data/state/

[22] As a robustness check, we conducted an SCM analysis where the New England region is considered the treated unit. The year of intervention was the first year in which a state in New England passed RPS, 1999. The finding was consistent with the state level results. There was not a significant influence of RPS on renewable capacity. These results are available upon request.

[23] In 2009, beyond our analysis period, the stringency of the initial policy was increased and the final mandate was increased to 25 percent by 2025. See http://www.dsireusa.org/incentives/incentive.cfm?Incentive_Code=NV01R.

mandate was that the share that must come from Class 1 renewables was 0.74 percent.[24] This may explain why there was no capacity expansion through 2008.

In Maine, at the time of the passage of RPS, the generation constraint was not binding. Maine has significant hydroelectric generation capacity, and generation from these resources exceeded the initial mandate. The Maine RPS was subsequently updated to require that a portion of the renewable capacity be installed after 2005. The mandate was small however, requiring 1 percent of electricity be produced from new renewable capacity in 2008.

In Wisconsin, the initial RPS mandate applied only to Investor Owned Utilities (IOUs) and Rural Electric Cooperatives (Coops), requiring them to obtain 2.2 percent of their electricity from renewable sources by 2012. The policy was strengthened in 2006, with a utility-wide requirement of 10 percent by 2015.[25]

V.5. Discussion: Efficacy of Texas RPS

We observe that Texas producers reached 10,000 MW of wind generation capacity by 2010 reaching the RPS target years ahead of the mandated timeline. This, however, does not indicate that RPS was not binding. In the presence of non-convex adjustment costs, indivisibilities, and irreversibilities of wind generation capital, optimal investment is unlikely to be incremental and more likely to exhibit bursts of large-scale capital accumulations (Adda and Cooper 2003, Cooper and Haltiwanger 2006). As a result, the level and timing of optimal investment may very well exceed and precede the mandate, as was the case in Texas.

Additionally, firms may have predated wind generation capacity in order to secure the federal Production Tax Credit (PTC) benefits. The PTC applies to wind farms for the first 10 years of

[24] http://www.dsireusa.org/summarytables/rrpre.cfm
[25] http://www.dsireusa.org/incentives/incentive.cfm?Incentive_Code=WI05R&re=0&ee=0.

production and lowers the cost of wind generated electricity production by about one third (Wiser, 2007).[26] The credit was originally created under the Energy Policy Act of 1992, but it has expired and been extended several times since its inception (Wiser, Bolinger, and Barbose 2007, p. 1-2).[27] Its lapses over the years are correlated with decreases in wind capacity additions and are often blamed for those declines (AWEA 2005, p. 4). Barradale (2010) finds that uncertainty in the federal PTC leads to investment volatility, as producers delay production in non-PTC years and ramp up production when the PTC is active.

V.6. Discussion: Early Adopter States

Because RPS mandates do not become immediately binding but are implemented through a series of intermediate goals leading up to the final mandate, we only focused on early adopter states (i.e., states that enacted RPS between 1997 and 2000). This allowed us sufficient post-intervention years to capture the effect of RPS. Indeed, with two exceptions, Massachusetts and California, for states that passed their RPS between 2000 and 2008, the earliest intermediate mandate is 2006.[28] While the available post-intervention periods may not be sufficient for carrying out SCM impacts of RPS in Massachusetts and California, we have still carried out the estimates. We do not find any impact of RPS on renewable capacity in Massachusetts. As for California, we are unable to establish a pre-intervention matching. This is because California had by far the largest renewable capacity for the pre-intervention period (1990-2002); California had at least 8 times the renewable capacity of

[26] The PTC is currently worth $22 per MWh (2011 dollars). In 2013, Texas accounted for 22% of the 167 million MWh of total power generated from wind nationwide. See http://www.eia.gov/todayinenergy/detail.cfm?id=8870 (EIA-PTC) and http://www.eia.gov/todayinenergy/detail.cfm?id=15851 (EIA-Texas).

[27] The PTC expired and was extended in 2000, 2002, 2004, and 2012. It was extended in 2010 prior to expiration.

[28] Massachusetts, which passed its RPS in 2002, required renewable generation of 1 percent of sales in 2003, increasing by 0.5 percent annually through 2009. California, which passed its RPS in 2003, included a requirement that utilities increase renewable generation annually by a minimum of 1 percent of their sales.

any other state for this period. As a result, no weighted average of states can approximate the pre-intervention renewable capacity of California.[29]

VI. Conclusion

Variation across states in their policy environment, electricity market structure, and availability of renewable energy resources suggest that empirical identification of the effect of RPS relies crucially on the accurate determination of the control states. We employ the SCM case study approach which, we argue, uses a more appropriate counterfactual for impact evaluation compared to the approaches estimating average treatment effects. We find that RPS have heterogeneous impacts on renewable capacity development.

The renewable policy environment across states is at a crossroads. This is particularly true for RPS in light of the recent legal and legislative efforts to repeal or weaken RPS in a number of states including California, Colorado, Kansas, Massachusetts, Minnesota, and Ohio (Plumer 2013; Gallucci 2013). In May 2014, Ohio legislators voted to halt the continued implementation of the state's RPS, which was passed in 2009 (Cardwell 2014). Similar bills have also been introduced in Wisconsin, West Virginia, Minnesota and Texas. While RPS survived repeal bills early in 2014 in Kansas and North Carolina, they are expected to be picked up again later in the year.

On the backdrop of the previous findings that RPS are not contributing to renewables development (Delmas and Montes-Sancho 2011, Shrimali and Kniefel 2011, Hitaj 2013, and Maguire 2014), these repeal efforts may pick up steam. But the findings in this paper suggest that the impact of RPS may not be generalized; instead, the success of a particular RPS may be

[29] In contrast, consider Texas, for instance. Texas's average non-renewable capacity during the pre-intervention period (1990-1998) fell between the median and the 75th percentile among the U.S. states. As a result, the feasibility of finding a weighted average of control states that would mimic Texas's pre-intervention non-renewable capacity was not an issue.

contingent on the features of the policy itself and the characteristics of the pertinent electricity markets.

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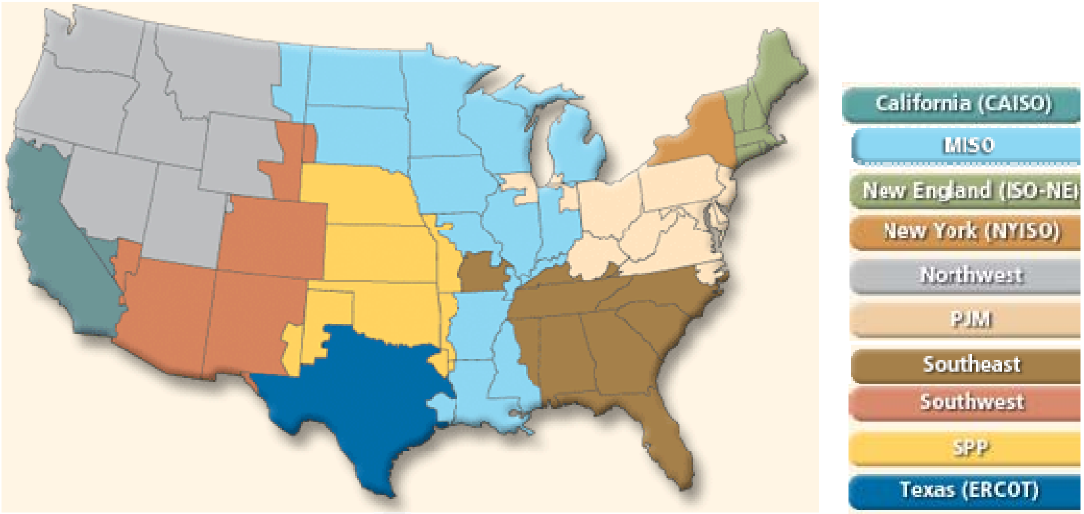
Figures

Figure 1: FERC Electric Power Markets: National Overview



Source: http://www.ferc.gov/market-oversight/mkt-electric/overview.asp

Figure 2: U.S. RPS and Renewable Generation Capacity

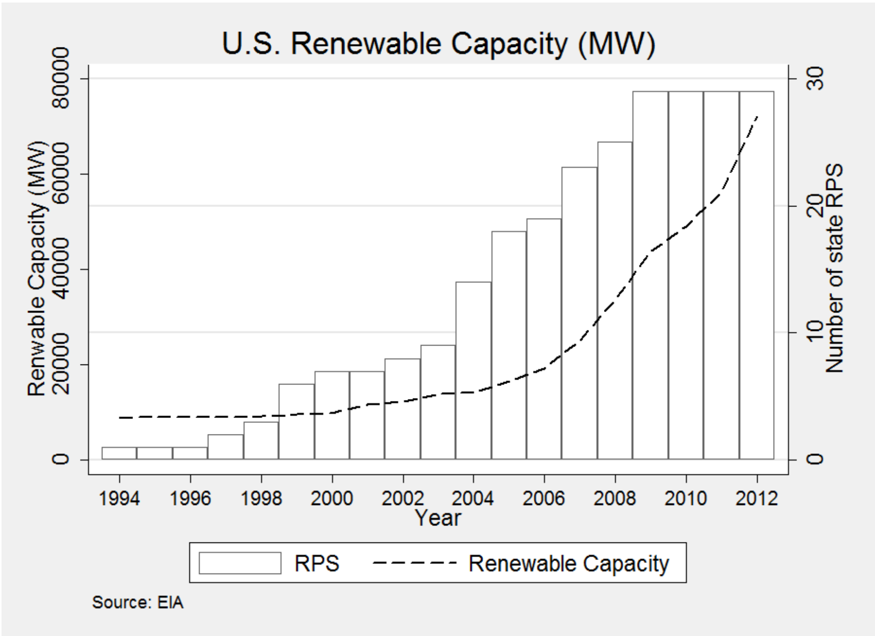
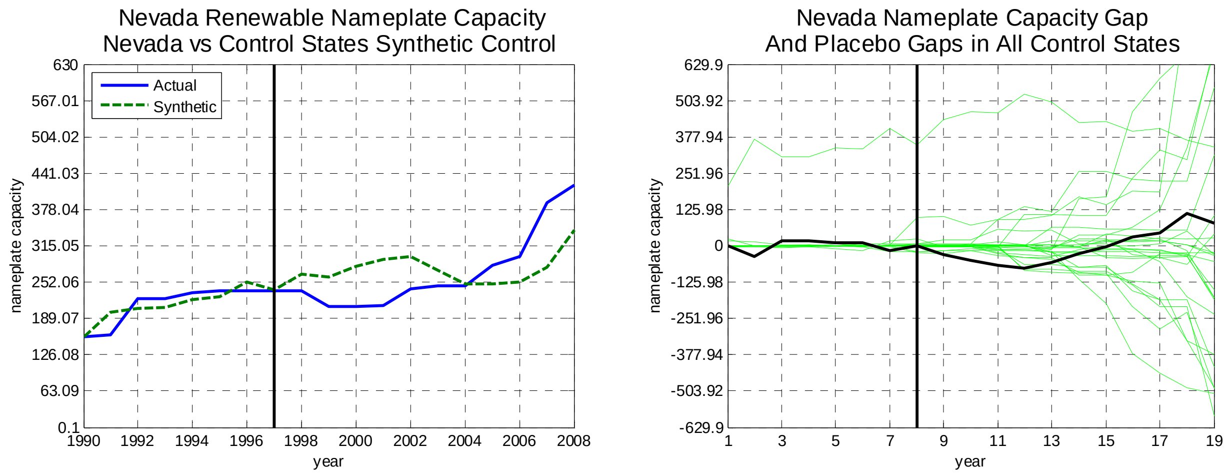
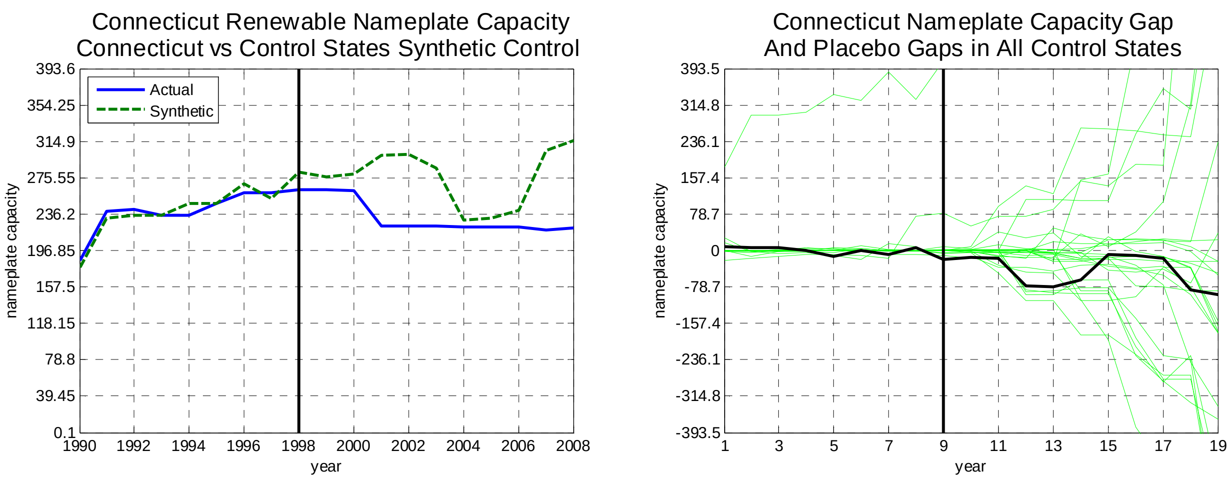


Figure 3: SCM Estimates of the Impact of RPS on Renewables Capacity

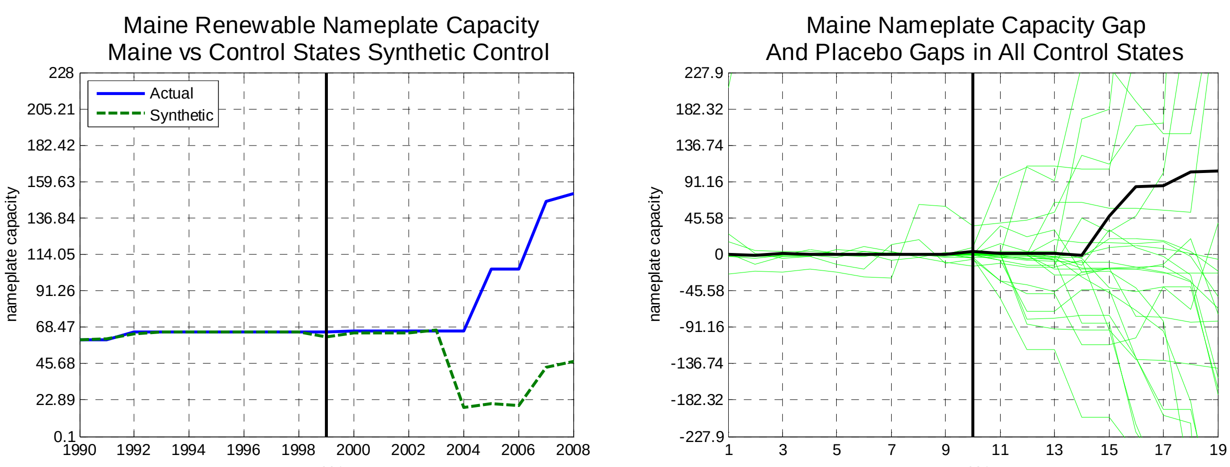
Panel A: Nevada



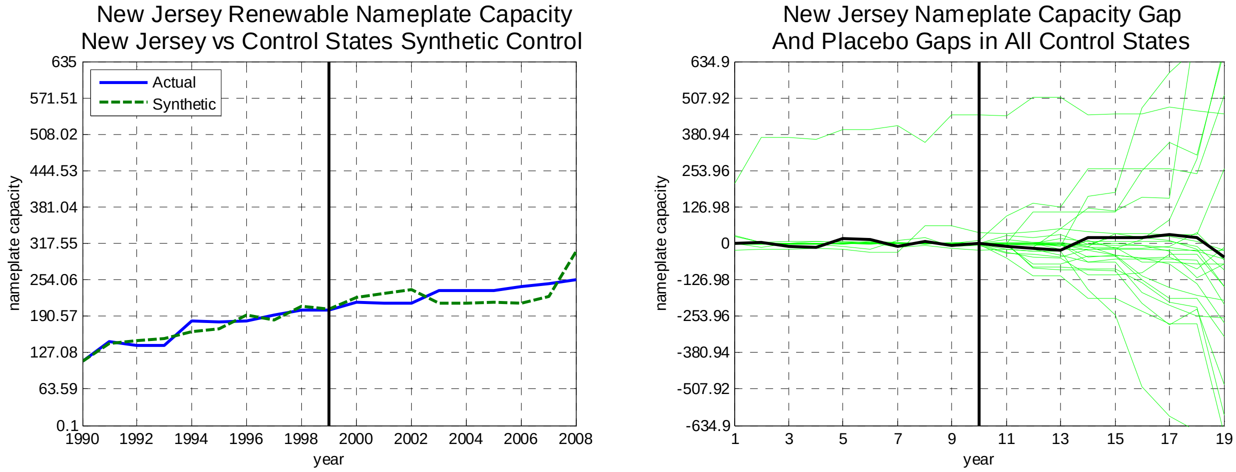
Panel B: Connecticut



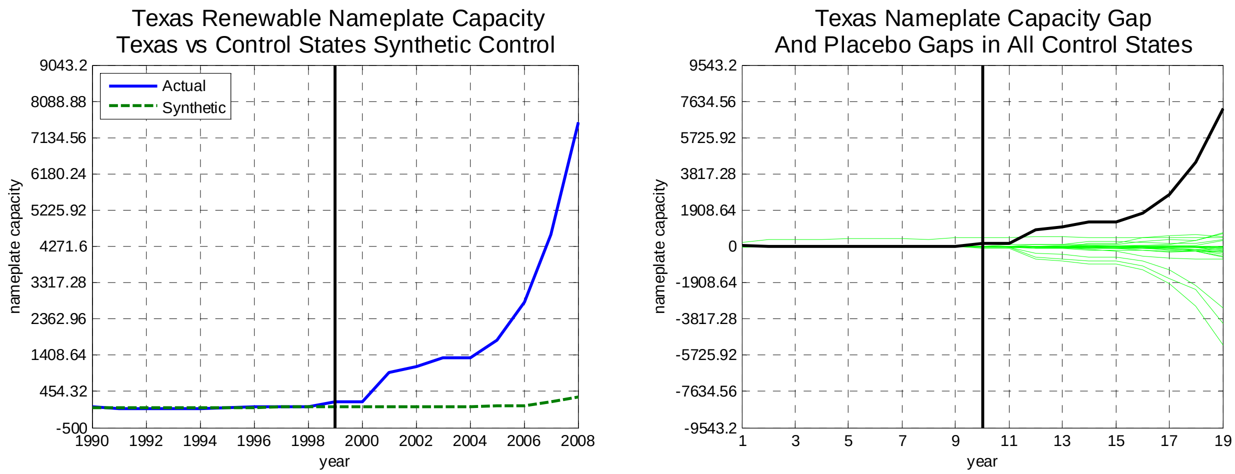
Panel C: Maine



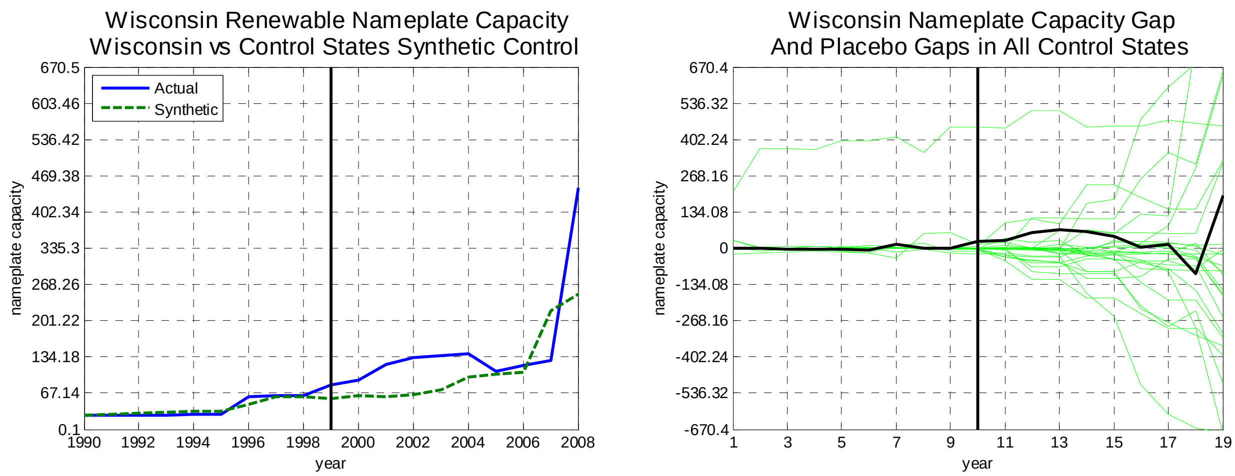
Panel D: New Jersey



Panel E: Texas



Panel F: Wisconsin



Notes: (a) Outcome variable is renewables capacity of geothermal, biofuels, solar, and wind. (b) These are the pictures of the estimates that are further described in Table 2.

Tables

Table 1: Summary Statistics (1990-2008)

	Donor pool (26 states)				Treatment State Means					
	Mean	SD	Min	Max	NV	CT	ME	NJ	TX	WI
Renewable nameplate capacity (MW)	79.90	166.81	1.00	1130.00	247.32	235.08	78.17	198.31	1162.30	97.23
Total nameplate capacity growth	37.99	28.49	0.35	117.41	7.15	164.52	13.07	249.06	34.46	25.62
Coal generation share	0.58	0.29	0.00	0.99	0.53	0.13	0.03	0.16	0.39	0.70
Natural gas generation share	0.10	0.16	0.00	0.65	0.35	0.15	0.21	0.31	0.48	0.04
Real electricity price	7.29	1.74	4.48	13.57	7.99	12.50	11.43	11.79	8.11	7.01
Growth of total customer	1.15	0.13	0.90	1.65	1.56	1.06	1.11	1.08	1.22	1.15
Real PC personal income ($)	28709.57	4698.39	18152.14	45222.82	33078.03	43696.99	28482.82	40186.85	29529.13	30577.93
Growth of PC personal income	1.22	0.16	0.98	1.82	1.19	1.21	1.20	1.19	1.24	1.23
Percent of population below poverty	13.17	3.57	5.70	26.40	10.32	8.75	11.67	8.71	16.51	9.67
Share of mfg. earnings	0.11	0.05	0.02	0.22	0.03	0.12	0.11	0.09	0.10	0.18
Wind potential (1991)	239.08	405.16	0.00	1210.00	50.00	5.00	56.00	10.00	1190.00	56.00
Wind potential (2010)	227.74	325.94	0.00	952.37	7.25	0.03	11.25	0.13	1901.53	103.76
Photovoltaic potential (2010)	3168.83	2024.67	36.55	9005.30	3742.84	17.13	660.61	276.43	20565.29	3240.76
Biopower-solid potential (2010)	1.17	0.77	0.06	3.52	0.04	0.06	0.54	0.15	2.04	1.42
Geo- & hydro-thermal potential (2010)	0.23	0.62	0.00	2.18	5.75	0.00	0.00	0.00	0.00	0.00
January mean hours of sunlight	147.13	25.34	105.14	197.64	200.00	161.75	156.25	152.24	182.59	133.54
Average summer cooling degree days	289.38	136.47	23.67	584.33	486.75	168.11	71.42	227.60	531.56	145.00
Average summer heating degree days	24.49	36.12	0.00	212.00	13.21	13.14	62.96	5.46	0.00	47.23

Notes: (a) For the donor pools N=494, except for 1991 wind potential, sunlight and degree days that are unavailable for Alaska (i.e., N=475). (b) Renewables include geothermal, biofuels, solar, and wind. (c) Total nameplate capacity is measures in MWh per 100 square miles. (d) All monetary values are in 2005 constant dollars. (e) Standard state codes used: Nevada (NV), Connecticut (CT), Maine (ME), New Jersey (NJ), Texas (TX), Wisconsin (WI), Massachusetts (MA). (f) Year of the enacting RPS in the treatment states: Nevada (1997), Connecticut (1998), Maine (1999), New Jersey (1999), Texas (1999), and Wisconsin (1999). (g) Following states enacted RPS on or before 2008 and therefore excluded from the donor pool: Iowa (1983), Massachusetts (2002), California (2003), Colorado (2004), Hawaii (2004), Maryland (2004), New York (2004), Rhode Island (2004), Delaware (2005), District of Columbia (2005), Montana (2005), Oregon (2005), Pennsylvania (2005), Washington (2006), Arizona (2007), Minnesota (2007), New Hampshire (2007), New Mexico (2007), Michigan (2008), Missouri (2008), North Carolina (2008). (h) 1991 wind potential is in energy units (annual '000 GWh), the rest of the potential measures are measured as power (GW).

Table 2: SCM Estimate of the Impact of RPS on Renewables Capacity

	Nevada	Connecticut	Maine	New Jersey	Texas	Wisconsin
Estimation summary						
Pre-intervention difference (D1)	0.34	0.69	0.03	0.13	-0.54	-0.54
Post-intervention difference (D2)	-4.52	-46.59	47.65	1.78	2301.25	42.62
DID = |D2|-|D1|	4.19	45.91	47.62	1.65	2300.71	42.08
P-value: DID	0.89	0.56	0.59	0.96	0.00	0.59
DID rank	25	16	17	27	1	17
W-weights						
Alabama	0.00	0.00	0.00	0.00	0.00	0.00
Alaska	0.00	0.00	0.23	0.00	0.00	0.00
Arkansas	0.00	0.00	0.00	0.00	0.00	0.00
Florida	0.25	0.32	0.00	0.17	0.00	0.00
Georgia	0.00	0.00	0.00	0.00	0.00	0.55
Idaho	0.00	0.00	0.00	0.00	0.00	0.00
Illinois	0.00	0.04	0.00	0.00	0.13	0.16
Indiana	0.00	0.00	0.00	0.00	0.79	0.15
Kansas	0.00	0.00	0.00	0.00	0.00	0.00
Kentucky	0.00	0.00	0.00	0.00	0.00	0.00
Louisiana	0.00	0.00	0.00	0.00	0.00	0.00
Michigan	0.45	0.00	0.00	0.55	0.00	0.00
Mississippi	0.00	0.00	0.03	0.00	0.00	0.00
Missouri	0.00	0.00	0.00	0.00	0.00	0.00
Nebraska	0.00	0.00	0.00	0.00	0.00	0.00
North Dakota	0.00	0.00	0.00	0.00	0.00	0.00
Ohio	0.26	0.65	0.54	0.00	0.00	0.00
Oklahoma	0.00	0.00	0.00	0.00	0.00	0.00
South Carolina	0.00	0.00	0.00	0.00	0.00	0.00
South Dakota	0.00	0.00	0.00	0.00	0.00	0.00
Tennessee	0.00	0.00	0.00	0.00	0.00	0.00
Utah	0.04	0.00	0.13	0.00	0.00	0.00
Vermont	0.00	0.00	0.04	0.28	0.00	0.00
Virginia	0.00	0.00	0.03	0.00	0.08	0.14
West Virginia	0.00	0.00	0.00	0.00	0.00	0.00
Wyoming	0.00	0.00	0.00	0.00	0.00	0.00

List of Predictors

(a) Common set of predictors: Total nameplate capacity growth, coal generation share, natural gas generation share, electricity price, growth of total customer, 2010 wind potential, 2010 photovoltaic potential, 2010 biopower-solid potential, 2010 geo- & hydro-thermal potential, real PC personal income, growth in real PC personal income, poverty, share of manufacturing income. (b) 1990 to pre-intervention renewables capacity (depending on the year of intervention for each treatment state).

Notes: (a) Outcome variable is renewables capacity of geothermal, biofuels, solar, and wind. (b) Year of the enacting RPS: Nevada (1997), Connecticut (1998), Maine (1999), New Jersey (1999), Texas (1999), and Wisconsin (1999). (c) Donor pool includes Alaska, therefore the set of predictors does not include the geographical variables and 1991 wind potential. However, 2010 measure of wind potential is included. (d) Weights less than 0.01 are reported as zero.

Table 3: SCM Estimate of the Impact of RPS on Renewables Capacity (Robustness Check with Geographical Variables)

	Nevada	Connecticut	Maine	New Jersey	Texas	Wisconsin
Estimation summary						
Pre-intervention difference (D1)	0.35	0.61	-0.04	0.69	-0.74	-0.57
Post-intervention difference (D2)	-4.56	-45.00	-12.32	-9.67	2137.23	21.64
DID = |D2|-|D1|	4.20	44.38	12.28	8.97	2136.49	21.07
P-value: DID	0.92	0.62	0.85	0.88	0.00	0.85
DID rank	25	17	23	24	1	23
W-weights						
Alabama	0.00	0.00	0.00	0.00	0.00	0.00
Arkansas	0.00	0.00	0.00	0.00	0.00	0.00
Florida	0.25	0.32	0.00	0.24	0.00	0.00
Georgia	0.00	0.00	0.00	0.07	0.00	0.00
Idaho	0.00	0.00	0.00	0.00	0.00	0.00
Illinois	0.00	0.03	0.00	0.06	0.18	0.15
Indiana	0.00	0.00	0.00	0.00	0.00	0.60
Kansas	0.00	0.00	0.24	0.00	0.63	0.00
Kentucky	0.00	0.00	0.00	0.00	0.00	0.00
Louisiana	0.00	0.00	0.00	0.01	0.00	0.00
Michigan	0.45	0.00	0.00	0.14	0.00	0.00
Mississippi	0.00	0.00	0.00	0.04	0.00	0.00
Missouri	0.00	0.00	0.00	0.00	0.00	0.00
Nebraska	0.00	0.00	0.00	0.00	0.00	0.00
North Dakota	0.00	0.00	0.00	0.02	0.09	0.12
Ohio	0.26	0.65	0.54	0.00	0.00	0.00
Oklahoma	0.00	0.00	0.00	0.01	0.00	0.00
South Carolina	0.00	0.00	0.00	0.11	0.00	0.00
South Dakota	0.00	0.00	0.00	0.00	0.00	0.00
Tennessee	0.00	0.00	0.00	0.00	0.00	0.00
Utah	0.05	0.00	0.14	0.00	0.00	0.00
Vermont	0.00	0.00	0.04	0.27	0.00	0.00
Virginia	0.00	0.00	0.03	0.02	0.10	0.12
West Virginia	0.00	0.00	0.00	0.00	0.00	0.00
Wyoming	0.00	0.00	0.00	0.00	0.00	0.00
List of Predictors						
(a) Common set of predictors: Total nameplate capacity growth, coal generation share, natural gas generation share, electricity price, growth of total customer, 2010 wind potential, 2010 photovoltaic potential, 2010 biopower-solid potential, 2010 geo- & hydro-thermal potential, real PC personal income, growth in real PC personal income, poverty, share of manufacturing income, 1991 wind potential, January sunlight, summer cooling degree days, summer heating degree days. (b) 1990 to pre-intervention renewables capacity (depending on the year of intervention for each treatment state).						

Notes: (a) Outcome variable is renewables capacity of geothermal, biofuels, solar, and wind. (b) Year of the enacting RPS: Nevada (1997), Connecticut (1998), Maine (1999), New Jersey (1999), Texas (1999), and Wisconsin (1999). (c) Geographic variables and 1991 wind potential measure are missing for Alaska; therefore, Alaska is excluded from the donor pool. (d) Weights less than 0.01 are reported as zero.

Table 4: SCM Estimate of the Impact of RPS on Renewables Capacity in Texas (Additional Robustness Checks)

	(1)	(2)
Estimation summary		
Pre-intervention difference (D1)	1.34	13.30
Post-intervention difference (D2)	2060.78	2090.37
DID = |D2|-|D1|	2059.44	2077.07
P-value: DID	0.00	0.00
DID rank	1	1
W-weights		
Alabama	0.00	0.00
Alaska	0.00	0.00
Arkansas	0.00	0.00
Florida	0.00	
Georgia	0.00	
Idaho	0.00	0.00
Illinois	0.24	
Indiana	0.00	0.00
Kansas	0.00	
Kentucky	0.00	0.00
Louisiana	0.00	0.06
Michigan	0.00	
Mississippi	0.00	0.00
Missouri	0.00	
Nebraska	0.00	0.00
North Dakota	0.00	0.00
Ohio	0.00	
Oklahoma	0.76	0.94
South Carolina	0.00	
South Dakota	0.00	0.00
Tennessee	0.00	0.00
Utah	0.00	
Vermont	0.00	
Virginia	0.00	
West Virginia	0.00	
Wyoming	0.00	0.00

List of Predictors

(a) Common set of predictors: Total nameplate capacity growth, coal generation share, natural gas generation share, electricity price, growth of total customer, 2010 wind potential, 2010 photovoltaic potential, 2010 biopower-solid potential, 2010 geo- & hydro-thermal potential, real PC personal income, growth in real PC personal income, poverty, share of manufacturing income. (b) Column 1 includes 1998 renewables capacity as the only pre-intervention outcome. (c) Column 2 includes 1990-1998 renewables capacity as the pre-intervention outcome.

Notes: (a) To check if matching on capacities is driving the results, in column (1) matching in done only on 1998 capacity. In column (2) donor pool includes states that are both non-RPS and non-deregulated states. (b) Outcome variable is renewables capacity of geothermal, biofuels, solar, and wind. (c) Year of intervention is 1999 (the year RPS enacted in Texas). (d) The common set of predictors is the same as that in Table 2. (e) Weights less than 0.01 are reported as zero.

Appendix A: RPS Mandate by State and Year of Implementation

State	Year effective	Final Mandate	State	Year effective	Final Mandate
Arizona	2007	15% by 2025	Montana	2005	15% by 2015
California	2003	25% by 2016	Nevada	1997	25% by 2025
Colorado	2005	20% by 2020	New Hampshire	2007	25% by 2025
Connecticut	1998	27% by 2020	New Jersey	1999	22.5% by 2021
Delaware	2005	25% by 2025	New Mexico	2004	20% by 2020
Hawaii	2004	40% by 2030	New York	2004	29% by 2015
Illinois	2011	25% by 2025	North Carolina	2008	12.5% by 2021
Iowa	1983	105 MW by 1999	Ohio	2009	12.5% by 2024
Kansas	2009	20% by 2020	Oregon	2007	25% by 2025
Maine	1999	40% by 2017	Pennsylvania	2005	18% by 2020
Maryland	2004	20% by 2022	Rhode Island	2004	16% by 2019
Massachusetts	2002	15% by 2020	Texas	1999	10,000 MW by 2025
Michigan	2008	10% by 2015	Washington	2007	15% by 2020
Minnesota	2007	25-30% by 2020	Wisconsin	1999	10% by 2015
Missouri	2009	15% 2021			

Notes: (a) States in bold are the early adopter states. (b) Although Iowa adopted an RPS in 1983, their implementation predates the capacity data available and they are therefore not analyzed. (c) The final mandates of the policies have evolved over time, often becoming more stringent. The latest policy in effect during the 1994-2012 period is listed. (d) In the 'Final Mandate' column, the percentages indicate the percent of electricity to be generated from renewable energy.

Appendix B: Procedure to obtain $\mathbf{W}^*$

Let $(T_0 \times 1)$ vector $\mathbf{K} = (k_1,\ldots,k_{T_0})'$ define a linear combination of pre-intervention outcomes $\tilde{Y}_i^{\mathbf{K}} = \sum_{s=0}^{T_0} k_s Y_{is}$. Define $\mathbf{X}_1 = (\mathbf{Z}_1', \tilde{Y}_1^{\mathbf{K}_1},\ldots,\tilde{Y}_1^{\mathbf{K}_M})'$ as a $(k \times 1)$ vector of pre-intervention characteristics for the exposed state where $k = r + M$.[30] Similarly, define a $(k \times J)$ matrix $\mathbf{X}_0$ that contains the same variables for the unexposed states. The $j-$th column of $\mathbf{X}_0$, thus, is $(\mathbf{Z}_j', \tilde{Y}_j^{\mathbf{K}_1},\ldots,\tilde{Y}_j^{\mathbf{K}_M})'$.

Let $\mathbf{V}$ be a $(k \times k)$ symmetric positive semidefinite matrix. Then,

(4) $$\mathbf{W}^* = \underset{\mathbf{W}}{\operatorname{argmin}} (\mathbf{X}_1 - \mathbf{X}_0\mathbf{W})'\mathbf{V}(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W}) \ni \{w_j \geq 0 \mid j = 2,\ldots,J+1\} \text{ and } \sum_{j=2}^{J+1} w_j = 1.$$

Following Abadie and Gardeazabal (2003) and Abadie, Diamond and Hainmueller (2010), we choose $\mathbf{V}$ among positive definite and diagonal matrices such that the mean squared prediction error (MSPE) of the outcome variable is minimized for the pre-intervention periods.

As Abadie, Diamond and Hainmueller (2010) argue, it is important to note that unlike the traditional regression-based difference-in-difference model that restricts the effects of the unobservable confounders to be time-invariant so that they can be eliminated by taking time differences, SCM allows the effects of such unobservables to vary with time.

More details of the synthetic control, the procedure to calculate $\mathbf{W}^*$, and permutation/randomization tests or the inference can be found in Abadie et al. (2010) or obtained from the authors on request.

[30] For example, if $M = 2$, $\mathbf{K}_1 = (1,0,\ldots,0)'$ and $\mathbf{K}_2 = (0,0,\ldots,1)'$ then $\mathbf{X}_1 = (\mathbf{Z}_1', Y_1, Y_{T_0})'$, that is the outcome values of Texas for the first year (year 2000) and the year before the passing of the RPS (year 2004) are included in $\mathbf{X}_1$.