The Disparate Influence of State Renewable Portfolio Standards (RPS) on Renewable Electricity Generation Capacity

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Forthcoming in
Land Economics

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, wind energy, 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). However, of the several policies typically proposed to promote renewable energy development for electricity generation, RPS is the most frequently advanced policy (Fischer 2010). We examine whether RPS is having the intended effect of increasing renewable generation capacity.

Several papers have implemented state-year 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 although RPS implementation did not have a significant influence, in the years after RPS adoption an additional year of RPS had a positive effect. Delmas and Montes-Sancho (2011) analyzed capacity rather than generation and found that RPS led to declining renewable electricity

[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.

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 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. RPS 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, Table A1, for a list of RPS states and final mandates).[2] Our set of treatment states are

[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

Nevada (1997), Connecticut (1998), New Jersey (1999), Maine (1999), Texas (1999) and Wisconsin (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.[4,5]

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.[6] RPS in Texas, passed in 1999, had intermediate mandates in 2002 and 2007 with their final mandate initially binding in 2010 and then subsequently amended to 2025. A similar pattern is observed in the other RPS

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size of the donor pool.

[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] Analyzing renewable capacity rather than renewable generation mitigates the influence of dynamic local wind, solar, and weather conditions which could lead to variability in renewable generation. Small localized weather changes will not lead to variation in annual state renewable capacity, making renewable capacity a better measure to evaluate the effect of the RPS policy. In addition, dynamic, short-term price differences between renewable and conventional fuels may lead to variability in the use of renewable generation on a daily or weekly basis by utilities. This variability will be mitigated in the renewable capacity measure.

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

states where the final mandate is effective on a future date preceded by a series of intervening targets.

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.

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. The finding about Texas is particularly important because of the impact of Texas in the national context: Of the modern renewable capacity added in the United States between 1999 and 2008, approximately thirty percent was added in Texas.[7] In 2013, Texas accounted for 22 percent 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.[8]

The finding about Texas also highlights that the success and failure of the RPS policy need to be assessed in the context in which it was implemented. While Texas is the only early adopter state to witness an impact of RPS on its renewable capacity, Texas is also the

[7] The modern renewables include the EIA categories: Wind, Solar Thermal and Photovoltaic, Geothermal, and Other Biomass (http://www.eia.gov/electricity/data/state/).
[8] 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.

only early adopter state with substantial modern renewable potential (Table A2 of Appendix A). Additionally, the energy market characteristics of Texas are quite unique: Texas is 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.[9] 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 60 GW to 87 GW over the same period. Geothermal capacity is predicted to triple and biomass capacity is predicted to double. Overall, modern renewable generation is predicted to exceed hydroelectric generation and comprise two-thirds of all renewable generation by 2040.[10]

[9] http://www.eia.gov/todayinenergy/detail.cfm?id=16051
[10] http://www.eia.gov/forecasts/aeo/MT_electric.cfm#cap_natgas

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.[11] Within the Interconnections, there are nine Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs) that coordinate the trading of electricity generation across states. 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.[12] 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.[13] Because in these states utilities are allowed to import and export renewable generation from other states, utilities may import rather than add additional renewable 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

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

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

[13] 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 Electric Reliability Council of Texas (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).

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).[14] (Appendix A, Table A2, details the renewable electricity market characteristics for the early adopter states.)

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).[15] 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.[16] 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

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[14] 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.

[15] 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).

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

potential.[17] Other states with significant renewables potential that have enacted RPS include Washington, California, Oregon and 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, Table A1, 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.[18]

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

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[17] 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 Lopez et al (2012) for more information on the calculation of each renewable energy potential measure.

[18] 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).

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.[19] For instance, Connecticut and New Jersey mandated three categories of renewables each with their own generation requirements. All of 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 comparison units 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

[19] For both Connecticut and New Jersey Class 1 renewables include modern renewables, namely, wind, solar, geothermal and other forms of renewable energy such as sustainable biomass, and wave or tidal power (http://programs.dsireusa.org/system/program/detail/195, http://programs.dsireusa.org/system/program/detail/564). In contrast Class 2 or 3 renewables include existing sources such as hydroelectric power.

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 that are assigned to each state in the control group based on *pre-intervention* characteristics, thus making explicit the relative contribution of each state to the counterfactual of interest (Abadie and Gardeazabal 2003; Abadie et al., 2010). With reduced discretion in the choice of the comparison units, the researcher is required 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.[20]

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,

[20] 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."

(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,

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

where $\bar{Y}^{post}_{TR,actual}$ is the average of the post-intervention actual outcome of the treatment state, $\bar{Y}^{post}_{TR,synthetic}$ is the average of the post-intervention outcome of the counterfactual. Similarly, $\bar{Y}^{pre}_{TR,actual}$ is the average of the pre-intervention actual outcome of treatment state, and $\bar{Y}^{pre}_{TR,synthetic}$ 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). With J being the total number of control units, the number of units in the donor pool for each of these placebo runs is $J-1$. 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 $\boldsymbol{\Delta}$ 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). The DID is the measure of the impact of the intervention (equation 4) and the interpretation of a large DID is that the difference in the post-intervention outcome between the actual and the synthetic is much larger compared to the same during pre-intervention. Therefore, 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, Table A1). Figure 1 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 NREL data on the technical potentials for each modern renewable energy source: wind, photovoltaic, biopower (solids), and geothermal-hydrothermal (NREL 2010, Lopez et al. 2012). These technical potential measures indicate the amount of renewable energy by source that a state is theoretically capable of producing under a specific set of technological and land use assumptions, excluding transmission limitations.[21] Table 1 presents a summary description of all the variables used in the analysis.

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 2 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 number of states in the donor pool for each treatment state is 26. In case of the permutations tests, each donor pool states is picked and a placebo SCM is run; thus the number of states in the donor pool for each placebo run is 25. The picture on the right presents the permutations/randomization or the placebo tests: the dark line is the absolute gap

[21] For instance, the installed capacity calculations for wind are based on an assumption of 5 MW/km^2 of installed capacity.

between actual and synthetic for the treatment state, whereas each grey line is the absolute 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 2 and column 2 of Table 2), Maine (panel C of Figure 2 and column 3 of Table 2), New Jersey (panel D of Figure 2 and column 4 of Table 2) and Wisconsin (panel F of Figure 2 and column 6 of Table 2). In each of these cases we find that the DID rank is high and the DID measure is 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 2, 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 absolute gap between actual and synthetic for Texas stands out from 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): 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 climate related variables January sunlight and summer cooling degree days. Alaska is dropped from the donor pool because these variables are not available for Alaska. 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. In case of Texas, summer cooling degree days does exhibit itself to be an important predictor (not shown) and the distribution of w-weights change somewhat (Table 3). The inference, however, remains the same.

V.3. Additional Tests for Texas

Tables 2 and 3 show that RPS had a statistically significant impact on renewable capacity in Texas only. From these estimates, we calculate that the impact of RPS in Texas was the following: according to the estimates presented in Table 2, by 2008 renewables capacity in Texas increased by 7,228 MW (7,339 MW according to the estimates presented in Table 3). This is perhaps best displayed in Panel E of Figure 2 (graphical representation of the estimates in Table 2): we observe that the renewables capacity in actual Texas starts to increase while the same in synthetic Texas remains more or less stagnant; this increasing 'gap' between the actual and the synthetic culminates in a magnitude of 7,228

MW in 2008. Table 4 sheds more light on the Texas estimates where we present the characteristics matches between actual and synthetic Texas.[22]

In each SCM estimate 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.[23] 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 5, 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.

Our analyses above included states that subsequently passed an RPS. In 2009, four large states adopted RPS: Kansas, Michigan, Missouri and Ohio; also, Illinois passed an RPS in 2011.[24] Michigan, Missouri and Ohio are states with larger populations and Kansas's per capita energy consumption is closely comparable to that of Texas. In order to determine if the inclusion of these potentially comparable states affected our findings above, we run an alternative donor pool and exclude these five states. The results reported in column 2 of

[22] Share of natural gas generation stands out in this table as a poor match. Realistically, it is unlikely that one will be able to find a good match for Texas in terms of share of natural gas generation because, between 1990 and 1998, TX had approximately 25 percent share of U.S. natural gas generation. This, however, does not impact the result; we have carried out a robustness check excluding natural gas generation from the set of predictors with no discernible change in the estimates.
[23] This is the standard procedure followed in SCM due to Abadie et al. (2010) and Bohn et al. (2014).
[24] Michigan and Missouri passed RPS at the end of 2008 while Ohio and Kansas passed RPS in 2009.

Table 5 indicate that our finding of a significant impact of RPS in Texas is not influenced by the inclusion of these states.[25]

Another issue is that the Texas RPS includes some degree of restructuring in the electricity market. To determine if the effect of restructuring in the control group is confounding the findings, in column 3 of Table 5 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 of Table 2. Again, we arrive at the same conclusion that RPS had a significant impact on renewable capacity in Texas.[26]

In each estimate for Texas presented in Tables 2, 3, and 5, we observe that either Indiana or Oklahoma carries more than 50 percent of the weight in the donor pool. To check if our finding is sensitive to this, we carried out a robustness check. For this analysis, we equally distributed the w-weights to the six states that received at least 1 percent of the weight in any of the estimates (i.e., Georgia, Illinois, Indiana, Louisiana, Oklahoma and Virginia). Our finding of a significant impact of RPS on the renewable capacity in Texas remains robust to this test as well.[27]

[25] This analysis was completed for the other early adopter states as well. The findings indicate that RPS was not a significant predictor of renewable capacity development in those states. The pre-intervention matching for these states, however, was not as strong as the results presented in Table 2. Results available upon request.

[26] The Texas RPS was implemented in 1999 as part of Senate Bill 7. The legislation mandated the deregulation of the retail electricity market, and became effective across the ERCOT managed electricity market in 2002. Due to the fact that the same law implemented RPS and restructuring of the retail electricity market, it is not possible to entirely separate the effects of the two policies. The inclusion of restructuring and RPS in the same legislation is not unique to Texas, however, and does not by itself explain the influence of the policy on renewable capacity additions. All of the early adopter states with the exception of Wisconsin also included restructuring requirements as part of their RPS legislation.

[27] Results not shown, available upon request.

As an additional robustness check, following Abadie et al. (2014) and Mideksa (2013), we carry out a placebo test regarding the timing of the intervention. Estimating the impact of a placebo RPS policy with an implementation year of 1994 rather than 1999 should not result in a significant finding. To test this hypothesis we ran an analysis with a placebo RPS in Texas in 1994 and tested its impact over the post-intervention period 1995-1998. We use our main specification (i.e., the same set of predictors as listed in Table 2). We do not find a significant DID measure and the DID rank is 5. A non-significant estimate of this placebo treatment implies that we can have more confidence in our finding of a significant impact of the actual RPS in Texas in 1999.[28]

Finally, in Table 4 we observe that the wind potentials of the two synthetics are 20-25 percent lower than that of actual Texas. In order to determine if Texas's large renewables potential, specifically onshore wind and solar photovoltaics, is driving our finding, we carry out additional robustness checks.

Texas's high rankings in wind and solar potentials are partly due to the large land base of the state. We, therefore, carry out the SCM estimates for Texas by normalizing the following variables with land area: wind potential, photovoltaic potential, biopower potential, geo- & hydro-thermal potential, and renewable nameplate capacity (the outcome). Table 6 reports these results in detail. Column 1 is the main specification (similar to Table 2). In column 2, climate related variables are added to the set of predictors and Alaska has to be dropped (similar to Table 3). In column 3, land area is added to the set of predictors instead of the climate variables, and Alaska is put back in the

[28] Results not shown, available upon request.

donor pool. This is because Alaska is the only state with a larger land area than Texas; without it Texas's land area falls outside the domain for matching.

First, we see that the inference in each of the three specifications remains the same as our main result: the DID rank is 1 and the p-values are significant at the 1 percent level. The donor pool weights change with Alaska, Kansas, Louisiana, South Dakota and Oklahoma now contributing the most to the synthetic. Not surprisingly, Alaska takes a more prominent role in the construction of the synthetic in column 3 (when land area is included as a predictor).

Importantly, we find that the pre-intervention matching, particularly for wind potentials, is markedly improved. In the case of column 3, we also obtain a strong match for land area. The strengthening of our pre-intervention matching on wind potential leads us to conclude that the significant finding for RPS is not driven by the large renewable potential in Texas.

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 has significant renewable generation potential, far exceeding that of the other early adopter states. It ranks first in wind and solar potential (Appendix A, Table A2).

Second, grid interconnectivity may be an important factor in the expansion of instate renewable capacity. Texas is the only mainland state with its own grid and unlike other REC programs, the Electric Reliability Council of Texas (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 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.[29] 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).

Third, 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.[30] Texas, on the other hand, was the largest energy producing state for every year between 1990 and 2012.[31] The share of modern renewable capacity in Texas increased from two percent of U.S. renewable capacity in 1999 to twenty-two percent in 2008.[32] The size of the Texas electricity market may have given Texas an edge in adding renewable capacity.

Lastly, RPS policy stringency and compliance may have played a role. 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

[29] 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.

[30] It is important to note that while states such as New Jersey have smaller electricity markets than Texas, they still have 20,000 MW of electricity generating capacity and are required to generate or import electricity for their nearly 9 million residents. As of 2010 they had only 320 MW from modern renewable sources, which leaves significant potential for growth in renewable capacity.

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

[32] The modern renewables include the EIA categories: Wind, Solar Thermal and Photovoltaic, Geothermal, and Other Biomass (http://www.eia.gov/electricity/data/state/).

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 Nevada, only NV Energy was initially required to meet a low minimum renewables mandate that increased by 2 percent every 2 years beginning in 2001 reaching a maximum of 15 percent in 2013.[33] Nevada did not meet 100 percent of their RPS obligation until 2008.[34] 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 share that must come from Class 1 renewables was 0.74 percent.[35] This may explain why there was no capacity expansion through 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.[36]

Texas, on the other hand, is an exception in terms of its RPS policy design. First, Texas specifies 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. Additionally, the Texas RPS mandated the installation of at least 2,000 MW of additional renewable capacity by 2009 and at least 5,880 MW by 2015. The Texas mandate does not stand out in terms of its magnitude in percentage of total

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[33] http://programs.dsireusa.org/system/program/detail/373.

[34] 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.

[35] http://www.dsireusa.org/summarytables/rrpre.cfm.

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

generation, but because of the size of the Texas market, a small percentage requirement entailed a relatively large increase in renewable capacity.[37] In fact, Texas capacity increased from 188 MW in 1999 to over 7,500 MW in 2008.[38]

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 production and lowers the cost of wind generated electricity production by about one third (Wiser, 2007).[39] 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,

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[37] 2,000 MW translates to roughly 1.2-1.6 percent (5,880 MW to 3.6-5 percent) of total generation. The information on the percentage requirements was calculated as a percentage of 1999 total generation using a capacity factor of 25-35 percent.
[38] http://www.eia.gov/electricity/data/state/.
[39] The PTC is currently worth $22 per MWh (2011 dollars). In 2013, Texas accounted for 22 percent 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).

Bolinger, and Barbose 2007, p. 1-2).[40] 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 development in non-PTC years and ramp up development when the PTC is active. The combination of significant renewables potential and the PTC may have accelerated the timing of renewable capacity development in Texas, but our findings indicate that the RPS policy provided the impetus for this expansion.

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.[41] While the available post-intervention periods may not be sufficient for carrying out SCM impacts of RPS in Massachusetts and California, we examined these states as well. We do not find any impact of RPS on renewable capacity in Massachusetts. As for California, we are unable to establish 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 any other

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

[41] 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.

state for this period. As a result, no weighted average of states can approximate the pre-intervention renewable capacity of California.[42]

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 that estimate 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, North Carolina, Ohio, Texas, Wisconsin, and West Virginia (Plumer 2013; Gallucci 2013, Brandt 2015). In May 2014, Ohio voted to halt the continued implementation of the state's RPS and imposed a two year freeze on the RPS requirements pending further study of the economic impacts (Gallucci 2014). West Virginia became the first state to repeal their RPS in January 2015. Kansas legislators also decided to eliminate the state's mandated renewables requirement in May 2015. It will be replaced with a voluntary goal (Overton 2015, NA WindPower 2015). And finally, in April 2015, the Texas Senate voted to eliminate the state's RPS by the end of 2015 (Brandt 2015).

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[42] 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.

On the backdrop of the previous findings that RPS are not contributing to renewables development (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 contingent on the features of the policy itself and the characteristics of the pertinent electricity markets.

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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 manufacturing earnings	0.11	0.05	0.02	0.22	0.03	0.12	0.11	0.09	0.10	0.18
Wind potential (GW)	228000.00	326000.00	0.00	952000.00	7247.10	26.50	11251.20	131.80	1900000.00	104000.00
Photovoltaic potential (GW)	3168.83	2024.67	36.55	9005.30	3742.84	17.13	660.61	276.43	20565.29	3240.76
Biopower-solid potential (GW)	1.17	0.77	0.06	3.52	0.04	0.06	0.54	0.15	2.04	1.42
Geo- & hydro-thermal potential (GW)	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

Notes: (a) For the donor pools N=494, except for 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), North Carolina (2008).

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, wind potential, photovoltaic potential, biopower-solid potential, 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 the 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) There are 26 states in the donor pool, which also includes Alaska. Therefore the set of predictors does not include the climate related variables that are missing for Alaska. (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 Climate Related Variables)

	Nevada	Connecticut	Maine	New Jersey	Texas	Wisconsin
Estimation summary						
Pre-intervention difference (D1)	0.94	0.96	0.01	0.21	-0.54	-0.58
Post-intervention difference (D2)	-0.11	-42.97	-24.99	-60.46	2301.64	21.24
DID = |D2|-|D1|	-0.83	42.01	24.97	60.25	2301.10	20.66
P-value: DID	0.96	0.65	0.69	0.54	0.00	0.85
DID rank	26	18	19	15	1	23
States						
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	0.35	0.32	0.01	0.19	0.00	0.00
Georgia	0.00	0.00	0.00	0.00	0.11	0.00
Idaho	0.00	0.00	0.00	0.00	0.00	0.00
Illinois	0.00	0.03	0.00	0.00	0.13	0.15
Indiana	0.00	0.00	0.00	0.00	0.68	0.60
Kansas	0.00	0.00	0.15	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	0.00	0.00	0.00	0.43	0.00	0.00
Mississippi	0.00	0.00	0.00	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	0.37	0.00	0.12
Ohio	0.00	0.66	0.53	0.00	0.00	0.00
Oklahoma	0.00	0.00	0.11	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	0.65	0.00	0.06	0.00	0.00	0.00
Vermont	0.00	0.00	0.12	0.00	0.00	0.00
Virginia	0.00	0.00	0.02	0.00	0.08	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, wind potential, photovoltaic potential, biopower-solid potential, geo- & hydro-thermal potential, real PC personal income, growth in real PC personal income, poverty, share of manufacturing income, January sunlight, summer cooling degree days. (b) 1990 to pre-intervention renewables capacity (depending on the year of intervention for each treatment state).

Notes: (a) Outcome variable is the 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) Climate related variables are missing for Alaska, therefore, Alaska is excluded from the donor pool. Thus, the donor pool includes 25 states. (d) Weights less than 0.01 are reported as zero.

Table 4: Pre-intervention Characteristics Match between Actual and Synthetic Texas

Characteristics	Texas	Synthetic Texas under main specification	Synthetic Texas with climate related variables
Total nameplate growth	29.23	65.17	62.58
Coal generation share	0.41	0.86	0.82
Natural gas generation share	0.47	0.02	0.02
Electricity price ($)	7.73	7.11	7.29
Total customer growth	1.08	1.06	1.06
Real PC personal income ($)	10.16	10.20	10.20
Real PC personal income growth	1.08	1.08	1.08
Poverty	17.11	11.43	11.80
share of manufacturing income	0.11	0.20	0.18
Wind potential (GW)	14.46	11.64	10.87
Photovoltaic potential (GW)	9.93	8.02	8.02
Bio-solid potential (GW)	0.71	0.67	0.67
Geo-hydro thermal potential (GW)	-4.61	-4.61	-4.61
January sunlight	182.59		133.79
Summer cooling degree days	6.27		5.48

Notes: (a) The 'main' specification refers to the results presented in Table 2, the column with climate related variables refers to the specification presented in Table 3. (b) Real PC income, summer degree days, and the technical potential variables are in logarithm.

Table 5: SCM Estimate of the Impact of RPS on Renewables Capacity in Texas (Additional Robustness Checks)

	(1)	(2)	(3)
Estimation summary			
Pre-intervention difference (D1)	1.34	-1.01	13.30
Post-intervention difference (D2)	2060.78	2336.95	2090.37
DID = |D2|-|D1|	2059.44	2335.94	2077.07
P-value: DID	0.00	0.00	0.00
DID rank	1	1	1
W-weights			
Alabama	0.00	0.00	0.00
Alaska	0.00	0.00	0.00
Arkansas	0.00	0.00	0.00
Florida	0.00	0.00	
Georgia	0.00	0.00	
Idaho	0.00	0.00	0.00
Illinois	0.24	0.89	
Indiana	0.00		0.00
Kansas	0.00		
Kentucky	0.00	0.00	0.00
Louisiana	0.00	0.00	0.06
Michigan	0.00		
Mississippi	0.00	0.00	0.00
Missouri	0.00		
Nebraska	0.00	0.00	0.00
North Dakota	0.00	0.00	0.00
Ohio	0.00		
Oklahoma	0.76	0.00	0.94
South Carolina	0.00	0.00	
South Dakota	0.00	0.00	0.00
Tennessee	0.00	0.00	0.00
Utah	0.00	0.00	
Vermont	0.00	0.00	
Virginia	0.00	0.11	
West Virginia	0.00	0.00	
Wyoming	0.00	0.00	0.00

List of Predictors

(a) Common set of predictors (same as Table 2): Total nameplate capacity growth, coal generation share, natural gas generation share, electricity price, growth of total customer, wind potential, photovoltaic potential, biopower-solid potential, 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) Columns 2 and 3 have the same set of predictors as Table 2, i.e., 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 is done only on 1998 capacity. The donor pool includes 26 states (same as Table 2). (b) Column 2 excludes five states that did not have RPS over our study period, but subsequently passed an RPS. (c) In column 3, the donor pool includes states that are both non-RPS and non-deregulated states (14 states). (d) The outcome variable is the renewables capacity of geothermal, biofuels, solar, and wind. (e) Year of intervention is 1999 (the year RPS enacted in Texas). (f) Weights less than 0.01 are reported as zero.

Table 6: Robustness Check with Variables Normalized by Land Area

	(1)	(2)	(3)	(4)
	Synthetic Control Estimates of Texas			Actual Texas
	Main specification	With climate related variables	With land area	
Panel A: Estimation statistics				
Pre-intervention difference (D1)	-0.01	-0.04	0.01	
Post-intervention difference (D2)	7.55	6.96	7.68	
DID = |D2|-|D1|	7.54	6.92	7.66	
P-value: DID	0.00	0.00	0.00	
DID rank	1	1	1	
Panel B: W-weights				
Alaska	0.06	--	0.14	
Kansas	0.46	0.58	0.42	
Louisiana	0.32	0.36	0.25	
Oklahoma	0.00	0.06	0.00	
South Dakota	0.16	0.00	0.19	
Panel C: Pre-intervention characteristics				
Total nameplate growth	22.42	26.41	18.60	29.23
Coal generation share	0.46	0.54	0.44	0.41
Natural gas generation share	0.22	0.23	0.23	0.47
Electricity price	8.18	7.90	8.55	7.73
Total customer growth	1.05	1.04	1.05	1.08
Real PC personal income	10.14	10.14	10.16	10.16
Real PC personal income growth	1.09	1.09	1.08	1.08
Poverty	15.00	15.38	14.21	17.11
share of manufacturing income	0.10	0.11	0.10	0.11
Wind potential / 100 mi^2	725.65	726.16	725.22	726.34
Photovoltaic potential / 100 mi^2	6.92	7.38	6.55	7.86
Bio-solid potential / 100 mi^2	0.00	0.00	0.00	0.00
Geo-hydro thermal potential / 100 mi^2	0.01	0.01	0.01	0.01
January sunlight	--	167.39	--	182.59
Summer cooling degree days	--	6.00	--	6.27
Land area (mi^2)	--	--	11.41	12.48

Note: (a) These estimates are run using the following variables normalized with land area: wind potential, photovoltaic potential, biopower potential, geo- & hydro-thermal potential, as well as renewable nameplate capacity (the outcome). These variables are now expressed as GW per 100 mi^2 (not in logarithms) (b) Column 1 is the main specification (similar to Table 2, with 26 states in the donor pool). In column 2 climate related variables are added to the set of predictors (similar to Table 3), and Alaska has to be dropped. In column 3, land area is added to the set of predictors instead of the climate variables, and Alaska is put back in the donor pool. (c) For easier comparison of characteristics, column 4 presents the characteristics of actual Texas (d) Real PC income, summer degree days, and land area are in logarithm. (e) Only donor pool states with w-weight ≥ 0.01 are reported.

Figures

Figure 1: U.S. RPS and Renewable Generation Capacity

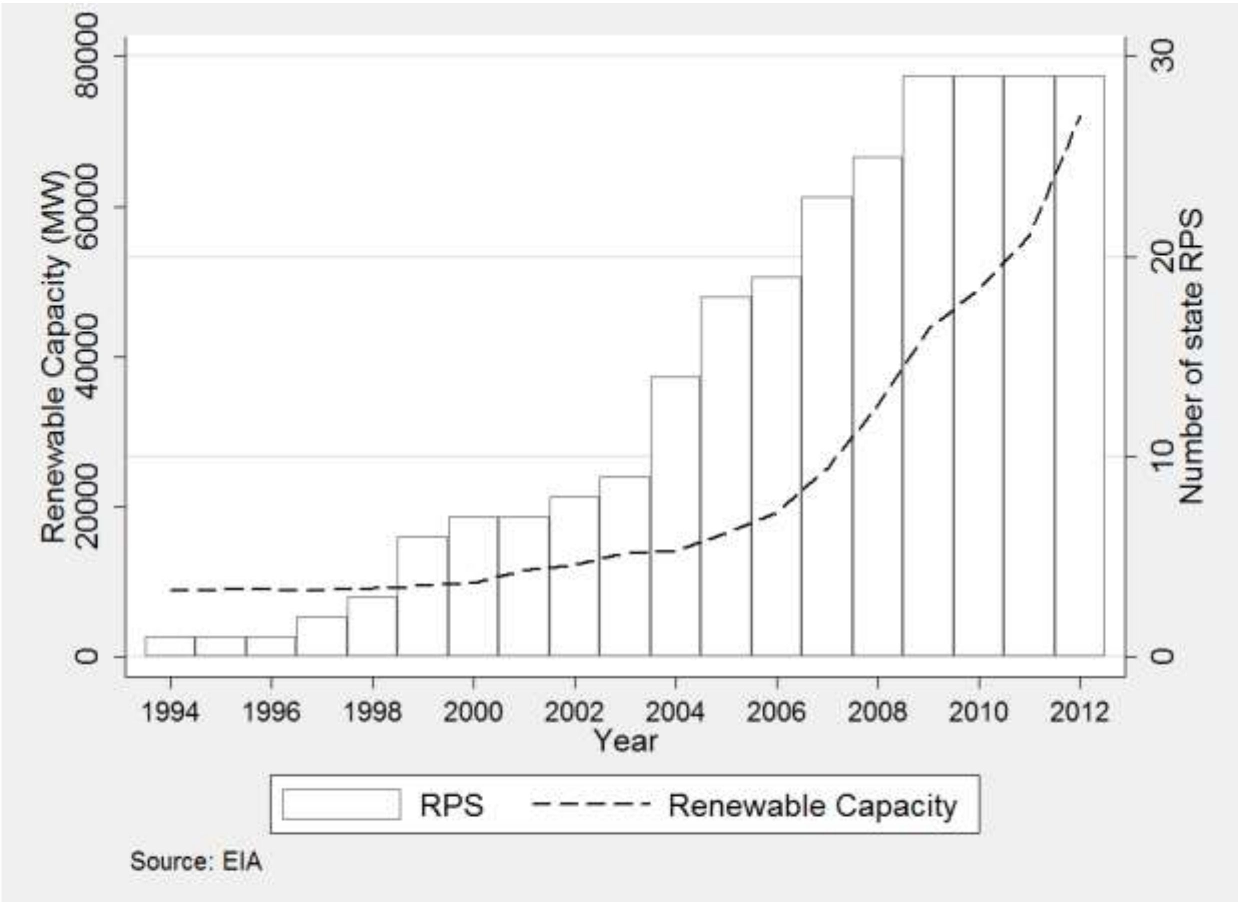
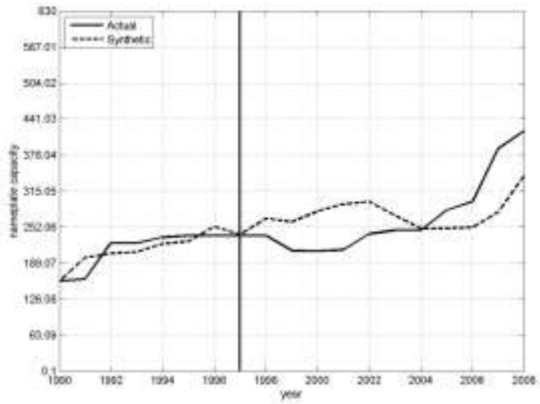


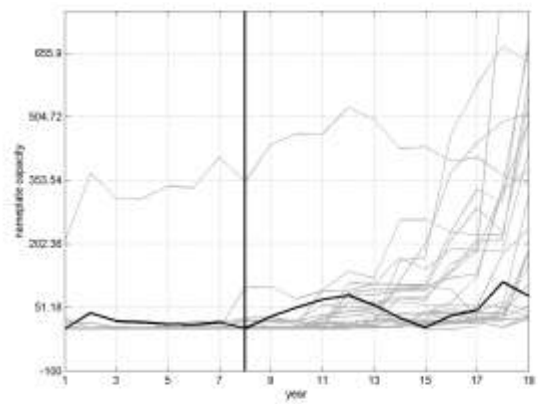
Figure 2: SCM Estimates of the Impact of RPS on Renewables Capacity

Panel A: Nevada

Actual and Synthetic

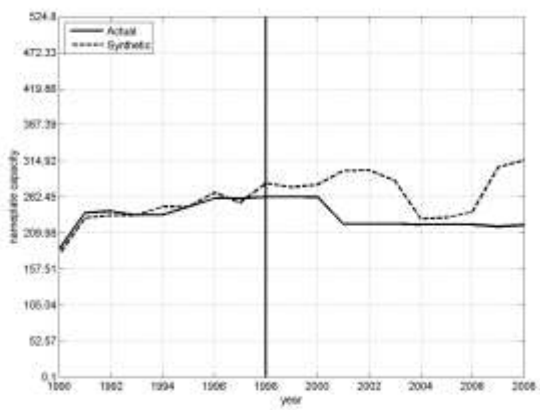


Placebo Test



Panel B: Connecticut

Actual and Synthetic



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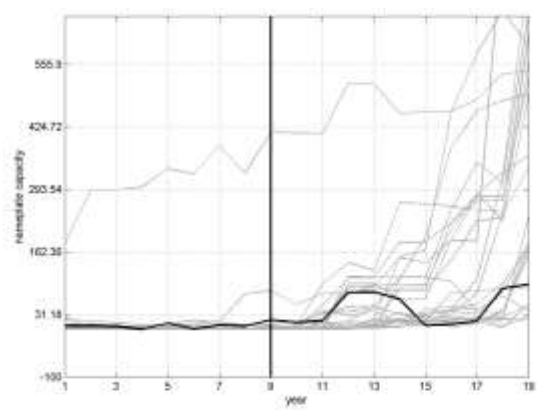
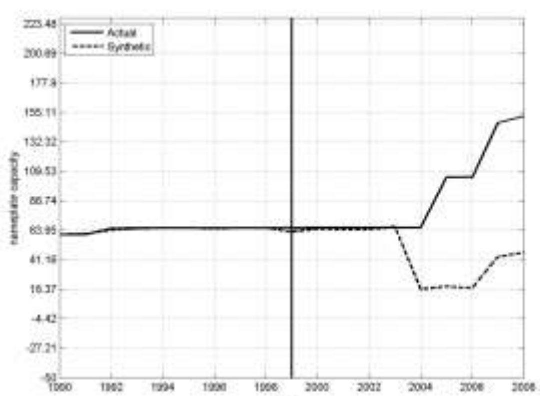


Panel C: Maine

Actual and Synthetic



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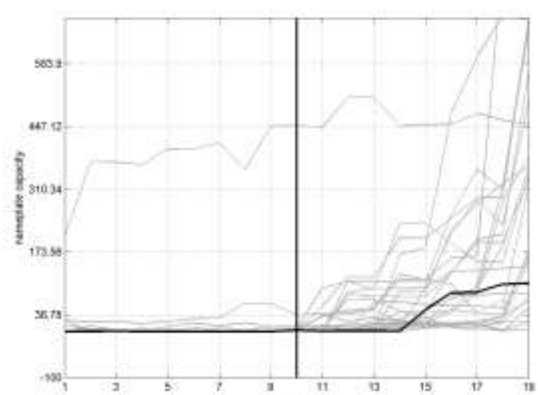
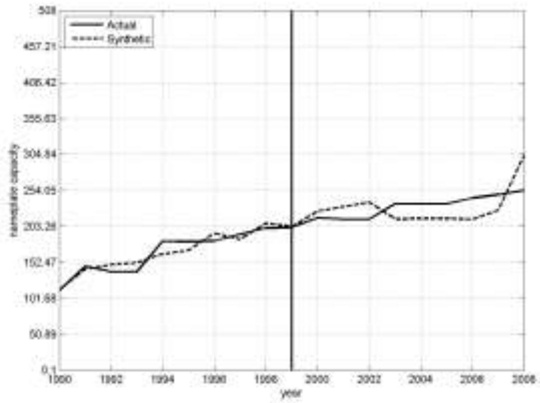


Panel D: New Jersey

Actual and Synthetic



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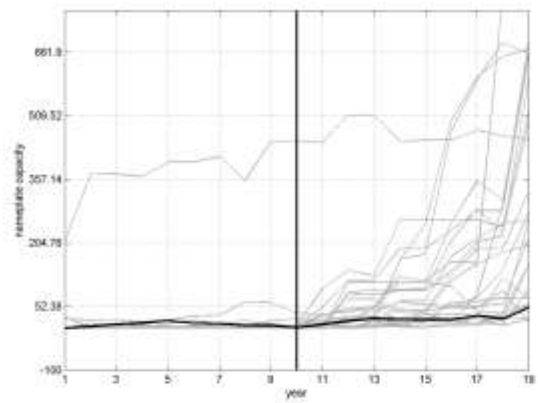
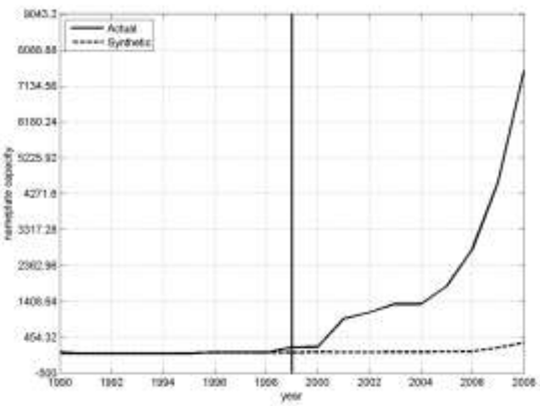


Panel E: Texas

Actual and Synthetic



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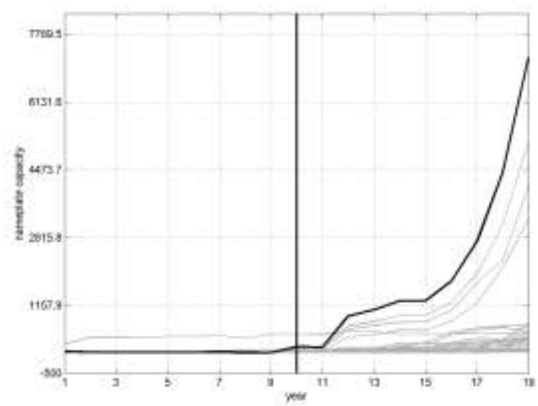
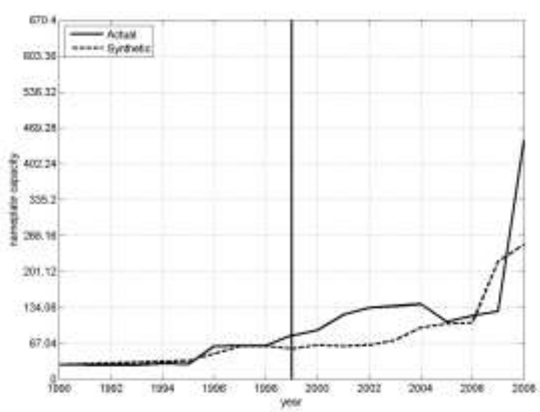
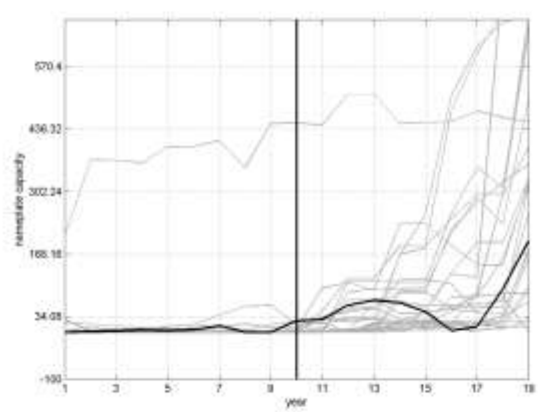


Panel F: Wisconsin

Actual and Synthetic



Placebo Test



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

Appendix A: RPS Mandates across U.S. States

Table A1: 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	2008	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. (e) Michigan and Missouri passed their RPS in October and November 2008 respectively. RPS passed at the end of the year are treated as effective in the following year.

Table A2: Renewable Electricity Market Characteristics

State	Potential ranking (Wind/PV/Biopower)	REC market start date	Sufficient existing renewable capacity	Compliance Failure	Restructuring included in RPS Law
Nevada	29/16/49	2007/2008		x	x
Connecticut	47/49/46	07/2002			x
Maine	26/39/32	07/2002	x		x
New Jersey	42/42/37	09/2005			x
Texas	1/1/5	01/2002			x
Wisconsin	17/18/17	07/2007			

Notes: (a) Each state is ranked (out of 50) based on GW of renewable potential. (b) Nevada and Texas require that renewable energy traded in the REC market is produced in-state, although Nevada allows limited out-of-state production. All other REC markets in the U.S. besides those shown in this table started in 2009 or later (Heeter and Bird 2011, p. 7) (c) Maine had existing hydroelectric capacity in excess of the initial RPS mandate. (d) Nevada failed to meet 100 percent of their RPS target until 2008. (Barbose 2013) (e) For more information on renewable potentials and restructuring, see http://www.nrel.gov/gis/re_potential.html and http://www.eia.gov/electricity/policies/restructuring/ restructure_elect.html, respectively.

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 $k = r + M$.[43] 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,

$$\text{(B1)} \quad \mathbf{W}^* = \underset{\mathbf{W}}{\operatorname{argmin}} \ (\mathbf{X}_1 - \mathbf{X}_0\mathbf{W})'\mathbf{V}(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W}) \ \ni \{w_j \geq 0 \mid j = 2, \ldots, J+1\} \text{ and } \sum_{j=2}^{J+1} w_j = 1.$$

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.

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[43] For example, if $M = 2$, $\mathbf{K}_1 = (1,0,\ldots,0)'$ and $\mathbf{K}_2 = (0,0,\ldots,1)'$ then $\mathbf{X}_1 = (\mathbf{Z}_1', Y_1, Y_{T_0})'$.