Electricity Price Increase in Texas: What is the Role of RPS? A Synthetic Control Analysis

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Abstract

Over the last two decades, more than half of the states in the United States have adopted a Renewable Portfolio Standard (RPS). While vital environmental goals underlie the rationale for RPS there is a rising concern that the policy may lead to increased electricity prices. Using the Synthetic Control Method (SCM) we conduct a comparative case study of Texas, an early adopter of RPS and arguably a success story. We find that the state's RPS was not a contributing factor in its electricity price increase.

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

I. Introduction

As of January 2012, 30 states and the District of Columbia had enacted an RPS or other mandated renewable capacity policies, and seven states had voluntary goals for renewable generation. States have implemented RPS in order to exploit renewable energy to meet current and future electricity demands and to address emissions concerns from existing fossil fuel generation. RPS require that electricity producers within a given jurisdiction supply a portion of their electricity from designated renewable resources; these can include wind, solar, geothermal, biomass, some types of hydroelectricity, and other resources such as landfill gas, municipal solid waste, and tidal energy. While vital environmental goals underlie the rationale for RPS there is also the potential for the policy to increase electricity prices. This paper focuses on addressing not whether the addition of renewables is beneficial, but whether the implementation of RPS as a correction for an emissions externality increased the electricity price.

An understanding of the extent to which the Renewable Portfolio Standards (RPS) policy affects the electricity market is essential not only to determine the success of the policy but also for the survival of the policy itself. This is particularly true in light of recent legal and legislative efforts to repeal or weaken RPS in a number of states including California, Colorado, Kansas, Massachusetts, Minnesota, and Ohio due to concerns over the costs of implementing the renewables mandates (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). While RPS survived repeal bills early this year in Kansas and North Carolina, they are expected to be picked up again later in the year. Similar bills have also been introduced in Wisconsin, West Virginia, Minnesota and Texas. The debate hinges on a number of political and economic factors; however, concerns over costs of implementation are a recurring theme in these debates.[1]

In order to examine the effect of a state's RPS on its electricity price, we conduct a comparative case study of Texas using the Synthetic Control Method (SCM). Texas is the first state with substantial modern renewables potential to enact a significant RPS, which they did in 1999. RPS is credited with significantly increasing the amount of wind capacity in Texas (Langniss and Wiser 2003).[2] In 2010, Texas reached 10,000 MW of wind generation capacity, remarkable growth from 33.6 MW in 1998. The 10,000 MW represented 14 percent of the 2010 installed generation capacity in the Electric Reliability Council of Texas (ERCOT) region and exceeded the initial RPS mandate of 5880MW set by the Texas legislature years ahead of its 2015 target.[3] Not only is it more than any other state has installed (California being a distant second), if Texas were a country it would be sixth in the world in wind capacity following China, the United States, Germany, Spain, and India.[4]

Texas provides fertile ground for a case study because of the relative isolation of the state's electricity grid. The electricity system in the United States consists of three regions: the Eastern Interconnection, the Western Interconnection, and the Texas Interconnection. Operated by ERCOT, the Texas Interconnection is separated from the rest of the nation, making Texas the

[1] There is currently an argument put forward in the popular press by the Wind Action Group asserting that states with significant wind capacity additions also have significantly higher electricity prices, although the American Wind Energy Association (AWEA) has reached the opposite conclusion. (Taylor 2014; http://www.aweablog.org/blog/post/fact-check-new-evidence-rebuts-heartlands-bogus-rps-claims, accessed 06/29/14). The AWEA is the U.S. national trade association for the wind industry while the Wind Action Group "was formed to counteract the misleading information promulgated by the wind energy industry and various environmental groups." http://www.windaction.org/about.

[2] The NPR reports, "The Texas RPS is one of the most effective and successful in the nation, widely considered a model RPS. It is one of the greatest influences on the rapid growth of the Texas wind energy industry." (http://stateimpact.npr.org/texas/2013/07/05/how-texas-won-the-race-to-harness-the-wind/). See section II.3 for a detailed discussion of Texas's RPS vis-à-vis RPS in other states.

[3] http://www.ercot.com/content/news/presentations/2011/ERCOT+Quick+Facts+-+Aug+2011.pdf.

[4] EIA (http://www.eia.gov/state/?sid=TX, 062613), ERCOT Time-line (http://www.ercot.com/about/profile/history), Office of the Governor (www.TexasWideOpenForBusiness.com), Hurlbut (2008).

only mainland state with its own grid. ERCOT manages electric power for approximately 85 percent of the state's total electric load.[5]

The primary rationale underlying the hypothesis that RPS may lead to an electricity price increase is the cost associated with the building of renewables capacity. Renewables generation requires the installation of new capital such as wind turbines, solar panels, etc., that typically have greater capital costs per megawatt of electricity generated (see section II.4 below for details). The integration of renewables entails large infrastructure updates, the expansion of the existing power grid, and the addition of reserve capacity to address the intermittency of solar and wind. In addition, there may be investment adjustment costs typically associated with a wave of capital investment at the firm level (Adda and Cooper 2003). European markets provide some evidence of large price increases following the implementation of a renewables mandate. Germany has invested heavily in renewables generation, tripling the share of renewables between 2000 and 2012, to approximately 20 percent. (Berlin and Niebull 2012) A study by the Cologne Institute for Economic Research finds that, "Energy prices for industry in Germany are about 40 percent more expensive than in France and the Netherlands, and 15 percent more expensive than the E.U. average" (Bhatti 2013).

Figure 1 shows the trend in the electricity price in Texas against that of the U.S. average. For the nine years prior to 1999, the year Texas adopted RPS, Texas's average electricity price was 28 percent lower than the national average, but, over the period 2000-2010, Texas's average price was 5 percent higher than the national average. Compared to its 1999 level, the year RPS was enacted in Texas, the average price in Texas over the 2000s was 18 percent higher. In this paper, we examine if RPS had a causal effect on the state's observed electricity price increase.

[5] 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).

Much of the existing literature on RPS has focused on whether RPS has been a successful policy in attaining increased renewables generation (Menz and Vachon 2006; Carley 2009; Yin and Powers 2010; Shrimali and Kniefel 2011; Delmas and Montes-Sancho 2011; Maguire 2013; Hitaj 2013).[6] Empirical estimates of the impact of RPS on the electricity market, however, are generally rare.[7] The existing research on the impact of RPS on price primarily uses numerical simulations to evaluate the role of a hypothetical national RPS. While Bernow, Dougherty, and Duckworth (1997) found minimal price impacts, Palmer and Burtraw (2005) and Fischer and Newell (2008) found increased electricity prices with the implementation of an RPS (Bernow, Dougherty, and Duckworth 1997; Palmer and Burtraw 2005; Fischer and Newell 2008). Fischer and Newell (2008), in particular, argue that as a policy for greenhouse emissions reductions, RPS is twice as costly as an emissions tax. In a notable departure from the numerical simulation approach, Fischer (2010) constructed a behavioral model of aggregate price determination in energy markets to explore how energy price may be affected by RPS; she emphasized the importance of the costs of RPS as a regulatory constraint (Fischer 2010).

In order to evaluate the impact of a policy intervention such as RPS we believe a case study approach is most appropriate. State RPS are disparate; they vary on key characteristics such as the magnitude and timing of the final renewables mandate, the timing and magnitude of intermediate mandates, the sectors which are required to meet the RPS mandate (i.e., investor owned utilities or municipal/cooperative utilities), and the inclusion of restructuring requirements.[8] This wide variation in RPS makes the examination of the average effect of the

[6] See section II.1 for a discussion of the literature on the environmental impacts of RPS.
[7] The only empirical work on the effect of RPS on electricity price is Tra (2009), a working paper, which used a fixed effects framework. (Tra 2009) finds that RPS implementation, on average, increased electricity price.
[8] The Texas RPS bill SB 7 was effective in 1999 with intermediate binding goals in 2002, 2009, 2011, and 2013, and with an update in 2005. The RPS applied to both investor owned utilities (IOU) and retail suppliers while municipal utilities and electric cooperatives could opt in. The bill also incorporated some deregulation measures that were effective in phases starting in 2002. They allow customers served by an IOU (not necessarily by municipal utilities

policy across states difficult and a conclusion regarding the influence of RPS on the electricity price across states dubious. We employ the Synthetic Control Method or SCM (Abadie and Gardeazabal 2003; Abadie, Diamond, and Hainmueller 2010) for our case study of Texas. We discuss below the advantages of this methodology especially for our research question.

First, in program evaluation, researchers often select comparison states based on subjective measures of similarity between the affected and the unaffected states. However, neither the set of all non-RPS states nor a single non-RPS state approximates the most relevant characteristics of Texas. Synthetic control, in contrast, is a weighted average of the available control units. It makes explicit the relative contribution of each control unit to the counterfactual of interest. 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. 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 using observed characteristics (Abadie and Gardeazabal 2003; Abadie, Diamond, and Hainmueller 2010).

Secondly, even when aggregate data are employed (as in this paper) uncertainty remains 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. This type of uncertainty is not reflected by the standard errors constructed with traditional inferential techniques for comparative case studies. As Buchmueller, DiNardo, and Valleta (2011) explain, in a 'clustering' framework, inference is based on the asymptotic assumption, i.e., the number of states grow large (Buchmueller, DiNardo, and Valletta 2011). Naturally, this does not apply in our case, as

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and electric cooperatives) to choose their electricity service from a variety of Retail Electric Providers (REP) while the incumbent utility in the area still owned and maintained the local power lines and were not subject to deregulation (http://www.ercot.com). See section II.2 for a detailed discussion.

our focus is one state. 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). In other words, it becomes impossible to argue that the observed conditional difference in measured outcome is entirely due to the policy intervention (Bertrand et al. 2004). We, therefore, apply the permutations or randomization test that is rendered easily by SCM (Bertrand, Duflo, and Mullainathan 2004; Buchmueller, DiNardo, and Valletta 2011; Abadie, Diamond, and Hainmueller 2010; Bohn, Lofstrom, and Raphael forthcoming).

Finally, because the choice of a synthetic control does not require access to post-intervention outcomes, 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 each particular decision affects the conclusions of the study is a safeguard against actions motivated by a ‘desired’ finding (Rubin 2001).

Our SCM estimates indicate that RPS was not a contributing factor in the large increase in electricity price in Texas that we observed in the aftermath of the implementation of RPS. Our finding is robust to a wide range of perturbations. In what follows, we provide some background information on RPS 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 Portfolio Standard (RPS): The Intervention

Renewable energy sources provided 12 percent of total U.S. electricity generation in 2012, 44 percent of which is from wind, biomass, geothermal, and solar, i.e., non-hydroelectric sources (EIA). Today, the United States produces the most electricity from non-hydroelectric renewable sources, followed by China and Germany. EIA projects that, between 2012 and 2040, non-hydroelectric renewables will account for 28 percent of the overall growth in the United States in electricity generation.

II.1. RPS and the Environment

The primary rationale for renewable electricity generation is that it helps to resolve the negative emissions externality from fossil fuel generated electricity. Muller, Mendelsohn and Nordhaus (2011) argue that coal generated electricity is the largest industrial contributor to external costs in the nation; they estimate that utilities are responsible for 34 percent of aggregate air pollution damages (Muller, Mendelsohn, and Nordhaus 2011). While the benefits of RPS in reducing pollution externalities have yet to be fully quantified, some estimates point to substantial benefits. According to the EIA 2012 Environment Report, "The carbon intensity of the energy supply declined by 1 percent or more in four of the last five years, while in prior years since 2000 it either rose or declined only slightly. Increased use of natural gas for electricity generation in high-efficiency combined cycle plants and increases in renewable energy generation, especially wind, has contributed to this decline."[9] Novan (2011) finds that, between 2007 and 2009, wind generated electricity in Texas had offset an estimated 3.5 percent of the CO_2 emissions, 4.5 percent of the NO_x emissions, and 2.6 percent of the SO_2 emissions. (Novan 2011)

II.2. The Texas RPS

The Texas RPS was implemented in 1999 as part of Senate Bill 7 (SB 7, 1999).[10] The legislation called for the installation of 2,000 MW of additional renewable resources by 2009. In 2005, the Texas Legislature increased the target for renewable resources to 5,880 MW by 2015

[9] EIA: Environment (http://www.eia.gov/environment/emissions/carbon/?src=Environment-b1).
[10] http://www.capitol.state.tx.us/BillLookup/Text.aspx?LegSess=76R&Bill=SB7#.

and established a state goal of 10,000 MW by 2025. To encourage the development of renewables other than wind, the 2005 update set a voluntary goal specifying that 500 MW of the 5,880 MW should come from a source other than wind. Legislation carving out a mandatory set-aside for non-wind generation failed in the 2007 legislative session.[11] The 2007 update made additional changes corresponding to tradable Renewable Energy Credits (REC), in particular, making a distinction between 'voluntary' and 'required' REC, which in effect raised the RPS requirement.

SB 7 (1999) also included deregulation measures that became effective in 2002. Due to the potential influence of deregulation on electricity price, we completed a separate SCM analysis using 2002 deregulation as the policy intervention (See Section V.5). The deregulation measures allowed customers served by Investor Owned Utilities (IOUs) to choose their electricity service from a variety of Retail Electric Providers (REP), while the incumbent utility in the area still owned and maintained the local power lines and was not subject to deregulation.[12] Municipal utilities and rural electric cooperatives had the option to join the deregulated market but were not required to do so. As of 2006, only one Texas cooperative and no municipal utilities had opted in.[13] Residential consumers were somewhat slow to implement their consumer choice, with 14 percent served by the deregulated market at the end of 2003, but 45 percent served by the end 2008.[14] Currently, 60 percent of Texas residents purchase retail electricity in the deregulated market. A traditional, regulated market outside of ERCOT or a non-

[11] For more details, see http://www.dsireusa.org/rpsdata/index.cfm and www.window.state.tx.us/specialrpt/energy.
[12] http://www.ercot.com.
[13] Texas Comptroller of Public Accounts (http://www.window.state.tx.us/specialrpt/energy/uses/electricity.php).
[14] As of 2003, "in the secondary energy market, consisting of most commercial and some small industrial customers, about 19% of customers representing 42% of all load have switched to competitive providers." By 2008, it had increased to nearly 55 percent. See http://www.puc.texas.gov/industry/electric/reports/RptCard/rptcrd/mar04rptcrd.pdf and http://www.puc.texas.gov/industry/electric/reports/RptCard/PastRC.aspx.

opt-in entity (NOIE) serves the remainder.[15]

II.3. Texas RPS and RPS in Other States

Due to the fact that RPS are state-adopted standards, there is significant variation in the policy characteristics across states, which is another important reason why we believe a case study approach is more appropriate. RPS vary on key characteristics such as the magnitude and timing of the final renewables mandate, and the timing and magnitude of intermediate mandates. California's RPS requires 20 percent renewable generation by 2010 while Minnesota requires 25 percent by 2025. RPS typically incorporate a series of intermediate goals and targets that also vary widely across states. The Texas RPS bill SB 7 was effective in 1999 with intermediate binding goals in 2002, 2009, 2011, and 2013, and with an update in 2005. In addition there is variation in the sectors which are required to meet the RPS mandate (i.e., investor owned utilities or municipal/cooperative utilities), and the inclusion of restructuring requirements. In Texas, RPS is applied to both IOUs and retail suppliers while municipal utilities and electric cooperatives could opt in.

In addition, 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. While the portfolio typically includes solar, wind, hydroelectric, landfill gas, biomass, geothermal, and ocean/tidal, several states define renewable energy to include fuel cells powered by nonrenewable sources.

Another difference among state RPS are the rules about whether renewable energy generated outside the state can qualify for renewable energy credit within the state. In some cases, there are limits on the amount or type of renewable energy import that can be applied

[15] See Texas Comptroller of Public Accounts http://www.window.state.tx.us/specialrpt/energy/uses/electricity.php for more details.

toward meeting the requirement. In other cases, it depends on whether the in-state load has the contractual right to energy generated by the out-of-state renewable resources. Focusing our analysis only on Texas mitigates concerns over the possibility of dubious cross-state generalizations regarding the effects of RPS.

While other states such as Connecticut, Massachusetts, and Nevada implemented RPS just prior to Texas, these states do not have the unique market structure and the rapid addition of renewable energy that characterize Texas. They are also very small not only in renewables generation but also among the smallest in the nation in total electricity generation. The same applies to New Jersey and Wisconsin, which adopted RPS at the same time as Texas.[16,17]
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, hydro-electricity constitutes the largest share of non-renewables generation and most of the hydroelectric capacity existed in these states before their respective RPS were enacted. In Texas, on the other hand, renewables energy generation was virtually non-existent before its RPS passed in 1999.[18]

Another important feature of Texas RPS is that it sets the target in terms of capacity and not in terms of the percentage of generation. Kneifel (2007) argues that RPS has little impact unless it is based on capacity as opposed to the percentage of renewables generation (Kneifel

[16] For example, Connecticut allows for the regional purchase of renewable electricity within the ISO New England jurisdiction and Nevada did not meet 100% of their RPS obligation until 2008.
[17] See http://www.eia.gov/renewable/state/#tabs_gen-1 for cross state comparisons.
[18] In Texas, the share of hydro-electricity before and after RPS has been very close to zero. Wind is by far the main renewable energy source. In 1998, the year before the passing of its RPS, combined nameplate (summer) capacity of wind, solar and biomass accounted for only 0.07 percent of nameplate (summer) capacity of coal and natural gas.

2007). The only other state that set its RPS based on capacity was Iowa, but their target was small.[19]

Finally, the Texas REC trading program was the first of its kind (Hurlbut 2008).[20] REC are designed to provide an accurate account of eligible renewable energy production, and to be tradable between producers and retailers.[21] 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.[22]

II.4. RPS Implementation Costs in Texas

As mentioned in Section I, the integration of renewables entails large infrastructure updates, the expansion of the existing power grid, and the addition of reserve capacity to address the intermittency of solar and wind. It requires the installation of new capital such as wind turbines, solar panels, etc., that typically have greater capital costs per megawatt of electricity generated.[23] In addition, a significant source of costs in the electricity market is transmission and distribution. According to ERCOT, installing one mile of transmission line costs between $1 and $2.6 million depending on what kV transmission line is installed. Unlike traditional sources of energy generated from hydrocarbons, renewable energy is diffuse (Diffen 2009). Figure 2 shows

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[19] Iowa's RPS mandated 105 MW of renewable capacity. (http://www.dsireusa.org/incentives/incentive.cfm?Incentive_Code=IA01R&re=1&ee=1)

[20] Power generated from renewable resources is used to create REC, which are measured in energy units. In Texas, one REC represents 1 MWh of qualified renewable energy that is generated and metered in Texas. For more details see: http://www.dsireusa.org/incentives/incentive.cfm?Incentive_Code=TX03R.

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

[22] 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.

[23] For example, a 620 MW conventional combined cycle natural gas plant has an overnight capital cost of $917/kW, whereas a 100 MW onshore wind plant has an overnight capital cost of $2,213/kW. See EIA for details (http://www.eia.gov/oiaf/beck_plantcosts).

that in Texas the wind-rich areas are in remote locations, away from the metro areas where demand is highest. In Texas, ERCOT estimates that the potential costs to build transmission lines to West and Northwest Texas to transport electricity generated from wind power would cost between \$3 and \$6 billion depending on the length and capacity of transmission lines built. In 2007, the total cost for transmission approved by the PUC was \$1.2 billion.[24]

In addition, renewable energy from wind, in particular, is not a dispatchable generation technology, meaning that it is outside the control of the system operator. Large variability in renewables generation due to the intermittency of wind results in average capacity factors that are almost half of those from coal and gas.[25] The adjustments associated with the intermittency also require additional reserve capacity, typically natural gas generation, in order to mitigate the variability and to account for forecast errors.

III. Synthetic Control Method for Comparative Case Study

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 outcome is the electricity price, the exposed state is Texas, the intervention is the RPS that passed in Texas in 1999, and the donor pool (unexposed/control states) consists of states that did not have the policy for the observed period.

III.1. The Synthetic Control

The following exposition is based on 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 is exposed to the intervention (RPS) at $T_0 \in (1,T)$. The observed outcome for state i at time t is,

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[24] "The Energy Report," Texas Comptroller of Public Accounts, 2008, page 342.
[25] National Renewable Energy Laboratory (NERL): http://www.nrel.gov/analysis/tech_cap_factor.html.

(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 existence of the RPS 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. Thus, state i is exposed to the intervention in periods $T_0 + 1$ to T . We assume that the passage of the RPS had no effect on the outcome in Texas before the implementation period. We restrict the donor pool to states that did not have an RPS over the period $t = 1,...,T$, and assume that the outcomes of the untreated states were not affected by the passage of RPS in Texas.[26]

Indexing the exposed state Texas as state 1, we want to estimate $(\alpha_{1T_0+1},...,\alpha_{1T})$. From equation (1) we note that $\alpha_{1t} = Y_{1t} - Y_{1t}^N$ for $t \in \{T_0 + 1,...,T\}$, and while Y_{1t} is observed Y_{1t}^N is unobserved. We, therefore, need to estimate Y_{1t}^N .

Suppose Y_{it}^N is given by the model,

(2) $$Y_{it}^N = \delta_t + \boldsymbol{\theta}_t \mathbf{Z}_t + \boldsymbol{\lambda}_t \boldsymbol{\mu}_i + \varepsilon_{it} ,$$

where, δ_t is an unknown common factor constant across states, $\mathbf{Z}_t$ is a $(r \times 1)$ vector of observed covariates (not affected by the intervention), $\boldsymbol{\theta}_t$ is a $(1 \times r)$ vector of unknown parameters, $\boldsymbol{\lambda}_t$ is a $(1 \times F)$ vector of unobserved time-varying common factors, $\boldsymbol{\mu}_i$ is a $(F \times 1)$ vector of unknown unit specific factors, and ε_{it} are the unobserved transitory shocks at the state level with zero mean.

[26] According to the information from the DSIRE database, in Texas, while tradable REC are to be used to meet the RPS requirement the electricity for each REC must be generated and metered within Texas.

Consider a $(J \times 1)$ vector of weights $\mathbf{W} = (w_2,..., w_{J+1})'$ such that $\{w_j \geq 0 \mid j = 2,..., J+1\}$ and $\sum_{j=2}^{J+1} w_j = 1$. Each value of the vector $\mathbf{W}$ represents a weighted average of the control states and, hence, a potential synthetic control. Abadie, Diamond and Hainmueller (2010) show that, there exist $\mathbf{W}^* = (w_2^*,..., w_{J+1}^*)'$ such that, $Y_{1t}^N = \sum_{j=2}^{J+1} w_j^* Y_{jt}$, $t = 1,...T_0$, and $\mathbf{Z_1} = \sum_{j=2}^{J+1} w_j^* \mathbf{Z}_j$ (that is, pre-intervention matching with respect to the outcome variable as well as the covariates, henceforth referred to as predictors), then under standard conditions we can use,

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

as an estimator for α_{1t}. The term $\sum_{j=2}^{J+1} w_j^* Y_{jt}$ on the right-hand-side of (4) is simply the weighted average of the observed outcome of the control states for $t \in \{T_0 + 1,..., T\}$ with weights $\mathbf{W}^*$.

Below we describe the procedure to obtain $\mathbf{W}^*$. Let $(T_0 \times 1)$ vector $\mathbf{K} = (k_1,..., k_{T_0})'$ define a linear combination of pre-intervention outcomes $\tilde{Y}_i^{\mathbf{K}} = \sum_{s=0}^{T_0} k_s Y_{is}$. Define $\mathbf{X}_1 = (\mathbf{Z}_1', \tilde{Y}_1^{\mathbf{K}_1},..., \tilde{Y}_1^{\mathbf{K}_M})'$ as a $(k \times 1)$ vector of pre-intervention characteristics for the exposed state where $k = r + M$.[27] Similarly, define a $(k \times J)$ matrix $\mathbf{X}_0$ that contains the same variables for the unexposed states. The $j-\text{th}$ column of $\mathbf{X}_0$, thus, is $(\mathbf{Z}'_j, \tilde{Y}_j^{\mathbf{K}_1},..., \tilde{Y}_j^{\mathbf{K}_M})'$.

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

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

[27] For example, if $M = 2$, $\mathbf{K}_1 = (1,0,...,0)'$ and $\mathbf{K}_2 = (0,0,...,1)'$ 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 $\mathbf{X}_1$.

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 equation (2) generalization and that the traditional regression-based difference-in-difference model can be obtained if we impose that $\boldsymbol{\lambda}_t$ be constant for all t. Thus, 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, this model allows the effects of such unobservables to vary with time. In particular, Abadie, Diamond and Hainmueller (2010) show that a synthetic control can fit $\mathbf{Z_1}$ and a long set of pre-intervention outcomes, $Y_{11},\ldots,Y_{1T_0}$, only as long as it fits $\mathbf{Z_1}$ and μ_1 (unknown factors of the exposed unit).

III.2. Inference

Once an optimal weighting vector $\mathbf{W}^{*}$ is chosen, the "synthetic Texas" is obtained by calculating the weighted average of the donor pool. The post-intervention values of the synthetic serve as our counterfactual outcome for Texas. Following Abadie, Diamond, and Hainmueller (2010) we calculate the ratio of post-intervention to pre-intervention Mean Square Prediction Error or MSPE (the squared difference between the actual outcome and the synthetic outcome), denoted by Δ_{TX}. This ratio puts the magnitude of post intervention gap (between the actual and the synthetic outcome) in the context of the pre-intervention fit (between the actual and the synthetic outcome): the larger the ratio the greater is the impact of the intervention.

To formally test the significance of this estimate, we apply the permutations test suggested by Bertrand et al. (2002), Buchmueller et al. (2009), Abadie et al. (2010), and Bohn et al. (forthcoming). First, for each state in the donor pool, we carry out an SCM estimate as if the state had passed the RPS in 1999 (i.e., apply a fictitious policy intervention). We can then calculate the post-pre MSPE ratio for each of these states. The distribution of these "placebo" post-pre MSPE ratios (Δ) then provides the equivalent of a sampling distribution for Δ_{TX}. 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 $\Delta_{TX} > 0$ is given by $F(\Delta_{TX})$ (Bohn et al. forthcoming). Note that this answers the question, how often would we obtain an effect of RPS of a magnitude as large as that of Texas if we had chosen a state at random, which is the fundamental question of inference (Bertrand, Duflo, and Mullianathan 2002; Buchmueller et al. 2009; Abadie, Diamond and Hainmueller 2010).

Abadie, Diamond and Hainmueller (2010) utilize the placebo tests for inference with a more straightforward criterion. They examine the ranking of the magnitude of the post-pre MSPE ratio of the exposed state vis-à-vis those of the placebos. If the exposed state is ranked first, then they consider it significant, the rationale being that for the treatment effect to be significant no placebo effect should be larger than the actual effect estimated for the exposed state. We adopt both these criteria and consider the impact of RPS to be significant if Texas's post-pre MSPE ratio is ranked first with a statistically significant p-value.

IV. Data

We collected the data for the outcome variable, electricity price, from the Energy Information Administration (EIA). Much of the remaining energy data, including electricity generation, generating capacity, and number of customers were also collected from the EIA. We used information on geographical features such as temperature and sunlight as well as natural amenities from Economic Research Service (ERS) of the United States Department of Agriculture (USDA). Population as well as economic indicators such as per capita personal income, manufacturing earnings share, and poverty rates were obtained from the Bureau of Economic Analysis (BEA).

In addition, we collected data on wind potential, the theoretical potential for wind production in each state from the Pacific Northwest Laboratory. There are two wind potential measures. The first measure is derived from wind potential estimates produced by the Pacific Northwest Laboratory in 1991 (Elliott, D.L., L.L. Wendell, and G.L. 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 assumptions, excluding transmission limitations. The installed capacity calculations are based on an assumption of 5 MW/km2 of installed capacity. The second measure is an updated 2010 wind potential measurements constructed by NREL.[28] The 1991 measure is available for the contiguous states only while the 2010 measure is available for every state. Table 1 presents a summary description of all variables described above.

V. Results

V.1. Synthetic Control Method (*SCM*) *Estimates of the Impact of RPS on Texas Electricity Price*

We construct the synthetic Texas electricity price as a convex combination of states in the donor pool in terms of pre-intervention (RPS) characteristics, determined by optimal weights as discussed in Section III. Our donor pool consists of 21 states that did not pass a law similar to mandatory RPS.

Figure 3a is a graphical representation of the SCM estimate for Texas's electricity price. Figure 3a shows the actual electricity price of Texas and that of synthetic Texas. The pre-intervention match indicates that the synthetic Texas electricity price coincides well with the actual Texas electricity price over the period 1990-1998. Post-intervention, the actual price

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

diverges from the synthetic price. In the absence of the RPS policy, Texas's electricity price is predicted to have remained at the lower level represented by the synthetic Texas electricity price. The next issue is to determine if the estimated post-intervention gap in electricity price between actual and synthetic Texas shown in Figure 3a is statistically significant.

Figure 3b presents the gap between actual and synthetic Texas (the darker line) as well as the gaps between actual and synthetic of each donor pool placebo (the gray lines). As explained in section III.2, we examine the comparison of the post-pre MSPE ratios from the placebo tests. For a significant finding, we expect that Texas would have the largest ratio as compared with the placebo states. Figure 3c shows the post-pre MSPE ratios for Texas and the donor pool; we find that Texas's post-pre MSPE ratio is dwarfed by a number of placebos.

Column 1 of each panel in Table 2 describes the SCM estimates presented in Figure 3. Column 1 of Panel A presents the predictors based on which the pre-intervention matching was performed. We find that real per capita income growth has the largest influence on the matching, followed by growth in the number of customers and the share of manufacturing earnings. In other words, these three variables, given the other predictors, have the most power in predicting electricity price in Texas. As predictors, we also used the pre-intervention electricity prices, which is standard practice in the literature (see Abadie et al 2010, Bohn et al., forthcoming). Column 1 of Panel B presents the estimated optimal weights that are assigned to each donor pool state (W-weights): we see that Florida and West Virginia received the largest weights. Many of the control states have very small weights, which is also common in SCM studies of state policy impacts (Abadie and Gardeazabal 2003; Abadie, Diamond, and Hainmueller 2010).

Column 1 of Panel C summarizes the inference of the estimate. Our pre-intervention matching is very strong as evidenced by the three ratios we produce: pre-intervention MSPE to pre-intervention actual mean (0.0002), pre-intervention MSPE to pre-intervention actual variance

(0.1390) and pre-intervention absolute prediction error to pre-intervention actual mean (0.0078). The p-value indicates that the post-pre MSPE ratio that measures the effect of RPS on Texas's electricity price is significant at 10 percent level (p-value = 0.091), but the post-pre MSPE ratio is ranked third. We, therefore, conclude that RPS did not have a causal effect on the post-intervention electricity price increase in Texas.

As shown in Figure 1, Texas electricity price growth was greater than the national average throughout 1990-1999 and this growth was especially high for most of the 2000s. An immediate robustness check, therefore, is to estimate the impact of RPS on electricity price growth in Texas. The growth variable was created by dividing each year's price with that of 1990. This allows us to focus on changes in price over time and retain the number of pre-intervention observations. The results are detailed in Column 2 of each panel in Table 2. V-weights of the predictors in Column 2 of Panel A are similar to Column 1. In Column 2 of Panel B, we find that West Virginia, Alaska, Louisiana and Oklahoma carry the largest weights. From Column 2 of Panel C we conclude that RPS did not contribute to the price growth, Texas is ranked third with a p-value of 0.0909.

V.2. Electricity Price by Sector

Energy Information Association (EIA) reports disaggregated electricity prices for three sectors: residential, commercial, and industrial. We analyze each price category separately in order to determine if there is disparate RPS influence across sectors and find that the results are generally consistent across categories. Table 3 reports these results. From Panel C of Table 3 we find that Texas is not significantly different from the placebo states. In each category, the p-value is not significant.

V.3. Alternative Sets 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 alternative sets of predictors using the same donor pool. We include the two wind potential measures and geographic and weather variables in order to more thoroughly capture a state's capability for producing wind energy. Alaska is dropped from the donor pool as the 1991 wind potential measure and the geographic variables are not available for this state. Panel C of Table 4 shows that with the additional variables Texas post-pre MSPE ratio is significant at the 10 percent level, but is ranked third. Overall, we conclude that our finding in section V.1 is robust to the change in the set of predictors.

V.4. Alternative Post-intervention Horizon and Alternative Sets of Donor Pool

Our main analysis above covered the period 1990-2010. In 2009, four large states adopted RPS: Kansas, Michigan, Missouri and Ohio.[29] Michigan, Missouri and Ohio are states with larger populations and Kansas's per capital energy consumption is closely comparable to that of Texas. Additionally, Michigan and Ohio are states that have been exposed to deregulation over the same period as Texas. In order to determine if the inclusion of these potentially comparable states affects our findings, we run an alternative sample period, through 2008, and include these four states.

The results are reported in the first column of Table 5. We do not find any impact of RPS on Texas's electricity price (Texas post-pre MSPE ratio is ranked fourth with a non-significant p-value). Note that this robustness check serves an additional purpose. In 2009, Texas electricity prices fell substantially and continued to fall in 2010; by 2010, the price had fallen by 17 percent from its 2008 level. The results reported in the first column of Table 5 show that our finding is not driven by this large price decline over the final two periods of our analysis.

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[29] Michigan and Missouri passed RPS at the end of 2008 while Ohio and Kansas passed RPS in 2009.

Finally, we address the issue of states with optional RPS. States with an optional RPS may experience price effects despite the fact that RPS implementation is not legally mandated. Four states in our donor pool, North Dakota, South Dakota, Utah and West Virginia have passed an optional RPS rather than a mandated RPS. We run the SCM estimate where these states are excluded from the donor pool.[30] The results reported in the second column of Table 5 demonstrate that our main findings in section V.1 are robust to this alternative donor pool.

V.5. Deregulation

Texas bill SB 7 that enacted RPS in 1999 also included deregulation measures that became effective in 2002. Given that Texas deregulated their electricity market in 2002, it is natural to wonder if the electricity price increase is due to deregulation. It is important to point out that in our analysis so far the RPS intervention was identified not only by its timing, in 1999, but also by the make-up of the donor pool. The synthetic Texas price was constructed from a donor pool of states that were not exposed to RPS, which included states such as Virginia, in the main specification, and Michigan and Ohio, in the alternative sample period specification (see Table 5), that experienced deregulation.

While there is not an easy way to disentangle the influence of deregulation from that of RPS, we conducted an alternative SCM investigation using Texas deregulation in 2002 as the policy intervention. For this analysis, we constructed an alternative donor pool that consisted of all states that did not have deregulation (30 states). Note that eleven of these states had RPS (See Table 6). Thus, this SCM analysis treats deregulation as a distinct policy intervention that

[30] We run this analysis through 2008 in order to maintain a sufficient number of states in the donor pool. The exclusion of these four states using our main sample period (which also excludes the 2008 and 2009 RPS states) would have resulted in a much smaller the donor pool. However, we have also carried out the estimate with this smaller donor pool for the 1990-2010 period. The results continue to show no effect of RPS. These results are not reported but available on request.

occurred in 2002 in Texas and uses a donor pool of non-restructured states without consideration as to whether the state had RPS or not.

Figures 4a-4c and Table 6 present these results. Our pre-intervention matching is again very strong (Panel C of Table 6). Based on the p-value of Texas's post-pre MSPE ratio, and that it is ranked ninth, we conclude that the effect of deregulation on Texas's electricity price is not significant. While this analysis may not settle the debate over the role of deregulation in determining electricity price, a more exhaustive examination of deregulation is left for future research.

V.6. Discussion

A large and conspicuous policy change such as RPS with its higher costs of production, additional distribution costs, and inherent regulatory costs (Fischer 2010) often becomes the easy explanation for a price increase. In this paper, our focus was to examine whether RPS implementation in fact explains Texas's large electricity price increase. We show that RPS did not contribute to the price increase observed in the state in the years following the enactment of the policy. Our findings leave open questions for future researchers; in particular, what were the factors that did contribute to increased electricity prices in Texas.

There have been growing concerns that higher demand for electricity in Texas, due to population pressures and increased industrial demand, is not being sufficiently met with capacity expansions.[31] The PUC, which sets the cap on peak wholesale electricity price, has recently been increasing this rate in hopes of spurring increased investment in the grid, which some argue has declined under deregulation.[32] This, however, may not sufficiently explain price increases in the early 2000s, when, according to the North American Electric Reliability Corporation (NERC)

[31] http://stateimpact.npr.org/texas/2012/05/31/texas-power-slim-reserves-getting-slimmer.
[32] https://stateimpact.npr.org/texas/2012/05/21/keeping-the-lights-on-in-texas-will-big-profits-spur-new-power-plants.

Reliability Assessments, the capacity was sufficient. In addition, capacity margins have recently been declining in other regions as well. An adequate explanation of Texas electricity price increase may extend beyond considerations of demand and capacity constraints.[33] We believe that these are important questions, which merit future research.

VI. Conclusion

The value of RPS hinges on a robust estimation of the costs and benefits. As states determine whether to adopt new RPS policies or repeal existing ones, the costs of RPS in terms of its influence on electricity price is a crucial consideration. For those who feel that the environmental goals of the RPS policies are unimportant, any resulting increase in electricity prices may be used as a justification to abandon the policy. For those who place a significant value on the potential environmental benefits of the RPS, a limited increase in price may be inconsequential.

Variation across states in market structures, costs, and availability of renewable energy resources indicate that empirical identification of the effect of RPS on electricity price relies crucially on the accurate determination of the control states. We employ the SCM approach, which uses a more appropriate control compared to the traditional case study approaches. Our preferred empirical tests, using SCM, demonstrate that Texas RPS did not play a causal role in the electricity price increase in the state.

Our findings suggest that the much-anticipated costs of RPS in the form of an electricity price increase may not be of concern for Texas. This, however, does not necessarily translate to a general conclusion across states. Price changes may depend on the nature of RPS implementation in terms of both the RPS and electricity market characteristics. In fact, our findings highlight the importance of considering local conditions and idiosyncrasies when studying the impact of RPS.

[33] http://www.nerc.com/pa/RAPA/ra/Pages/default.aspx

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Figures

Figure 1: Electricity Price – Texas versus the United States

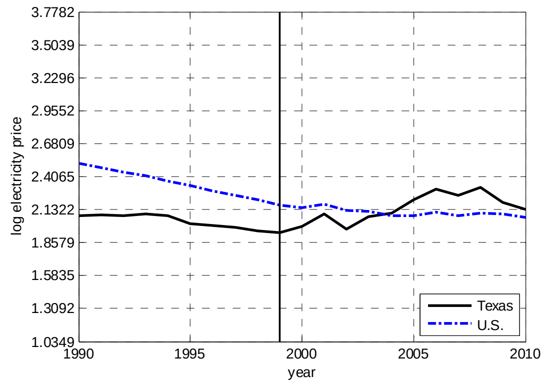


Figure 2: Wind Farm Locations in Texas

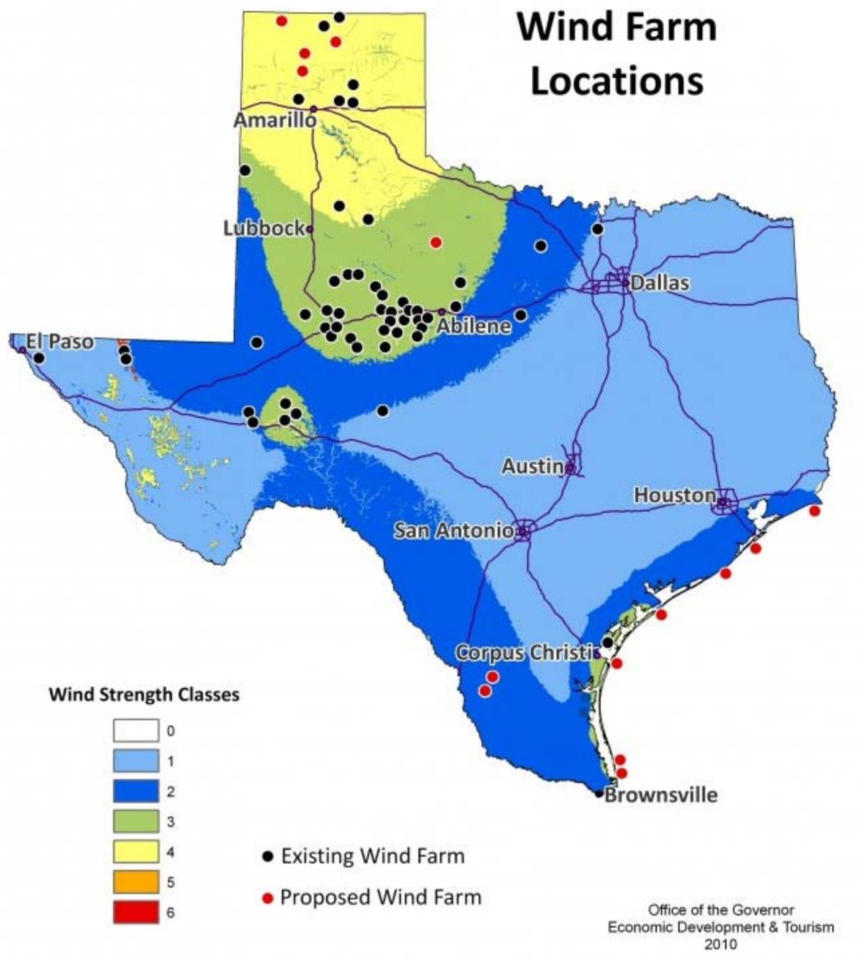


Figure 3: SCM Estimate of Impact of 1999 RPS on Texas Electricity Price

Figure 3a

Texas Electricity Price

Texas vs Control States Synthetic Control

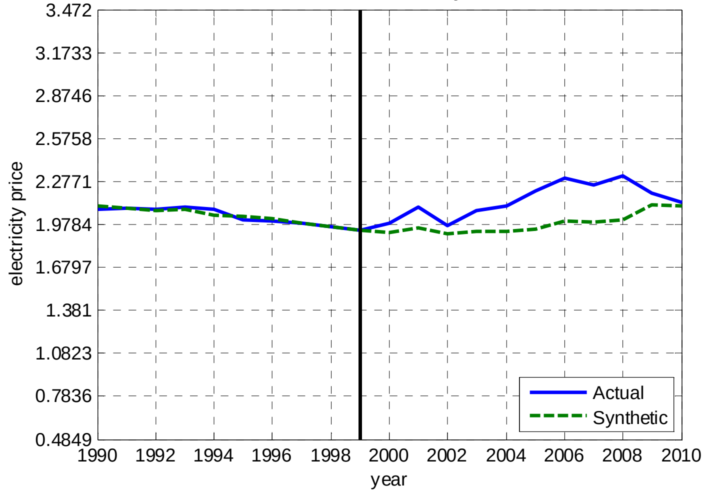


Figure 3b

Texas Electricity Price Gap

And Placebo Gaps in All Control States

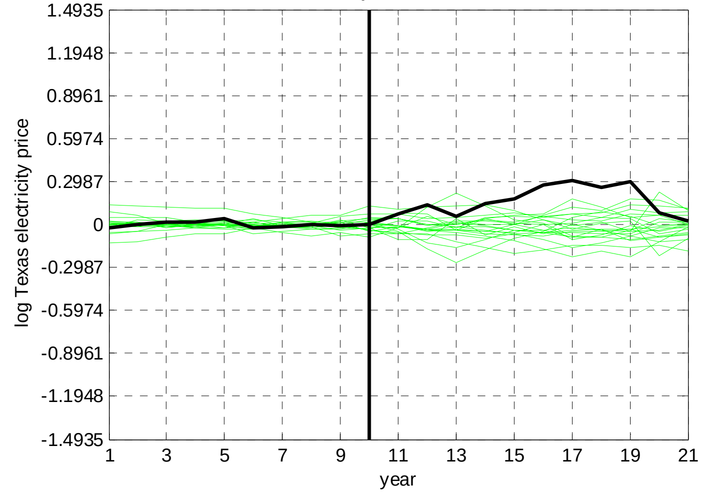


Figure 3c

Post/pre SYGL MSPE: Donor Pool and Texas

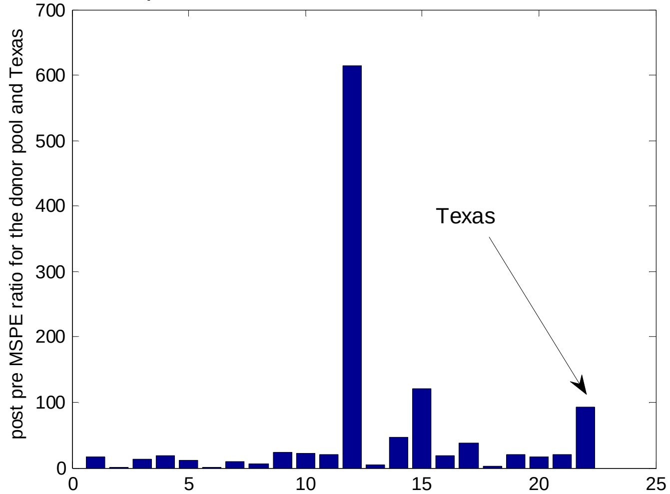
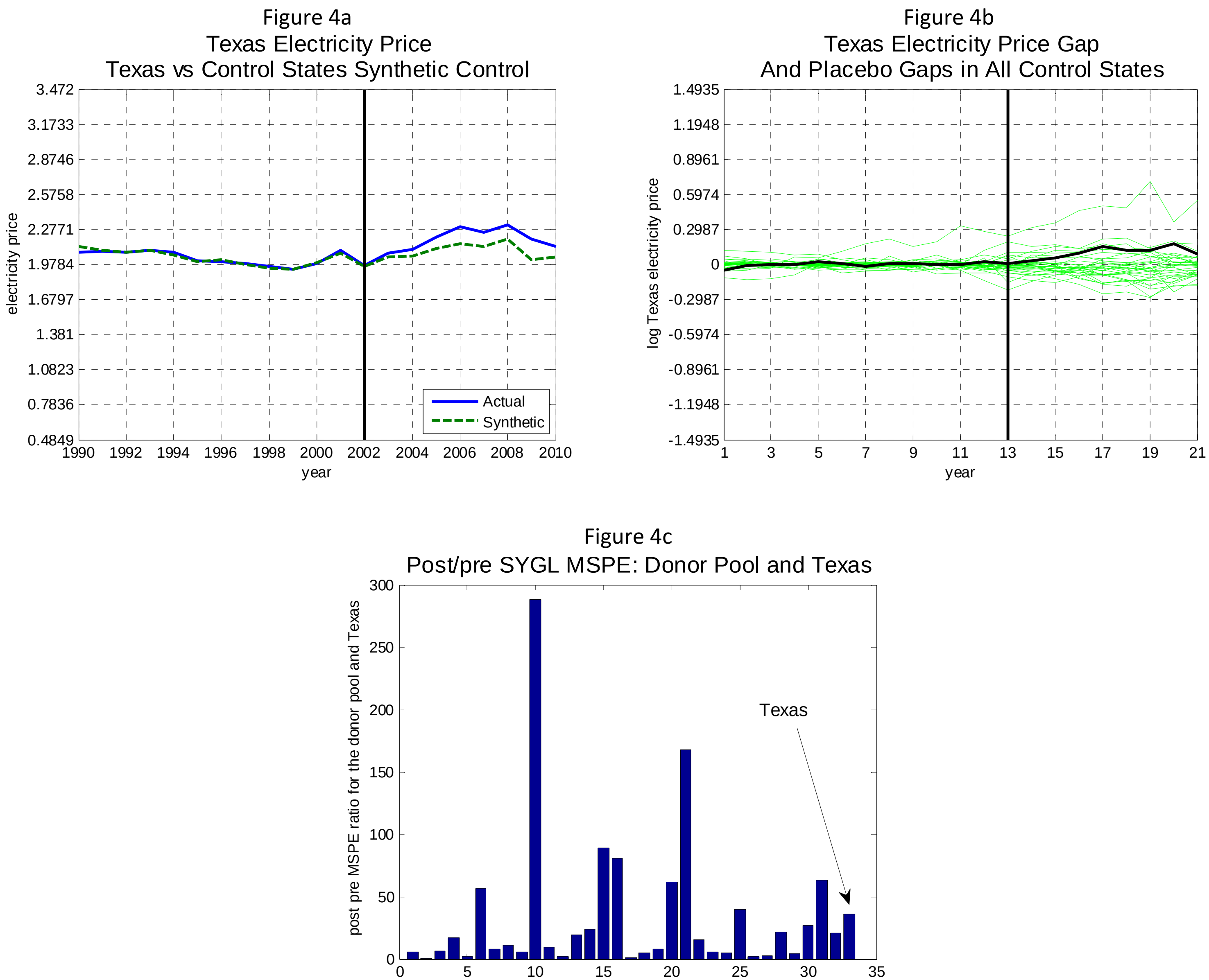


Figure 4: SCM Estimate of Impact of 2002 Deregulation on Texas Electricity Price



Tables

Table 1: Summary Statistics (1990-2010)

	Full sample (N=1050)				No mandatory RPS states (N=525)				Texas (N=21)
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean
Electricity price (cents/kWh)	2.08	0.29	1.50	3.29	1.96	0.22	1.50	2.62	2.09
Sectorial electricity price									
Residential	2.27	0.26	1.75	3.40	2.15	0.19	1.79	2.75	2.31
Industrial	1.78	0.33	1.07	3.18	1.65	0.24	1.11	2.57	1.74
Commercial	2.13	0.27	1.56	3.31	2.03	0.20	1.56	2.58	2.14
Predictors									
Nameplate capacity	9.40	1.00	6.43	11.68	9.41	0.96	6.99	11.12	11.42
Summer capacity	9.33	0.99	6.33	11.59	9.33	0.94	6.88	10.99	11.35
Coal generation	15.78	4.91	-6.91	18.83	16.08	4.99	-6.91	18.73	18.74
Natural gas	14.08	4.02	-6.91	19.11	13.97	2.81	-6.91	18.67	18.95
Total customers	14.31	0.98	12.37	16.51	14.16	0.95	12.37	16.08	16.04
Residential customers	14.17	0.99	12.18	16.38	14.01	0.97	12.18	15.96	15.89
Industrial customers	8.88	1.13	5.39	12.04	8.94	1.07	5.39	10.72	11.38
Commercial customers	12.18	0.93	10.34	14.41	12.07	0.87	10.36	13.94	13.95
Growth of number of customers	1.18	0.16	0.90	2.16	1.17	0.14	0.90	1.68	1.24
Total population	15.05	1.01	13.02	17.44	14.87	0.97	13.02	16.75	16.85
Real PC personal income	10.33	0.18	9.81	10.87	10.26	0.16	9.81	10.72	10.30
Proportion to 1990: real PC personal income	1.23	0.16	0.96	1.82	1.24	0.17	0.98	1.82	1.25
Share of manufacturing earnings	0.84	0.17	0.41	1.54	0.87	0.18	0.47	1.54	0.86
Percent of population below poverty level	12.33	3.32	6.30	24.16	13.42	3.36	8.66	24.16	16.45
Wind potential: 1991	2.40	4.09	-6.91	7.10	1.08	5.10	-6.91	7.10	7.08
Wind potential: 2010	8.93	4.24	-6.91	14.46	8.60	4.96	-6.91	13.77	14.46
January mean temperature (°F)	30.84	10.89	7.29	58.01	32.73	12.12	7.29	58.01	45.92
January mean hours of sunlight	151.17	33.66	61.49	248.40	147.48	25.80	105.14	197.64	182.59
July mean temperature (°F)	74.26	4.71	66.39	83.17	75.90	4.58	68.50	82.34	83.17
Natural amenities scale	0.56	2.13	-2.88	6.73	-0.08	1.53	-2.50	3.41	1.27

Notes: (a) The full sample consists of 50 states (District of Columbia is excluded as a number of variables are missing for them). (b) Columns 5-8 present information on 25 states that did not have mandatory RPS between 1990 and 2008 as well as Kansas and Ohio. (c) Except for the geographical variables, shares and growth measure, all variables are in logarithm. Wind potential, coal generation and natural gas generations are zero in a few states; these values were replaced with 0.001 before taking log. (d) Poverty rates are available for 1990-2004. Geographical variables (temperature, sunlight, and natural amenities) and 1991 measure of wind potential are not available for Alaska and Hawaii.

Table 2: Synthetic Control Method (SCM) Estimates of Impact of 1999 Renewable Portfolio Standards (RPS) on Texas Electricity Price Level and Texas Electricity Price Growth (1990-2010)

Panel A: V-weight

	(1)	(2)
Predictors	Electricity price	Electricity price growth
Real PC personal income	1.0000	1.0000
Real PC income growth	15.9596	15.9612
Poverty rate	0.0260	0.4268
Coal generation	0.5711	0.0011
Nameplate capacity	0.1362	0.0000
Summer capacity	0.1632	0.0000
Natural gas generation	0.0000	0.0005
Number of customers	0.0001	0.0000
Growth of number of customers	8.3816	8.3815
Population	0.0046	0.0000
Manufacturing earnings share	2.2007	2.2136
Pre-intervention price	yes	yes

Panel C: Estimation Statistics

	Electricity price	Electricity price growth
SCM: Pre-intervention Fit		
MSPE to mean ratio	0.0002	0.0003
MSPE to variance ratio	0.1390	0.1157
Absolute prediction error to mean ratio	0.0078	0.0156
SCM Inference: Permutations Test		
Pre-intervention MSPE (M1)	0.0004	0.0003
Post-intervention MSPE (M2)	0.0373	0.0599
Post-pre MSPE ratio (M2/M1)	92.9621	195.8956
P-value: Post-pre MSPE ratio	0.0910	0.0909
post/pre MSPE ratio rank	3	3

Panel B: W-weight

	(1)	(2)
State	Electricity price	Electricity price growth
Alabama	0.0000	0.0000
Alaska	0.0000	0.2001
Arkansas	0.0000	0.0000
Florida	0.5708	0.0009
Georgia	0.0000	0.0000
Idaho	0.0000	0.0000
Indiana	0.0000	0.0000
Kentucky	0.0000	0.0000
Louisiana	0.0000	0.1614
Mississippi	0.0000	0.0000
Nebraska	0.0000	0.0000
North Dakota	0.0000	0.0000
Oklahoma	0.0000	0.0513
South Carolina	0.0000	0.0000
South Dakota	0.0000	0.0000
Tennessee	0.0000	0.0000
Utah	0.0000	0.0000
Vermont	0.0000	0.0000
Virginia	0.0000	0.0000
West Virginia	0.4292	0.5863
Wyoming	0.0000	0.0000

Notes: (a) In each panel, column (1) is associated with electricity price and column (2) is associated with electricity price growth. Growth measure: ratio of current electricity price to 1990 electricity price. (b) Panel A presents the V-weights of the predictors. (c) The set of predictors include the pre-intervention electricity prices for the years 1990-1998 in case of price level, and years 1991-1998 in case of price growth (because it is 1 for every state in 1990). Weights are available on request. (d) Panel B presents the W-weights of states in the donor pool. (e) Panel C summarizes the inference of the SCM estimate.

Table 3: Synthetic Control Method (SCM) Estimates of Impact of RPS on Texas Electricity Price by Sector (1990-2010)

Panel A: V-weights

Predictors	Residential	Industrial	Commercial
Real PC personal income	1.0000	1.0000	1.0000
Real PC income growth	15.9612	16.0031	15.9612
Poverty rate	0.0010	39.2601	0.0008
Coal generation	0.0005	357.2772	0.0004
Nameplate capacity	0.0102	0.0000	0.0102
Summer capacity	0.0106	0.0000	0.0106
Natural gas generation	0.0012	10.5192	0.0012
Number of customers	0.0103	0.0000	0.0125
Growth of number of customers	8.3825	8.4536	8.3825
Population	0.0103	0.0000	0.0102
Manufacturing earnings share	2.2131	2.6846	2.2131
Pre-intervention price	Yes	yes	Yes

Panel B: W-weights

State	Residential	Industrial	Commercial
Alabama	0.0000	0.7837	0.0000
Florida	0.6154	0.2163	0.6403
Louisiana	0.3846	0.0000	0.3596

Panel C: Estimation Statistics

	Residential	Industrial	Commercial
SCM: Pre-intervention Fit			
MSPE to mean ratio	0.0003	0.0022	0.0008
MSPE to variance ratio	0.2945	0.6125	0.5957
Absolute prediction error to mean ratio	0.0088	0.0311	0.0136
SCM Inference: Permutations Test			
Pre-intervention MSPE (M1)	0.0007	0.0036	0.0017
Post-intervention MSPE (M2)	0.0174	0.0617	0.0024
Post-pre MSPE ratio (M2/M1)	24.0023	17.3506	1.3891
P-value: Post-pre MSPE ratio	0.1818	0.2727	0.8636
post/pre MSPE ratio rank	5	7	20

Notes: (a) Panel A presents the V-weights of the predictors. Sector specific customer numbers used. (b) The set of predictors include the pre-intervention electricity prices for the years 1990-1998. Weights are available on request. (c) Panel B presents the W-weights of states in the donor pool. Only states with larger weights are reported. (d) Panel C summarizes the inference of the SCM estimate.

Table 4: Synthetic Control Method (SCM) Estimates of Impact of RPS on Texas Electricity Price (1990-2010) with Different Predictors

Panel A: V-weight

Predictors	V-weights
Real PC personal income	1.0000
Real PC income growth	18.5605
Poverty rate	0.0000
Wind potential 1991 measure	0.0000
Wind potential 2010 measure	0.0485
Coal generation	0.0160
Nameplate capacity	0.0179
Summer capacity	0.0185
Natural gas generation	0.0000
Number of customers	0.0191
Growth of number of customers	6.1984
January temperature	0.7692
January sunlight	0.0000
July temperature	0.0000
USDA natural amenities scale	0.0000
Population	0.0230
Manufacturing earnings share	1.6228
Pre-intervention price	yes

Panel B: W-weight

State	W-weight
Alabama	0.0000
Arkansas	0.0000
Florida	0.3727
Georgia	0.0000
Idaho	0.0000
Indiana	0.0000
Kentucky	0.0000
Louisiana	0.0000
Mississippi	0.0000
Nebraska	0.0000
North Dakota	0.0000
Oklahoma	0.6273
South Carolina	0.0000
South Dakota	0.0000
Tennessee	0.0000
Utah	0.0000
Vermont	0.0000
Virginia	0.0000
West Virginia	0.0000
Wyoming	0.0000

Panel C: Estimation Statistics

SCM: Pre-intervention Fit	
MSPE to mean ratio	0.0002
MSPE to variance ratio	0.1747
Absolute prediction error to mean ratio	0.0090
SCM Inference: Permutations Test	
Pre-intervention MSPE (M1)	0.0005
Post-intervention MSPE (M2)	0.0224
Post-pre MSPE ratio (M2/M1)	44.4446
P-value: Post-pre MSPE ratio	0.0952
post/pre MSPE ratio rank	3

Notes: (a) Panel A presents the V-weights of the predictors. (c) The set of predictors include the pre-intervention electricity prices for the years 1990-1998. Weights are available on request. (c) Panel B presents the W-weights of states in the donor pool. (d) Panel C summarizes the inference of the SCM estimate.

Table 5: Synthetic Control Method (SCM) Estimates of Impact of RPS on Texas Electricity Price – Different Post-intervention Horizon (1990-2008) and Different Sets of Donor Pool

Panel A: V-weights

Predictors	Full donor pool	Excluding optional RPS states
Real PC personal income	1.0000	1.0000
Real PC income growth	17.8921	15.9307
Poverty rate	0.0017	0.0018
Coal generation	0.5452	0.4704
Nameplate capacity	0.0027	0.0020
Summer capacity	0.0034	0.0148
Natural gas generation	0.0030	0.0025
Number of customers	0.0004	0.0027
Growth of number of customers	9.3532	9.4982
Population	0.0030	0.0114
Manufacturing earnings share	2.3804	6.4360
Pre-intervention price	yes	yes

Panel B: W-weights

State	Full donor pool	Excluding optional RPS states
Alabama	0.1750	0.1765
Alaska	0.0000	0.0000
Arkansas	0.0000	0.0000
Florida	0.1020	0.1029
Georgia	0.0000	0.0000
Idaho	0.0000	0.0000
Indiana	0.0004	0.0001
Kansas	0.0000	0.0000
Kentucky	0.0000	0.0000
Louisiana	0.0000	0.0000
Michigan	0.0000	0.0000
Mississippi	0.0000	0.0000
Missouri	0.0000	0.0000
Nebraska	0.0000	0.0000
North Dakota	0.0000	--
Ohio	0.7226	0.7205
Oklahoma	0.0000	0.0000
South Carolina	0.0000	0.0000
South Dakota	0.0000	--
Tennessee	0.0000	0.0000
Utah	0.0000	--
Vermont	0.0000	0.0000
Virginia	0.0000	0.0000
West Virginia	0.0000	--
Wyoming	0.0000	0.0000

Panel C: Estimation Statistics

	Full donor pool	Excluding optional RPS states
SCM: Pre-intervention Fit		
MSPE to mean ratio	0.0003	0.0003
MSPE to variance ratio	0.2102	0.2101
Absolute prediction error to mean ratio	0.0099	0.0099
SCM Inference: Permutations Test		
Pre-intervention MSPE (M1)	0.0006	0.0006
Post-intervention MSPE (M2)	0.0334	0.0333
Post-pre MSPE ratio (M2/M1)	54.9852	54.9210
P-value: Post-pre MSPE ratio	0.1154	0.0909
post/pre MSPE ratio rank	4	3

Notes: (a) The first column is for the time period 1990-2008 (i.e., excluding the post-intervention outcome of 2009-2010). The states with RPS in 2008 and 2009 therefore are included. (b) In the second column time period is still 1990-2008, but we exclude the optional RPS states from the donor pool. (c) Panel A presents the V-weights of the predictors. (d) Panel B presents the W-weights of states in the donor pool. (e) Panel C summarizes the inference of the SCM estimates.

Table 6: Synthetic Control Method (SCM) Estimates of Impact of 2002 Deregulation on Texas Electricity Price (1990-2010)

Panel A: V-weights

Predictors	V-weights
Real PC personal income	1.0000
Real PC personal income growth measure	11.6745
Wind potential	0.0000
Coal generation	0.0000
Nameplate capacity	0.0000
Summer capacity	0.0000
Natural gas	0.0041
Number of customers	0.0000
Number of customers growth measure	3.6369
Natural amenities	0.0000
Population	1.6203
Population growth measure	0.2682
Pre-intervention price	yes

Panel B: W-weights

State	W-weight
Alabama	0.0000
Alaska	0.0000
Arkansas	0.0000
Colorado	0.0012
Florida	0.1968
Georgia	0.0000
Hawaii	0.0000
Idaho	0.0000
Indiana	0.0000
Iowa	0.0000
Kansas	0.0000
Kentucky	0.0000
Louisiana	0.6459
Minnesota	0.0000
Mississippi	0.0000
Missouri	0.0000
Montana	0.0000
Nebraska	0.0000
Nevada	0.1561
New Mexico	0.0000
North Carolina	0.0000
North Dakota	0.0000
Oklahoma	0.0000
South Carolina	0.0000
South Dakota	0.0000
Tennessee	0.0000
Utah	0.0000
Vermont	0.0000
Washington	0.0000
West Virginia	0.0000
Wisconsin	0.0000
Wyoming	0.0000

Panel C: Estimation Statistics

SCM: Pre-intervention Fit	
MSPE to mean ratio	0.0002
MSPE to variance ratio	0.1010
Absolute prediction error to mean ratio	0.0065
SCM Inference: Permutations Test	
Pre-intervention MSPE (M1)	0.0004
Post-intervention MSPE (M2)	0.0129
Post-pre MSPE ratio (M2/M1)	36.1739
P-value: Post-pre MSPE ratio	0.2424
post/pre MSPE ratio rank	9

Notes: (a) Panel A presents the V-weights of the predictors. (b) The set of predictors include the pre-intervention electricity prices for the years 1990-1998. Weights are available on request. (c) Panel B presents the W-weights of states in the donor pool. (d) Panel C summarizes the inference of the SCM estimate. (d) The donor pool includes states that did not have deregulation within 1990-2010. Note that the following states in this donor pool are RPS states: Colorado, Iowa, Kansas, Minnesota, Missouri, Montana, Nevada, New Mexico, North Carolina, Washington, and West Virginia.