

Shrimali, Gireesh; Jenner, Steffen; Groba, Felix; Chan, Gabriel; Indvik, Joe

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Have state renewable portfolio standards really worked? Synthesizing past policy assessments to build an integrated econometric analysis of RPS effectiveness in the US

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Opinions expressed in this paper are those of the author(s) and do not necessarily reflect views of the institute.

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DIW Berlin
German Institute for Economic Research
Mohrenstr. 58
10117 Berlin

Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
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Have State Renewable Portfolio Standards Really Worked?

Synthesizing Past Policy Assessments to Build an Integrated Econometric Analysis of RPS Effectiveness in the U.S.

Gireesh Shrimali ^a, Steffen Jenner ^b, Felix Groba ^c, Gabriel Chan ^d, Joe Indvik ^{e,1}

^a Monterey Institute of International Studies, 460 Pierce St Monterey, CA 93940, gshrimali@miis.edu, Tel.: +1-650-353-8221.

^b Tübingen Univ., Melanchthonstr. 36, 72076 Tübingen, Germany, steffen.jenner@uni-tuebingen.de, Tel.: +49-7071-29-72927.

^c German Institute of Economic Research, Mohrenstr. 58, 10117 Berlin, Germany, fgroba@diw.de, Tel.: +49-30-89789-681.

^d Harvard University, 79 JFK Street, Cambridge, MA 02138, gabe_chan@hksphd.harvard.edu, Tel.: +1-415-533-6103.

^e ICF International, 1725 I Street N.W., Washington, D.C. 20006, joe.indvik@gmail.com, Tel.: +1-515-230-4665.

Abstract: Renewable portfolio standards (RPS) are the most popular U.S. state-level policies for promoting deployment of renewable electricity (RES-E). While several econometric studies have estimated the effect of RPS on in-state RES-E deployment, results are contradictory. We reconcile these studies and move toward a definitive answer to the question of RPS effectiveness. We conduct an analysis using time series cross sectional regressions – including the most nuanced controls for policy design features to date – and nonparametric matching analysis. We find that higher RPS stringency does not necessarily drive more RES-E deployment. We examine several RPS design features and market characteristics (including REC unbundling, RPS in neighboring states, out-of-state renewable energy purchases) that may explain the gap between effective and ineffective policies. We also investigate other RES-E policies and technology-specific effects. Ultimately, we show that RPS effectiveness is largely explained by a combination of policy design, market context, and inter-state trading effects.

Keywords: Renewable energy, Renewable portfolio standards, Panel data models, Matching analysis.

JEL: C23, H23, Q42, Q48.

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¹ The findings in this paper do not reflect the views of ICF International.

1 Introduction

Policymakers in the United States have sought to stimulate electricity generation from renewable sources (RES-E) to reduce pollutants from fossil fuel combustion, to cut emissions of greenhouse gases which contribute to climate change, and to stimulate job growth and industrial productivity (Schmalensee, 2011). While the cost of electricity generation from many renewable energy sources has been declining, RES-E technologies are not cost-competitive in many markets and therefore often depend on government intervention (Green and Yatchew, 2012; NREL, 2010).

In the U.S., many federal-level policies in support of renewable energy, such as the production and investment tax credit have been introduced. However, there is a lack of coordinated and comprehensive action by the federal government, as evident by the absence of a nation-wide cap-and-trade program or a clean energy standard. On the other hand, many state and local governments have taken initiatives to increase RES-E capacity and generation (Engel and Orbach, 2008), with most of the 50 states enacting some form of policy to encourage the use of renewable energy in their state (DSIRE, 2012). State-level initiatives are wide-ranging, including: renewable energy incentives, integrated resource planning programs, and cap-and-trade programs (Wasserman, 2010).

Renewable portfolio standards (RPS) are arguably the most popular state-level policy to promote RES-E deployment. RPS policies are a type of quantity regulation that mandate energy suppliers to ensure that a certain fraction of their total electricity sales is from electricity generated from renewable energy sources. Energy suppliers can meet their quota by producing renewable energy, buying renewable energy credits from other suppliers, or paying a penalty. According to the Database of State Incentives for Renewables and Efficiency (DSIRE, 2012), twenty-one states and the District of Columbia have a mandatory RPS program. Ten other states have legislated RPS policies with effective start dates in the future.

States also use other policies to promote RES-E. Sixteen states have used public benefit funds to support renewable energy programs. In most states, these programs raise revenue by charging consumers an additional fee on their electricity bill to fund renewable energy investments, among other energy programs. Eight states have a mandatory green power option, which requires energy suppliers to provide consumers the option to buy electricity from renewable energy sources. In forty-two states, net metering mechanisms have been adopted, allowing households that generate their own electricity to pay for only the difference between their own generation and their own consumption – even if they do not occur at the same moment. Net metering typically favors small and distributed RES-E generation. Though states use multiple policies, RPS is considered a flagship RES-E policy tool.

Given the decentralized policy making, the individual state policies and the renewable power deployment show a great deal of heterogeneity. While a number of factors might explain both the growth of renewable energy and the disparity in renewable capacity among states, policies adopted by state governments, including changes in the regulatory environment for electricity,

are expected to play an important role. Considering the number and duration of RPS policies, ex-post analysis of their effectiveness in achieving the stated goal of increasing RES-E penetration is possible. Much work has been done in this area. However, results are contradictory, varying from showing the impact of RPS policies on renewable deployment as positively significant (Menz and Vachon, 2006; Yin and Powers, 2010) to insignificant (Carley 2009) to negatively significant (Shrimali and Kneifel, 2011). Thus, there is a need to explain these contradictory results and establish a robust answer to the question of RPS impact on in-state RES-E deployment.

We explain and reconcile the differences in the results presented in the literature by examining differences in datasets, analytical techniques, and the time period over which the impact of policies is examined. We use recently released data and show that differences in results are due to the application of different datasets and not because of different methodologies. In particular, we show that the key result in Yin and Powers (2010) – that RPS policies have driven renewable deployment – may be based on the use of an incorrectly specified dataset. In this process, we also attempt to replicate the results in other papers (e.g., Carley, 2009; Shrimali and Kneifel, 2011), and achieve different degrees of success, with the variability potentially due to differences in control variables.

The two datasets primarily used in previous studies are publicly available; we refer to them as the “state-level” dataset and the “generator-level” dataset. We show that the former is the correct dataset because of irreconcilable discrepancies introduced in the latter due to a change in classification methodology in the middle of the time series. Using this state-level dataset, we show that the stringency of a state’s RPS – a proxy introduced by Yin and Powers (2010) – is actually negatively correlated with RES-E capacity. However, if we exclude an outlier state, Maine, from the sample – a strategy introduced by Shrimali and Kneifel (2011) – we find that RPS stringency has no statistically significant effect on RES-E capacity.

We add richness to our results by considering the following: (1) RPS features such as alternative compliance payments, renewable energy certificate (REC) unbundling and trading, neighborhood effects, and trading restrictions. (2) Other RES-E policies, allowing for an examination of policy complementarities. (3) The effect of RPS on deployment of specific RES-E technologies, namely biomass, geothermal, solar, and wind. (4) Robustness checks that complement our regression results with a causal, nonparametric matching analysis.

The remainder of this paper is structured as follows. Section 2 provides a literature review. Section 3 presents our regression model. Section 4 discusses the variables as well as different datasets under consideration. Section 5 presents the results and discusses them. Section 6 concludes.

2 Literature Review

2.1 Samples

There are several quantitative studies that estimate the impact of RPS policies on renewable energy deployment in the U.S.: Alagappan et al. (2011), Carley (2009), Delmas and Montes-Sancho (2011), Dong (2012), Menz and Vachon (2006), Shrimali and Kneifel (2011), Yin and Powers (2010). Further, there is an emerging series of studies focusing on other regions. Marques et al. (2010; 2011) and Groba et al. (2011) study the effect of renewable energy policy in the EU. Salim and Rafiq (2012) conduct a similar study for several major emerging economies.

2.2 Models

With the exception of the descriptive analysis of Alagappan et al. (2011), all studies use some form of a time series cross-section regression model. Menz and Vachon (2006) run OLS regressions without fixed effects for a sample of 37 U.S. states over 5 years. Carley (2009), Dong (2012), Groba et al. (2011), Marques et al. (2010), and Yin and Powers (2010) control for time trends and state-level effects. Shrimali and Kneifel (2011) additionally control for state-specific time trends. Delmas and Montes-Sancho (2011) apply a two-stage regression – logit and tobit – to cover public choice variables such as the influence of private interest groups on policymaking. Marques et al. (2011) assess the impact of socio-economic factors on RES-E development with a quantile regression. Salim and Rafiq (2012) run modified and dynamic OLS regressions.

2.3 Policy Covariates

The level of sophistication to capture the impact of policies also varies broadly. Menz and Vachon (2006), Marques et al. (2010), Alagappan et al. (2011), and Dong (2012) use binary variables to represent the existence of renewable energy policies. Carley (2009) applies nominal variables to capture heterogeneity in policy design. Delmas and Montes-Sancho (2011) use the predicted probabilities of RPS adoption from their first stage regression as a covariate in the second stage regression. Shrimali and Kneifel (2011) use a “nominal” value of RPS stringency – also referred to as the annual RPS fraction – as reported in DSIRE (2012). Yin and Powers (2010) introduced the *incremental share indicator (ISI)* to quantify “the mandated increase in renewable generation in terms of the percentage of all generation” (Yin and Powers, 2010: 1142) of RPS policies. Groba et al. (2011) apply the *ISI* to an EU member countries sample.

We discuss the dependent variable selection the Section 4. Table 1 summarizes the research designs and major policy findings of previous econometric analyses.

Table 1 Relevant empirical studies of renewable energy policy effectiveness

Article	Sample	Time Frame	Model Type	Dependent Variable	Findings
Alagappan et al. (2011)	14 transmission providers	Summer 2010	- descriptive statistics	- RES-E capacity ratio	° FIT binary
Carley (2009)	48 U.S. states (without CA, TX)	1998-2006	- FE regression - FE vector decomposition regression	- log of non-hydro RES-E generation ratio - absolute non-hydro RES-E generation	* <i>RPS binary</i> * RPS trend * regional RPS *** <i>tax index</i> *** <i>financial incentive index</i> *** <i>deregulation binary</i>
Delmas and Montes-Sancho (2011)	650 U.S. utilities in 48 U.S. states (without AK, HI)	1998-2007	- 1st stage: logit - 2nd stage: tobit	- absolute RES-E capacity of utility	* <i>RPS binary</i> ** MGPO binary ** <i>predicted RPS</i> ** predicted MGPO * <i>DP binary</i> * <i>financial incentive index</i>
Dong (2012)	53 countries	2005-2009	- FE regression	- annual wind capacity - absolute wind capacity	** <i>RPS binary</i> * FIT binary
Groba et al. (2011)	26 EU member countries	1992-2008	- FE regression	- log of annual wind capacity - log of annual solar capacity	*** ROI ° ISI * <i>tender binary</i> * <i>tax binary</i>
Marques et al. (2010)	24 European countries	1990-2006	- FE regression - FE vector decomp.	- log of non-hydro RES-E generation ratio	* <i>EU 2001 binary</i>
Marques et al. (2011)	24 European countries	1990-2006	- OLS regression - quantile regression	- log of RES-E generation ratio	
Menz and Vachon (2006)	37 U.S. states (states with wind capacity)	1998-2003	- OLS regression	- absolute wind capacity in 2003 - growth after 1998/2000	** RPS binary ° GDR binary *** MGPO binary * <i>PBF binary</i> * <i>retail choice binary</i>
Salim and Rafiq (2012)	Brazil, China, India, Indonesia, Philippines, Turkey	1980-2006	- modified OLS - dynamic OLS - Granger causality	- absolute RES-E consumption	
Shrimali and Kneifel (2011)	50 U.S. states	1991-2007	- FE regression with state-year fixed effects	- capacity ratios: non-hydro RES-E, biomass, geothermal, solar, wind	* <i>RPS + capacity stringency</i> *** <i>RPS + sales stringency</i> * <i>GPP binary</i> *** MGPO binary *** CEF binary
Yin and Powers (2010)	50 U.S. states	1993-2006	- FE regression	- non-hydro RES-E capacity ratio	** ISI * <i>RPS binary</i> * <i>RPS trend</i> ** <i>RPS fraction</i> ** MGPO binary * <i>PBF binary</i> * <i>NM binary</i>

Black: positive impact; grey/italic: negative impact; Significance: *<1%, **<5%, *<10%, ° not statistically significant.** CEF: clean energy funds; DP: disclosure program; FIT: feed-in tariff; GDR: generation disclosure requirement; GPP: green power purchasing; ISI: incremental share indicator (RPS); MGPO: mandatory green power option; NM: net metering; PBF: public benefit funds; ROI: return on investment (FIT).

2.4 Results

Menz and Vachon (2006) find a significant positive effect of RPS policies on the development of wind capacity in the U.S. Since their model does not control for state characteristics and time

trends, one can argue that the findings are not accurate enough to actually make a statement about real impact of RPS policies. Menz and Vachon (2006) do not explain why a random effects model is appropriate, for example by a Hausman (1978) Test. In contrast, almost all other studies – including ours – have shown that state and year effects can be a major biasing factor.

Carley (2009) does not find a significant link between an RPS binary indicator and the share of electricity generated from RES-E in the U.S. Dong (2012), however, finds a negative and significant coefficient on the RPS binary indicator using cumulative wind capacity as the dependent variable. But, the coefficient is no longer significant when standard errors are clustered in a model that includes year trends, thus supporting the finding in Carley (2009). Carley (2009) also finds a positive and significant impact of an RPS trend variable, which represents the number of years since RPS enactment, on absolute generation. However, she shows that, after removing the state effects, the standard error on the RPS trend variable decreases, a finding which is consistent with state characteristics being an important driver of absolute RES-E deployment.

Yin and Powers (2010) show that a RPS binary indicator and RPS trend variable do not have a significant relationship with the percentage of RES-E capacity in the U.S., with the former supporting and latter contradicting Carley (2009). However, they estimate a negative and significant coefficient on the annual RPS fraction using the RES-E ratio as the dependent variable, a result that is also found in Shrimali and Kneifel (2011). They conclude that a more nuanced measure, the *ISI*, is needed to more accurately represent the stringency of RPS policies. In each of their regressions specifications, they find that the *ISI* variable has a positive and significant impact on renewable deployment. However, Groba et al. (2011) do not find a significant coefficient of RPS policies (as measured by the *ISI* indicator) in six EU member countries using wind and solar PV added capacities as dependent variables.

In summary, Yin and Powers (2010) is the only study (that we are aware of) that showed that RPS policies have positively impacted aggregate RES-E deployment. Nearly every other study has found either a negative or no connection between RPS policies and RES-E development. At the technology-specific level, Menz and Vachon (2006) found a positive effect of RPS policies on wind capacity. However, their model does not include fixed effects, and Shrimali and Kneifel (2011), using fixed effects, report an completely opposite result.

3 Empirical Model

The primary objective of this paper is to estimate the historical effect of RPS policies on development of in-state renewable energy deployment. We estimate this effect using a panel dataset enriched and improved relative to those used in previous studies. Following the theoretical approach outlined by Carley (2009), we estimate the capacity (and generation) development for renewable energy in state i in year t using the following model:

$$Y_{it} = \beta_0 + \beta_x X_t + \beta_p P_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (1)$$

where Y represents a measure of RES-E deployment calculated differently across specifications; β_0 is a constant; X represents a vector of social and economic variables that are expected to have an impact on RES-E deployment; and P is a vector of policy variables to control for policy effects, interactions between policies, and specific policy design elements aimed at encouraging RES-E deployment.

The proper estimation of this model requires addressing several econometric issues, as standard OLS estimation yields inconsistent or inefficient estimates. First, since we exploit a panel of individual states, unobserved state and year heterogeneity is likely and will lead to inconsistent estimates if not controlled. Therefore, we use a model controlling for state fixed effects, α , and time fixed effects, γ . While state fixed effects control for existing differences among states, such as renewable energy potential and existing renewable energy capacity (or generation), time fixed effects control for exogenous factors such as technological progress and macroeconomic trends that affect all states. A Hausman (1978) Test on each of the specifications rejects random effects, suggesting that a fixed effect specification is more appropriate in this context. Controlling for these effects and using clustered robust standard errors on the remaining error term, ε , accounts for heteroskedasticity.

4 Variables and Data

4.1 Renewable Energy Supply

4.1.1 Quantification

Previous econometric studies on the effectiveness of RES-E policies intended to stimulate state-level deployment differ with respect to the selection of the dependent variable. Quantifying RES-E deployment can be characterized along three dimensions. First, RES-E deployment can be measured in terms of capacity (watts) or actual generation (watt-hours). Second, multiple data sets on RES-E deployment are made available by the U.S. Energy Information Administration (EIA). State-level data can be aggregated from the raw EIA annual generator surveys – also referred to as the “generator-level dataset.” Alternatively, state-level aggregated RES-E data can be directly downloaded – we refer to this as the “state-level dataset”. Third, renewable energy can be quantified in absolute terms or as a percentage of total electricity capacity (generation). The characterization of RES-E dependent variables in previous studies is shown in Table 2.

Table 2 Dependent variable selection in previous studies

		Generation	Capacity
Relative (%)	Generator Level		Yin and Powers (2010)
	State Level	Carley (2009) <i>Marques et al. (2011)</i>	Shrimali and Kneifel (2011)
Absolute	Generator Level		Delmas and Montes-Sancho (2011)
	State Level	Carley (2009) <i>Groba et al. (2011)</i> Salim and Rafiq (2012)	<i>Dong (2012)</i> Menz and Vachon (2006)

The *italic* studies investigate EU member countries, while the other studies work with the U.S. sample. Delmas and Montes-Sancho (2011) compiled data for 650 utilities while the other studies use the state as their core unit of analysis. Salim and Rafiq (2012) analyzed RES-E consumption in six major emerging countries.

4.1.2 Sources

The U.S. Energy Information Administration (EIA) provides data for generation and capacity at both the state level and the generator level in the U.S. The EIA forms and documents that collect this data and their brief descriptions are shown in Table 3.

Table 3 EIA data sources

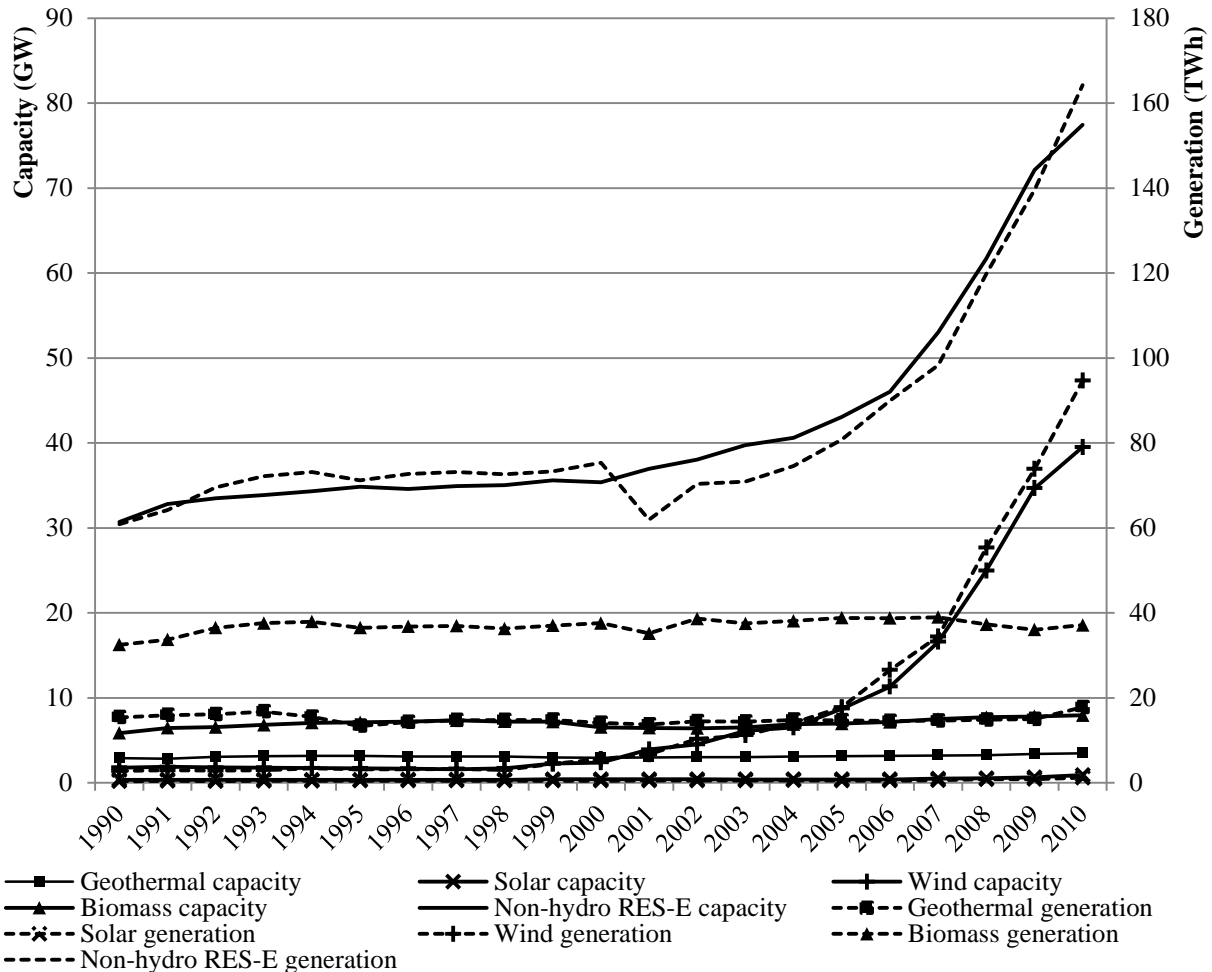
	Generation	Capacity
Generator-Level	EIA Form EIA-906, EIA-920, and EIA-923 Data <i>“The EIA-906, EIA-920, EIA-923 and predecessor forms provide monthly and annual data on generation and fuel consumption at the power plant and prime mover levels. A subset of plants, steam-electric plants 10 MW and above, also provides boiler level and generator level data.”</i> http://205.254.135.24/cneaf/electricity/page/eia906_920.html	EIA Form EIA-860 Annual Electric Generator Reports <i>“The Form EIA-860 is a generator-level survey that collects specific information about existing and planned generators and associated environmental equipment at electric power plants with 1 megawatt or greater of combined nameplate capacity.”</i> http://www.eia.gov/cneaf/electricity/page/eia860.html
State-Level	EIA Electric Power Annual <i>“Detailed State Data: 1990-2010: Net Generation by State by Type of Producer by Energy Source”</i> http://www.eia.gov/electricity/data/state/	EIA Electric Power Annual <i>“Detailed State Data: 1990-2010: Existing Nameplate and Net Summer Capacity by Energy Source, Producer Type and State”</i> http://www.geia.gov/electricity/data/state/

4.1.3 State-level data

Most studies use the state-level data of the total electric power industry’s RES-E generation and capacity that is provided by the EIA Electric Power Annual. However, some studies aggregate generator-level data, as provided in the forms EIA-860 and EIA-906, to compile the required dependent variables. Therefore, our task was to investigate whether the two approaches result in

similar datasets and hence similar results. Figure 1 presents aggregate and technology specific RES-E generation and capacity development.

Figure 1 State-level generation and capacity development



4.1.4 Aggregated generator-level data

Yin and Powers (2010) use generator-level data. However, aggregating 1990-2010 data from the EIA generator-level data we faced two major challenges related to data classification changes in 2001. First, the classification of sources in the EIA generator-level data changed for both generation and capacity. The changes in the EIA's classification scheme are complex and, despite our best efforts, are difficult to completely reconcile. Some changes are as simple as slight name changes (e.g. from "Anthracite" to "Anthracite Coal"), while other changes merged classifications (e.g. from "Plutonium" and "Uranium" to "Nuclear") or split classifications into two or more groups (e.g. from "Wood and Wood Waste" into "Wood Waste Solids" and "Wood Waste Liquids"). More difficult to reconcile changes are that dropped some sources from being

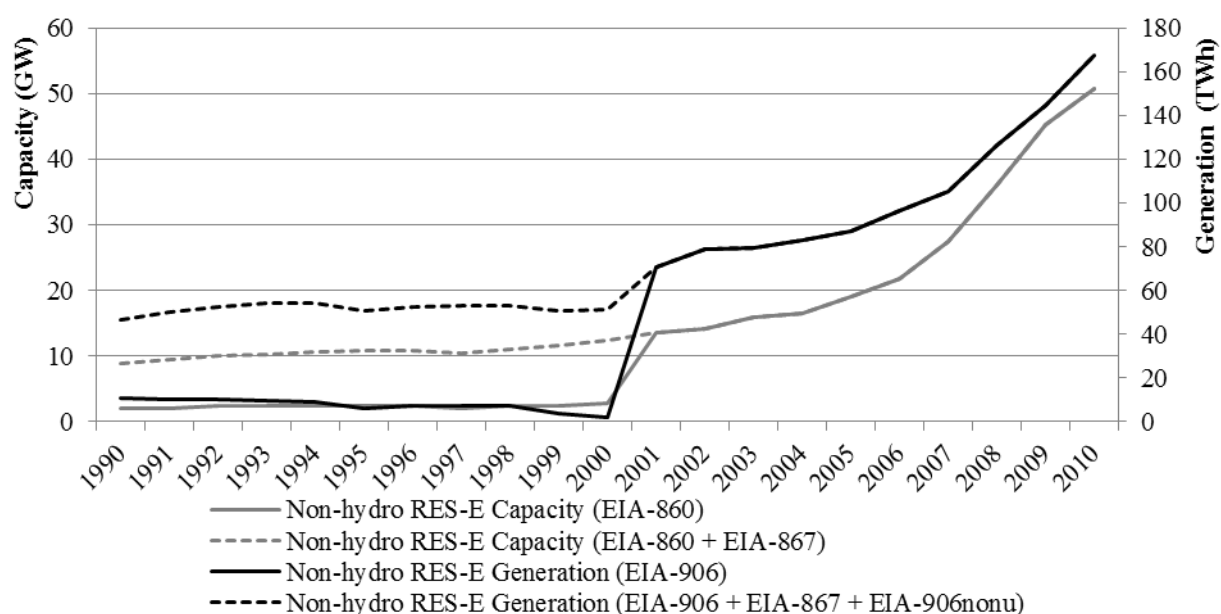
recorded at all (e.g. “Methanol”) or added new sources (e.g. “Agriculture Crop Byproducts/Straw/Energy Crops”). Table 16 in the Appendices shows the classification in annual reports from 1990 to 2000 in comparison to the classification in annual reports from 2001 to 2012.

Second, and more important, in addition to the changes in classification, in 2001 the EIA also included data for non-utility power generators in the EIA-906 and EIA-860 forms. However, this introduces an inconsistency – while the EIA-906/EIA-860 data contains both non-utility generators and utility generators starting with 2001, pre-2001 data only contains data for utility generators. We worked closely with EIA to synchronize the databases as much as possible.

Figure 2 presents the non-hydro generation (EIA-906) and capacity (EIA-860) data that does not account for the exclusion of non-utilities prior to 2001 as solid lines, whereas the dashed lines include the non-utility generators prior to 2001, using additional data from the EIA. This additional (i.e., non-utility generator) data for the years up to 2000 is from forms EIA-867 (for capacity) and EIA-906nonu (for generation) with some additional capacity data provided by EIA.

Comparing the solid and dashed lines, it is apparent that the sharp increase in the solid lines in 2001 is mainly caused by the exclusion of non-utility generators prior to 2001. The solid lines illustrate that generation and capacity as recorded by the EIA-906 and EIA-860 forms increase abruptly after 2000. When we add non-utilities data from 1990 to 2000, as shown by the dashed lines, this abrupt increase vanishes. The remaining inaccuracy between 2000 and 2001 is most likely caused by the changes in classification as outlined above.

Figure 2 Generator-level generation and capacity development



4.1.5 Consequences on previous findings

Yin and Powers (2010) is a unique study for two reasons: it used aggregated generator-level data and is the only econometric study to date that has demonstrated a robust positive impact of RPS policies on non-hydro RES-E deployment. Thus, its results require closer scrutiny, and they are questionable from two perspectives. First, the authors state that they use capacity as the dependent variable, and that the capacity data is compiled from the EIA-906 forms. However, EIA-906 collects generation data; EIA-860 collects capacity data. Second, it is not clear that they accounted for the non-utility generators prior to 2001. This omission may have resulted in misleading results: if we run a replication of their model with dependent variables that include the non-utility generator-level data prior to 2001, we find that the main conclusion of their paper is reversed. We discuss this issue in detail in Section 5.

4.2 Policy and Policy Feature Variables

In previous studies, RPS policies have mostly been represented by a dummy variable (*RPS Binary*) that equals 1 if an RPS is enacted and in enforcement and 0 otherwise. Carley (2009) provides an indicator which quantifies RPS policies by the number of years since policy implementation (*RPS Trend*). Yin and Powers (2010) provide an indicator which quantifies RPS policies by the yearly RES-E deployment requirement as a percent of total generation (*RPS Yearly Fraction*). Yin and Powers (2010) also introduced a more nuanced version of *RPS Yearly Fraction*, the *incremental share indicator (ISI)*. The *ISI* attempts to capture “the mandated increase in renewable generation in terms of the percentage of all generation” (Yin and Powers, 2010). The *ISI* is a metric for RPS policy stringency, and is constructed as follows for state i in year t with RPS enactment year T :

$$ISI_{it} = \frac{\eta_{it}^{RES} * \kappa_{it}^{RES} * q_{it}^{total} - Q_{iT}^{RES}}{q_{it}^{total}} \quad (2)$$

where η_{it}^{RES} represents the RPS’s requirement of RES-E generation as a percent of total electricity generation; κ_{it}^{RES} represents the percentage load capacity that is legally eligible to meet η_{it}^{RES} ; q_{it}^{total} represents annual total electricity generation; and Q_{iT}^{RES} represents the existing absolute RES-E generation in the year of RPS enactment. Data for the policy parameters has been provided by DSIRE (2012). We built the *ISI* in three different ways: first, using the generator-level dataset that was presumably used by Yin and Powers (2010), “*ISI (YP)*”; second, using the generator-level dataset without the erroneous 2001 “jump” in the data, “*ISI (GL)*”; and third, using the state-level dataset that has been used by many other studies, “*ISI (SL)*.”

In addition to the RPS variables above measuring the stringency of RPS policies (*RPS Binary*, *RPS Trend*, *RPS Yearly Fraction*, *ISI (YP)*, *ISI (GL)*, and *ISI (SL)*), we also collect binary variables to represent the existence of other RES-E policies: public benefit funds (PBF), net

metering policies (NM), and mandatory green power options (MGPO). We also interact these independent policies with *RPS Binary* to evaluate their impact if a RPS is already in place.

We go beyond most previous studies by also testing the impact of policy design on the effectiveness of RPS policies. We account for the following RPS features: The (i) alternative compliance payments (ACP) represents the penalty in \$ that an electricity supplier must pay for each MWh of RES-E its portfolio falls short of the mandated RPS quota. The (ii) maximum effective retail rate increase (MERRI) represents the highest possible percentage increase in the average retail rate after accounting for cost caps of the ACP (Wiser and Barbose, 2008). The (iii) unbundled REC trading binary indicates whether RECs are allowed to be traded separately from the renewable electricity from which they originate. If the binary equals 0, RECs can only be used in a bundle with the underlying power to meet the mandated RES-E quota. The (iv) allowance of REC trading binary indicates whether energy suppliers are allowed to trade RECs with other suppliers to meet their RES-E quota if they produce too many or too few RECs themselves. The (v) contracting mechanism binary indicates whether states provides incentives to encourage long-term investment in RES-E systems and reduce uncertainty over the return on investment in RES-E systems (Wiser and Barbose, 2008). These provisions range from contract duration requirements to credit protections and special funds.

Table 4 RPS features for states with a RPS effectively enacted in 2010

State with RPS	ACP (\$/MWh)	MERRI (%)	Unbundling	Trading	Contracting	DTX Index	DFX Index
AZ	0	100.0	0	0	0	0.5	0
CA	0	100.0	0	1	1	0.5	0
CO	0	1.7	1	1	1	0	0
CT	0	6.5	1	1	1	0	0.5
DE	400	16.3	1	1	0	0	1
HI	0	100.0	0	0	0	0	0
IL	0	1.4	1	0	1	0	0
MA	600	3.3	1	1	1	0	0.5
MD	400	2.1	1	1	1	0	0.5
ME	0	4.8	1	1	0	0	1
MN	0	100.0	1	0	0	0	0
MT	0	0.1	1	1	1	0.5	0
NH	160	8.3	1	1	0	0	0.5
NJ	711	10.6	1	1	0	0	1
NM	0	1.8	1	1	0	0.5	0
NV	0	100.0	1	1	1	1	0
NY	0	0.9	1	1	1	0.5	0
OH	450	100.0	0	1	0	0	0
PA	550	100.0	1	1	1	0	0
RI	0	6.4	1	1	1	0	0.5
WI	0	100.0	1	1	0	0.5	0
Count	7	21	17	17	11	7	8

State policymakers usually want new RES-E systems to be built in their state as the investment might come with various economic and political benefits (Schmalensee, 2011). Thus, some RPS schemes contain requirements that limit the geographical eligibility of RES-E to meet the RPS target (Wiser and Barbose, 2008). We build indices to capture these electricity delivery requirements. The (vi) delivery *to* regions index (DTX) captures if a state allows sharing the transmission inter-tie with out-of-state generators. The DTX index equals 0.5 if inter-ties are shared for some products in limited cases and 1 if all direct transmission inter-ties are shared. The (vii) delivery *from* regions index (DFX) captures the degree of flexibility to buy RES-E from out-of-state generators. The DFX index equals 0.5 for if generators in limited out-of-state areas are eligible to sell RECs into the state with the RPS and 1 for generators anywhere outside the region. These features (i)-(vii) only exist as elements of RPS policies, and not all RPS policies include all features. Data for the RPS features has been taken from DSIRE (2012) and Wiser and Barbose (2008). Table 4 shows which states with an RPS (in 2010) include these policy features (i)-(vii).

In some specifications, we use Yin and Power's (2010) RPS market size (RPSMS) control to capture the effect of the regional REC trading market size. The *RPSMS* (viii) is constructed as:

$$RPSMS_{it} = \frac{\sum_a^A (\eta_{at}^{RES} * \kappa_{at}^{RES} * q_{at}^{total} - Q_{at}^{RES}) * TRADE_{at}}{SALES_{it}} \quad (3)$$

with A representing the number of neighboring states a to state i ; $TRADE_{at}$ representing a binary code that equals 1 if out-of-state trading is allowed and 0 otherwise; and $SALES_{it}$ representing the total electricity sales. Data to construct the *RPSMS* was taken from EIA (2012a) and DSIRE (2012). In some specifications, we also follow Chandler (2009) and include the percent of neighboring states that have a RPS in place to control for cross-state effects using data from DSIRE (2012).

4.3 Controls

Our full model includes state and year fixed effects. State effects control for preexisting RES-E capacity and time-invariant characteristics such as renewable energy resource availability. Time effects control for federal economic and policy impacts, economic and technological developments that are invariant across states but affect the overall development of RES-E. In our initial regressions, we use the suite of controls mirroring Yin and Power's (2010) in order to provide comparable estimations. We control for:

- *State Income*, represented by the median income of a 4-person household in 1000 \$. We expect RES-E to increase more rapidly in wealthier states since they would be in the best position to absorb the additional costs involved in the shift from conventional to renewable energy production.

- *Electricity Price* represents the mean state electricity price in \$ cents/ kWh. High electricity prices may lower market barriers for RES-E by making them appear more cost-competitive, and support their deployment. On the other hand, high electricity prices may foster reluctance to add further burden to the electricity bills due to RES-E capacity development. We lag this variable once – as in Yin and Powers (2010) – in order to avoid reverse causality.
- *Import Ratio* controls for the imbalance between domestic sales and out-of-state power generation. Following Yin and Powers (2010), we quantify the import ratio as the percentage of net electricity imports and total electricity sales of the previous year. In order to reduce energy dependence, a high import ratio presumably advances domestic RES-E capacity building.
- The *LCV Score*, an index created by the League of Conservation Voters (LCV) that tracks the voting behavior of state-level representatives and senators on environmental issues.
- Data for the variables has been compiled from various EIA sources (see above), DSIRE (2012), the U.S. Census Bureau (2011), Wiser and Barbose (2008), Wiser et al. (2010), and the League of Conservation Voters (2011). Table 5 presents the summary statistics.

The state income and the electricity price variable distribution are skewed, potentially requiring taking logarithms. However, in order to keep the suite of controls as close to Yin and Powers (2010) as possible, we end up not logging the variables. Though we sacrifice some rigor for comparability of results, we feel that this is justifiable because the overall estimates do not change much. In the matching analysis in Section 4.1 we also introduce variables that measure the technical potential of renewables at the state level, calculated using GIS data (NREL, 2012). These variables are only used in this section and are described there.

Table 5 Summary Statistics

	Obs	Mean	Std. Dev.	Min	Max	Unit
RES-E Capacity Ratio (YP)	1050	1.46	3.02	0	23.93	%
RES-E Capacity Ratio (GL)	1050	2.00	3.40	0	23.93	%
RES-E Capacity Ratio (SL)	1050	4.31	4.86	0	27.59	%
RES-E Generation Ratio (YP)	1050	1.56	3.02	0	26.08	%
RES-E Generation Ratio (GL)	1050	2.42	3.69	0	26.08	%
RES-E Generation Ratio (SL)	1050	2.72	4.23	0	37.14	%
ISI (YP) ¹	1000	0.87	3.83	0	32.10	%
ISI (GL) ¹	1000	0.87	3.83	0	32.10	%
ISI (SL) ²	1000	0.87	3.83	0	32.10	%
RPS Binary	1050	0.09	0.29	0	1	Binary
RPS Trend	1050	0.32	1.21	0	11	Years
RPS Yearly Fraction	1050	0.97	4.10	0	33	%
Alternative Compliance Payments	1050	14.66	89.79	0	711	\$/MWh
Maximum Effective Retail Rate Increase	1050	0.03	0.17	0	1	%
Unbundled REC	1050	0.08	0.27	0	1	Binary
REC Trading	1050	0.08	0.27	0	1	Binary
Contracting Mechanism	1050	0.05	0.22	0	1	Binary
Delivery to Region Index	1050	0.02	0.11	0	1	0-0.5-1
Delivery from Region Index	1050	0.03	0.17	0	1	0-0.5-1
RPS Market Size	1050	2.27	9.56	0	93.08	%
Neighbors with RPS	1050	16.42	25.24	0	100	%
Public Benefit Fund	1050	0.18	0.38	0	1	Binary
Net Metering	1050	0.37	0.48	0	1	Binary
Mandatory Green Power Option	1050	0.04	0.19	0	1	Binary
State Income	1050	50.16	7.99	30.44	73.60	1000 \$
Electricity Price	1050	7.62	2.77	3.37	29.20	cents/kWh
Import Ratio	1000	-18.43	63.00	-301.11	99.87	%
LCV Score	1050	47.20	26.92	0	100	0-100 index

5 Results

Considering the attention that Yin and Powers (2010) has received in the literature evaluating the effectiveness of RPS policies (according to Google Scholar, the article has received 43 citations as of October 2012), we first attempt to replicate their results in Table 6 and Table 7. Table 8 presents regressions with the *ISI* covariate under additional specifications of the dependent variable. Table 9 shows the results from our basic specification that uses state-level capacity data. Table 10 uses RPS indicators (other than the *ISI*) that capture additional channels through which RPS may affect RES-E development. Table 11 presents similar regressions with a host of

² The three *ISI* variables appear to have the same summary statistics. This is partly due to rounding to two decimal points. Further, recalling that the *ISI* consists of the RPS yearly fraction, the coverage of the RPS, total electricity sales, and RES-E generation in the previous year, only the latter parameter differs between the *ISI (YP)* and the other two, *ISI (GL)* and *ISI (SL)*. In 2001, the year with the erroneous “jump” in the data that led us to distinguish between *GL* and *YP*, only Maine had a RPS effectively implemented. Thus, the difference between the three *ISI* variables is very small.

additional policy interactions. Table 12 highlights the effects of additional RPS policy features. Finally, Table 13 presents the technology-specific estimates.

5.1 Replication of Yin and Powers (2010)

Table 6 and Table 7 present regression results for a dataset that replicates one used by Yin and Powers (2010). As detailed in Section 4, this dataset includes the erroneous 2001 “jump” in the data. In each of the two tables, Specification (1) estimates the relationship between the *ISI* covariate and the dependent variables without any control variables. Specification (2) adds state fixed effects to remove time-constant state-level characteristics, such as renewable energy potential or past planning regimes. Specification (3) adds time fixed effects to remove state-invariant time bias in the error term. Specifications (4) and (5) incorporate other policy variables and socio-economic controls. These specifications also include both state and year fixed effects and clustered standard errors, as in Yin and Powers (2010). While Specifications (1)-(4) use data for 1990-2010, Specification (5) limits the dataset to 1993-2006 as in Yin and Powers (2010).

Table 6 Recreation of Yin and Powers (2010) with capacity ratio as dependent variable

	(1)	(2)	(3)	(4)	(5)
ISI (YP)	0.325*** (0.023)	0.311*** (0.026)	0.134*** (0.024)	0.160* (0.092)	0.190*** (0.042)
Public Benefit Fund Binary				0.411 (0.395)	0.085 (0.260)
Net Metering Binary				-0.564 (0.542)	0.157 (0.324)
Mandatory Green Power Binary				3.588** (1.557)	0.882 (1.297)
State Income				0.145*** (0.025)	0.078*** (0.022)
Electricity Price, lagged				-0.095 (0.309)	0.481* (0.284)
Import Ratio				0.010 (0.014)	-0.007 (0.008)
LCV Score				0.018** (0.008)	0.008* (0.005)
State Effects		yes	yes	yes	yes
Year Effects			yes	yes	yes
State Clusters (robust)				yes	yes
Time Frame	1990-2010	1990-2010	1990-2010	1990-2010	1993-2006
N	1,000	1,000	1,000	1,000	700
R-Squared	0.164	0.422	0.604	0.664	0.791

Standard errors in parentheses. The dependent variable is the percentage of RES-E capacity to total annual electricity capacity on the base of generator-level data without correcting for the 2001 inconsistency. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

The *ISI (YP)* has a positive and significant effect on RES-E capacity across all specifications, indicating that the *ISI* covariate appears to positively correlate with the share of renewable

capacity in the uncorrected dataset. The result is fairly robust across the six specifications shown in Table 6, although the specifications with state and time fixed effects and with controls estimate a lower impact of the *ISI* variable on RES-E capacity (Specifications 3-5). Under Specification (5), we re-estimate our model as closely as possible to Yin and Powers (2010), limiting the data to the time period used in Yin and Powers (2010), 1993-2006. Under this specification, the size of the impact marginally increases relative to Specification (4), which uses the full times series available to us. However, our estimate of the coefficient remains less than half of the estimate presented in Yin and Powers (2010).

In Table 7 we use generation as the dependent variable, and estimate regression coefficients that match more closely with the results presented in Yin and Powers (2010), despite the fact that Yin and Powers claim to be using capacity data. We estimate +0.394 for the *ISI* (*YP*) coefficient (with a standard error of 0.062) whereas Yin and Powers (2010) estimated the same coefficient at +0.558 (with a standard error of 0.175). While our estimate is within one standard error of the result in Yin and Powers (2010), we cannot precisely replicate their results. Given that our results for generation data match more closely to the results presented in Yin and Powers (2010), they support our hypothesis that Yin and Powers (2010) used generation data, not capacity, as claimed. This hypothesis is corroborated by Yin and Powers' reference to the EIA-906 forms which contain generation, not capacity, data.

However, when we repeat the exercise with either the generator-level dataset that corrects for the erroneous "jump" or the state-level dataset, we do not arrive at the same conclusion as Yin and Powers (2010). Table 8 summarizes our efforts to explore datasets that could lead us to the conclusions in Yin and Powers (2010). The table shows the coefficient on the *ISI* covariate when we regress different specifications of the dependent variable. The dependent variable varies by originating data source (either manually aggregated from generator-level data, "GL," or EIA-aggregated state-level data, "SL"); and by type (generation or capacity). Further, the SL data either measures total generation/capacity of the electric power industry, "SL-T"; or of electric utilities only, "SL-U." Finally, the GL data either includes the 2001 "jump," "GL-T*"; or corrects it by properly accounting for 2001 changes EIA classification methodology, "GL-T." A regression model with an identical set of controls as in is run on three different time frames: the full period for which data is available (1990-2010), the period after the change in classification in the generator-level data (2001-2010), and the period used by Yin and Power (1993-2006).

Table 7 Recreation of Yin and Powers (2010) with generation ratio as dependent variable

	(1)	(2)	(3)	(4)	(5)
ISI (YP)	0.534*** (0.019)	0.484*** (0.022)	0.351*** (0.020)	0.336** (0.137)	0.394*** (0.062)
Public Benefit Fund Binary				0.091 (0.394)	-0.163 (0.354)
Net Metering Binary				-0.236 (0.369)	0.344 (0.275)
Mandatory Green Power Binary				2.112** (0.960)	-0.103 (0.904)
State Income				0.057* (0.033)	0.038* (0.022)
Electricity Price, lagged				-0.156 (0.260)	0.259 (0.246)
Import Ratio				-0.015 (0.012)	-0.021* (0.013)
LCV Score				0.007 (0.007)	0.006 (0.006)
State Effects		yes	yes	yes	yes
Year Effects			yes	yes	yes
State Clusters (robust)				yes	yes
Time Frame	1990-2010	1990-2010	1990-2010	1990-2010	1993-2006
N	1,000	1,000	1,000	1,000	700
R-Squared	0.442	0.596	0.721	0.745	0.810

Standard errors in parentheses. The dependent variable is the percentage of RES-E generation to total annual electricity generation on the base of generator-level data without correcting for the 2001 inconsistency. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Table 8 The coefficient on ISI under different specifications of the dependent variable

Capacity			
	1990-2010	2001-2010	1993-2006
GL-T*	+ 0.160*	- 0.065	+ 0.190***
GL-T	- 0.106***	- 0.065	- 0.132***
SL-T	- 0.105***	- 0.089	- 0.158***
SL-U	- 0.153**	- 0.036*	- 0.134**
Generation			
	1990-2010	2001-2010	1993-2006
GL-T*	+ 0.336**	- 0.027	+ 0.394***
GL-T	- 0.015	- 0.027	- 0.061*
SL-T	- 0.116***	- 0.023	- 0.184***
SL-U	- 0.121	- 0.043	- 0.062

GL: generator-level; SL: state-level; T*: sample with 2000-2001 bias presumably used by Yin and Powers (2010); T: total electric power industry; U: electric utilities only. *Sources:* Capacity data: (GL-T*) from EIA-860A; (GL-T) from EIA-860A and EIA-867; (SL-T) from EIA Electric Power Annual; (SL-U) from EIA Electric Power Annual. Generation data: (GL-T*) from EIA-906; (GL-T) from EIA-906, EIA-867, and EIA-906nonu; (SL-T) from EIA Electric Power Annual; (SL-U) from EIA Electric Power Annual. The sign of the coefficients on the remaining control variables are the same as in Table 6 and Table 7, Specification (5) (Public Benefit Fund, Net Metering, Mandatory Green Power, State Income, Electricity Price, Import Ration, LCV Score). The sign of their coefficients remain the same throughout and is not reported here.

The key insight from this exercise is that the coefficient on the *ISI* is positive if and only if the 2000-2001 change in classification that exists in the GL data remains in the dependent variable (i.e. the GL-T* variable in the 1990-2010 and 1993-2006 time frames). All other specifications yield *ISI* coefficients that are negative, although only some are significant. In this set of specifications, RPS stringency only appears to have a positive and significant impact on RES-E when the incorrect generator-level dataset is used; when this error is corrected, the generator-level dataset yields results similar to those derived from state-level datasets. Therefore, going forward, we use state-level datasets only, as in Carley (2009), Menz and Vachon (2006), and Shrimali and Kneifel (2011).

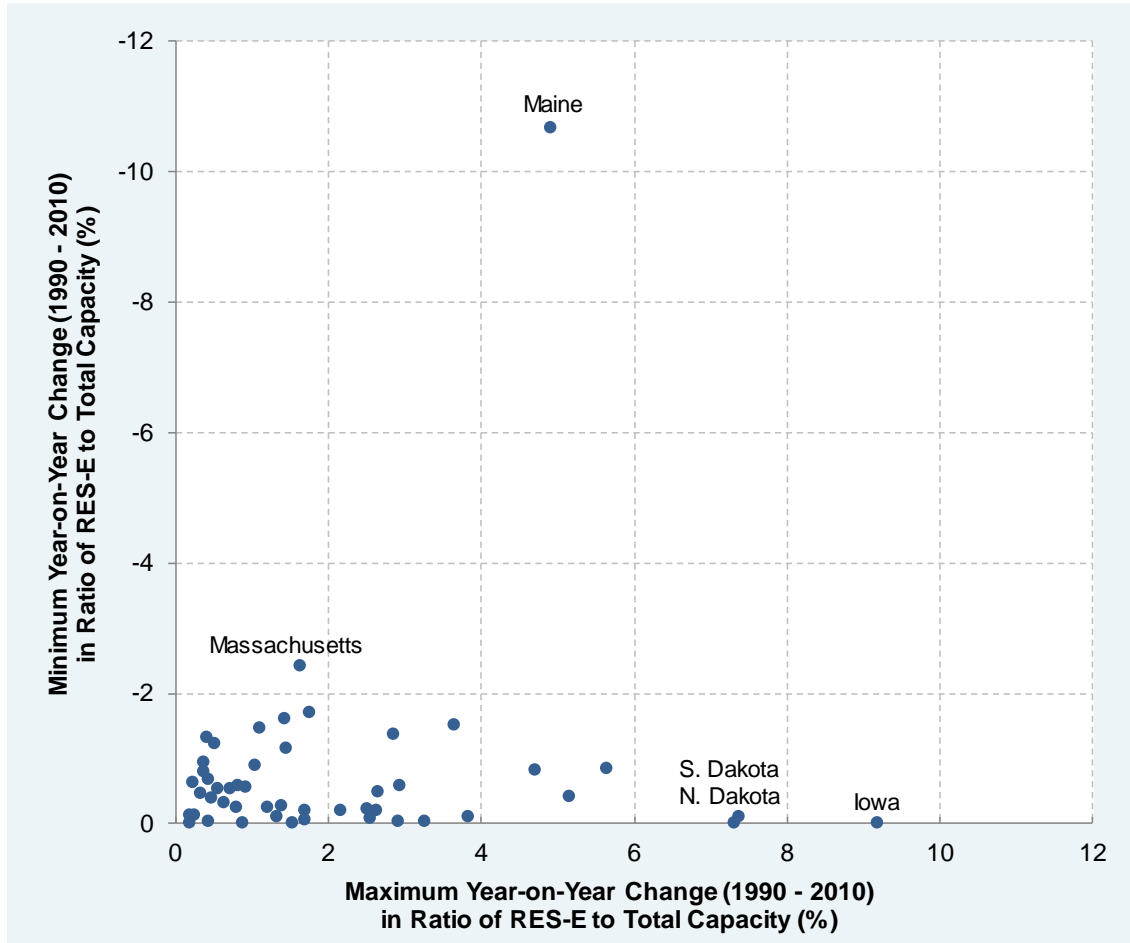
5.2 Maine: An Outlier

Figure 3 presents the range of year-to-year changes for RES-E capacity ratio for the 50 U.S. states over 1990-2010. Figure 5 in the Appendix provides the corresponding line plots by state. Both figures show that Maine's RES-E ratio appears to sharply decline from 1999 to 2000. This was due to the fact that, by the end of 1999, Maine added roughly 1,500 MW of natural gas capacity to its total capacity of roughly 3,000 MW. Thus, Maine's total electricity capacity increased by 50%, whereas its RES-E capacity remained relatively stable. As a result, the RES-E capacity ratio sharply decreased from 27% in 1999 to 16% in 2000.

This event in Maine seems to be unprecedented in the panel as no other states shows such an abrupt decrease. The uniqueness of the time series of electricity capacity in Maine is independently corroborated in the matching analysis in Section 5.7, where the matching algorithm performs the worst for Maine due to the inability to find suitable matches for Maine's unique RES-E ratio development.

We also calculated the interquartile range (IQR) and found that some of Maine's data points are greater – by a factor of more than 1.5 times the IQR – than the third quartile maximum. In line with the commonly used “1.5*IQR” criteria, we declare Maine to be an outlier in the sample. Henceforward, we will present our full regressions model on the base of the full sample and without Maine in order to test the robustness of our full model. Shrimali and Kneifel (2011) also followed a similar strategy.

Figure 3 Plot of maximum and minimum year-on-year change in RES-E capacity ratio



5.3 Our Model

Table 9 presents the results of our main model to measure the impact of the *ISI* variable, using the state-level dataset with and without state and year fixed effects and various controls. A Hausman (1978) test rejects the null hypothesis of consistent and efficient random effects, supporting the application of a fixed effects specification in this context. We also conduct a series of Wald and likelihood ratio tests. The tests confirm that heterogeneity is present in the panel, supporting our use of state and year fixed effects.

Specification (1)-(5) replicate the structure we used in Table 6 and Table 7. Specifications (1)-(3) present the results on only the *ISI*. Specification (2) adds state fixed effects, and Specification (3) adds year fixed effects. Specifications (4)-(6) include the full set of other policy variables and controls with clustered standard errors. Specification (5) uses the time frame from Yin and Powers (2010), 1993-2006. Finally, Specification (6) based on findings in Section 5.2 excludes the state of Maine. In Specification (1), we do not account for state-level heterogeneity in the random effects model and the *ISI* coefficient is estimated to be positive. This is suggestive

evidence of an omitted variable bias and inconsistent estimation, which we further confirm by means of a Hausman Test. Therefore, in the remaining specifications, we use a fixed effects model. Specifications (4) and (5), which also include a suite of control variables, we estimate a negative and significant coefficient for the *ISI (SL)* covariate. This result is also verified by a non-parametric match analysis in Section 4.7. Given that RPS is one of the most popular RES-E support policies, this finding is surprising.

Table 9 Basis model results with capacity ratio as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
ISI (SL)	0.411*** (0.038)	-0.042* (0.025)	-0.188*** (0.023)	-0.105*** (0.036)	-0.158*** (0.034)	-0.095 (0.069)
Public Benefit Fund Binary				0.593 (0.486)	0.277 (0.405)	0.394 (0.450)
Net Metering Binary				-1.058** (0.491)	-0.343 (0.313)	-1.126** (0.500)
Mandatory Green Power Binary				3.882*** (1.434)	2.437*** (0.841)	4.071*** (1.530)
State Income				0.118** (0.049)	0.046* (0.027)	0.121** (0.050)
Electricity Price, lagged				-0.268* (0.142)	-0.096 (0.200)	-0.265* (0.149)
Import Ratio				0.031*** (0.010)	0.014*** (0.003)	0.032*** (0.011)
LCV Score				0.019** (0.009)	0.010* (0.005)	0.018** (0.009)
State Effects		yes	yes	yes	yes	yes
Year Effects			yes	yes	yes	yes
State Clusters (robust)				yes	yes	yes
Time Frame	1990-2010	1990- 2010	1990-2010	1990-2010	1993-2006	1990-2010
N	1,000	1,000	1,000	1,000	700	980
R-Square	0.104	0.789	0.844	0.883	0.962	0.857

Standard errors in parentheses. The dependent variable is the percentage of RES-E capacity to total annual electricity capacity on the base of state-level data. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Three different explanations are possible for this counter-intuitive result. One possible explanation is that the RPS stringency by itself is not an adequate representation of the richness of an RPS policy, and specific RPS policy features, such as automatic compliance payment or regional trading, may cause RPS schemes to be more or less effective. A second related hypothesis is that more stringent RPS schemes have a positive effect on RES-E deployment overall but the new installations are not necessarily brought online inside the state. Since 17 of the 21 states that have a RPS effectively in place also allow trading of RECs, it could be that electricity suppliers import RES-E from out-of-state facilities in order to comply with the RPS requirement. This effect may be intensified with a more stringent RPS. We test these hypotheses in Section 5.5 by estimating the impact of RPS features--including the DFX index, which

measures the flexibility in meeting RPS targets via out-of-state sources, and regional characteristics such as the share of neighboring states with an RPS in place.

A third possible explanation is the presence of outlier states, such as Maine, as discussed in Section 5.2. We observe that the coefficient for *ISI* decreases in magnitude and becomes insignificant when we drop Maine in Specification (6).³ These results indicate that the negative and significant result on *ISI* in some specifications may be driven by Maine, so we include an additional specification that drops Maine from the most complete specification in each analysis moving forward.

The other coefficients remain robust and we interpret them next. We include a control for public benefit funds, employed in 16 states: CA, CT, DE, HI, IL, MA, ME, MI, MN, MT, NJ, OR, PA, RI, VT, and WI. We do not find a significant impact of these funds on RES-E deployment in Specifications (4)-(6). This is consistent with Menz and Vachon (2006) and Yin and Powers (2010).

We also control for the existence of mandatory green power options, employed in 8 states: CO, IA, ME, MT, NM, OR, VA and WA. We estimate a robust positive and significant coefficient across all model specifications. This is in line with Delmas and Montes-Sancho (2011), Menz and Vachon (2006), Shrimali and Kneifel (2011), and Yin and Powers (2010). Specifically, this policy seems to drive a 4 percentage point increase in the RES-E share in electricity capacity, as indicated in Specifications (4) and (6).

Net metering has been implemented in almost every U.S. state. It appears to have a sizeable negative effect on RES-E deployment in Specifications (4) and (6). We posit that the usual eligibility caps of net metering schemes at system sizes of less than 1MW and the EIA data coverage minimum at 1MW invalidate further interpretation. A more specific examination of the impact of net metering schemes is needed in future research.

We estimate a positive impact of state income on RES-E deployment. This might be expected, as wealthier states would be more willing to invest in renewable energy. Carley (2009) found a similar relationship and Groba et al. (2011) found a positive effect of GDP per Capita on annual wind capacity in Europe.

The coefficient for lagged electricity price is negative and significant at the 10% level in Specifications (4) and (6). This may be because high electricity prices make policymakers and utilities reluctant to incorporate expensive renewables that would further increase costs and therefore prices. Carley (2009) and Delmas and Montes-Sancho (2011) presented similar results, but Shrimali and Kneifel (2011) did not.

³ We performed an additional regression with logged (to correct for a skewed distribution) absolute renewable capacity as the dependent variable, with appropriate adjustment for the state-size by including the total electricity capacity as an independent variable. However, this regression also revealed a negative and non-significant result for *ISI*.

We also find a positive and significant link between electricity import ratio and RES-E capacity deployment. A potential interpretation is that producers may believe that switching from imported electricity to domestically generated renewable electricity will be more lucrative than continuing to buy power from other states. Marques et al. (2011) and Yin and Powers (2010) also found positive and significant links for similar covariates.

We estimate a positive and significant relationship between the LCV Score and RES-E capacity deployment in Specifications (4)-(6). This is consistent with the interpretation that a culture and political environment that is supportive of environmental and renewable energy policy may also promote the adoption of RES-E capacity through non-policy mechanisms. Carley (2009) also found a positive relationship between the LCV Score and RES-E generation.

5.4 Replication of Previous Studies

We now examine additional RPS indicators that have been proposed in previous studies (e.g., Carley, 2009; Yin and Powers, 2010; Shrimali and Kneifel, 2011). Table 10 Specifications (1)-(6) use the full sample, while Specifications (7)-(9) exclude Maine. All specifications apply state and year fixed effects and robust standard errors.

The interpretation of the coefficients on the RPS indicators in Specifications (1), (3) and (5), which use the complete dataset, can be interpreted as follows: the negative coefficient on the binary indicator in Specification (1) indicates that – all else equal – if a state without an RPS enacts an RPS, the ratio of RES-E capacity to total electricity capacity decreases by 0.98 percentage points. The negative coefficient on the *RPS Trend* variable in Specification (3) indicates that the ratio of RES-E to total electricity continues to decline by an additional 0.38 percentage points per year after an RPS is enacted. Finally, the coefficient on *RPS Yearly Fraction* in Specification (5) indicates that RPS policies that require one additional percent of renewable deployment decrease the ratio of RPS capacity to total electricity generation by 0.1 percentage points.

Specifications (1), (3), and (5) use the complete dataset and the full timeframe. Specifications (2), (4), and (6) examine many of the findings in the literature that used state-level data (i.e. Carley, 2009; Shrimali and Kneifel, 2011). In these cases, we use the complete dataset but adjust the timeframe to match time frames of previous studies. The reader should note two caveats. First, given that we kept the suite of independent control variables from our main analysis (Sections 5.1 and 5.3), they do not match previous studies exactly due to differences in data sources. For now, the reader should focus on the signs and standard errors of the RPS coefficients only. Second, note that because Specifications (1)-(6) include Maine, which we have shown to be an outlier, these results should be interpreted with caution. They are provided for comparison purposes only.

Table 10 Recreation of results on RPS indicators in previous studies with capacity ratio as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RPS Binary	-0.980* (0.583)	-1.401 (0.948)					-0.768 (0.586)		
RPS Trend			-0.376** (0.147)	-0.655*** (0.209)				-0.363** (0.184)	
RPS Yearly Fraction					-0.082** (0.040)	-0.096** (0.043)			-0.057 (0.061)
Public Benefit	0.547 (0.469)	0.146 (0.364)	0.568 (0.465)	-0.029 (0.281)	0.539 (0.484)	0.310 (0.413)	0.392 (0.450)	0.414 (0.449)	0.345 (0.446)
Fund Binary									
Net Metering	-1.054** (0.481)	-0.267 (0.262)	-1.062** (0.479)	-0.316 (0.271)	-1.055** (0.491)	-0.393 (0.343)	-1.092** (0.492)	-1.095** (0.490)	-1.115** (0.498)
Binary									
Mandatory	3.867*** (1.426)	1.850*** (0.569)	3.893*** (1.427)	1.787*** (0.580)	3.898*** (1.434)	2.929*** (0.784)	4.113*** (1.515)	4.005*** (1.528)	4.115*** (1.525)
Green Power Binary									
State Income	0.120** (0.048)	0.028 (0.033)	0.126** (0.049)	0.035 (0.037)	0.117** (0.049)	0.060** (0.028)	0.121** (0.050)	0.125** (0.050)	0.119** (0.050)
Electricity	-0.272* (0.142)	0.061 (0.147)	-0.231* (0.123)	0.025 (0.132)	-0.275* (0.145)	-0.141 (0.159)	-0.279* (0.149)	-0.230* (0.130)	-0.283* (0.157)
Price, lagged									
Import Ratio	0.033*** (0.009)	0.020*** (0.006)	0.031*** (0.009)	0.016*** (0.004)	0.032*** (0.010)	0.017*** (0.004)	0.032*** (0.011)	0.031*** (0.011)	0.032*** (0.011)
LCV Score	0.021** (0.009)	0.004 (0.007)	0.019** (0.009)	0.005 (0.008)	0.020** (0.009)	0.012** (0.006)	0.018** (0.009)	0.018** (0.009)	0.018** (0.009)
State Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
State Clusters (robust)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time Frame	1990-2010	1998-2006	1990-2010	1998-2006	1990-2010	1990-2007	1990-2010	1990-2010	1990-2010
N	1,000	450	1,000	450	1,000	850	980	980	980
R-Square	0.882	0.960	0.884	0.962	0.882	0.955	0.857	0.860	0.857

Standard errors in parentheses. The dependent variable is the percentage of RES-E capacity to total annual electricity capacity on the base of state-level data. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

We are able to recreate the results of past studies with moderate success. Specification (6), which attempts to replicate Shrimali and Kneifel (2011), finds a similar coefficient on *RPS Yearly Fraction*. This result remains relatively stable when the underlying period is changed from 1990-2007 to 1990-2010 in Specification (5). On the other hand, Specifications (2) and (4), which attempt to recreate the results in Carley (2009), achieve only partial success. Like Carley (2009), Specification (2) shows that the impact of *RPS Binary* is negative but insignificant. The result matches more closely with Carley (2009) when the period is extended from 1998-2006 to 1990-2010 in Specification (1). However, Specification (3) and Specification (4) are not able to replicate the positive coefficient of the *RPS Trend* variable in Carley (2009), perhaps because Carley (2009) used not only a different set of independent variables but also logged RES-E generation ratio as the dependent variable.

Overall, we estimate that for the three variables that previous studies have used as proxies for RPS policies, there is a negative and significant coefficient over the 1990-2010 timeframe. Once Maine is dropped from the sample, the coefficients on the binary and yearly fraction variables

become insignificant with increasing p values. The coefficient on the RPS variable is not significant at the 10% level without Maine in the sample. However, the trend variable remains negative and significant at the 5% level.

Given that the three RPS variables used here do not capture the full variation in incentives that different RPS policy designs create, we return to using the *ISI* for the rest of the paper.

5.5 Other Policies

We now examine policy interactions to analyze potential complementarities among policies (Table 12). Specification (1) and (3) replicate our main model and are identical to Specifications (5) and (7) in Table 9. Specifications (2) and (4) add interactions terms to (1) and (3), respectively. The interaction terms represent the simultaneous presence of an RPS and one of the other policies.

Table 11 Policy interaction results with capacity ratio as dependent variable

	(1)	(2)	(3)	(4)
ISI (SL)	-0.105*** (-0.036)	-0.074* (-0.038)	-0.095 (-0.069)	-0.050 (-0.069)
Public Benefit Fund (PBF) Binary	0.593 (-0.486)	0.713 (-0.501)	0.394 (-0.450)	0.494 (-0.455)
RPS x PBF Interaction		-0.586 (-0.581)		-0.469 (-0.539)
Net Metering (NM) Binary	-1.058** (-0.491)	-1.055** (-0.493)	-1.126** (-0.500)	-1.101** (-0.507)
RPS x NM Interaction		-0.139 (-0.550)		-0.322 (-0.523)
Mandatory Green Power (MGPO) Binary	3.882*** (-1.434)	4.072** (-1.880)	4.071*** (-1.530)	4.139** (-1.869)
RPS x MGPO Interaction		-0.851 (-1.947)		-0.336 (-1.817)
State Income	0.118** (-0.049)	0.119** (-0.050)	0.121** (-0.050)	0.122** (-0.050)
Electricity Price, lagged	-0.268* (-0.142)	-0.261* (-0.138)	-0.265* (-0.149)	-0.261* (-0.147)
Import Ratio	0.031*** (-0.010)	0.031*** (-0.010)	0.032*** (-0.011)	0.032*** (-0.011)
LCV Score	0.019** (-0.009)	0.019** (-0.008)	0.018** (-0.009)	0.018** (-0.009)
State Effects	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes
State Clusters (robust)	yes	yes	yes	yes
Time Frame	1990-2010	1990-2010	1990-2010	1990-2010
N	1,000	1,000	980	980
R-Square	0.883	0.883	0.857	0.858

Standard errors in parentheses. The dependent variable is the percentage of RES-E capacity to total annual electricity capacity on the base of state-level data. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Previous results on individual policy effectiveness estimated in Table 9 hold when interactions are included. Again, after dropping Maine from the sample, we fail to establish a significant link between the *ISI* and RES-E capacity at the 10% level. Further, we observe that the simultaneous presence of an RPS and a public benefit fund, net metering, or green power option does not significantly impact the RES-E share. RPS policies do not appear to gain or lose strength by having these other policies in place.

5.6 RPS Features

We now investigate if individual RPS policy design features not included in the *ISI* impact the efficacy of RPS (Table 13). Specifications (1) and (2) examine the effect of individual RPS features excluding the suite of controls with and without fixed effects and robust errors specifications. Specification (3) runs the full model with controls. Specification (4) drops the REC Trading Binary as it strongly correlates with the Unbundled REC Binary. Specification (5) drops Maine from the sample.

We observe that the inclusion of other RPS features renders the *ISI* coefficient insignificant whenever Maine is included in the sample, with the apparent negative impact observed in previous analysis now attributed to other RPS features, such as DFX (Specification 4). Upon dropping Maine in Specification (5), the *ISI* coefficient becomes positive and statistically significant at the 5% level. This result implies that every 1% increase in RPS stringency results in an approximately 0.3% increase in renewable share. In other words, once we 1) include a full set of controls, 2) incorporate information about both RPS stringency and other RPS design features, and 3) drop the outlier state of Maine from the sample, we find a positive and statistically significant effect of RPS stringency on RES-E deployment. This is the most complete specification in the paper. However, it must be considered with caution given that 1) many RPS features may have a moderately high correlation with the *ISI* and 2) the results are not particularly robust to small changes in specification.

The MERRI variable, which captures the maximum allowed electricity rate increase due to RPS, is not significant in the full model once fixed effects are included, but it is consistently negative and becomes significant after dropping Maine in Specification (5). Thus, we can assert with reasonable confidence that the MERRI variable has a negative impact on renewable share. This is probably because limits on the increase in electricity rates puts downward pressure on RPS compliance, as suppliers are allowed to hold back on meeting RPS targets if the cost of doing so becomes exorbitant.

The unbundled REC binary, which captures whether RECs are allowed to be traded separately from the underlying power, positively affects the renewable share. In fact, the magnitude is large – greater than 2% – which is consistent with the hypothesis that the flexibility provided by unbundling has a positive impact on renewable share. Unbundling seems to support RES-E deployment by bypassing geographical constraints of power delivery in order to achieve greater RPS compliance, as intended (Wiser and Barbose, 2008).

Table 12 Results for RPS features with capacity ratio as dependent variable

	(1)	(2)	(3)	(4)	(5)
ISI (SL)	1.143*** (0.133)	0.035 (0.074)	0.015 (0.090)	0.017 (0.090)	0.281** (0.117)
Alternative Compliance Payments (ACP)	0.014*** (0.003)	0.001 (0.002)	0.000 (0.002)	-0.000 (0.002)	0.001 (0.001)
MERRI	-4.712*** (1.537)	-2.589** (1.087)	-1.187 (0.902)	-1.343 (0.832)	-2.020*** (0.668)
Unbundled REC Binary	-2.544 (1.562)	2.344* (1.279)	2.792*** (1.033)	2.330*** (0.874)	2.581*** (0.804)
REC Trading Binary	4.080* (2.082)	0.794 (1.372)	-1.027 (1.234)		
Contracting Mechanism Binary	1.517 (1.208)	-1.443** (0.667)	-1.276** (0.534)	-1.442** (0.573)	-1.789*** (0.594)
Delivery to Regions Index (DTX)	1.145 (2.605)	1.166 (1.513)	0.902 (1.154)	0.637 (1.221)	1.036 (1.173)
Delivery from Regions Index (DFX)	-14.170*** (2.855)	-7.632*** (1.550)	-4.325*** (1.641)	-4.781*** (1.554)	-6.080*** (1.369)
RPS Market Size	-0.248*** (0.049)	-0.060** (0.027)	-0.027 (0.030)	-0.033 (0.031)	-0.090*** (0.030)
Neighbors with RPS	0.014** (0.007)	0.022* (0.012)	0.017* (0.010)	0.017* (0.010)	0.023** (0.010)
Public Benefit Fund Binary			0.522 (0.548)	0.494 (0.541)	0.117 (0.465)
Net Metering Binary			-1.101** (0.481)	-1.093** (0.481)	-1.134** (0.484)
Mandatory Green Power Binary			3.823** (1.512)	3.787** (1.503)	4.260*** (1.579)
State Income			0.111** (0.047)	0.108** (0.047)	0.104** (0.047)
Electricity Price, lagged			-0.189 (0.137)	-0.185 (0.136)	-0.168 (0.135)
Import Ratio			0.030*** (0.010)	0.030*** (0.010)	0.031*** (0.011)
LCV Score			0.014* (0.008)	0.013 (0.008)	0.009 (0.008)
State Effects		yes	yes	yes	yes
Year Effects		yes	yes	yes	yes
State Clusters (robust)		yes	yes	yes	yes
Time Frame	1990-2010	1990-2010	1990-2010	1990-2010	1990-2010
N	1,000	1,000	1,000	1,000	980
R-Square	0.141	0.857	0.889	0.889	0.867

Standard errors in parentheses. The dependent variable is the percentage of RES-E capacity to total annual electricity capacity on the base of state-level data. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

The REC contracting variable, which captures state-provided provisions to encourage long-term investment in RES-E systems, has a negative and significant effect on RES-E ratio in Specifications (3)-(5). These provisions may not have had the desired effect in the short run. However, as there are large planned capacities in the U.S. – e.g. 3.2 GW of mostly large-scale solar PV projects being realized in 2012 (SEIA, 2012) – the real effect of the long-term provisions may not yet be captured in the data.

The delivery-from-region index, which captures the degree of flexibility on where electricity is delivered from (i.e. in-state only vs. limited out-of-state areas vs. any out-of-state area), seems to have a negative impact on renewable share. This implies that states granting their energy suppliers greater flexibility on where to buy RES-E have a lower in-state RES-E deployment ratio than states that strictly limit the eligible area. This result could be explained by electricity suppliers benefitting from the option to choose RES-E imports from presumably cheaper producers over local RES-E capacity building.

The neighbors with RPS variable, which captures the percentage of neighboring states that have an RPS policy in place, seems to have a statistically significant and positive impact on renewable share. This provides evidence of network effects: if a state's neighbors have implemented RPS policies, it may create a better environment (e.g. through improved infrastructure) for renewable development in the region. This result, combined with the previous result on delivery-from-region index, adds credibility to the hypothesis in Section 5.3 that more ambitious RPS policies may actually be driving out-of-state deployment of RES-E instead of in-state deployment.

The RPS market size variable, which captures the size of the market that the RECs generated in a state can be sold into, appears to have a negative effect that only becomes significant after dropping Maine. Yin and Powers (2010) also found a negative but insignificant link using a similar variable.

Synthesizing the three coefficients just discussed – the positive effect of the neighbors-with-RPS variable and the negative effect of the RPS market size variable and delivery-from-region index – provides evidence of an inter-state trading effect. The existence of RPS policies in neighboring states supports in-state RES-E deployment. However, once cross-border trading is allowed and the trading zone becomes larger, in-state deployment appears to decrease in most states in favor of RES-E installations in a few states. That is, RES-E production can move to the most attractive places. This effect is accelerated once trading restrictions are removed, as shown by the delivery-from-region index.

Allowing REC trading does not appear to have a significant impact. Further, the variable is highly correlated with the unbundling covariate and is therefore not well identified. Thus, we drop the REC trading variable from Specifications (4) and (5). The correlation between REC trading and unbundling makes sense, as the allowance to unbundle RECs from the underlying energy requires the allowance to trade RECs in the first place. Finally, neither the ACP, which captures the amount of financial penalties that are levied on responsible parties in case of non-compliance, nor the delivery-to-region index, which captures the strictness of requirements

placed on where the underlying electricity is delivered to, seem to have a statistically significant impact on renewable share.

5.7 Technology Analysis

Similar to Section 5.5, we now examine the impact of RPS and other policies on the capacity of specific RES-E technologies: biomass, geothermal, solar, and wind. Table 13 presents the key results. Specification (1) presents the results from the RES-E (i.e., total non-hydro renewable capacity) model. The technology-specific results in Specification (2)-(5) can then be compared to the RES-E results. Because of the dominant share of biomass in total renewable energy capacity, we split the biomass regression into Specification (2A) and (2B), with the latter excluding Maine.

Table 13 model results with technology-specific capacity ratios as dependent variables

	RES-E	Biomass		Geothermal	Solar	Wind
	(1)	(2A)	(2B)	(3)	(4)	(5)
ISI (SL)	-0.105*** (0.036)	-0.106** (0.052)	0.001 (-0.012)	-0.008 (0.007)	0.002 (0.003)	0.001 (0.041)
Public Benefit Fund (PBF) Binary	0.593 (0.486)	0.547** (0.243)	0.323*** (-0.104)	-0.026 (0.044)	-0.024 (0.018)	0.151 (0.353)
Net Metering (NM) Binary	-1.058** (0.491)	0.068 (0.125)	0.063 (-0.115)	-0.014 (0.018)	0.019 (0.012)	-1.095** (0.433)
Mandatory Green Power (MGPO) Binary	3.882*** (1.434)	-0.002 (0.176)	0.198 (-0.147)	0.025 (0.025)	-0.001 (0.016)	3.834*** (1.473)
State Income	0.118** (0.049)	0.017* (0.010)	0.013 (-0.011)	-0.002 (0.001)	-0.000 (0.001)	0.104** (0.048)
Electricity Price, lagged	-0.268* (0.142)	0.081 (0.056)	0.013 (-0.016)	0.002 (0.011)	0.003 (0.003)	-0.292 (0.181)
Import Ratio	0.031*** (0.010)	0.007** (0.003)	0.003** (-0.002)	-0.000 (0.000)	0.000 (0.000)	0.023** (0.010)
LCV Score	0.019** (0.009)	0.002 (0.002)	0.000 (-0.002)	0.001 (0.000)	0.000 (0.000)	0.013* (0.007)
State Effects	yes	yes	yes	yes	yes	yes
Year Effects	yes	yes	yes	yes	yes	yes
State Clusters (robust)	yes	yes	yes	yes	yes	yes
Time Frame	1990- 2010	1990- 2010	1990- 2010	1990- 2010	1990- 2010	1990- 2010
N	1,000	1,000	980	1,000	1,000	1,000
R-Square	0.883	0.968	0.943	0.986	0.794	0.608

Standard errors in parentheses. The dependent variable is the percentage of RES-E, biomass, geothermal, solar, or wind capacity to total annual electricity capacity on the base of state-level data. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

In general, the regressions with biomass turn out to be similar to the full model results in Section 5.4. Since biomass capacity is by far the largest among all RES-E capacities, we argue that biomass deployment potentially drives the result on *ISI* in Specification (1): *ISI* has a significant

negative effect on biomass deployment but no significant effect on any of the other technologies. That is, the negative impact of *ISI* on total renewable share is driven by the corresponding impact on biomass. However, after excluding Maine, the significance disappears for biomass in Table 13. Again, the outlier seems to bias the coefficient of the full sample.

The presence of a public benefit fund has a statistically significant positive impact on biomass deployment, which is consistent with the hypothesis that biomass-burning power plants have been the principal beneficiaries of this policy.

On the other hand, the results on net-metering and mandatory green power option seem to be driven by wind. This result demonstrates the need to explore the impact of policies on individual renewable technologies; given that the corresponding analysis for total RES-E capacity may not be nuanced enough to detect underlying impacts. We estimate a significant negative coefficient on the existence of net metering for wind development and insignificant coefficients for biomass and solar capacity. Mandatory green power options have a statistically significant positive effect on wind capacity development, but no apparent effect on other technologies. Hence, the presence of an MGPO policy appears to benefit wind power development that in turn determines the MGPO coefficient in the regression with total renewable share as the dependent variable. State income has robust positive and significant effect throughout the model specifications.

Table 13 shows that the overall *ceteris paribus* effect of income on RES-E capacity can be narrowed down to strong positive effects on wind capacity and a small positive – albeit less significant – effect on biomass capacity. This is consistent with the hypothesis of wealthier states being more able to invest in wind parks with high upfront costs. The import ratio – a proxy for state energy dependence – shows a similar pattern. Biomass and wind capacity development is positively affected by an increase in electricity imports over exports. However, the effect on other technologies is very small.

5.8 Estimation of State-Level Causal Effects of RPS Enactment

So far, we have used regression adjustment and fixed effects to estimate causal effects in a parametric fashion that relies on conventional assumptions on the functional form of the response function. We now estimate state-level effects of enacting an RPS on future RES-E capacity deployment without any functional form assumptions. Rather than controlling for covariates that may drive RES-E development, we match states on important characteristics to develop causal estimates of the effect of enacting an RPS. This allows us to estimate effects of the RPS on individual states rather than average effects for all states. Further, these estimates have causal interpretations (Rubin, 2006).

In the matching framework, we define enactment of an RPS as a “treatment” and therefore we have 21 treated units (i.e., states) and 29 control units that never enact an RPS. We use six covariates to create matched synthetic control units. As in Abadie, Diamond, and Hainmueller (2010), we match on pre-treatment values of the dependent variable. We include the ratio of solar and wind technical potential (NREL, 2012) to total generation in pre-treatment years to

account for renewable energy development effort prior to enacting an RPS. We also include three demographic variables – per -household income, GDP growth, and population growth – in the 5 years prior to enacting an RPS to account for various socioeconomic factors that may affect how renewable deployment in a state may be affected by adopting an RPS. The matching covariates that we use to create synthetic controls are summarized in Table 14.

Table 14 Matching covariates

Variable	Years Matched On
State-level capacity ratio of RES-E to total electricity	1990 – year before RPS enacted
Ratio of solar energy technical potential to total generation	1990 – year before RPS enacted
Ratio of wind energy technical potential to total generation	1990 – year before RPS enacted
Per-household income	1 – 5 years prior to RPS enactment
GDP growth rate	1 – 5 years prior to RPS enactment
Population growth rate	1 – 5 years prior to RPS enactment

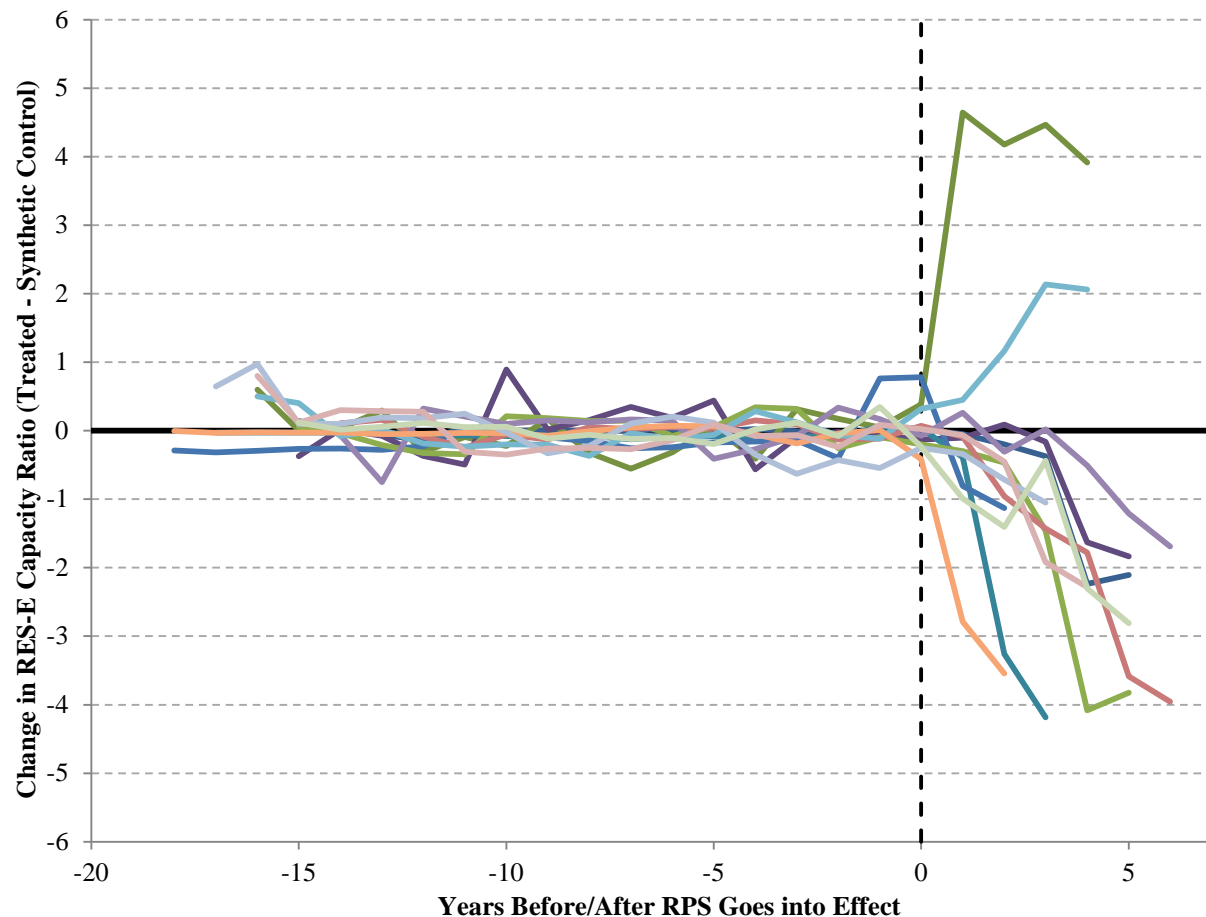
We run the synthetic control algorithm described in detail in Abadie, Diamond, and Hainmueller (2011) to find optimal control units. For each of the 21 states that implement an RPS between 1990-2010, the optimal synthetic control unit is defined as the convex combinations of the 29 control units that minimize the distance (mean squared prediction error) between the treated and control unit during the pre-treatment period on the matching covariates listed in Table 14. Some of the treated states cannot be matched well with a synthetic control unit. We drop states that differ from their optimal synthetic control by two percentage points in the dependent variable during their pre-treatment period. These states are CA, HI, MA, ME, MN, MT, NH, NM. Notably, Maine differs from its optimal synthetic control unit by the largest amount, 12.5 percentage points – this provides complementary evidence for dropping Maine in the regressions described in Section 5. Causal effect estimates are the difference in the outcome variable (RES-E ratio) in the post-treatment period between the treated unit and the weighted average of the control units, where the weights are given by the synthetic control algorithm. Annual causal effect estimates for the thirteen individual states that we are able to find suitable synthetic control matches for are displayed in Table 15. The values in Table 15 are presented graphically in Figure 4.

Table 15 State-level causal effect estimates of RPS enactment

	Years Relative to RPS Enactment																
	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
AZ	0.00	0.01	0.00	0.01	0.02	-0.01	0.02	-0.01	-0.10	0.01	0.02	-0.05	-0.20	-0.37	-2.23	-2.11	
CO	-0.22	0.17	-0.32	-0.56	-0.32	0.06	-0.41	0.32	0.18	0.05	0.38	4.64	4.18	4.46	3.91		
CT	0.90	0.02	0.15	0.35	0.19	0.44	-0.56	-0.10	-0.02	-0.07	-0.13	-0.10	0.09	-0.16	-1.63	-1.84	
DE	-0.08	-0.08	-0.08	-0.12	-0.09	-0.08	-0.08	-0.08	-0.10	0.06	0.04	-0.39	-3.26	-4.18			
IL	0.03	-0.10	-0.15	-0.25	-0.24	-0.17	-0.16	-0.14	-0.40	0.76	0.78	-0.81	-1.13				
MD	0.21	0.18	0.14	0.15	-0.07	0.05	0.34	0.32	-0.26	-0.09	-0.20	-0.30	-0.46	-1.46	-4.08	-3.82	
NJ	-0.06	-0.13	0.05	0.02	0.05	0.03	0.15	0.10	-0.13	-0.12	0.07	-0.09	-0.96	-1.43	-1.78	-3.58	-3.95
NV	0.10	0.15	0.12	0.17	0.15	-0.41	-0.27	-0.08	0.34	0.17	-0.07	0.26	-0.31	0.02	-0.51	-1.21	-1.69
NY	-0.20	-0.20	-0.37	-0.03	-0.13	-0.06	0.29	0.12	-0.06	-0.12	0.32	0.45	1.17	2.13	2.06		
OH	-0.04	-0.08	-0.01	0.05	0.07	0.06	-0.06	-0.19	-0.04	0.01	-0.41	-2.79	-3.55				
PA	-0.03	-0.33	-0.22	0.10	0.21	0.12	-0.35	-0.63	-0.43	-0.55	-0.25	-0.34	-0.71	-1.05			
RI	-0.35	-0.26	-0.25	-0.27	-0.14	0.09	-0.08	-0.07	-0.24	0.09	0.02	-0.06	-0.45	-1.92	-2.28		
WI	0.06	-0.11	-0.06	-0.12	-0.10	-0.20	0.02	0.12	-0.08	0.35	-0.23	-0.99	-1.40	-0.44	-2.30	-2.81	
AVG	0.02	-0.06	-0.08	-0.04	-0.03	-0.01	-0.09	-0.02	-0.10	0.04	0.03	-0.04	-0.54	-0.40	-0.98	-2.56	-2.82

Differences in the state-level capacity ratio of RES-E to total electricity of states that enact an RPS relative to their synthetic control unit. Values in the grey columns with negative headers help assess the quality of the matches: the closer these values are to zero, the better the match. Treated states that differ from their synthetic control unit in the dependent variable by more than 2 percentage points in any pre-treatment year are dropped from the table. Dropped states are CA, HI, MA, ME, MN, MT, NH, NM.

Figure 4 State-level causal effect estimates of RPS enactment



For eleven of the thirteen states that we assess, the estimated causal effect of enacting an RPS is negative in the most recent year of data, 2010. Causal effect estimates are only positive in 2010 for Colorado and New York. Two years after RPS enactment, the mean causal effect estimate is a decrease of 0.5 percentage points. Four years after RPS enactment, the mean causal estimate doubles to a decrease of 1.0 percentage points. The largest negative effect is for Delaware in 2010, a 4.2 percentage point drop in the outcome variable three years after enacting an RPS. Given that the average value of RES-E over all states and in all years is 4.3 percent, these are economically significant effect estimates. The sign and magnitude of this effect is consistent with the negative effects we estimate in Table 9 and Table 10. It suggests that renewables are being deployed in states with and without RPS's but, on average, states that do not use an RPS appear to have deployed renewables more rapidly, perhaps by finding ways to deploy renewables through means other than an RPS. However, this analysis does not incorporate information about RPS policy design features or inter-state trading effects. Instead, it considers an RPS policy to be a binary "treatment" that is either in place or not. Therefore, these matching results do not contradict our findings in Table 13.

6 Conclusion

Renewable portfolio standards (RPS) are considered a key policy instrument in the U.S. for promoting renewable energy deployment. More than 30 states have adopted an RPS, yet it remains unclear whether these policies have been effective in practice. The existing empirical literature on RPS has been contradictory, with studies finding all possible impacts ranging from negative (Shrimali and Kneifel, 2011) to none (Carley, 2009) to positive (Yin and Powers, 2010). Our work brings existing literature into a common empirical and econometric framework by closely identifying the sources of differences and attempting to reconcile them.

We find that most of the differences in results of previous studies may be due to the use of different datasets and RPS indicators. We are able to reconcile most of these differences while introducing a more advanced set of controls that explains much of the difference between effective and ineffective RPS policies. Specifically, while we find a negative or insignificant impact of RPS on RES-E deployment in most of our basic specifications, it appears to be driven by measureable factors including the presence of outlier states in our sample, the influence of other RPS features, and inter-state trading effects. When we account for these factors, the effect of RPS stringency on RES-E appears to turn positive but with substantial caveats.

We have introduced a fairly complicated set of results, so here we summarize the key takeaways from each step in our analysis:

First, we examine the results of Yin and Powers (2010), who found that RPS stringency has a positive and significant impact on RES-E deployment. Their study was unique because it included a measure of RPS stringency (*ISI*) that incorporated information about policy design and market context. Previous studies had used binary variables or simple nominal variables representing RPS strength and had found a consistently insignificant or negative effect of RPS on

RES-E. We are able to replicate the significance and direction of Yin and Powers' *ISI* coefficient (but not its magnitude) as well as most of the results from other previous studies.

Second, we correct for the erroneous 2001 “jump” in the data presumably used by Yin and Powers (2010). This reverses their results, causing the coefficient on *ISI* to become negative and significant. This is consistent with the negative impact of RPS found in Shrimali and Kniefel (2011) and is driven primarily by biomass.

Third, we show that this negative result is largely attributable to Maine, which is an outlier. Once Maine is removed from the sample, it appears that *ISI* actually has no effect on RES-E deployment in most specifications. This is consistent with the insignificant results found by Carley (2009). Our matching analysis (which is not affected by Maine) nonetheless finds a negative effect of RPS on RES-E that is growing over time. However, the matching analysis is inconclusive because it employs a binary RPS variable only and does not account for policy design features.

Fourth, in our most complete analysis we account for a more extensive list of RPS design features, market characteristics, and inter-state trading factors than in any previous analysis while also including those used in Yin and Powers (2010). When Maine is dropped from the sample and this full list of controls is included, we find a positive and significant effect on RPS stringency and significant coefficients on several other new variables. Specifically, our results imply that every 1% increase in RPS stringency results in an approximately 0.3% increase in renewable share. Thus, it appears that much of the negative or insignificant effect of RPS stringency in more basic specifications is actually explained by other RPS features. However, this result comes with many caveats, as it is not robust to relatively small changes in specification.

In sum, the experience of U.S. states has shown that enacting a strong RPS does not guarantee an increase in RES-E. In some cases, RPS may be better thought of as a “floor” to RES-E investment rather than a driver of investment. However, we have identified and analyzed several policy design features, market characteristics, and trading effects that may explain much of the difference between effective and ineffective policies. Our study is the most advanced to date in parsing out those factors.

One important contribution is that we identify and begin to quantify an inter-state trading effect. The presence of RPS policies in neighboring states supports in-state RES-E deployment, but as cross-border trading is allowed and the trading zone becomes larger, in-state deployment appears to decrease in most states and concentrate in a few states—presumably where it is most cost-effective. This effect is increased in states with fewer trading restrictions. We also find that REC unbundling increases renewable share by 2-3%; state provisions to allow long-term contracting of RECs do not appear to have worked, at least in the short term; and limits on the maximum increase in electricity rates appear to reduce RES-E deployment.

In addition to RPS, we examine the impact of other major renewable policies. Similar to Menz and Vachon (2006) and Yin and Powers (2010), we find that the public benefit funds do not have a statistically significant impact. Further, similar to Delmas and Montes-Sancho (2011), Menz and Vachon (2006), Shrimali and Kneifel (2011), and Yin and Powers (2010), we find that mandatory green power options have an economically and statistically significant and positive impact – the presence of a mandatory green power option increases renewable deployment by about 4%. However, we also observe that the impact of this policy is reduced when it is present along with the RPS. Finally, we find that net metering policies have a significant and negative impact on renewable deployment, though this is likely due to data limitations.

We also examine the impact of RPS (and other policies) on technology-specific renewable deployment. We show that the supposedly negative impact of RPS stringency is primarily driven by an equivalent result for biomass, again driven by the outlier state, Maine. Once Maine is removed from the sample, the RPS stringency parameter becomes insignificant. Examining the results for other policies, we observe that public benefit funds have actually a statistically significant positive impact on biomass deployment, indicating that this policy may primarily support biomass. Finally, the results for mandatory green option and net metering are primarily driven by the corresponding results for wind, indicating that these policies have mostly impacted wind.

We believe that this is the most comprehensive work to date on the empirical effectiveness of RPS schemes. Our use of a variety of methodological approaches adds robustness to our conclusions. This work can help inform policymaking, but our results should be re-examined as RPS policies become more stringent. Currently, the minimum renewable share requirement is not binding in 9 of the 21 states that have effectively adopted an RPS (LBNL, 2012). As RPS policies become more stringent, thereby creating greater incentives for RES-E deployment, the power of econometric models to evaluate the effectiveness of policies and policy design characteristics will invariably grow. This paper has laid out an empirical strategy that has avoided the pitfalls of poor data sources, endogenous covariates – in part due to inter-state trading effects, and a one-off historic idiosyncrasy in Maine that created a powerfully distorting outlier. We hope that future research will incorporate the lessons learned in this paper but also 1) explore how RES-E trading affects in-state deployment more fully, 2) examine differences in RPS effectiveness due to market dynamics in different regions, 3) explore technology-specific effects in more detail, and 4) assess the cost-effectiveness of RPS policies.

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8 Appendices

Table 16 Classification

1990 – 2000 classifications		2001 – 2012 classifications	
ANT	Anthracite	AB	Agriculture Crop Byproducts/Straw/Energy Crops
BFG	Blast Furnace Gas	ANT	Anthracite Coal
BIT	Bituminous Coal	BFG	Blast-Furnace Gas
COG	Coke Oven Gas	BIT	Bituminous Coal
COL	Coal (generic)	BLQ	Black Liquor
COM	Coal-Oil Mixture	CUR	Water, Current
CRU	Crude Oil	DFO	Disillate Fuel Oil (all Diesel, and No. 1, No. 2, and No. 4 Fuel Oils)
CWM	Coal-Water Mixture	GEO	Geothermal
FO1	No. 1 Fuel Oil	JF	Jet Fuel
FO2	No. 2 Fuel Oil	KER	Kerosene
FO4	No. 4 Fuel Oil	LFG	Landfill Gas
FO5	No. 5 Fuel Oil	LIG	Lignite
FO6	No. 6 Fuel Oil	MWH	Megawatt Hour (MWh)
GAS	Gas (generic)	MSW	Municipal Solid Waste
GST	Geothermal Steam	NA	Not Available at this Time
JF	Jet Fuel	NG	Natural Gas
KER	Kerosene	NUC	Nuclear (Uranium, Plutonium, Thorium)
LIG	Lignite	OBG	Other Biomass Gases (Digester Gas, Methane, and other Biomass Gases)
LNG	Liquified Natural Gas	OBL	Other Biomass Liquids (Fish Oil, Liquid Acetonitrile Waste, Medical Waste, Tall Oil, ethanol, Waste Alcohol, and other Biomass Liquids not specified)
LPG	Liquified Propane Gas	OBS	Other Biomass Solids (Animal Manure and Waste, Solid Byproducts, and Other Solid Biomass not specified)
MF	Multifueled	OG	Other Gas (Coke-Oven, Coal Processes, Butane, Refinery, Other Process)
MTH	Methanol	OTH	Other (Batteries, Chemicals. Hydrogen, Pitch, Sulfur, Misc. technologies)
NG	Natural Gas	PC	Petroleum Coke
PC	Petroleum Coke	PG	Propane
PET	Petroleum (generic)	PUR	Purchased Steam
PL	Plutonium	RC	Refined Coal
REF	Refuse, Bagasse and all other nonwood waste	RFO	Residual Fuel Oil (Include No. 5, and No. 6 Fuel Oil, and Bunker C Fuel Oil)
RG	Refinery Gas	SG	Synthetic Gas, other than coal-derived
RRO	Re-Refined Motor Oil	SGC	Coal-Derived Synthetic Gas
SNG	Synthetic Natural Gas	SLW	Sludge waste
STM	Steam	SUB	Subbituminous Coal
SUB	Subbituminous Coal	SUN	Solar (Photovoltaic, Thermal)
SUN	Solar	TDF	Tires
TOP	Topped Crude Oil	TID	Water, Tides
UR	Uranium	WAT	Water, Conventional or Pumped Storage
WAT	Water	WC	Waste/Other Coal (Culm, Gob, Coke, and Breeze)
WD	Wood and Wood Waste	WDL	Wood Waste Liquids (Red Liquor, Sludge Wood, Spent Sulfite Liquor, and other Wood Related Liquids not specified)
WH	Waste Heat	WDS	Wood/Wood Waste Solids (Paper Pellets, Railroad Ties, Utility Poles, Wood Chips, and Other Wood Solids)
WND	Wind	WH	Waste Heat
OT	Other	WND	Wind
		WO	Oil-Other, and Waste Oil (Butane (liquid), Crude Oil, Liquid Byproducts, Propane (liquid), Oil Waste, Re-Refined Motor Oil, Sludge Oil, Tar Oil)
		WV	Water, Waves

The grey cells indicate non-hydro renewable energies.

Figure 5 Line Plot of RES-E capacity ratio by state

