Evaluating Renewable Portfolio Standards for In-State Renewable Deployment: Accounting for Policy Heterogeneity

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ONLINE APPENDIX – HAVE STATE RENEWABLE PORTFOLIO STANDARDS PROMOTED IN-STATE RENEWABLE DEPLOYMENT?

Literature Review

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.

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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.

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.

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 regerssion	- log of non-hydro RES-E generation ratio - absolute non-hydro RES-E generation	_° RPS binary_ __* RPS trend__ __* regional RPS__ _*** tax index_ _*** financial incentive index_ _*** deregulation binary_
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	_° RPS binary_ __** MGPO binary__ _** predicted RPS_ __** predicted MGPO__ _° DP binary_ _° financial incentive index_
Dong (2012)	53 countries	2005-2009	- FE regression	- annual wind capacity - absolute wind capacity	_** RPS binary_ __* 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__ _° tender binary_ _° tax binary_
Marques et al. (2010)	24 European countries	1990-2006	- FE regression - FE vector decomp.	- log of non-hydro RES-E generation ratio	_° EU 2001 binary_
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__ _° PBF binary_ _° retail choice binary_
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	_° RPS + capacity stringency_ _*** RPS + sales stringency_ _° GPP binary_ __*** MGPO binary__ __*** CEF binary__
Yin and Powers (2010)	50 U.S. states	1993-2006	- FE regression	- non-hydro RES-E capacity ratio	__** ISI__ _° RPS binary_ _° RPS trend_ _** RPS fraction_ __** MGPO binary__ _° PBF binary_ _° NM binary_

__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).

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.

Data Review

Quantification

Previous econometric studies on the effectiveness of policies that are intended to stimulate RES-E deployment differ with respect to dependent variable selection. 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) *Marques et al. (2011)*	Shrimali and Kneifel (2011)
Absolute	Generator Level		Delmas and Montes-Sancho (2011)
	State Level	Carley (2009) *Groba et al. (2011)* Salim and Rafiq (2012)	*Dong (2012)* 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.

Sources

The U.S. Energy Information Agency (EIA) provides data for generation and capacity at both the generator level and the state 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** *"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."* http://205.254.135.24/cneaf/electricity/page/eia906_920.html	**EIA Form EIA-860 Annual Electric Generator Reports** *"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."* http://www.eia.gov/cneaf/electricity/page/eia860.html
State-Level	**EIA Electric Power Annual** *"Detailed State Data: 1990-2010: Net Generation by State by Type of Producer by Energy Source"* http://www.eia.gov/electricity/data/state/	**EIA Electric Power Annual** *"Detailed State Data: 1990-2010: Existing Nameplate and Net Summer Capacity by Energy Source, Producer Type and State"* http://www.geia.gov/electricity/data/state/

State-level data

Most studies use state-level data of the total electric power industry's RES-E generation and capacity that is provided by the EIA Electric Power Annual. Figure 1 presents aggregate and technology-specific RES-E generation and capacity development.

Figure 1: State-level generation and capacity development

Aggregated generator-level data

Yin and Powers (2010) use generator-level data. However, aggregating 1990-2010 data from the EIA generator-level data faces several major challenges.

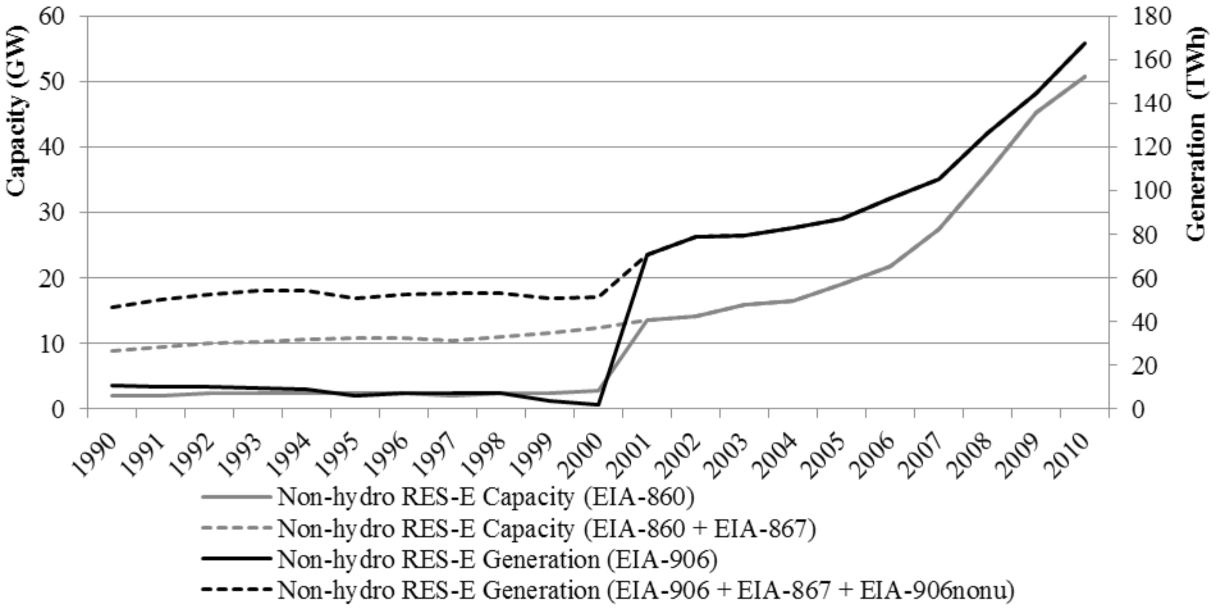
In 2001, the classification of sources in the EIA generator-level data changed for both generation (EIA-906) and capacity (EIA-860). The change in the EIA's classification scheme is complex and difficult to reconcile. Some changes are as simple as slight name changes (e.g. from "Anthracite" to "Anthracite 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 4 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.

Most importantly, 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. The dashed lines show the same data but 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 taken from the EIA-867 (for capacity) and EIA-906nonu (for generation) forms. EIA also provided us with capacity data that was not available in EIA-867.

We find that the sharp increase of the solid lines 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 alone increase abruptly after 2000. When we add the data from non-utilities for 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 that we outlined above.

Figure 2: Generator-level generation and capacity development



Classification Changes

Table 4: Classification Changes

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 Acetonitrite 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.

Control Specification

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 from Yin and Powers (2010) to produce comparable results. In subsequent specifications, we adopt additional controls.

State Income captures 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.

The electricity *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* is an index created by the League of Conservation Voters (LCV) that tracks the voting behavior of state-level representatives and senators on environmental issues. We expect high LCV Scores to positively correlate with RES-E development since a voting record in favor of environmental issues intends to support renewable energy technologies.

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). Error: Reference source not found presents the summary statistics.

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)	1000	0.87	3.83	0	32.10	%
ISI (GL)	1000	0.87	3.83	0	32.10	%
ISI (SL)	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

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.

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 we also introduce variables that measure the technical potential of renewables at the state level, calculated using GIS data (NREL, 2012). These variables are presented in Error: Reference source not found.

Table 6: 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

Maine: An Outlier

Error: Reference source not found presents the range of year-to-year changes for RES-E capacity ratio for the 50 U.S. states over 1990-2010. Figure 4 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, 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 in Section 4.7 of the paper, 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

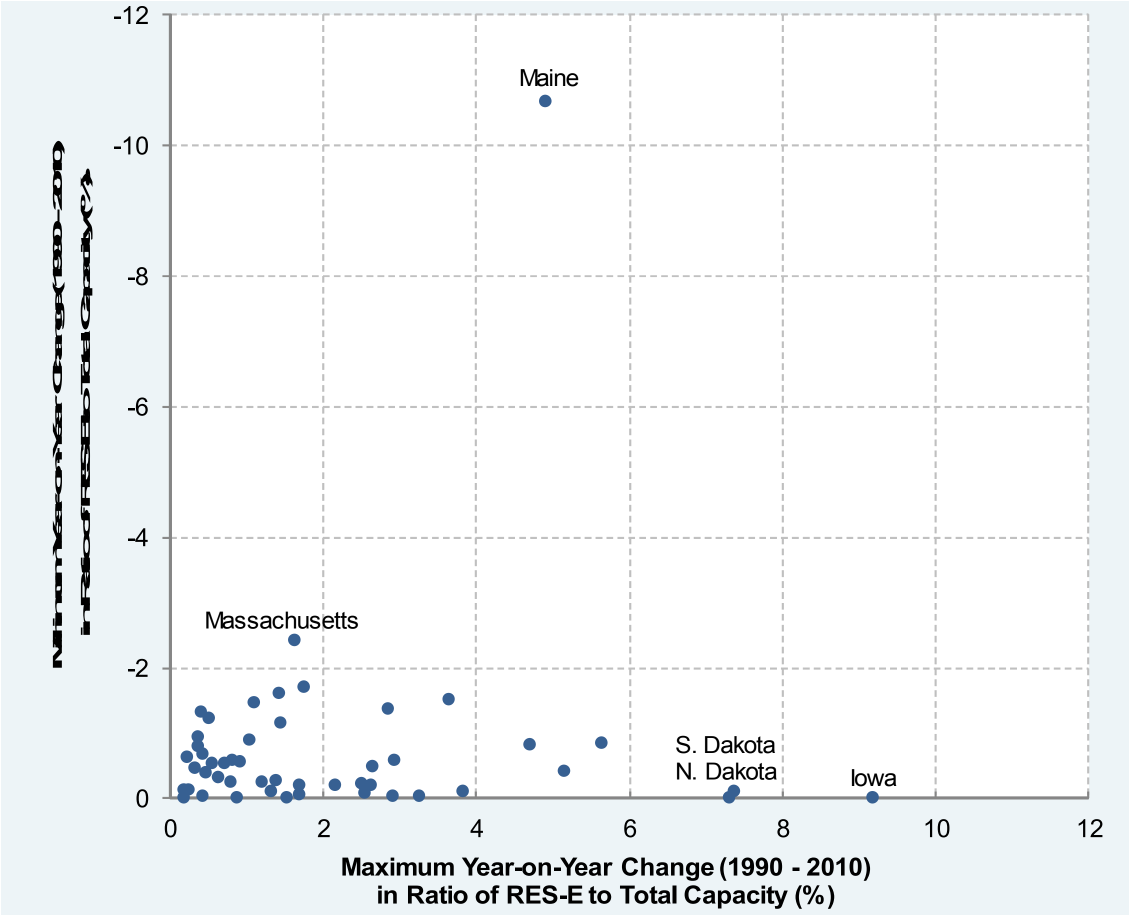


Figure 4: Line Plot of RES-E capacity ratio by state

Technology Analysis

In this section, we examine the impact of RPS and other polices on the capacity of specific RES-E technologies, namely biomass, geothermal, solar, and wind. Table 7 presents the key results. Specification (1) shows 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). The latter excludes Maine to test if the outlier is singlehandedly driving the value of the *ISI* coefficient.

Table 7: Full model results with technology-specific capacity ratios as dependent variables

	RES-E	**Biomass**		**Geothermal**	**Solar**	**Wind**
	(1)	**(2A)**	**(2B)**	**(3)**	**(4)**	**(5)**
	-0.105***	-0.106**	0.001	-0.008	0.002	0.001
ISI (SL)						
	(0.036)	(0.052)	(-0.012)	(0.007)	(0.003)	(0.041)
Public Benefit Fund (PBF)	0.593	0.547**	0.323***	-0.026	-0.024	0.151
Binary	(0.486)	(0.243)	(-0.104)	(0.044)	(0.018)	(0.353)

	-1.058**	0.068	0.063	-0.014	0.019	-1.095**
Net Metering (NM) Binary						
	(0.491)	(0.125)	(-0.115)	(0.018)	(0.012)	(0.433)
Mandatory Green Power	3.882***	-0.002	0.198	0.025	-0.001	3.834***
(MGPO) Binary	(1.434)	(0.176)	(-0.147)	(0.025)	(0.016)	(1.473)
	0.118**	0.017*	0.013	-0.002	-0.000	0.104**
State Income						
	(0.049)	(0.010)	(-0.011)	(0.001)	(0.001)	(0.048)
	-0.268*	0.081	0.013	0.002	0.003	-0.292
Electricity Price, lagged						
	(0.142)	(0.056)	(-0.016)	(0.011)	(0.003)	(0.181)
	0.031***	0.007**	0.003**	-0.000	0.000	0.023**
Import Ratio						
	(0.010)	(0.003)	(-0.002)	(0.000)	(0.000)	(0.010)
	0.019**	0.002	0.000	0.001	0.000	0.013*
LCV Score						
	(0.009)	(0.002)	(-0.002)	(0.000)	(0.000)	(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 our full model in the article. Since biomass capacity is by far the largest among all RES-E capacities, we argue that biomass deployment potentially drives the overall results.

ISI has a statistically significant negative effect on biomass capacity development, while no statistically significant link could be established between *ISI* and any of geothermal, solar, or wind development. 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 7. 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 capacity development. This finding is consistent with the hypothesis that biomass-burning power plants have been the principal beneficiaries of this policy. On the other hand, no statistically significant link could be found between public benefit funds and the deployment of other renewable technologies. 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 on wind development and insignificant coefficients on biomass and solar capacity. Mandatory green power options have a statistically significant positive effect on wind capacity development, while no statistically significant link could be found between the MGPO binary and any of biomass, geothermal, or solar development. That is, the presence of an MGPO policy appears to benefit wind power development that in turn determines the coefficient on the MGPO variable in the regression with total renewable share as the dependent variable.

State income – a proxy for state economic wealth – has been robustly positive and significant throughout the previous model specifications. Table 7 shows that the overall ceteris paribus effect of wealth 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 wealthier states being more able to invest in wind parks with high upfront costs, everything else being equal. 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 is very small.

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 6 in the Online Appendix.

We run the synthetic control algorithm 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 mean squared prediction error between the treated and control unit during the pre-treatment period on the matching covariates. 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 8. The values in Table 8 are presented graphically in .

Table 8: 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	-	-	-	-	-	-	-	-	-	0.06	0.04	-	-	-			

	0.08	0.08	0.08	0.12	0.09	0.08	0.08	0.08	0.10			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. Values in the columns with positive headers are causal effect estimates in years since an RPS was enacted.

Figure 5: 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 the article. 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 the article.