Effects of Renewable Portfolio Standards on Bioenergy: An Econometric Approach

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Introduction

Renewable portfolio standards (RPS) aim to increase electricity generation from and capacity for renewable sources. Benefits of renewable energy can include improved air quality, increased energy security, and reductions in greenhouse gas emissions (Olz, 2007). However, renewable energy sources vary in terms of cost, availability, predictability, etc. For example, wind and solar have no direct fuel input costs but are subject to weather for the timing of generation. Whereas bioenergy facilities require fuel inputs (wood waste, landfill gas, etc.) and can be used regardless of weather conditions or time of day. Therefore, biomass-based energy facilities are better suited for baseload power generation than other intermittent energy resources. Adding to the heterogeneity, RPS policies are implemented at the state-level and vary state by state.

Currently there are 32 RPS policies in place in the US (including the District of Columbia, Puerto Rico, and other territories) in addition to 9 other state renewable portfolio goals, which all vary across a multitude of dimensions. For example, some RPS policies impose mandatory requirements on policy implementation, while some states' renewable energy goals remain voluntary. RPS policies may also be implemented in conjunction with other policies that incentivize renewable energy (e.g., tax incentives). For enforcement, an RPS often uses renewable energy credits (RECs) or may restrict compliance to only additional capacity. Commonly, RPS policies use RECs, which allows for flexibility in how utilities comply as they can choose between increasing generation from renewables using existing capacity, adding additional renewable energy capacity, or co-firing.

For some states with an RPS policy, explicit targets for bioenergy are included in the RPS. These requirements are intended to increase usages of biomass for electricity generation. This may include increased generation from biomass-fired powerplants or increased usage of co-firing at existing fossil fuel burning powerplants. Additionally, new capacity may be installed to meet RPS targets. Given the nuances of an RPS policy, the variety of potential policy interactions, and the different compliance options, the question remains: How effective are RPS policies at achieving goals of increasing electricity generation from and capacity for renewable sources, in particular for energy produced from biomass?

In characterizing the overall effectiveness of RPS policies to increase biomass use for energy, we analyze three questions. First, on average, what is the overall effect of RPS policies on levels of biomass consumption for electricity production at dedicated bioenergy facilities, and how do changes in biomass consumption levels compare to those of other renewable energy resources incentivized by the same RPS policies? To address this question, we use a difference-in-differences (DiD) model and exploit the differences between RPS states and non-RPS states as well as the differences before and after RPS policies are implemented.

Second, given the heterogeneity in RPS policies across states, what are the state-specific effects of RPS policies on levels of biomass consumption at dedicated bioenergy facilities? Adding to the DiD framework, we implement the synthetic control method (SCM). Implementing the SCM in conjunction with the DiD framework allows us to compare to an estimated counterfactual (synthetic control group) that is closer to the theoretically ideal counterfactual[1] than the observed counterfactual. The resulting synthetic control group is created via a data-driven and transparent process. Additionally, unlike traditional matching estimators, time-varying unobserved heterogeneity can be controlled for if a long pre-treatment period can be fitted with the model (Abadie, Diamond, & Hainmueller, 2010).

[1] Ideally, we would observe the same state or power plants, during the same period, with and without the RPS policy. Thus, the theoretically ideal counterfactual would be outcomes for a state in an alternative reality where the RPS policy is never implemented.

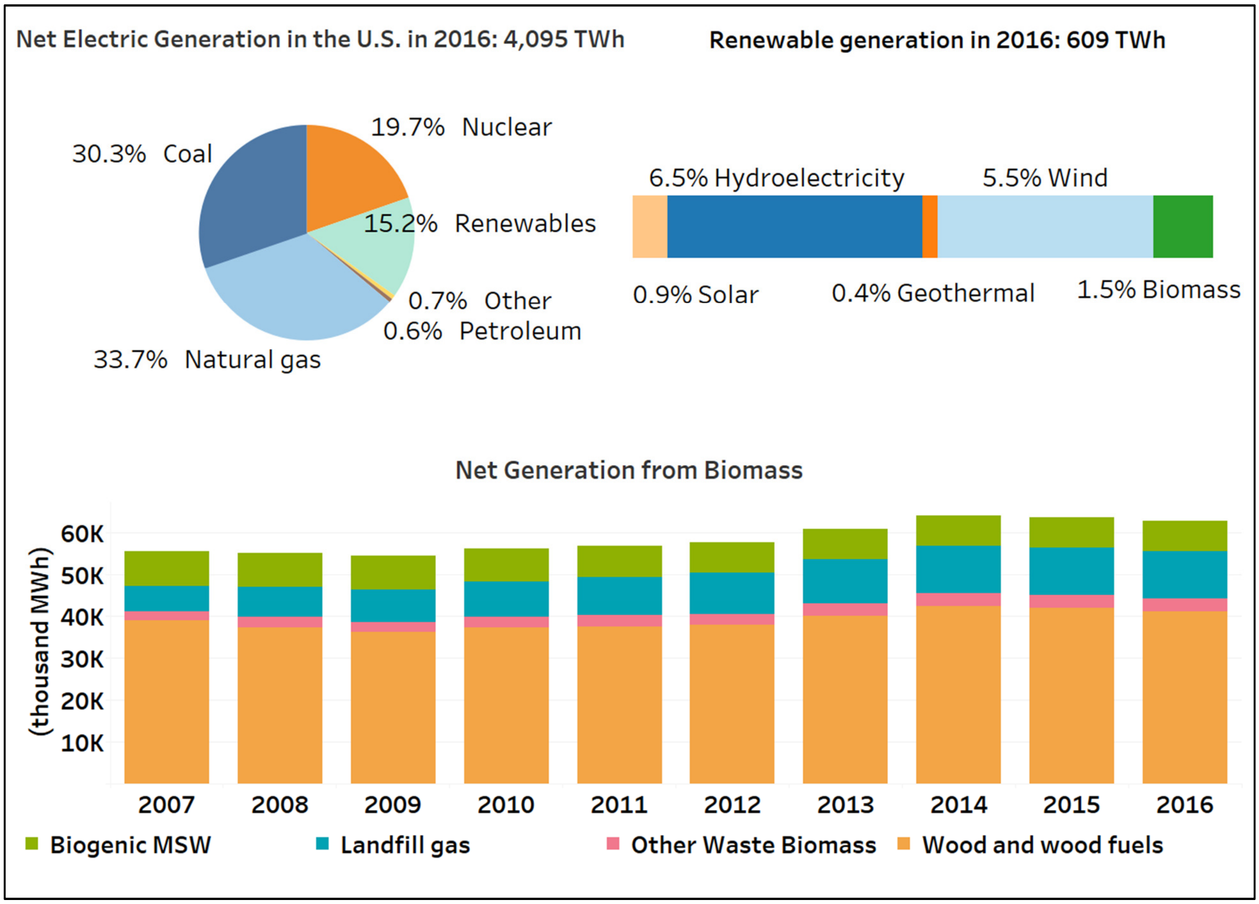
Third, how do RPS policies affect the consumption of biomass co-firing at coal-fired powerplants? To meet RPS requirements, some states allow for co-firing to count towards renewable generation requirements[2]. Understanding the effectiveness of an RPS policy on the relative magnitude of co-firing provides insight into whether utilities are making investments on the intensive or extensive margins as a result of an RPS policy. For initial analysis on the co-firing question, we estimate a DiD model where the outcome of interest is share of total generation from biomass.

Role of Biomass across the US

Of the 4,095-terawatt hours (TWh) of total US net electricity generated in 2016, renewable energy made up approximately 15%[3], as shown in Figure 1. Hydroelectric and wind generation accounted for 12% of net generation while biomass accounted for only 1.5%. Of the electric power generated by biomass, wood and wood derived fuels are the most prevalent as fuel used for electricity generation. From 2009 to 2016, US net electricity generation from biomass increased with most of the additional generation coming from landfill gas wood/wood fuels.

[2] Vermont is capacity based and not REC based. This means only additional renewable capacity is counted towards its RPS, excluding co-firing.
[3] Renewable energy refers to electricity generation from wind, solar, geothermal, hydro, and biomass powerplants.

Figure 1: Total Generation in the United States (2016)



Source: 2016 EIA form 923

For states with RPS policies, biomass generally is considered an eligible renewable energy technology. However, the definition of biomass and how it can be used toward an RPS' goals vary state by state. Some states limit the use of biomass for achieving RPS targets by stipulating the types of biomass fuels eligible under the program. Some states, such as Massachusetts, require that biomass energy must take greenhouse gas emissions, old-growth forests, sustainable forestry, and best management practices into consideration, among other environmental requirements. Another example is Connecticut, which excludes biomass products such as, "construction and demolition waste, finished biomass products from sawmills, paper mills or stud mills, organic refuse fuel derived separately from municipal solid waste, or biomass from old growth timber stands"[4]. In the North Carolina RPS policy biomass is defined as, “agricultural waste, animal waste, wood waste, spent pulping liquors, combustible residues, combustible liquids, combustible gases, energy crops, or landfill methane.” The policy specifies that in 2018, and each year after, at least 0.2% of total electricity sold must be supplied from swine waste. Similarly, by 2014 and after, 900,000 MWh of electricity sold must come from poultry waste resources.

Given the national availability and use of bioenergy across the US, as well as the heterogeneity in state RPS policies and their treatment of bioenergy, we estimate state-specific effects for Maine, New Hampshire, North Carolina, Oregon, Vermont, and Washington. These states are chosen for representation of differing policies, electricity markets, and availability of biomass fuels.

Fuel Consumption Data (EIA 923)

The main outcome of interest for this analysis is biomass fuel consumption levels for electricity generation. Fuel consumption data is from the EIA Form 923. This analysis focuses on the years 2001 to 2016[5]. Form 923 asks power plants to report information on net generation and fuel consumption at monthly and annual levels. The published data also includes plant characteristics such as operator, census region, NERC region, and primary fuel. The generation and fuel consumption data are downloaded as annual cross-sections directly from the EIA website[6].

Table 1 shows the average fuel consumption in mmBTUs used for electricity generation at bioenergy facilities only. Averages are calculated for before and after a state’s RPS policy is

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[4] Conn. Gen. Stat. §16-1. (39)
[5] From 2001 to 2007 EIA forms 906 and 920 reported generation and fuel consumption data.
[6] The current URL for the download page is the https://www.eia.gov/electricity/data/eia923/ .

implemented and a t-test is performed to test if the difference between the two means is significantly different from zero. For Maine, Oregon, and Washington, there is no significant difference in average bioenergy fuel consumption at bioenergy facilities before and after an RPS policy is implemented. However, average bioenergy fuel consumption decreases significantly for North Carolina and Vermont by 0.442 and 0.859, respectively.

Table 1: Average Fuel Consumption (mmBTU) for Electricity Generation at Bioenergy Facilities

State	Average % Pre-RPS	Average % Post-RPS	Difference
Maine	1.434	1.252	-0.261 [0.265]
New Hampshire	1.147	1.573	0.425** [0.041]
North Carolina	1.103	0.661	-0.442** [0.019]
Oregon	0.703	0.616	-0.086 [0.487]
Vermont	2.396	1.536	-0.859* [0.076]
Washington	1.001	0.941	-0.060 [0.7406]

*** p<0.01, ** p<0.05, * p<0.1
For the t-test, the p-value is presented in brackets [P-value]

Methods

Since Card (1990), the workhorse for estimating treatment effects in the public policy realm has been the difference-in-differences (DiD) approach. In the DiD framework, as presented in Athey & Imbens (2006), the outcome for an individual plant-*i* is as follows:

$$Y_i = Y_i^C \cdot (1 - I_i) + I_i \cdot Y_i^T$$

where I_i is an indicator for receiving the policy (treatment). When $I_i = 0$ the *i*-th plant does not receive the policy and the outcome is $Y_i = Y_i^C$. When $I_i = 1$, the *i*-th plant does receive the policy and the outcome is $Y_i = Y_i^T$. Generalizing to the two-period and two-group scenario, let

$I_i = RPS_i * Post_i$. Where RPS_i is an indicator for a state that implements an RPS policy and $Post_t$ is an indicator for the post-treatment period[7].

In the absence of an RPS policy, within the DiD model, the outcome (i.e., fuel consumption for electricity generation) for the *i*-th plant is represented by:

$$Y_i^N = \beta_0 + \beta_1 RPS_i + \beta_2 Post_i + \varepsilon_i \tag{1}$$

where β_0 is a constant, β_1 is the time-invariant group-specific effect, β_2 is the time effect (before versus after the RPS policy is passed), and ε_i is a plant-specific error term.

In the two-period and two-group scenario, the DiD model estimates a treatment effect by comparing the difference before and after a point in time and compares this difference across two groups. In the context of an RPS, the difference in biomass consumption before and after an RPS policy is implemented, compared between the plants in RPS states and plants not in RPS states.

Suppose an RPS is implemented within the DiD framework, the outcome for the *i*-th plant is represented by:

$$Y_i = \beta_0 + \beta_1 RPS_i + \beta_2 Post_t + \beta_3 RPS_i * Post_t + \varepsilon_{it}. \tag{2}$$

The interaction of $RPS_i * Post_t$ represents the treatment group, post-treatment. Thus, the coefficient β_3 is the coefficient of interest and is the average effect of a plant being in a state with an RPS policy after an RPS policy is implemented. In other words, β_3 is the average treatment effect of an RPS policy.

We can modify Eq. 2 and split the treatment group into two subgroups, bioenergy and other renewables:

[7] Treatment is assigned to the year an RPS policy is implemented.

$$Y_i = \beta_0 + \beta_1 Post_i + \beta_2 RPS_i * Bio_i + \beta_3 RPS_i * OthRenew_i + \beta_4 RPS_i * Bio_i * Post_t + \beta_5 RPS_i * OthRenew_i * Post_t + \varepsilon_{it}. \quad (3)$$

Where β_4 and β_5 represent the effects of RPS on fuel consumption in mmBTUs for bioenergy and other renewables, respectively[8].

The advantage of the DiD approach is its simplicity. Estimates can be interpreted easily, estimation is not computationally intense, and DiD uses a well-established framework (linear regression) familiar to researchers and policy makers. However, DiD has its disadvantages. First, the parallel trend assumption implies that the control group is not impacted at all by the treatment (Meyer, 1995). Another drawback is the sensitivity of results to control group selection. Since DiD requires that the researcher make judgements on picking the control group, these judgements have direct implications for results. Ancillary policies, differing economic environments, and spillovers all pose challenges to the researcher in producing an adequate representation of what the treatment group would have been in the absence of the treatment. Due to these two disadvantages, DiD on its own may not be appropriate for estimating a treatment effect of policies at a state or regional level (Abadie et al., 2010).

Synthetic Control Method

To address these two issues regarding the DiD approach, one option is to implement the *Synthetic Control Method (SCM)* and use all the potential control units but weight each unit based on its similarity to the treatment group during the pre-treatment period. By weighting and aggregating the control group, a synthetic counterfactual is created that may provide a closer

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[8] Fuel consumption for other renewables (i.e. wind and solar) are back-calculated by the EIA based off of their net generation and what their fuel consumption would have been for a comparable non-renewable source.

approximation to the true counterfactual than the DiD setup. Examples of the SCM in practice are Abadie & Gardeazabal (2003), Abadie et al. (2010), and Doudchenko & Imbens (2016).

The idea behind the SCM is straightforward; generate a weight matrix such that the distance[9] between the treatment group and the control group, pre-treatment, is minimized. The weight matrix is then applied to the control group to create a weighted average of the outcome variable, post-treatment. The difference between the observed outcome variable for the treatment group, post-treatment, and the estimated outcome variable for the synthetic control group is the estimated treatment effect.

Following the framework from Abadie et al. (2010), let Y_{it}^N be the outcome variable when the treatment is not present for units $i = 1 \ldots J + 1$, where $J =$ the number of control units and the first unit receives the treatment, and time periods $t = 1 \ldots T$. Let Y_{it}^I be the counterfactual outcome and T_0 represent the number of pre-treatment periods. Assume that the treatment does not have any effect on the outcome during the pre-treatment periods. For all pre-treatment time periods $Y_{it}^N = Y_{it}^I$.

To define the treatment effect, let $\alpha_{it} = Y_{it}^I - Y_{it}^N$ and D_{it} be an indicator for the treatment. Thus, the observed outcome for any given unit and time-period is:

$$Y_{it} = Y_{it}^N + \alpha_{it} D_{it} \tag{4}$$

Recall that the first unit is the treatment group, resulting in the following:

$$D_{it} = \begin{cases} 1 & if\ i = 1\ and\ t > T_0 \\ 0 & otherwise \end{cases}$$

[9] In this context, distance is the difference between plants based off a set of characteristics (e.g. fuel type, capacity, and number of boilers).

The effects of interest are the differences between the observed outcome and what the outcome would have been without the treatment, post-treatment, $\left(\alpha_{1T_0+1} \dots \alpha_{1T}\right)$. Rearranging Eq (4), for all periods post-treatment $(t > T_0)$ the treatment effect is:

$$\alpha_{1t} = Y_{1t}^{I} - Y_{1t}^{N} = Y_{1t} - Y_{1t}^{N} \tag{5}$$

However, Y_{it}^{N} is unobserved for the control group in the post-treatment period. So, to estimate α_{1t} an estimate of Y_{1t}^{N} is necessary. Suppose that Y_{it}^{N} can be modeled as such:

$$Y_{it}^{N} = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{it} \tag{6}$$

Where δ_t is a time specific constant, Z_i is a vector of observable characteristics that are not impacted by the treatment, θ_t is a vector of unknown parameters, μ_i is a vector of unobservable time-invariant characteristics, λ_t is a vector of unknown parameters, and ε_{it} is an idiosyncratic error term.

Now consider a $(J \times 1)$ vector of weights $W = \left(w_2, \dots, w_{J+1}\right)'$ such that $w_j \geq 0$ for $j = 2, \dots, J+1$ and the weights sum to 1 $(w_2 + \cdots + w_{J+1} = 1)$. Thus, for each value W is a different weighted average of the control units or a potential synthetic control group. Combining the weight matrix with the linear model, the resulting outcome variable for each synthetic control group is:

$$\sum_{j=2}^{J+1} w_j Y_{jt} = \delta_t + \theta_t \sum_{J=2}^{J+1} w_j Z_i + \sum_{J=2}^{J+1} w_j \lambda_t \mu_i + \sum_{j=2}^{j+1} w_j \varepsilon_{it} \tag{7}$$

Then the question remains: Which value of W to choose?

Suppose that a weight matrix could be chosen such that the weighted average of the observables for control group is equal to the treatment group:

$$\sum_{j=2}^{J+1} w_j^* Y_{jt} = Y_{1t} \; \forall \; t = 1 \ldots T_0 \tag{8}$$

$$\sum_{J=2}^{J+1} w_j^* Z_j = Z_1 \tag{9}$$

Then with the choice of w^* as a weight matrix, the treatment effect can be estimated as:

$$\widehat{\alpha_{1t}} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}, \forall \; t > T_0 \tag{10}$$

Unfortunately, it is nearly impossible to know the true w^* in Eq (10) given the limitations of observable data. Instead, the next best option is to approximate w^*. One potential approximation of $w^*$is the choice of weight matrix which minimizes the differences between the treatment and control group observables, during the pre-treatment period.

To approximate w^*, and subsequently estimate the treatment effect, let X_1 be a $(K \times 1)$ vector of pre-treatment values of outcome predictors for the treatment group and X_0 be a $(K \times J)$ matrix of the same outcome predictors but for the control group during the pre-treatment period. Now let V be a diagonal matrix with diagonal elements being nonnegative and representing the importance of each of the outcome predictors in X_0 and X_1. Thus W^* is chosen such that it minimizes the distance between the outcome predictors for the treatment and control groups during the pre-treatment period. Formally,

$$W^* = argmin[(X_1 - X_0 W)' V (X_1 - X_0 W)] \; subject \; to$$

$$w_j \geq 0 \; (j = 1,2, \ldots, J) \tag{11}$$

$$w_1 + \cdots + w_J = 1$$

Note that solution for the weight vector in Eq (11) depends on the choice of variable weights (V). Variable weights can be chosen based on priors a researcher may have or by using the data at hand. To take a data driven approach, V is chosen such that the mean square prediction error of the synthetic group's outcome variable is minimized in the pre-treatment period.

Empirical Results

In our analysis we breakdown the question of RPS effectiveness into three parts. First, what is the average overall effectiveness of RPS policies on the consumption of biomass for electricity generation at dedicated bioenergy facilities? Second, what are the state-specific effects of RPS policies on the level of consumption of biomass for electricity generation at dedicated bioenergy facilities? Third, how do RPS policies affect levels of biomass co-firing at coal-fired powerplants?

Average Effects

Table 2 shows the DiD results for an average effect of RPS policies on biomass fuel consumption used for electricity generation at dedicated biopower facilities, at the state-level. The coefficients on the interaction terms *RPS*Bioenergy*Post* and *RPS*Other Renewables*Post* are the coefficients of interest. Across all four specifications, there is no significant impact of RPS policies on biomass fuel consumption at dedicated biopower facilities. However, in the fixed-effects specifications there is a significant and positive effect of RPS policies on consumption levels of other renewable resources. From Table 2 we also see evidence of all RPS states, on average, increasing biomass consumption for electricity generation throughout the window of observation[10].

[10] For the states we analyze, 2007 is the median year for assigning treatment.

Table 2: DiD Results for Fuel Consumption for Electricity

	Fuel Consumption for Electricity Generation (mmBTU)			
State-level	(1)	(2)	(3)	(4)
RPS	3.682*		4.467*	
	(1.934)		(2.437)	
RPS*Bioenergy	8.382**	8.394*		
	(3.982)	(4.040)		
RPS*Other Renewables	-1.345	-1.326		
	(2.222)	(2.260)		
RPS*Bioenergy*Post	-1.625	-1.509	-2.411	-2.517
	(2.546)	(2.608)	(2.945)	(3.024)
RPS*Oth. Renew.*Post	13.39	13.38	26.11*	25.99*
	(8.751)	(8.922)	(13.04)	(13.23)
Observations	463	463	463	463
R-squared	0.128	0.155	0.304	0.397
Year FE	No	Yes	No	Yes
State FE	No	No	Yes	Yes
Number of sid			36	36

Robust standard errors in parentheses. Clustering at state-level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The regression for Table 3 implements the same specifications as in Table 2 but for individual biomass powerplants. From Table 3 we can draw three conclusions. First, just as with the state-level regressions, there is insufficient evidence to suggest that RPS policies increase biomass fuel consumption at the average biomass powerplant. Second, the post-2007 period is associated with an increase in biomass consumption of 0.421 to 0.417 mmBTUs. Finally, there is some evidence to suggest that plants in states with RPS policies are associated with less biomass consumption compared to their counterparts in states without RPS policies, both before and after an RPS policy is implemented.

Table 3: DiD Results for Fuel Consumption for Electricity (Bioenergy only)

Plant-Level	Fuel Consumption for Electricity Generation (mmBTU)			
	(1)	(2)	(3)	(4)
RPS	-0.0630		-0.186**	
	(0.187)		(0.0815)	
Post-2007	0.421**	0.417**		
	(0.155)	(0.154)		
RPS*Post	-0.146	-0.142	0.0606	0.0624
	(0.223)	(0.223)	(0.0957)	(0.0925)
Observations	3,145	3,145	3,145	3,145
R-squared	0.020	0.026	0.014	0.043
Year FE	No	Yes	No	Yes
State FE	No	No	Yes	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Clustering at state-level

At both the state and plant units of observation, the DiD results show insufficient evidence of an RPS policy having a significant impact on biomass fuel consumption for electricity generation at dedicated biopower facilities. From Table 2 and Table 3 we can conclude that on average, across six states with a variety of RPS polices, there is no significant impact on biomass consumption for electricity generation.

State-Specific Effects

To determine if any specific state's RPS policy has an impact on biomass consumption for electricity generation at dedicated biopower facilities we estimate separate state-specific DiD regressions. For each state we estimate a DiD with the raw control group data and with the SCM-weighted control group data. In theory, the state-specific SCM-weighted control groups should provide better representations of what each state's biomass consumptions would be in the absence of an RPS policy. For each state's set of results, the coefficient on the variable *RPS* tells us how different the state is in comparison to the control group, on average, with respect to biomass consumption. If the SCM-weighting provides a better counterfactual, then the *RPS* coefficients should be closer to zero in the weighted results versus the unweighted results.

Beginning with Maine in Table 4, for the unweighted and weighted regressions, the RPS policy has a significant negative impact on biomass consumption at dedicated biopower facilities. Focusing on the specification with the year and state fixed-effects, the unweighted regression estimates a negative policy effect of 1.644 mmBTUs while the weighted regression estimates a negative policy effect of 4.1 mmBTUs.

Table 4: Maine DiD Results

	Plant-Level	Fuel Consumption for Electricity Generation (mmBTU)			
		(1)	(2)	(3)	(4)
Unweighted	RPS	4.667***	4.632***		
		(0.591)	(0.557)		
	Post-2009	-0.0419		0.0800	
		(0.437)		(0.479)	
	RPS*Post	-1.539***	-1.505***	-1.661***	-1.644***
		(0.437)	(0.486)	(0.479)	(0.535)
	Observations	743	743	743	743
	R-squared	0.044	0.048	0.157	0.160
Weighted	RPS	2.039**	2.142**		
		(0.443)	(0.354)		
	Post-2009	2.572***		2.424**	
		(0.198)		(0.403)	
	RPS*Post	-4.153***	-4.244***	-4.005***	-4.100**
		(0.198)	(0.331)	(0.403)	(0.533)
	Observations	226	226	226	226
	R-squared	0.013	0.023	0.018	0.028
	Year FE	No	Yes	No	Yes
	State FE	No	No	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Clustering at state-level

Differing from Maine, the DiD results for New Hampshire show no evidence of an effect of RPS policies on biomass consumption for electricity generation. From Table 5 we see that the coefficients on RPS go from approximately 2.5 mmBTUs and significant in the unweighted regression to approximately 0.85 mmBTUs and insignificant, indicating that the SCM weighting provides a closer approximation to the counterfactual of no RPS policy than the unweighted control group. Despite the differences in control groups, neither the unweighted or weighted regressions estimate a significant impact of New Hampshire's RPS policy on biomass consumption for electricity generation at dedicated biopower facilities.

Table 5: New Hampshire DiD Results

	Plant-Level	Fuel Consumption for Electricity Generation (mmBTU)			
		(1)	(2)	(3)	(4)
Unweighted	RPS	2.544***	2.477***		
		(0.503)	(0.495)		
	Post-2007	-0.112		0.00121	
		(0.603)		(0.630)	
	RPS*Post	0.760	0.824	0.646	0.696
		(0.603)	(0.633)	(0.630)	(0.665)
	Observations	717	717	717	717
	R-squared	0.025	0.031	0.179	0.183
Weighted	RPS	0.831	0.871		
		(0.453)	(0.476)		
	Post-2007	0.332		0.524	
		(1.823)		(1.836)	
	RPS*Post	0.315	0.273	0.123	0.0634
		(1.823)	(1.846)	(1.836)	(1.867)
	Observations	244	244	244	244
	R-squared	0.007	0.013	0.055	0.060
	Year FE	No	Yes	No	Yes
	State FE	No	No	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Clustering at state-level

Just as with New Hampshire, North Carolina shows no significant impact of their RPS policy on biomass consumption for electricity generation at dedicated biopower facilities. In Table 6, the unweighted regressions show that North Carolina biomass plants, on average, consume 1.596 to 1.568 mmBTUs greater than the unweighted control group plants. However, the weighted regressions show that the North Carolina plants consume, on average, 0.818 mmBTUs of biomass fuel compared to the weighted control group plants. The reduction in magnitude and significance of the RPS coefficients in the weighted regressions compared to the unweighted provides additional evidence that the SCM weighted control groups provide a better counterfactual than the unweighted control group.

Table 6: North Carolina DiD Results

	Plant-Level	Fuel Consumption for Electricity Generation (mmBTU)			
		(1)	(2)	(3)	(4)
Unweighted	RPS	1.596***	1.568***		
		(0.503)	(0.486)		
	Post-2007	-0.112		0.00121	
		(0.603)		(0.630)	
	RPS*Post	-0.742	-0.703	-0.856	-0.824
		(0.603)	(0.622)	(0.630)	(0.653)
	Observations	736	736	736	736
	R-squared	0.005	0.012	0.171	0.177
Weighted	RPS	0.818*	0.844		
		(0.372)	(0.415)		
	Post-2007	0.577		0.733	
		(1.069)		(0.896)	
	RPS*Post	-1.432	-1.387	-1.588	-1.535
		(1.069)	(1.070)	(0.896)	(0.905)
	Observations	332	332	332	332
	R-squared	0.005	0.017	0.064	0.078
	Year FE	No	Yes	No	Yes
	State FE	No	No	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Clustering at state-level

Oregon is unique compared to the rest of the analysis states. Focusing on the RPS coefficients in Table 7, there are no significant differences between Oregon's average plant-level biomass fuel consumption and the average consumption at plants in the unweighted or weighted control groups. Additionally, there is insufficient evidence to suggest that the RPS policy in Oregon increased biomass consumption for electricity production at dedicated biopower facilities.

Table 7: Oregon DiD Results

	Plant-Level	Fuel Consumption for Electricity Generation (mmBTU)			
		(1)	(2)	(3)	(4)
Unweighted	RPS	-0.365	-0.320		
		(0.503)	(0.507)		
	Post-2007	-0.112		0.00121	
		(0.603)		(0.630)	
	RPS*Post	0.821	0.754	0.707	0.647
		(0.603)	(0.583)	(0.630)	(0.616)
	Observations	727	727	727	727
	R-squared	0.001	0.007	0.177	0.182
Weighted	RPS	-0.629	-0.597		
		(0.771)	(0.759)		
	Post-2007	0.0395		0.217	
		(0.767)		(0.697)	
	RPS*Post	0.669	0.665	0.492	0.491
		(0.767)	(0.727)	(0.697)	(0.671)
	Observations	337	337	337	337
	R-squared	0.005	0.020	0.129	0.137
	Year FE	No	Yes	No	Yes
	State FE	No	No	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Clustering at state-level

Across both the unweighted and weighted regressions, the DiD results for Vermont in Table 8 show that the RPS policy in Vermont had a negative and significant impact on biomass consumption for electricity production at dedicated biopower facilities. Comparing the RPS coefficients between the unweighted and weighted regressions we can see that the SCM weighting reduces the differences between the plants in Vermont and the plants in the control group, aside from the RPS policy. However, the magnitudes and levels of significance in the estimated RPS effect (*RPS*Post*) decline in the unweighted regressions. Focusing on the fully specified model (year and state fixed effects), we find that the weighted regression reduces the average estimated impact of the RPS policy from a reduction of 3.756 mmBTUs to a reduction of 2.148 mmBTUs[11].

Table 8: Vermont DiD Results

	Plant-Level	Fuel Consumption for Electricity Generation (mmBTU)			
		(1)	(2)	(3)	(4)
Unweighted	RPS	5.044***	5.018***		
		(0.483)	(0.460)		
	Post-2007	-0.358		-0.156	
		(0.769)		(0.812)	
	RPS*Post	-3.558***	-3.534***	-3.761***	-3.756***
		(0.769)	(0.797)	(0.812)	(0.848)
	Observations	690	690	690	690
	R-squared	0.011	0.016	0.188	0.193
Weighted	RPS	3.674**	3.562**		
		(1.090)	(1.083)		
	Post-2005	-1.651		-1.625	
		(0.929)		(0.932)	
	RPS*Post	-2.266*	-2.124	-2.292*	-2.148
		(0.929)	(0.996)	(0.932)	(0.995)
	Observations	217	217	217	217
	R-squared	0.120	0.162	0.165	0.201
	Year FE	No	Yes	No	Yes
	State FE	No	No	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Clustering at state-level

[11] While this estimated effect is statistically insignificant at the 10% level, it is only marginally insignificant. As such the estimated effect should still be taken into consideration.

Table 9 shows the DiD results, unweighted and weighted, for Washington state. First looking at the coefficients on the *RPS* indicator we see that the Washington plants are insignificantly different from the unweighted control group. However, the average biomass fuel consumption at biopower plants in Washington is significantly less than the average consumption for the weighted control group plants. This difference suggests that the weighted control group provides a poorer representation of the theoretical counterfactual, compared to the unweighted control group. Regardless, both the unweighted and weighted regressions estimate no significant impact of Washington's RPS policy on biomass fuel consumption for electricity generation at dedicated biopower facilities.

Table 9: Washington DiD Results

	Plant-Level	Fuel Consumption for Electricity Generation (mmBTU)			
		(1)	(2)	(3)	(4)
Unweighted	RPS	-0.0251	-0.0226		
		(0.451)	(0.434)		
	Post-2007	-0.122		0.0338	
		(0.761)		(0.799)	
	RPS*Post	0.370	0.357	0.214	0.182
		(0.761)	(0.778)	(0.799)	(0.828)
	Observations	755	755	755	755
	R-squared	0.000	0.005	0.169	0.173
Weighted	RPS	-1.087***	-1.114***		
		(0.165)	(0.148)		
	Post-2006	2.541		2.661	
		(1.847)		(1.764)	
	RPS*Post	-2.294	-2.239	-2.414	-2.388
		(1.847)	(1.946)	(1.764)	(1.865)
	Observations	282	282	282	282
	R-squared	0.065	0.068	0.114	0.116
	Year FE	No	Yes	No	Yes
	State FE	No	No	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Clustering at state-level

Co-Firing

In most states, one possible option for a utility to meet RPS requirements is to co-fire biomass with fossil fuels[12]. For this part of our analysis, we focus on co-firing biomass at coal-fired powerplants. Utilizing the DiD framework, we reduced the sample down to coal-fired powerplants that exhibited co-firing for at least one year within the observation window. We then created an outcome variable that is the share of total generation from the facility that is due to co-firing biomass. If RPS policies impact the usage of biomass co-firing, then we should see a significant change in the share of total generation that is from co-firing.

Table 10 shows the co-firing DiD results. Focusing on the coefficient for the *Post-2007* indicator, we see that all plants in the sample increased co-firing, on average, after 2007. However, across all specifications, there is insufficient evidence to conclude that RPS policies directly influenced these increased co-firing levels. Despite insufficient evidence of a policy effect, we do see that the magnitudes of the estimated results are approximately the same across all four specifications and are positive. This leads us to infer that there may be an impact of RPS policies on co-firing but lack sufficient evidence in the data to make any claim about causality.

[12] Co-firing is defined as a power plant burning a secondary fuel (e.g., wood waste) in conjunction with their primary fuel (e.g., coal).

Table 10: DiD Results for Fuel Consumption for Electricity (Co-firing only)

Plant-Level	Share of Electricity Generation from Co-Firing			
	(1)	(2)	(3)	(4)
RPS	0.00660	0.00729		
	(0.0209)	(0.0208)		
Post-2007	0.114**		0.113**	
	(0.0384)		(0.0389)	
RPS*Post	0.0263	0.0279	0.0263	0.0285
	(0.0366)	(0.0272)	(0.0371)	(0.0277)
Observations	565	565	565	565
R-squared	0.077	0.007	0.086	0.027
Year FE	No	No	Yes	Yes
State FE	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Clustering at state-level

Conclusion

Using the EIA form 923 dataset in concert with DiD and the SCM, there are three preliminary conclusions we can draw about the relationship between RPS policies and bioenergy production. First, looking at results for all the states analyzed, RPS policies have no significant impact on levels of biomass consumption for electricity production at dedicated bioenergy facilities at both the average state or plant levels. Second, when estimating state-specific effects, most RPS policies also did not have a significant effect on biomass consumption for electricity generation Maine and Vermont, which show a significant but negative effect on biomass consumption for electricity generation at dedicated biopower facilities. Third, preliminary analysis shows that there is insufficient evidence to suggest coal-fired plants are co-firing increased levels of biomass in response to RPS policies. The next phase of this research will conduct further analysis of levels of biomass co-firing in response to RPS policies. Additionally, the analysis will expand to include additional states and a broader definition of co-firing to include other multi-fuel power plants.

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References

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association*, *105*(490), 493–505. https://doi.org/10.1198/jasa.2009.ap08746

Abadie, A., & Gardeazabal, J. (2003). The Economic Costs of Conflict: A Case Study of the Basque Country. *The American Economic Review*, *93*(1), 113–132.

Athey, S., & Imbens, G. W. (2006). Identification and Inference in Nonlinear Difference-in-Differences Models. *Econometrica*, *74*(2), 431–497.

Barbose, G. (2017) US Renewables Portfolio Standards: 2017 Annual Status Report. Lawrence Berkeley National Laboratory. Lab LBNL-2001031. Available at: https://emp.lbl.gov/projects/renewables-portfolio/ Card, D. (1990). The Impact of the Mariel Boatlift on the Miami Labor Market. *Industrial and Labor Relations Review*, *43*(2), 245–257. https://doi.org/10.2307/2523702

Doudchenko, N., & Imbens, G. W. (2016). *Balancing, Regression, Difference-In-Differences and Synthetic Control Methods: A Synthesis* (Working Paper No. 22791). National Bureau of Economic Research. https://doi.org/10.3386/w22791

"EIA - Annual Energy Outlook 2017." Energy Information Administration - EIA - Official Energy Statistics from the US Government, www.eia.doe.gov/oiaf/aeo/index.html.

La Capra Associates (2006) ANALYSIS OF A RENEWABLE PORTFOLIO STANDARD FOR THE STATE OF NORTH CAROLINA. Technical Report. Available at: http://www.ncuc.net/reps/NCRPSReport12-06.pdf

Lyon, T. P., & Yin, H. (2010). Why do states adopt renewable portfolio standards?: An empirical investigation. The Energy Journal, 133-157.

Meyer, B. D. (1995). Natural and quasi-experiments in economics. *Journal of Business & Economic Statistics*, *13*(2), 151.

Olz, S. (2007). Contribution of renewables to Energy Security, 74.

Wiser, R., Namovicz, C., Gielecki, M., & Smith, R. (2007). The experience with renewable portfolio standards in the United States. The Electricity Journal, 20(4), 8-20.

Wiser, R. (2008). Renewable portfolio standards in the United States-a status report with data through 2007. Lawrence Berkeley National Laboratory.

Wooldridge, J. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT Press.