Causal Effects of Renewable Portfolio Standards on Renewable Investments and Generation: The Role of Heterogeneity and Dynamics

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Abstract

Despite a 30-year long history, Renewable Portfolio Standards (RPS) remain controversial and debates continue to surround their efficacy in leading the low-carbon transition in the electricity sector. Contributing to the ongoing debates is the lack of definitive causal evidence on their impact on investments in renewable capacity and generation. This paper provides the most detailed analysis to date of the impact of RPSs on renewable electricity capacity investments and generation. We use state-level data from 1990-2019 and recent econometric methods designed to address dynamic and heterogeneous treatment effects in a staggered adoption panel data design. We find that, on average, RPS policies increase wind generation capacity by 600-700 MW, a 21% increase, but have no significant effect on investments in solar capacity. Additionally, we demonstrate that RPSs have slow dynamic effects: most of the capacity additions occur 5 years after RPS implementation. Estimates for wind and solar electricity generation mimic those for capacity investments. We also examine the possibility of policy spillover where the introduction of an RPS in one state leads to a change in capacity mix in the neighboring states, but find no systematic evidence for such spillovers.

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1 Introduction

Most industrialized countries now have commitments, or in a few cases laws, with targets to reach carbon neutrality status by 2050 or 2060. A central strategy to reach this target common across countries is the decarbonization of the electricity generation sector through expanding renewable resources. In the United States, the renewable portfolio standards (RPS), a state-level policy imposing standards for renewable electricity sales in a state, is one of the most prominent policies implemented to date with the goal of incentivizing decarbonization of the electricity sector. Beginning with Iowa in 1991, thirty states and Washington D.C have now enacted RPSs; these states represent more than 70 percent of the US population and 64% of total generation capacity in 2019.[1] As the U.S. federal government works toward its stated goal of 100% carbon-free electricity by 2035, many of the proposed federal policies mimic state-level RPS in how they displace fossil fuel use in electricity generation, reduce greenhouse gas emissions, and ensure reliable operation of the electrical grid.[2] Given the centrality of RPS to U.S. decarbonization goals, it is imperative to provide a better understanding how such policies affect the deployment of renewable electricity generation sources.

While RPSs have been designed and enacted to increase the share of renewable electricity supplied and sold in states adopting them, there is still limited consistent empirical evidence about their efficacy and whether RPS cause investments in renewable capacity. Two key issues complicate the identification of the causal effect of RPS on renewables. First, RPS policies are not randomly assigned across states, and previous studies suggest that political ideology, underlying renewable resource potential, labor market conditions, and interest group pressure are strong predictors of RPS adoption (Lyon (2016)). Second, due to significant differences in policy design and renewable resource endowments, RPS policies are likely to have dynamic and heterogeneous effects across states and have been adopted in a staggered manner since the mid 1990s (see Figure 1).

Causal identification in this setting is complicated by difficult to quantify state-specific characteristics such as political ideology and natural resource endowment which may correlate with both RPS implementation and the deployment of renewable energy generation. Further, national-level policies that are correlated with RPS implementation, such as the U.S. federal government Production Tax Credit also create challenges for causal identification. To address these identification concerns, virtually all of the prior empirical literature on the impact of RPSs uses panel data regressions with state and year fixed effects, often labelled as two-way fixed effects (TWFE) or sometimes difference-in-differences (DD) models. Recent econometric research has shown that in settings with heterogeneous treatment effects (like in the case of the RPS policy adoption), TWFE or DD estimators identify a weighted average of treatment effect parameters which may not correspond to the overall average treatment effect on the treated (ATT) (Sun and Abraham (2020), de Chaisemartin

[1] To date, more than 70 proposals for a national portfolio standard have been introduced but none has become law (Congressional Research Service, 2020).

[2] https://www.whitehouse.gov/briefing-room/statements-releases/2021/04/22/fact-sheet-president-biden-sets-2030-greenhouse-gas-pollution-reduction-target-aimed-at-creating-good-paying-union-jobs-and-securing-u-s-leadership-on-clean-energy-technologies/

and D'Haultfœuille (2020), Borusyak and Jaravel (2017), Goodman-Bacon (2021)).

We address these challenges by using the most comprehensive data available on RPS policies and renewable electricity capacity investments and generation in the U.S. and present new evidence on the causal effect of RPS policies on renewable electricity capacity investments and generation by renewable resource using state-level data for 1990-2019. We exploit the long time-series of data, combined with the staggered timing of RPS adoption across states to derive heterogeneity-robust estimates of the causal effect of RPS on renewables capacity and generation using the econometric methods recently developed in Callaway and Sant'Anna (2021). This approach, we believe, provides the first source-specific panel data evidence on the efficacy of RPS that is robust to treatment effect heterogeneity, a pervasive feature of such programs.

We find that, on average, RPS policies increase wind generation capacity by 600-700 MW but have no significant effect on investments in solar generation capacity. Relative to the average installed wind capacity in 2019 among ever-adopting states, the point estimates imply that wind generation capacity increased by 21% as the result of RPS, a sizeable increase. After modifying our empirical strategy to allow for treatment effect dynamics, we find that the impact of RPSs on wind capacity investments ramps up slowly: most of the capacity additions occur 5 years after RPS implementation. We also examine the possibility of policy spillover where the introduction of an RPS in one state leads to a change in capacity mix in the neighboring states. We find weak and limited evidence that RPS policies cause the mix of electricity generators to change in unregulated neighboring states.

Due to the now long history of RPS policies, dating back to 1991, and its significance for the electricity generation sector, a sizable literature examines its impact renewable generation capacity investments, carbon emissions, and electricity prices. In particular, the evidence from the previous literature on the impact of RPS policies on the deployment of renewable electricity generation is mixed. Several studies (e.g., Shrimali et al. (2015) and Yin and Powers (2010)) find a positive relationship between RPS requirements (or compliance) and renewable electricity generation using a difference-in-differences type empirical strategy, and highlight the importance of controlling for state-specific features of both determinants and characteristics of policies across states. At the same time, other studies find no evidence of an effect of RPS policies and deployment of renewable generating capacity (e.g., Greenstone and Nath (2020), Fullerton and Ta (2022), and Upton and Snyder (2017)). Notably most of this previous literature on RPS policies and the deployment of renewable electricity deployment implicitly relies on a staggered adoption empirical design with state and year fixed effects in an attempt to derive credible estimates (with the exception of Upton and Snyder (2017) who use the synthetic control method). As we argue below, the assumptions necessary to lend a causal interpretation standard TWFE (DD) estimates from this previous literature are not valid in the setting RPS policy adoption.

Several recent papers also study the effects of RPS policies on electricity prices, emissions, and renewables deployment using analytical general equilibrium models (Bento et al. (2018), Fullerton and Ta (2022)). While these papers generally conclude that more stringent RPS policies unambiguously increase the price of electricity, they have ambiguous predictions for the effect of RPSs on renewables deployment. Fullerton and Ta (2022) show that the effect on renewable capacity investments depends on state-specific transmission costs and natural resource endowments. For example, states with larger intermittent resource endowments (such as high wind class) may actually reduce renewable generation by increasing RPS stringency because the policy reduces demand for all electricity through higher retail prices. Thus a detailed empirical analysis is necessary to resolve the theoretical ambiguity.

We contribute to the empirical literature estimating the impacts RPS policies in four ways. First, we bring in recent data on renewable capacity investments up to 2019 and use a new estimator proposed by Callaway and Sant'Anna (2021) that is robust to treatment effect heterogeneity in presence of staggered treatment adoption. Treatment effect heterogeneity is a innate feature of RPS programs due to differences in policy design and underlying renewable resource endowments in each state. An additional consideration that emerges from the recent econometric literature is that the standard TWFE/DD estimator may provide a biased estimate of the average treatment effect on the treated in presence of treatment heterogeneity. This is a critical concern in this setting since virtually all the previous literature uses DD methods, which calls into question the validity of the resulting empirical evidence. Second, our analysis provide new insights by documenting the dynamic impacts of RPS policies in the longer-term, up to 11 years after policy implementation, which is made possible by our newly compiled data sets. This analysis is particularly important because most installations of utility-scale solar generating capacity have occurred since 2010 (see Figure 3 below) and most of the previous research has studied the impacts of RPS over the 2000s and early 2010s periods. Third, we show that RPS policies have increased wind generation while having no detectable effect on solar generation. This pattern suggests that, even within intermittent generation sources, differences in economic feasibility can lead to widely varying policy outcomes. Fourth, this paper extends the analysis in Hollingsworth and Rudik (2019) by estimating the impact of RPS policies on renewable generation deployment in neighboring states using an estimator which is robust to treatment effect heterogeneity.

The rest of this paper is organized as follows. Section 2 provides background on RPS policies and their implementation in the U.S. since 1991. Section 3 describes the data used in our analysis. Section 4 presents the empirical strategy and section 5 describes our results. Finally, section 6 concludes.

2 Details on RPS Programs in the United States

RPS requires retail electricity suppliers to provide a minimum percentage or amount of their retail load using eligible renewable electricity generation sources. Although RPS policies exist in 30 states and the District of Columbia as of 2021, their design differs significantly across states. Most significantly, minimum percentages or "targets" differ both in magnitudes and time frames across states. Furthermore, states differ in their eligibility requirements for existing renewable generation sources, exemptions for publicly owned utilities, enforcement mechanisms, incentives for specific renewable generation technologies, and compliance tracking systems. In the U.S., RPS policies apply to 58% of total retail electricity sales as of 2021 (Barbose (2021)).

Figure 1 shows the history of RPS adoption over time. While Iowa became the first state to adopt a mandatory RPS in 1991, most RPS states implemented their programs between 2000 and 2009. Typically, each state's annual percentage requirement increases gradually over time until it reaches its mandated goal. For example, California's RPS mandates that 60% of retail electricity sales come from renewable generation sources by 2030 and has interim targets of 44% by 2024 and 52% by 2027 (DSIRE (2021)). These time-varying targets within adopting states underscore the importance of examining the dynamic effects of the policy. Figure 2 plots the mean, 95th percentile, and 5th percentile of observed statutory RPS targets across all RPS states in the U.S. between 2000 and 2020. The statutory RPS targets have increased over time as more states adopt RPS policies and update existing legislation. While the average RPS target in 2000 was near 0 percent, the average statutory RPS target in the U.S. exceeded 20 percent in 2020. Although the RPS percentage requirement for each state may appear stringent, the effective standard may be much lower because some states allow existing renewable generation to qualify for compliance. For example, although California's standard was 20% of total retail electricity sales in 2010, it's effective standard was approximately 17% of sales after accounting for eligible existing generation. Such variation in how "constraining" RPS mandates are may introduce lags between the time a policy is first adopted and the time detectable impacts on renewable investments incentivized by the policy are made. In the bulk of the paper, we focus on estimating the causal effect of implementing any RPS legislation on renewables deployment using a method that accounts for potential dynamic impacts, and also consider variation in standard stringency in a robustness analysis.

While all states with RPS policies mandate that a share of retail electricity sales come from renewable generation sources, they often differ in what sources are considered renewable. The list of designated technologies always includes wind and solar electricity generation, but often states differ in their classification of sources such as hydroelectric and nuclear generation as renewable. Furthermore, some states such as California exempt publicly owned utilities from the RPS standard, while others such as Colorado set separate, lower standards for publicly owned utilities.

States further differ in how the RPS policy encourages renewable development. Some states mandate that a certain percentage of the renewable generation used to comply with the RPS policy come from specific technologies. For example, Delaware's solar carve-out currently stipulates that solar generating sources comprise at least 2.25% of renewable generation used for RPS compliance. Additionally, some states such as Delaware enforce RPS policies by charging a fee (typically termed an 'Alternative Compliance Payment') for each unit of renewable generation that would be required to bring a utility into compliance with the standard. Other states such as California allow regulators to levy financial penalties on non-compliant utilities.

Most states monitor compliance with RPS policies using Renewable Energy Credits (RECs) which certify that a given unit of electricity qualifies to meet the standard. Typically, RECs are issued by regional authorities that encompass multiple states and issue a unique serial number for every megawatt-hour of generation produced by registered compliant generators. While some trading of RECs may occur across regions, most RECs used for RPS compliance occurs within a region. We exploit this fact to explicitly model spillovers in wind and solar capacity additions from RPS-adopting states to non-RPS states using an approach similar to Hollingsworth and Rudik (2019).

As this brief overview highlights, RPS policies may appear straightforward, but in practice there is a large degree of heterogeneity across states in how they are implemented. This complexity requires sophisticated econometric methods in order to identify causal effects of the below, as we demonstrate below.

3 Data and Preliminary Analysis

In order to estimate the impact RPS policies on the deployment of utility-scale renewable electricity generation installations, we compile state-level panel data set on the relevant outcomes, policy variables, and predictors of renewable investments (Table A1). While many of the underlying data are recorded at the sub-state level (e.g., the county where wind turbines are located), we organize all the data at the state-level given that RPS policies are implemented by states. This section describes the data sources and presents summary statistics and preliminary analyses.

Figure 1 illustrates the timing of RPS policy adoption across states, focusing on the continental U.S. using data from Barbose (2021). This adoption will constitute the primary treatment indicator we consider in the empirical analysis. Each box represents a year, and are marked in gray once a state adopts the policy. For example, Alabama has yet to adopt an RPS policy, while Arizona enacted it in 2002. By the end of 2019, 27 states had enacted RPS policies, with Iowa being the earliest adopter (1992) and Vermont being the latest (2015). Since no state has disadopted these policies during our sample period, there is a large degree of autocorrelation in the 'treatment status', which we address using cluster-robust inference in the empirical analysis.

Data on operating capacity by source is obtained from the Energy Information Administration (EIA) Form 860, which contains generator-level information at electric power plants with at least 1 MW of combined nameplate capacity. For this study, we use information on installed capacity in wind and solar, which we complement with the same information for coal or gas units (all recorded in MW). Importantly, Form 860 includes information on all operable generators in a given year, as well as the list of retired generators (along with their year of retirement). For operable and retired generators we observe the first year of operation, which allows to reconstruct a complete history of the total cumulative installed capacity (henceforth 'installed capacity') over time, by source (wind, solar, coal, and gas) from 1990-2019.

Figure 3 reports the national trends in installed utility-scale wind and solar electricity capacity. The deployment of capacity for both renewable resources follows a similar pattern, with wind installations beginning to emerge in the early 2000s, while utility-scale solar takes off around 2010.

Growth in capacity appears roughly linear, reaching 100,000 MW for wind and 38,000 MW for solar by the end of the sample period in 2019. Many factors have contributed to the diffusion of these renewable technologies in addition to RPS policies, including reduction in levelized costs of operation, and federal and state-level production tax credits and other localized incentives (Hitaj 2013). The econometric methods detailed below are designed to control for the influence of those other factors.

We also analyze the impact of RPS adoption on actual generation of electricity by source. Data on generation are obtained from EIA Form 906 which reports annual data on generation at the power plant level. Other auxiliary data sources are described in the Data Appendix. Table 1 presents summary statistics tabulated for the 29 states that adopted an RPS policy during the period 1990-2019 and the 11 states that never adopted RPS. Columns (1) and (2) report sample averages while Column (3) reports the RPS state minus non-RPS state difference in means, with stars indicating statistical significance testing the null hypothesis of "no difference" based on an OLS linear regression with standard errors clustered by state. Panel A shows that on average, RPS states have marginally better infrastructure and wind speed endowments, with an additional 0.03 km of transmission per square km of state area, and average wind speed that is 0.3 meter per second higher. Solar irradiance, measured in kWh per square meter per year is a measure of total energy received from sun and a key determinant of solar electricity potential. The data in Table 1 indicates solar irradiance is weakly smaller in RPS states. The small magnitude of the differences reported in Panel A and the lack of statistically significant differences indicate that natural resource endowments do no appear to be a key driver of RPS policy enactment.

Panel B shows (as expected) that RPS states have higher levels of wind and solar capacity installed, on average, than non-RPS states, although the difference is only statistically significant for wind capacity. On average over 1990-2019, total installed wind capacity is 553 MW in states that ever-adopted an RPS. during that period, compared to 192 MW for states that never adopted the policy. At the same time, we note that coal and gas capacity is lower in states that adopt RPS policies. These differences in capacity by source are mirrored in the average generation by source in Panel C. RPS states produce more renewable electricity and less fossil-fueled electricity on average over 1990-2019, but none of the differences are statistically significant.

Panel D reports sample averages for various potential predictors of investments in renewables, including state-level GDP per capita, state-level electricity price and consumption, and League of Conservation Voters (LCV) scores for each state's senator and house of representative members.[3] This correlational analysis reveals marked differences between states adopting RPSs and states never adopting them. GDP per capita is notably higher in RPS states. Electricity prices are also higher in RPS states, by \$0.03 per kWh on average, as is total electricity consumption.[4]. Not

[3]We obtain annual LCV scores between 1993 and 2013 for each state from Hollingsworth and Rudik (2019) and annual scores between 2014 and 2019 directly from the LCV website. The LCV describes its scoring methodology in the following way: "Annual scores are based on a scale of 0 to 100 and calculated by dividing the number of pro-environment votes cast by the total number of votes scored except for excused absences."

[4]Prices are in adjusted to 2019 dollars and represent the electricity price for all end use sectors

surprisingly, RPS are more likely to be adopted in states that score higher in the LCV score index; the RPS - non-RPS difference is roughly 30 points and statistically significant. RPS states also have a higher fraction of counties that are designated 'Non-Attainment' for one or more criteria air pollutant. Finally, RPS compliance is also listed as 94% for RPS states. Since states that ever adopt RPS legislation differ from those that never adopt on a number of important observable margins, our preferred estimates will use not-yet-treated states (as opposed to never treated) as a control group. We test the sensitivity of our estimates to this choice in the robustness analysis.

4 Empirical Approach

4.1 Estimating Impact of RPSs with Staggered Adoption and Treatment Effect Heterogeneity

The primary goal of this paper is to estimate the causal effect of RPS policies on the deployment of renewable electricity capacity investments and generation using a staggered adoption research design. In order to estimate the impact of RPS policies on the various outcomes of interest, the previous literature has typically used a difference-in-differences design with a two way fixed effects (TWFE) estimator with state and year fixed effects (Yin and Powers (2010), Shrimali et al. (2015), Hollingsworth and Rudik (2019), and Greenstone and Nath (2020)). The canonical regression equation for such models is:

$$y_{it} = \beta RPS_{it} + X_{it}'\theta + \gamma_i + \delta_t + \varepsilon_{it} \tag{1}$$

Where in the context our study, y_{it} denotes utility-scale wind or solar electric capacity installed (or generation) in state i at year t, RPS_{it} is a binary variable taking a value of one for all years following RPS implementation, and X_{it} is a vector of state-specific time varying control variables. The state fixed effects (γ_i) capture time-invariant characteristics of each state, such as underlying wind class, that determine renewable capacity installations and correlate with the probability that each state implements an RPS policy. Similarly, the year fixed effects (δ_t) control for annual shocks that are common to all states, and may be correlated with both renewable capacity installations and the probability of implementing an RPS policy. For example, the year fixed effects account for changes in the federal production tax credit, helping us to isolate the causal impact of RPS policies alone on the deployment of renewable electricity generation. The coefficient of interest, β is the average treatment effect on the treated (ATT) of an RPS policy on the outcomes (utility-scale wind and solar capacity and generation).

OLS estimation of equation (1) is straightforward. However, recent advances in econometric research show that, in the presence of treatment effect heterogeneity (i.e., where β can vary over time or across cross-sectional units), the standard TWFE estimator identifies a weighted average of group-time specific treatment effects which may not correspond to the overall ATT (Sun and Abraham (2020), de Chaisemartin and D'Haultfœuille (2020), Borusyak and Jaravel (2017), Goodman-Bacon (2021)). As explained earlier, due to important differences in RPS policy design across states and advancement in renewable generation technologies over time, it is reasonable to expect sizable treatment effect heterogeneity in this setting. For example, California's initial RPS target was 11.85% for all utilities while Missouri's was 2% and included a carve out for solar electricity generation.

In order to address the issues with the TWFE estimator, we use the estimator proposed by Sant'Anna and Zhao (2020) and Callaway and Sant'Anna (2021) to estimate the impact of RPS policies. While researchers have proposed several different estimators which are robust to treatment effect heterogeneity, the Callaway and Sant'Anna (2021) estimator is well suited to staggered adoption research designs with a binary treatment indicator as in our setting.[5] Furthermore, we employ the estimator proposed by Callaway and Sant'Anna (2021) because it provides a flexible framework for aggregating group-time specific treatment effect parameters into dynamic treatment effects.

This estimator requires defining "adoption cohorts" which are groups of units that become treated at the same time. Due to limited overlap in RPS implementation years across adopting states (Figure 1), we define adoption cohorts using 3 year windows, so that all states implementing RPSs between 1998-2000, 2001-2003, 2004-2006, and 2007-2009 are assigned to the same cohort. In our setting, the estimator computes the treatment effect for each RPS adoption cohort by differencing each cohort's outcomes in a post implementation year t with its outcome in the year prior to implementation (akin to the pre/post difference for the treatment group in standard DD estimation), and then computing the same difference for a control group that is not treated as of year t (akin to the pre/post difference for the control group in standard DD estimation). For example, $ATT_{g,t}$ denotes the average treatment effect on the treated for all states that implemented a RPS policy in year g at post-treatment time t relative to the year before treatment, $g-1$. Adoption cohort-specific control groups are constructed by estimating a propensity score for each untreated state using baseline covariate values. The set of possible comparison groups for cohort g could be all of the states that never adopt an RPS policy during the sample period or the set of states that have not yet adopted a RPS policy at year g. We choose to use the set of *not yet treated* states to construct the control groups in the preferred analysis because (as documented in Table 1) ever treated and never treated states differ on a number of relevant characteristics. However, estimates using the never treated comparison group are similar to our main results, as shown in Table 4.

Estimation of the $ATT_{g,t}$ parameters in our setting relies on four assumptions. First, the data structure must be a panel or a repeated-cross section of states. Second, conditional common trends holds between the treated and not-yet-treated groups, conditional on covariates. Third, treatment follows a staggered adoption design (e.g., the treatment is binary, and never reverts back from "1" to "0"). Fourth, there is some overlap on baseline covariates between the treatment and control groups. Assumptions 1 and 3 are trivially satisfied in our setting since our sample consists

[5]See Sun and Abraham (2020), Goodman-Bacon (2021), de Chaisemartin and D'Haultfœuille (2020), Strezhnev (2018), Ben-Michael et al. (2021), Imai et al. (2019), Borusyak and Jaravel (2017) for other proposed estimators.

of a balanced panel of states from 1990 to 2019 and we treat each RPS policy as irreversible. While assumption 2 is impossible to formally test since it involves unobserved counterfactuals, we provide evidence that it is plausible by estimating pre-treatment period event study coefficients. Finally, to address assumption 4, we use the outcome regression estimand proposed by Callaway and Sant'Anna (2021) because there is limited covariate overlap between RPS states and their not-yet-treated counterparts, leading to imprecise inference procedures when using inverse probability weighting and doubly robust estimators (Khan and Tamer (2010)).

We control for state-level endowment characteristics which previous research has suggested influence renewables deployment such as: wind potential (wind speed), solar irradiance, and total length of electricity transmission lines. Wind potential and solar irradiance capture a state's latent potential for renewable electricity generation, while the length of transmission lines measures potential grid access for renewable generation sources. Furthermore, we control for a set of time-varying state level socioeconomic characteristics including gross domestic product (GDP) per capita, House and Senate League of Conservation Voting (LCV) scores, and electricity price per kilowatt hour of electricity in 1990 (the first year in our sample). The House and Senate LCV scores rank representatives and senators based on their environmental voting record. We use these variables to capture the underlying degree of pro-environmental attitudes in each state.

To conduct inference and compute standard errors, we use the multiplier bootstrap procedure described in Callaway and Sant'Anna (2021) which constructs simultaneous confidence intervals for the $ATT_{g,t}$ parameters. We cluster standard errors at the state level to allow for correlation in renewable capacity adoption within each state over time. Since some adoption cohorts are small, we group states that adopt RPS policies into 3-year bins corresponding to years 1998-2000, 2001-2003, 2004-2006, and 2007-2009.

To facilitate the interpretation of our results, we summarize the $ATT_{g,t}$ parameters in 4 ways using the did R package from Callaway and Sant'Anna (2021). The parameter 'Overall ATT (cohort)' correspond to the average effect of RPS policies experienced by all states that ever implement an RPS.[6] Similarly, we report the 'Overall ATT (year)' parameter, which corresponds to the average effect of implementing an RPS policy for states that have implemented an RPS for at least 11 years. This parameter first averages the heterogeneous effect of RPS policies across adoption-cohort groups within each time period for those states that we observe at least 11 years of post-implementation data, before averaging these parameters across time periods.[7] The last two average treatment effect parameters are the same as Overall ATT (year), except that they are computed separately for post-implementation years 1-5 and 6-11 respectively. This provides a simple metric to gauge dynamic effects of RPS policies on renewable capacity investments and

[6] Callaway and Sant'Anna (2021) recommend computing an overall ATT by first averaging the adoption-cohort, time specific treatment effects $\beta_{g,t}$ across post-implementation time periods for each cohort and then averaging the adoption cohort specific treatment effects.

[7] We chose to balance the panel of states when estimating the dynamic treatment effects because it prevents the treatment effect from being driven by changes in the composition of the RPS ever-adoption group over time Callaway and Sant'Anna (2021). This results in Iowa and Vermont (two RPS states) to drop from the main estimation sample. We evaluate the robustness of the results to this sample construction choice below.

generation.

4.2 Estimating the Impact of RPS Intensity

Since the binary treatment indicator ignores differences in RPS targets across states, we construct a continuous treatment of treatment intensity measure following Yin and Powers (2010) and Hollingsworth and Rudik (2019). The continuous treatment variable, RPS Intensity$_{it}$, accounts for several sources of RPS policy heterogeneity across states. First, it leverages differences in nominal RPS targets across states. For example, California's target specifies that 60% of retail electricity sales come from renewable sources by 2030 while New York's 2030 target is 70%. Second, the continuous treatment incorporates differences in RPS coverage and eligibility of existing renewable generation across states. More specifically, we define RPS intensity as follows:

$$RPS\ Intensity_{it} = \frac{\sum_{k=1}^{N_i^k}(Nominal\ RPS_{kit} \cdot Sales_{kit} - Existing_{kiT_i})}{Sales_{it}} \tag{2}$$

Where $Nominal\ RPS_{kit}$ is the nominal RPS requirement for utility type k in state i at year t and state i has N_i^k types of utilities covered by its RPS policy. We obtain annual RPS requirements for each state and utility type from Barbose (2021). $Coverage_{kit}$ denotes the share of total electricity load in state i serviced by utility type k at year t, and $Sales_{kit}$ is total retail electricity sales by utility type k in state i at year t. Finally, $Existing_{kiT_i}$ denotes the total amount of electricity generation at the year prior to RPS implementation (T_i) which utilities may use to meet the RPS requirement. We obtain generation data from EIA form 906. The Lawrence Berkeley National Lab provided information on policy coverage by utility type and allowances for existing generation.

Since the estimator proposed by Callaway and Sant'Anna (2021) is specific to staggered adoption settings for a binary treatment, we create a discrete treatment indicator equal to one in all periods after $RPS\ Intensity_{it}$ exceeds its sample average level. Defining treatment in this way means that there could be anticipatory treatment effects if renewable generation capacity responds to below-average levels of $RPS\ Intensity_{it}$.

5 Results: Impact of RPS Policies

5.1 Wind Capacity and Generation

The empirical analysis begins by analyzing the impact of RPS implementation on wind outcomes. Table 2 reports the results for installed wind capacity (Panel A) and wind generation (Panel B). The estimates in column (1) include no additional controls (besides the adoption cohort and year fixed effects implicitly accounted for by the Callaway and Sant'Anna (2021) estimator). Column (2) adds the 'natural endowments' controls (wind potential, solar irradiance, and total length of transmission lines in the state, see Table 1 for details), and column (3) adds the 'socioeconomic' controls (GDP per capita, House and Senate League of Conservation Voting scores, and the price per kilowatt hour of electricity in 1990). Standard errors for all estimates are computed using a multiplier bootstrap method with clustering at the state level (Callaway and Sant'Anna (2021), Kline and Santos (2012), Belloni et al. (2017), Chernozhukov et al. (2018)).

The preferred estimates in column (3) indicate that, on average, implementing an RPS policy increases installed wind capacity by 586 MW on average, across all states that ever adopted an RPS at any point during our sample period (Overall ATT (cohort)). This is a large effect, corresponding to 21% of the average installed wind capacity in 2019 among RPS states. Overall, across the estimates in columns (1) to (3), the size effect of the estimated ATT of RPS policy implementation ranges from 10% to 21%. Converting our preferred estimates to reflect the average percentage point change in the share of total capacity or generation attributable to wind resulting from a 1 percentage point increase in the RPS target implies that the share of capacity increase by 0.33 percentage point.[8] The average impact of RPSs for the group of states for which we have at least 11 years of pre and post-implementation data (Overall ATT (year)) is of similar magnitude, implying that RPS policies lead to 714 MW in capacity additions. Decomposing the effect by post-implementation event time suggests that most of the increase in wind capacity investment occurs 6-11 years after RPS implementation (1,000 MW on average), as opposed to 197 MW in years 1-5. While all these estimates are positive, indicating that RPS policies were important contributor to the development of in-state wind electricity installation, it should be noted that the statistical significance is sensitive to the chosen specification, with the column (1) and column (3) estimates being statistically different from 0 at the 5% significance level, while those in column (2) are not.

The results for annual wind generation are shown in Panel B and are generally mirror those for installed capacity. The Overall ATT (cohort) estimate is column (3) is 3,110 GWh while Overall ATT (year) is 3,710 GWh. The impact again is larger for years 6-11 after RPS implementation (compared to years 1-5), implying that, on average, RPS states increase annual wind generation by 5,350 GWh relative to their not-yet-treated counterparts. This effect corresponds to 136% of the mean wind generation and even 9% of mean coal generation among ever-adopting RPS states in our sample, again underscoring the importance of RPSs as drivers of renewables deployment. The statistical significance of the estimates of the impact of RPS policies on wind generation follows a similar pattern as those for wind capacity. The estimates in column (3), with the full set of natural endowments and socioeconomic controls are generally statistically significant the at the 5% level, while the column (2) estimates are qualitatively similar, but imprecisely estimated.

Figures 4 and 5 present the unconditional dynamic treatment effects for wind capacity investments and generation, respectively. Each point represents an event time-specific treatment effect which has been computed by averaging the group-time specific effects across adoption cohort groups, following the approach in Callaway and Sant'Anna (2021). Again, these are average effects for the subset of states for which we have 11 years of pre- and post-implementation data. We color-code the point estimates to reflect the pre-RPS adoption period (gray) and post RPS adoption period (orange). The corresponding 95% confidence intervals are represented by the length of the tickers.

[8] These results are consistent with estimates from Yin and Powers (2010) and Shrimali et al. (2015) who find that the share of electricity generated by renewables increases by 0.6 and 0.3 percentage points respectively.

The pre-RPS adoption treatment effect estimates to the left of 0 on the horizontal axis are small and provide supporting evidence for the parallel trends assumption for wind capacity investments across the treated and not-yet-treated groups. In the case of wind generation (Figure 5), the pre-RPS adoption estimates also support the parallel trend assumption. The combined evidence in Figures 4 and 5 indicate that the estimates of the impact of RPS policies in Table 2 can be interpreted as credible estimates of the ATT of the policy.

The post-RPS adoption treatment effect estimates confirm the results in Table 2: RPS policies cause wind capacity investments and generation to increase in the post-policy adoption period.[9] All the post-adoption point estimates are statistically significant at the conventional level for wind capacity investments, and 8 out of 11 are for wind electricity generation. In terms of dynamics, the treatment effects appear to grow roughly linearly with post-adoption time. Importantly, through the 11 years of post-adoption data we have, the estimated impact of RPS on capacity investments and generation show no sign of reverting back to a null effect. This indicates that RPS policies created long-lasting change to the electricity sector of the states adopting them.

5.2 Solar Capacity and Generation

Next, we examine how RPS legislation has impacted solar capacity and generation. Table 3 is configured as Table 2 and presents the ATT estimates for solar capacity and generation in panels A and B respectively. While most of the estimates of the impact of RPS policies on solar capacity investments and generation are positive (as expected), they are smaller than their wind counterparts and lack statistical precision. The preferred estimates in column (3) imply that, on average, implementing an RPS increases solar capacity by 28 MW in ever-adopting RPS states. The overall ATT (year) estimate similarly implies that wind capacity increases by 44 MW following RPS implementation. While statistically insignificant, the estimated impact of RPS on solar electricity generation range between 87 and 117 GWh. As is the case with wind energy, much of the estimated RPS impacts on solar capacity additions and generation occur between 6 and 11 years after RPS implementation. The estimated standard errors for all estimates in column (3) are large relative to the ATT estimates such that the 95 % confidence intervals for the RPS impact on solar energy all include zero.

Figures 6 and 7 display the estimated dynamic treatment effects for solar capacity and generation respectively, computed in the same way as its counterpart in Figures 4 and 5. The pre-implementation estimates provide suggestive evidence that the parallel trends assumption holds between treated and not-yet-treated states. Furthermore, the post-implementation estimates (shown in orange) are small and indistinguishable from zero, confirming the results in Table 3.

The estimate for generation in column 3 of Table 3 implies that solar generation increased by 18% relative to the mean level of solar generation for ever-adopting states, although the lack of precision makes this conclusion tenuous. One likely explanation for the imprecise estimates of the

[9] Note that the Overall ATT (year) estimates in Table 2 are just a weighted average of the event-time estimates from Figures 4 and 5.

effect on solar capacity and generation is that growth in solar capacity investment was limited prior to 2010. Figure 3 shows that while most of the wind capacity investment in the U.S. has occurred since 2000, similar increases in solar capacity investment did not meaningfully accumulate until 2010. This is consistent with evidence from Wiser et al. (2010) who suggest that wind generation proved more economically attractive and lower risk than solar in many regions of the U.S., leading to earlier investment in wind. For context, most solar electricity generation farms had installed capacity of 5 MW or less as of 2019 in the U.S.[10]

5.3 Robustness

We check the robustness of our estimates to a number of additional model specifications in Table 4. The rows alternate between installed capacity (MW) and annual generation (MWh). All specifications control for both the natural endowment and socioeconomic covariates. Rows 1 and 2 replicate our preferred estimates of ATT (Year) from Tables 2 and 3, while all other rows depart from the baseline specification in one of five possible ways: whether the panel of treated states is balanced for 11 pre- and post-treatment periods, whether the control group is the set of never treated states or not yet treated group (as in the preferred estimates specification of Tables 2 and 3), and finally modelling the RPS policy as a binary indicator for RPS adoption (legislation) or as a binary indicator for RPS intensity being above the sample average. Rows 3 and 5 replicate our preferred specification using the control group of states that have never adopted an RPS policy with installed capacity and generation as outcomes, respectively. The results for wind using the never-treated group as the control are slightly larger than our preferred estimates, and remain statistically significant at the 95% confidence level. For solar energy, the estimates are virtually identical using the never-treated and not-yet-treated groups as control groups and the results remain statistically insignificant.

Rows 4 and 6 replicate the preferred estimates using an unbalanced panel of treated states rather than the subset of treated states for whom we observe 11 years of pre- and post-treatment data. Using an unbalanced panel substantially increases the estimated treatment effect for both the capacity and generation outcomes. Consistent with the prior evidence, only the ATT estimates for wind are statistically significant at the 5% level. Callaway and Sant'Anna (2021) note that the estimates using the unbalanced panel of treatment units should be interpreted with caution since they may be driven by changes in the composition of treated units over time. For this reason, we find it reassuring that the unbalanced panel results are qualitatively similar to our preferred estimates based on the balanced panel.

Rows 7 and 8 use the treatment variable defined in section 4.2 which accounts for the stringency of each state's RPS rather than the policy implementation date. The estimates imply that, on average, implementing a RPS with stringent incentives increases solar capacity by 203 MW and wind capacity by 493 MW. For generation, the results suggest that implementing a RPS with stringent incentives increases solar generation by 563 GWh and increases wind generation by 2,570

[10] https://www.eia.gov/todayinenergy/detail.php?id=38272

GWh. All estimates are imprecise and the 95% confidence intervals include the null effect. Relative to the preferred estimates in rows 1 and 2, these effects are larger for solar generation and smaller for wind generation.

6 Discussion and Conclusion

Renewable portfolio standards are the most prominent policy lever to stimulate investments in renewable electricity in the United States. Despite their more than 30-year long history, RPSs remain controversial and debates continue to surround their efficacy in leading the low-carbon transition in the electricity sector. This paper provides a careful evaluation of the impact of RPSs on renewable electricity capacity investments and generation, using modern panel data econometric methods suited for the analysis of staggered policy adoption with heterogeneous effects and the most up-to-date data available.

The results of this study point to 3 ways by which RPS legislation have changed the composition of electricity generation in the U.S. First, RPS legislation dramatically increased wind capacity investments and generation and this increase persists up to eleven years after policy implementation. Second, dynamic responses to the policy, which had not been considered in the previous literature are important: RPS policies take time to affect renewable capacity installations and generation, with much of our estimated effect occurring 6-11 years after the policy's initial implementation. Third, we find no evidence that RPS legislation had any effect on solar capacity investment or generation. One caveat on this last finding is that due to the timing of utility-scale solar deployment in the U.S., our sample of data is not as well-suited to test the effect of RPSs on solar investments.

We can use our estimates to infer the contribution of RPS policies on total capacity installed in wind (we ignore solar due to the small ATT estimates and the lack of statistically significant evidence). The estimated ATT of RPS on capacity 11 years post RPS implementation (relative to the year prior to implementation) is an increase of approximately 1000 MW (Table 2). Applying this estimate to the 29 states with RPS legislation as of 2019 implies that 29 GW, almost 30% of the current aggregate wind capacity is a result of RPS policies. While this is admittedly a simple and crude calculation, it nevertheless highlights the key role RPS played in developing the wind sector in the United States.

The empirical analysis also highlights the importance of explicitly accounting for the considerable heterogeneity in RPS legislation across states in empirical analyses. Amongst papers in the previous literature, our findings most closely resemble the results from Yin and Powers (2010) and Shrimali et al. (2015), both of which only find a positive effect on renewable generation after controlling for aspects that differ across states' RPS policies. This is a reassuring result that helps to reconcile the wide variety of prior estimates of RPS policies' impact on renewable generation. Our estimates also build on the prior literature by separately identifying RPS policies' effect on wind and solar generation. Despite evidence from Wiser et al. (2010) that wind generation was more economically feasible than solar in most regions of the U.S. prior to 2010, most prior research has grouped wind and solar generation together as an outcome.[11]

The U.S. and many other advanced economies are at a turning point where detailed and aggressive decarbonization plans are established. The Clean Energy Standard proposed by President Biden in 2021 shares many features with RPSs as they have been implemented by U.S. states since 1991. Taken together, the evidence presented in this paper indicates that a national Clean Energy Standard may promote investments in wind and solar production capacity and actual generation of renewable electricity. An important topic for future research is whether these investments will be sufficient for the energy sector to reach targets of zero emissions by 2035.

[11] Another working paper by Fullerton and Ta (2022), find no effect of RPS policies on generation from wind and solar power using the same estimator from Callaway and Sant'Anna (2021). One possible explanation for the discrepancy between our estimates and theirs is that they are not separately estimating the effect on wind and solar power.

References

Barbose, G. L. (2021). U.s. renewables portfolio standards 2021 status update: Early release. Technical report.

Belloni, A., Chernozhukov, V., Fernández-Val, I., and Hansen, C. (2017). Program evaluation and causal inference with high-dimensional data. *Econometrica*, 85(1):233–298.

Ben-Michael, E., Feller, A., and Rothstein, J. (2021). Synthetic Controls with Staggered Adoption. *arXiv:1912.03290 [econ, stat]*. arXiv: 1912.03290.

Bento, A. M., Garg, T., and Kaffine, D. (2018). Emissions reductions or green booms? General equilibrium effects of a renewable portfolio standard. *Journal of Environmental Economics and Management*, 90:78–100.

Borusyak, K. and Jaravel, X. (2017). Revisiting Event Study Designs. SSRN Scholarly Paper ID 2826228, Social Science Research Network, Rochester, NY.

Butts, K. (2021). Difference-in-Differences Estimation with Spatial Spillovers. *arXiv:2105.03737 [econ]*. arXiv: 2105.03737.

Callaway, B. and Sant'Anna, P. H. C. (2021). Difference-in-Differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Chernozhukov, V., Fernández-Val, I., and Luo, Y. (2018). The sorted effects method: Discovering heterogeneous effects beyond their averages. *Econometrica*, 86(6):1911–1938.

de Chaisemartin, C. and D'Haultfœuille, X. (2020). Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review*, 110(9):2964–2996.

Fullerton, D. and Ta, C. L. (2022). What Determines Effectiveness of Renewable Energy Standards? General Equilibrium Analytical Model and Empirical Analysis. Working Paper 29783, National Bureau of Economic Research. Series: Working Paper Series.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*.

Greenstone, M. and Nath, I. (2020). Do Renewable Portfolio Standards Deliver Cost-Effective Carbon Abatement? SSRN Scholarly Paper ID 3374942, Social Science Research Network, Rochester, NY.

Hollingsworth, A. and Rudik, I. (2019). External Impacts of Local Energy Policy: The Case of Renewable Portfolio Standards. *Journal of the Association of Environmental and Resource Economists*, 6(1):187–213.

Holt, E. (2016). Potential RPS Markets for Renewable Energy Generators. Technical report.

Imai, K., Kim, I. S., and Wang, E. (2019). Matching Methods for Causal Inference with Time-Series Cross-Sectional Data. page 51.

Khan, S. and Tamer, E. (2010). Irregular Identification, Support Conditions, and Inverse Weight Estimation. *Econometrica*, 78(6):2021–2042. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA7372.

Kline, P. and Santos, A. (2012). A score based approach to wild bootstrap inference. *Journal of Econometric Methods*, 1(1):23–41.

Lyon, T. P. (2016). Drivers and impacts of renewable portfolio standards. *Annual review of resource economics*, 8(1):141–155.

Sant'Anna, P. H. C. and Zhao, J. B. (2020). Doubly Robust Difference-in-Differences Estimators. page 35.

Shrimali, G., Chan, G., Jenner, S., Groba, F., and Indvik, J. (2015). Evaluating Renewable Portfolio Standards for In-State Renewable Deployment: Accounting for Policy Heterogeneity. *EEEP*, 4(2).

Strezhnev, A. (2018). Semiparametric weighting estimators for multi-period difference-in-differences designs. page 44.

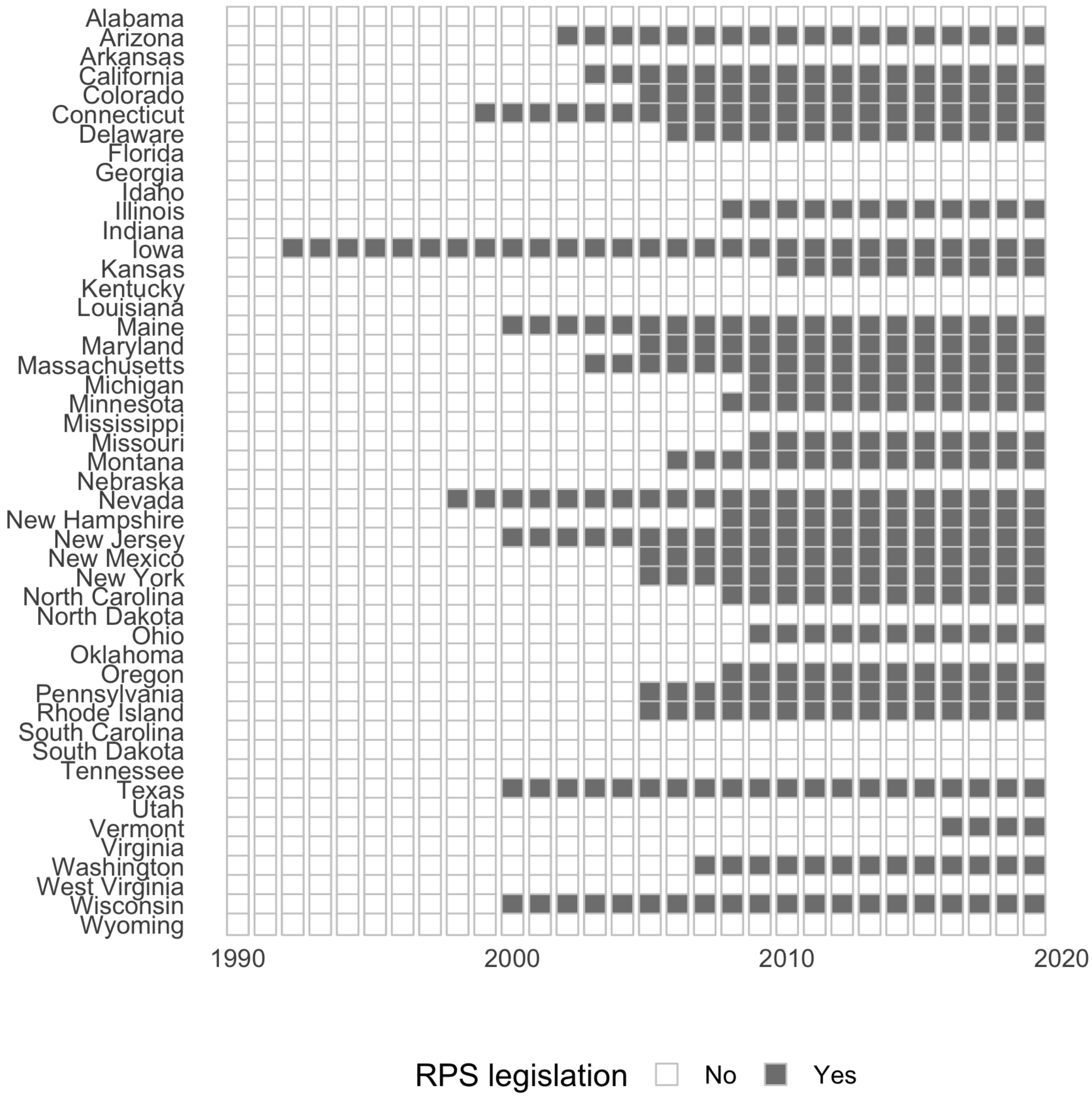
Sun, L. and Abraham, S. (2020). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*.

Upton, G. B. and Snyder, B. F. (2017). Funding renewable energy: An analysis of renewable portfolio standards. *Energy Economics*, 66:205–216.

Wiser, R., Barbose, G., and Holt, E. (2010). Supporting Solar Power in Renewables Portfolio Standards: Experience from the United States. Technical report.

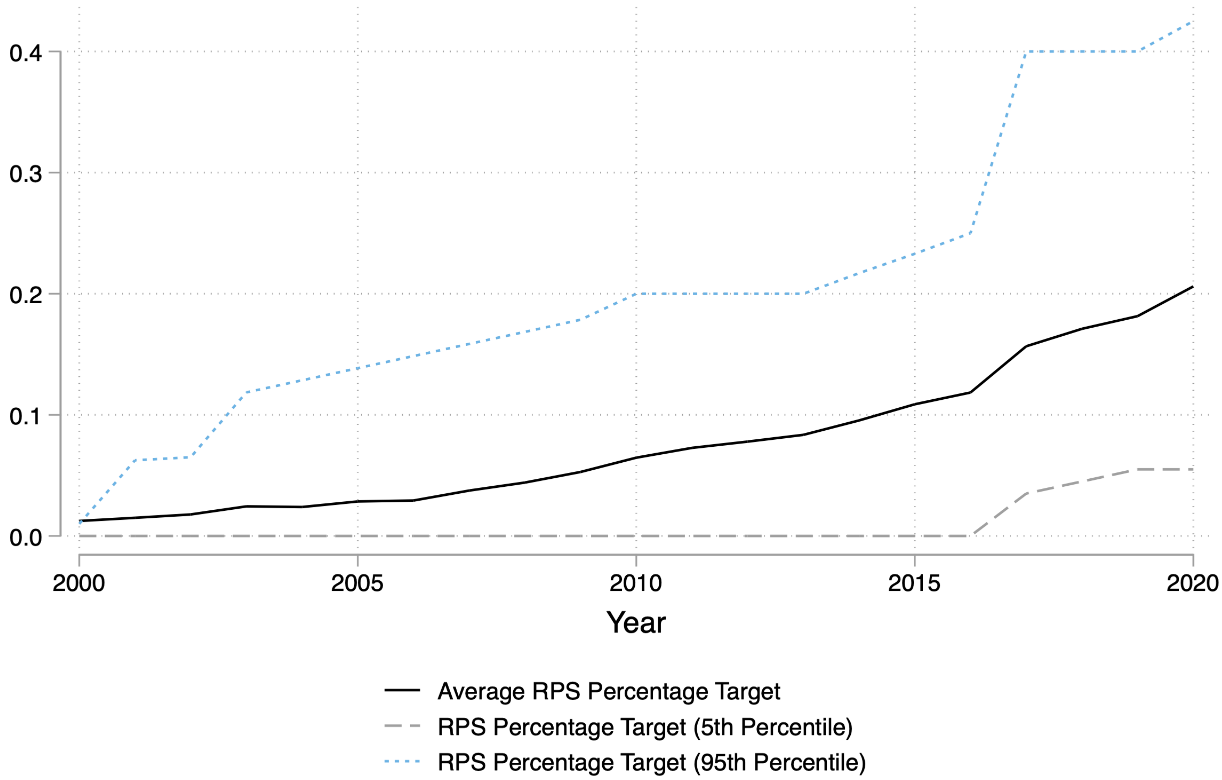
Yin, H. and Powers, N. (2010). Do state renewable portfolio standards promote in-state renewable generation? *Energy Policy*, 38(2):1140–1149.

Figure 1: Year of RPS Adoption by State



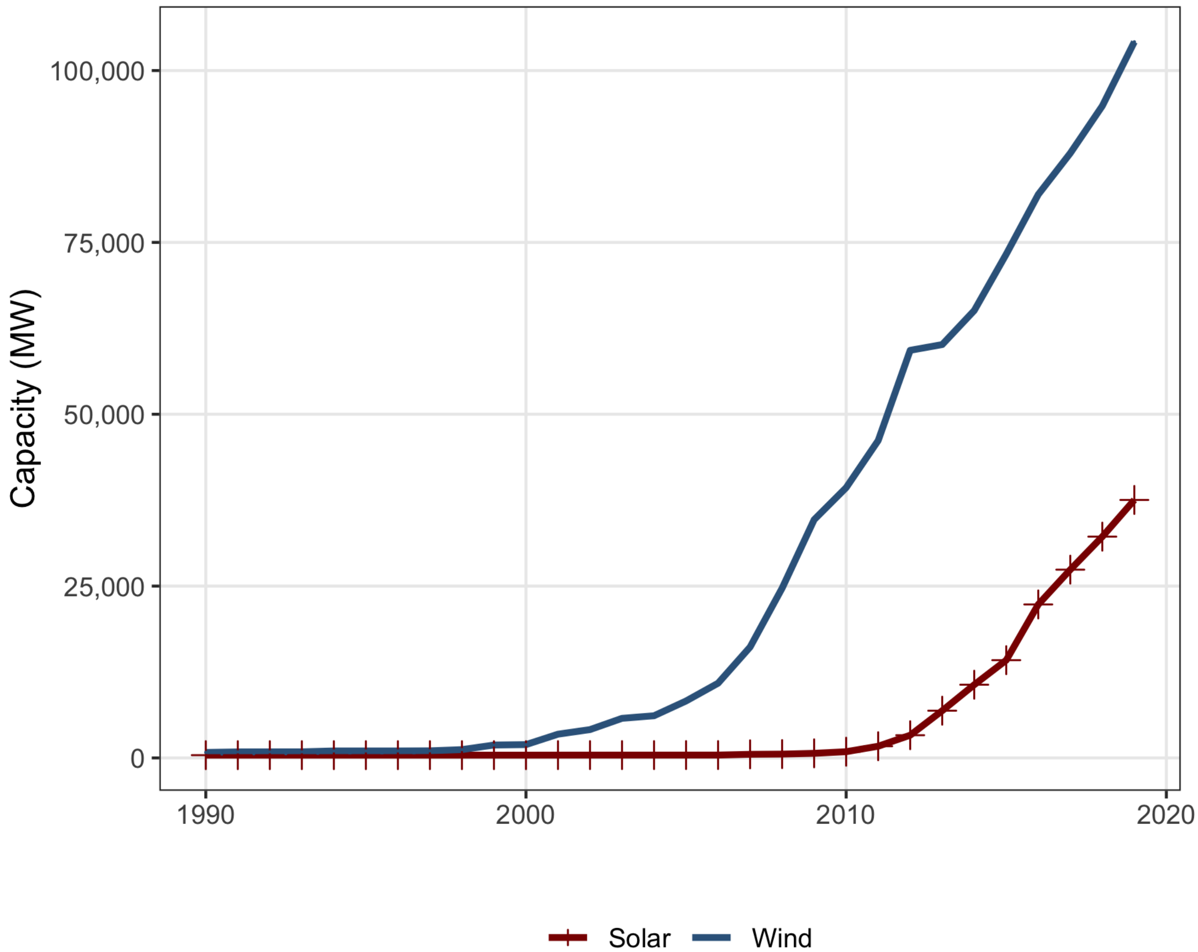
Notes: Each box is shaded gray starting in the first year that a state adopts any RPS policy. Information on RPS adoption date was taken from Greenstone and Nath (2020).

Figure 2: Nominal RPS Percentage Targets Over Time



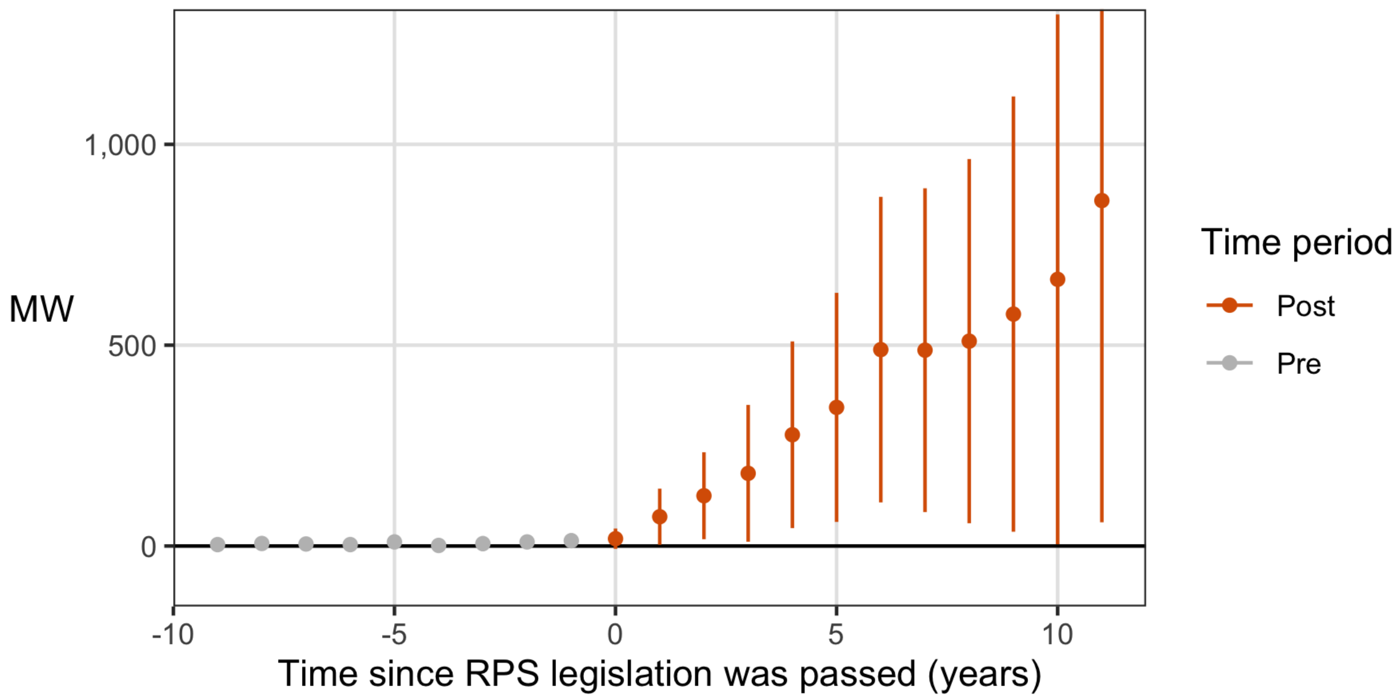
Notes: This figure shows the nominal RPS percentage targets over time based on data reported in Barbose (2021). Nominal RPS percentage targets measure the percent of applicable retail electricity sales required to be generated by renewable sources. Since the definition of a renewable resource, type of regulated entity (e.g. public vs. privately owned utilities), and incentives for certain types of renewable generation differ considerably across states, comparison of targets across states is inadvisable. This figure shows that targets have increased in stringency over time and vary widely across states.

Figure 3: Annual Renewable Electricity Generation Capacity (MW)



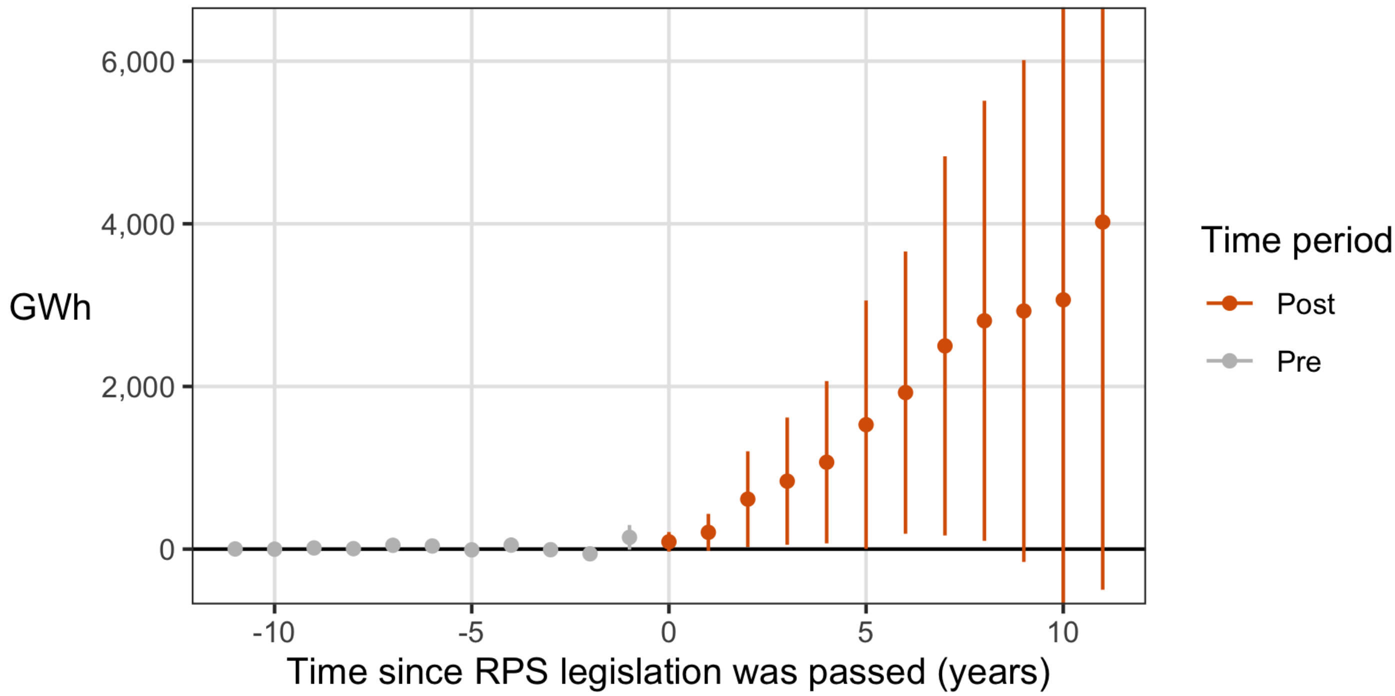
Notes: The blue (red with '+'s) lines plot the level of installed wind (solar) generation capacity in the continental U.S. annually between 1990 and 2019. Information on capacity installations by generation source was taken from the EIA Form 860 database.

Figure 4: Estimated Dynamic Treatment Effects of RPSs on Installed Wind Capacity (MW)



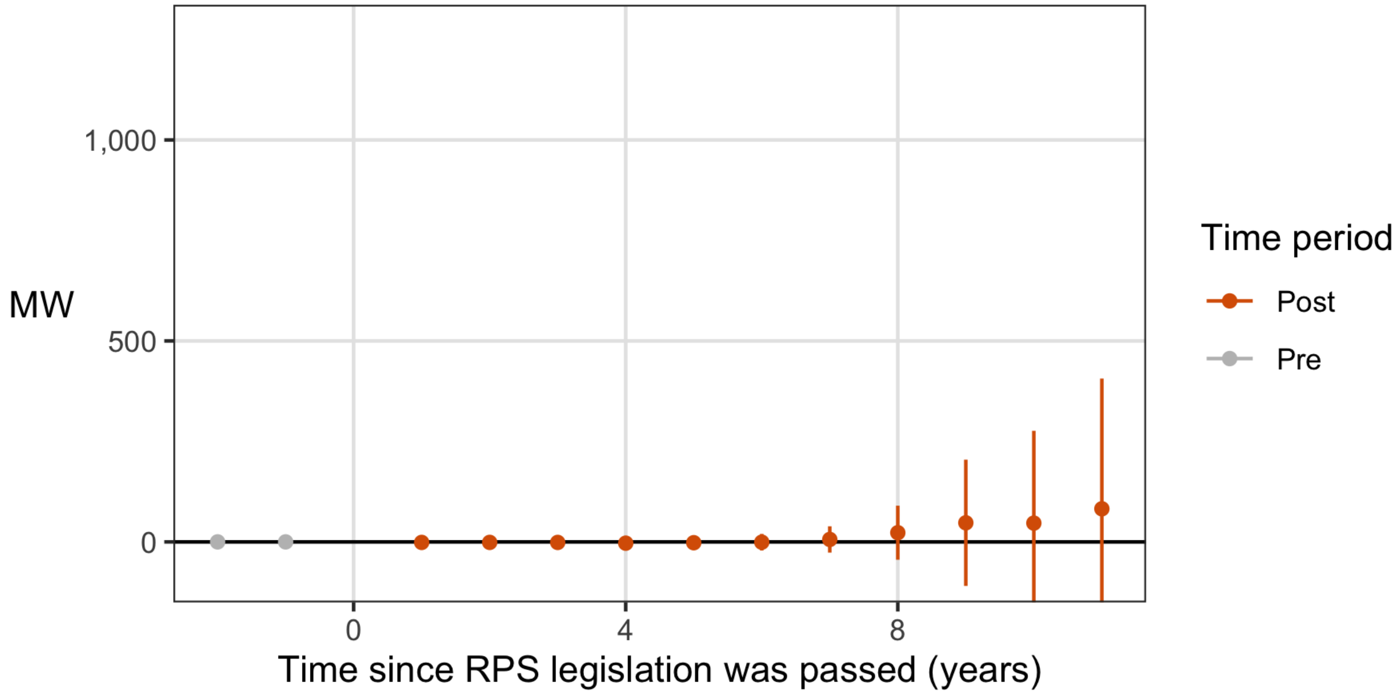
Notes: Each circle shows the estimated ATT averaged across treatment adoption cohorts and for each event-time period (t). The vertical bars represent the 95% confidence intervals for each point estimate. Standard errors are computed using a multiplier bootstrap and clustered at the state level. We include time invariant controls for wind potential, solar irradiance, length of transmission lines per square kilometer of state area, 1990 per capita GDP, 1990 House and Senate League of Conservation Voting scores, and the retail price per kilowatt hour of electricity in 1990 at the state level. Pre-policy adoption estimates that are statistically indistinguishable from zero are shown in gray.

Figure 5: Estimated Dynamic Treatment Effects of RPSs on Wind Electricity Generation (GWh)



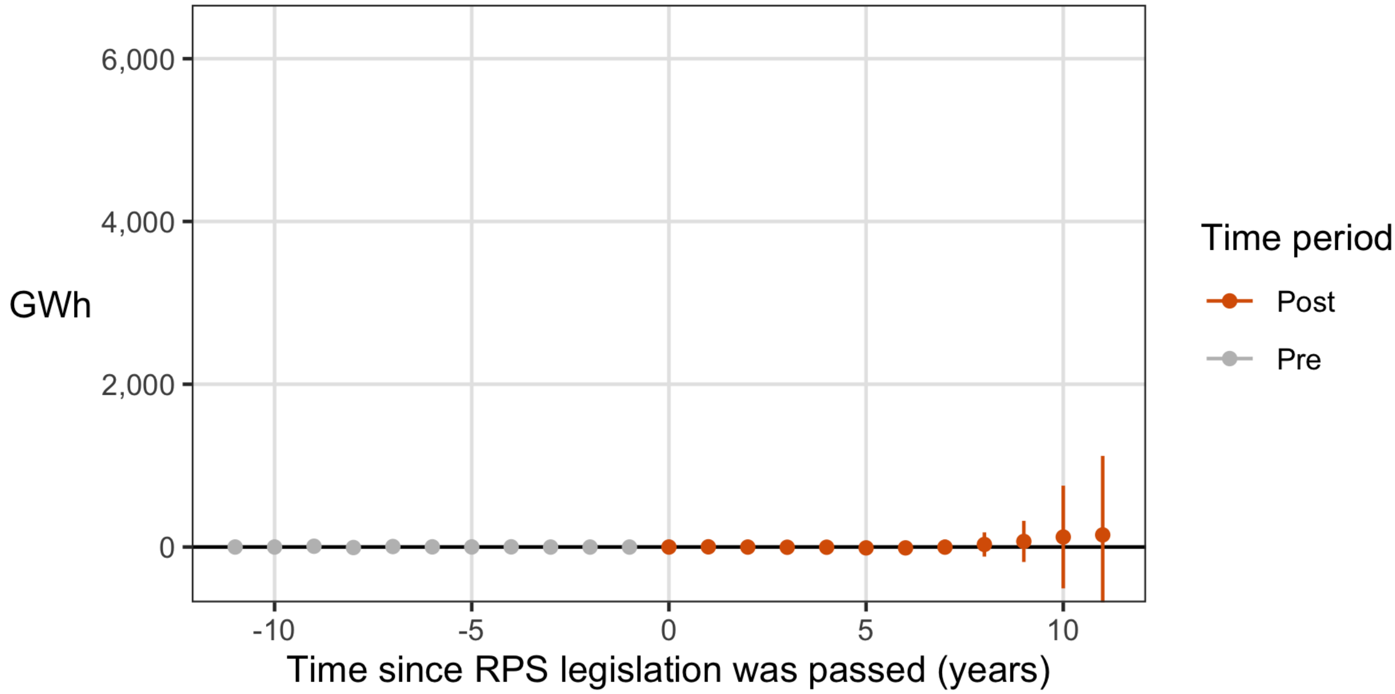
Notes: Each circle shows the estimated ATT averaged across treatment adoption cohorts and for each event-time period (t). The vertical bars represent the 95% confidence intervals for each point estimate. Standard errors are computed using a multiplier bootstrap and clustered at the state level. We include time invariant controls for wind potential, solar irradiance, length of transmission lines per square kilometer of state area, 1990 per capita GDP, 1990 House and Senate League of Conservation Voting scores, and the retail price per kilowatt hour of electricity in 1990 at the state level. Pre-policy adoption estimates that are statistically indistinguishable from zero are shown in gray.

Figure 6: Estimated Dynamic Treatment Effects of RPSs on Installed Solar Capacity (MW)



Notes: Each circle shows the estimated ATT averaged across treatment adoption cohorts and for each event-time period (t). The vertical bars represent the 95% confidence intervals for each point estimate. Standard errors are computed using a multiplier bootstrap and clustered at the state level. We include time invariant controls for wind potential, solar irradiance, length of transmission lines per square kilometer of state area, 1990 per capita GDP, 1990 House and Senate League of Conservation Voting scores, and the retail price per kilowatt hour of electricity in 1990 at the state level. Pre-policy adoption estimates that are statistically indistinguishable from zero are shown in gray.

Figure 7: Estimated Dynamic Treatment Effects of RPSs on Solar Electricity Generation (GWh)



Notes: Each circle shows the estimated ATT averaged across treatment adoption cohorts and for each event-time period (t). The vertical bars represent the 95% confidence intervals for each point estimate. Standard errors are computed using a multiplier bootstrap and clustered at the state level. We include time invariant controls for wind potential, solar irradiance, length of transmission lines per square kilometer of state area, 1990 per capita GDP, 1990 House and Senate League of Conservation Voting scores, and the retail price per kilowatt hour of electricity in 1990 at the state level. Pre-policy adoption estimates that are statistically indistinguishable from zero are shown in gray.

Table 1: Summary Statistics

	(1) RPS states	(2) Non RPS states	(3) Difference
Number of states	30	19	11
A. Infrastructure & Endowments			
Transmission lines (km per km^2)	0.16	0.14	0.02
Wind speed (meter per second)	6.3	6.1	0.2
Solar irradiance (kWh / m^2 /year)	4.3	4.6	-0.2
B. Installed Capacity (MW)			
Wind	785.0	518.8	266.6
Solar	166.5	40.9	125.56
Coal	6,415.4	7,291.0	-875.7
Gas	8,480.1	6,953.7	1,526.3
Total	20,795	19,192	1,603.1
C. Generation (GWh)			
Wind	4,095	2,971	1,124
Solar	599	131	467
Coal	71,857	80,294	-8,436
Gas	37,512	28,911	8,601
Total	78,747	74,377	4,369
D. Other Predictors			
GDP per capita	57,143	47,787	-11,356**
Electricity price (all end-use, $ / kWh)	0.12	0.09	0.03***
Electricity consumption (Bil. kWh)	72.9	62.4	10.5
House LCV score	56.4	27.4	29.0***
Senate LCV score	61.7	27.9	33.8***
Fraction counties non-attainment	0.53	0.17	0.36***

Notes: RPS states adopted any type of RPS legislation between 1990 and 2019 while Non-RPS states have never adopted any type of RPS legislation. Only states in the continental U.S. are included in the sample. All dollar dominated variables are in 2019 constant dollars. Column 3 reports the mean difference between RPS and non-RPS states for each variable and the stars indicate a significant difference across groups at the 0.05, 0.01, and 0.001 significance levels (*** $p<0.001$, ** $p<0.01$, * $p<0.05$).

Table 2: Estimated ATT of RPSs Impact on Installed Wind Capacity and Generation

	(1)	(2)	(3)
Panel A: Capacity (MW)			
Overall ATT (cohort)	380*	264	586**
	(158)	(155)	(218)
Overall ATT (year)	394*	307	710*
	(198)	(218)	(282)
1-5 years post	195*	129	197*
	(77)	(79)	(98)
6-11 years post	596*	417	1000**
	(262)	(275)	(353)
Panel B: Generation (GWh)			
Overall ATT (cohort)	1790*	1160	3110**
	(910)	(797)	(1220)
Overall ATT (year)	1740	1340	3700*
	(1050)	(1090)	(1550)
1-5 years post	838*	521	980*
	(361)	(376)	(443)
6-11 years post	2870*	1880	5350**
	(1470)	(1490)	(2040)
Controls			
Endowments		Yes	Yes
Sociopolitical			Yes
Observations	810	810	780

Table 2: Notes: Overall ATT (cohort) corresponds to the average effect of RPS policies experienced by all states that ever implement an RPS. Overall ATT (year), corresponds to the average effect of implementing an RPS policy for states that have implemented an RPS for at least 11 years. “1-5 years post” and “6-11 years post” are equivalent to Overall ATT (year), except that they are computed separately for post-implementation years 1-5 and 6-11 respectively. Standard errors are computed using a multiplier bootstrap procedure and clustered at the state level following Callaway and Sant’Anna (2021) (*** p<0.001, ** p<0.01, * p<0.05). Column 1 reports the unconditional estimates. Column 2 adds natural endowment controls for wind potential, solar irradiance, and length of transmission lines. Column 3 further introduces sociopolitical controls including 1990 per capita GDP, 1990 House and Senate League of Conservation Voting scores, and the retail price of electricity in 1990. Panel A reports estimates for megawatts of installed wind capacity as the outcome and panel B reports estimates for gigawatt-hours of wind electricity generation as the outcome.

Table 3: Estimated ATT of RPSs Impact on Installed Solar Capacity and Generation

	(1)	(2)	(3)
Panel A: Capacity (MW)			
Overall ATT (cohort)	16.3	48.3	29.7
	(34.2)	(36.2)	(38)
Overall ATT (year)	50.1	71	43
	(51.3)	(49.4)	(54.4)
1-5 years post	-1.84	4.7	2.64
	(3.73)	(3.62)	(4.56)
6-11 years post	34.1	92.7	57.3
	(70.3)	(70.5)	(76.9)
Panel B: Generation (GWh)			
Overall ATT (cohort)	28.7	142	92
	(84.1)	(94.7)	(108)
Overall ATT (year)	119	195	114
	(138)	(129)	(149)
1-5 years post	-2.89	14.5	10.4
	(9.92)	(10.7)	(13.9)
6-11 years post	59.8	272	175
	(174)	(183)	(226)
Controls			
Endowments		Yes	Yes
Sociopolitical			Yes
Observations	810	810	780

Table 3: Notes: Overall ATT (cohort) corresponds to the average effect of RPS policies experienced by all states that ever implement an RPS. Overall ATT (year), corresponds to the average effect of implementing an RPS policy for states that have implemented an RPS for at least 11 years. "1-5 years post" and "6-11 years post" are equivalent to Overall ATT (year), except that they are computed separately for post-implementation years 1-5 and 6-11 respectively. Standard errors are computed using a multiplier bootstrap procedure and clustered at the state level following Callaway and Sant'Anna (2021) (*** p<0.001, ** p<0.01, * p<0.05). Column 1 reports the unconditional estimates. Column 2 adds natural endowment controls for wind potential, solar irradiance, and length of transmission lines. Column 3 further introduces sociopolitical controls including 1990 per capita GDP, 1990 House and Senate League of Conservation Voting scores, and the retail price of electricity in 1990. Panel A reports estimates for megawatts of installed solar capacity as the outcome and panel B reports estimates for gigawatt-hours of solar electricity generation as the outcome.

Table 4: Robustness checks

Dependent variable	Balanced	Control	Method	Independent variable	Solar	Wind
Capacity MW	**Yes**	**NYT**	**C+S**	**RPS Legislation**	**43** **(54.4)**	**710*** **(282)**
Generation GWh	**Yes**	**NYT**	**C+S**	**RPS Legislation**	**114** **(149)**	**3700*** **(1550)**
Capacity MW	Yes	NT	C+S	RPS Legislation	43 (54.4)	735** (281)
Capacity MW	No	NYT	C+S	RPS Legislation	285 (248)	1970* (858)
Generation GWh	Yes	NT	C+S	RPS Legislation	114 (149)	3810* (1550)
Generation GWh	No	NYT	C+S	RPS Legislation	1400 (1070)	11700* (4940)
Capacity MW	Yes	NYT	C+S	RPS Intensity	202 (203)	498 (470)
Generation GWh	Yes	NYT	C+S	RPS Intensity	560 (603)	2620 (2250)

Notes: All specifications report Overall ATT (Year) which corresponds to the average effect of implementing an RPS policy for states that have implemented an RPS for at least 11 years. "Balanced" refers to whether the sample includes a balanced panel of states for 11 years before and after implementation of RPS legislation. The control group is either the set of Not Yet Treated (NYT) states or the set of Never Treated states (NT). All specifications use the estimator proposed by Callaway and Sant'Anna (2021). Specifications with "RPS Legislation" as the independent variable use a binary variable equal to one in all periods following implementation of an RPS policy as the treatment. The specifications with "RPS Intensity" as the independent variable use the treatment definition explained in section 4.2. Standard errors are computed using a multiplier bootstrap procedure and clustered at the state level following Callaway and Sant'Anna (2021) (*** $p<0.001$, ** $p<0.01$, * $p<0.05$).

Appendix A: Data Appendix

Table A1: Variable metadata

Variable	Units	Source
Transmission lines	km per km^2	Homeland Infrastructure Foundation-Level Data (HIFLD)
Wind speed	meters per second	NREL Wind Integration National Dataset (WIND)
Solar irradiance	kWh / m^2 /year	NREL Physical Solar Model version 3 Global Horizontal Irradiance Multi-year Annual Average
Installed capacity	MW	EIA Form EIA-860
Generation	GWh	EIA Form EIA-906
GDP per capita	$ per person	Bureau of Economic Analysis (BEA) dataset SAGDP2N
Electricity price	all end-use, $ / kWh	EIA State Energy Data System (SEDS)
Electricity consumption	Bil. kWh	EIA State Energy Data System (SEDS)
House LCV score	Scale $[0, 100]$	League of Conservation Voters (LCV) Scorecard
Senate LCV score	Scale $[0, 100]$	League of Conservation Voters (LCV) Scorecard
Fraction counties non-attainment	Share $[0, 1]$	Environmental Protection Agency (EPA) Greenbook

Appendix B: Estimates of RPS Spillover Effects

Previous research has found evidence that RPS policies increase wind generation and decrease fossil fuel generation in states eligible to trade Renewable Energy Credits (RECs) with RPS states Hollingsworth and Rudik (2019). In this section, we test for RPS spillover effects in neighboring states using a methodology adapted from Butts (2021).[12] Most states monitor compliance with RPS policies using RECs which certify that a given unit of electricity qualifies to meet the standard. Typically, RECs are issued by regional authorities that encompass multiple states and issue a unique serial number for every megawatt-hour of generation produced by registered compliant generators. While some trading of RECs may occur across regions, most RECs used for RPS compliance occurs within a region. As a result, we estimate the spillover effects on never-treated states when a state in the same REC-trading region implements an RPS policy. We define REC-trading regions using data from Holt (2016). For example, a renewable generator in Wyoming could sell RECs to generators in Colorado, Montana, Oregon, and Washington. Therefore, passage of an RPS policy in Colorado could increase the demand for RECs in Wyoming even though Wyoming has not implemented an RPS policy.

To estimate the spillover effects of RPS policies on renewable capacity installations and generation, we compare states that neighbor an RPS state to non-RPS states who never have a neighbor that implements RPS legislation using the estimator proposed by Callaway and Sant'Anna (2021).[13] We define a state as treated in all years following the first time one of its neighbors implement an RPS policy and we control for the same set of state-level endowment and sociopolitical characteristics described in section 4. Standard errors are clustered using a multiplier bootstrap procedure developed by Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). The results are reported in Table B1. While we find suggestive evidence that wind capacity and generation increased following the implementation of an RPS policy in a neighboring state, the results are imprecisely estimated. Overall, the empirical evidence is inconclusive on whether RPS policies have spillover effects that go beyond the implementing state borders.

[12]Butts (2021) shows that failure to account for spatial spillover of the treatment to control units induces two effects which bias the direct treatment effect. First, since treatment affects nearby control units, these units no longer represent valid counterfactuals of the outcome's evolution in treated units. Second, the outcomes of treated units may be impacted by spillover effects from neighboring treated units.

[13]We accomplish this by dropping RPS states with no neighbor that implements an RPS policy from the sample and use the never treated states as the control group.

Table B1: Estimates of RPS Impact on Neighboring States' Renewables

	Capacity (MW)		Generation (GWh)	
	Solar	Wind	Solar	Wind
Neighbor State Overall ATT (Year)	0.65	255	1.08	1390
	(2.34)	(187)	(5.24)	(973)
Controls				
Endowments	Yes	Yes	Yes	Yes
Sociopolitical	Yes	Yes	Yes	Yes
Observations	1350	1350	1350	1350

Notes: Table A1 reports estimates of Overall ATT (Year) which corresponds to the average treatment effect of implementing an RPS policy on renewable capacity investments and generation in *neighboring* states for states with a neighbor that has implemented an RPS for at least 11 years. All specifications use the estimator proposed by Callaway and Sant'Anna (2021) with never-treated states as the control group. We define neighboring states following the approach in Holt (2016). Standard errors are computed using a multiplier bootstrap procedure and clustered at the state level following Callaway and Sant'Anna (2021) (*** $p<0.001$, ** $p<0.01$, * $p<0.05$).