Do Renewable Portfolio Standards Deliver Cost-Effective Carbon Abatement?*

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Abstract

The most prevalent and perhaps most popular climate policies in the U.S. are Renewable Portfolio Standards (RPS) that mandate that renewable sources, such as wind and solar, produce a specified share of electricity, yet little is known about their efficiency. Using a comprehensive data set and a difference-in-differences style research design, we find that electricity prices are 11% higher seven years after RPS passage and carbon emissions are 10-25% lower. Point estimates suggest that the cost per ton of CO2 abatement ranges from \$60-\$300, though these estimates do not account for possible future cost reductions due to RPS-induced technological progress.

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1 Introduction

The United States has had great difficulty developing significant and enduring climate policy. One major exception has been renewable portfolio standards (RPS) that require a certain percentage of electricity supply in a state to be met by generation from sources designated as renewable. The first RPS was passed in Iowa in 1991 and, as of 2015, RPS policies have been enacted in 29 states and the District of Columbia.[1] These programs play a central role in existing U.S. climate policy, currently covering 18% of US CO_2 emissions compared to 8.4% for state and regional cap-and-trade programs. Further, such policies appear set to continue expanding in scale and scope. For instance, state level RPS programs that initially required the renewable share of electricity to increase by only a few percentage points have set ambitious 2030 targets of 35% (Massachusetts), 40% (Connecticut), 60% (California), and 70% (New York), and several proposals for national legislation - including President Biden's proposal for a clean electricity standard - recommend policies that expand features of existing RPS programs. There is little, if any, historical precedent for integrating renewables into the electricity generation system at such scale.

Despite the popularity of these policies, there is little systematic evidence on RPS' impacts on electricity prices, carbon emissions, or the cost per ton of avoided CO_2 at even the modest levels of stringency that have prevailed to date. Typical of existing work is a recent study that finds that RPS has increased retail electricity prices by about 2% (Barbose, 2018). However, this study (and similar research) cautions that it only captures the direct costs of renewable energy production. Specifically, it fails to capture several costs that renewables impose on the electricity market that are socialized and must be borne by some combination of distribution companies, generators, ratepayers, and potentially taxpayers. These include: the costs associated with renewables' intermittency that requires other sources to fill in when the sun or wind resources are unavailable;[2] the higher transmission costs associated with transporting renewable electricity from its most advantageous geographic locations to population centers (Mills, Wiser, and Porter, 2009); and payments to compensate electricity generators that have reduced utilization or are prematurely closed.

This paper estimates the aggregate costs and benefits of RPS by comparing states that did and did not adopt RPS policies using the most comprehensive panel data set ever compiled on program characteristics and key outcomes from 1990-2015. Importantly, there is variation in the timing of adoption of RPS programs across states, which lends itself to powerful event-study style figures that reveal no meaningful evidence of pre-existing differences in electricity price trends between

[1] An additional seven states enacted non-binding targets under similar programs.

[2] On average, utility scale solar plants have a capacity factor (i.e., average power generated divided by its peak potential supply over the course of a year) of about 25% according to the Energy Information Administration. Wind plants are not much higher at 34%. A frequent solution is that the installation of renewables is paired with the construction of natural gas "peaker" plants that can quickly and relatively inexpensively cycle up and down, depending on the availability of the intermittent resource.

adopting and non-adopting states. Further, we collect additional data that allow us to control for a wide range of potentially confounding electricity policies, including energy efficiency programs and investments, electricity market restructuring, net metering, green power purchasing programs, and public benefits funds. We also control for pollution regulations that could have affected costs faced by electricity producers, including the presence of nitrous oxide trading under the EPA's Acid Rain Program (Deschênes, Greenstone, and Shapiro, 2017) and attainment versus non-attainment designations under the Clean Air Act (Greenstone, 2002). This approach stands in contrast to what we believe is the nearly impossible task of a complete bottom up approach that separately measures each of the indirect mechanisms through which renewables affect total system costs, in addition to the direct differences in generation costs between renewables and other sources of electricity.[3]

There are four key findings. First, RPS policies' statutory requirements for renewable generation frequently overstate their *net* impact on generation, because they often include generation that existed at the time of the policy's passage. For example, seven years after New Hampshire adopted its RPS policy, its statutory or total requirement was that renewables account for 11.5% of generation. Yet at the time of adoption, renewables already accounted for 7.5% of generation. So, its net requirement in this year was 4.0%. Our best estimates are that 7 years after adoption the average adopting state's net requirement was 2.2% of generation and 12 years after it was 5.0%.

Second, electricity prices increase substantially after RPS adoption. The estimates indicate that in the 7th year after passage, average retail electricity prices are 1.2 cents per kWh or 11% higher, totaling about $30 billion of annual additional costs to consumers in RPS states. Twelve years later they are 1.9 cents, or 17%, higher. These estimates are statistically significant at the 5% level and robust to a variety of specification checks including: controlling for local shocks to electricity costs in a variety of ways, including in specifications with region-by-year fixed effects that compare states to only their closest geographic neighbors (e.g., to account for differences in access to inexpensive shale gas); the application of a synthetic controls estimator that matches RPS states with non-RPS states based on ex ante characteristics (Ben-Michael, Feller, and Rothstein, 2021); and the implementation of the Abraham and Sun (2019) method to account for the challenges with staggered treatment timing in the presence of heterogeneeous treatment effects. Further, we find evidence that suggests that higher transmission and distribution costs account for a substantial portion of the increase in electricity prices in RPS states.

Third, the estimates indicate that passage of RPS programs substantially reduces carbon emissions. Depending on the specification, we find that CO_2 emissions fall by 10-25% in the seventh year after RPS passage, and 23-36% in the 12th year after passage. Importantly, these estimates are obtained from specifications that attempt to account for cross-state spillovers in generation. It

[3]For instance, Gowrisankaran, Reynolds, and Samano (2016) measure the intermittency costs of solar energy in Arizona.

is noteworthy that the estimated reductions in CO_2 are two to six times larger than would be suggested by renewable sources one-for-one displacing coal generation. The analysis indicates that this discrepancy is because RPS adoption is associated with steep declines in coal and petroleum's share of electricity generation, suggesting that RPS polices have indirect effects on the broader "merit order" and which sources operate in periods when renewables are not operating.

Fourth, we put together the findings on electricity prices and emissions to calculate the implied cost of CO_2 abatement. Point estimates suggest that the cost to consumers per metric ton of CO_2 reduced ranges from \$60 to \$300, depending on specification, though confidence intervals cannot rule out substantially lower or higher abatement costs. For context, these estimates are higher than permit prices in existing carbon markets, but lower than abatement costs estimated for some other carbon policies (see, for instance, Fowlie, Greenstone, and Wolfram (2018), Holland, Hughes, and Knittel (2009), and the Gillingham and Stock (2018) survey). For additional context, the Biden Administration set the social cost of carbon at \$51 per ton on an interim basis, although it was estimated at \$125 per ton in recent work (Carleton and Greenstone, 2021). Finally, it is worth noting that these cost per ton of CO_2 estimates do not account for the possibility of future cost reductions in renewables due to RPS-induced technological progress.

This paper builds on a range of research on renewable energy and RPS programs. A substantial body of work focuses on assessing individual components of the indirect costs of renewable grid integration (Denholm and Margolis, 2007; Borenstein, 2008; Lamont, 2008; Joskow, 2011; Milligan et al., 2011; Cullen, 2013; Jacobson et al., 2015; Gowrisankaran et al., 2016). The literature on RPS program impacts in particular has primarily consisted of qualitative evaluations (Fischer, 2010; Schmalensee, 2012) and prospective evaluations that project minimal impacts on electricity prices, some of which have been commissioned by states considering adoption (Chen, Wiser, and Bolinger, 2007). A limited body of post-implementation work has found that RPS adoption increases electricity prices by roughly 2-4% (Heeter et al., 2014; Tuerck et al., 2013), although this literature has largely taken place outside peer-reviewed journals and does not account for all the indirect ways that these programs can affect system costs.[4] An important exception is Upton and Snyder (2017), who find that RPS programs substantially raise electricity prices and modestly reduce emissions, but do not account for cross-state spillovers in electricity trade and RPS compliance, the temporal pattern of RPS impacts on prices, and adjustments for a wide range of potentially confounding policies.

The paper proceeds as follows. Section 2 provides background on RPS policies and their typical

[4]Other papers focusing on specific aspects of RPS include Hollingsworth and Rudik (2019), which examines the effects of RPS on renewable generation in neighboring states, Johnson (2014) and Carley et al. (2018), which measure the effects of RPS on renewable generation and the elasticity of supply, Barbose et al. (2016), which uses modeling approaches to estimate the effects of RPS on emissions and economic activity, and Bento, Garg, and Kaffine (2018), which uses a calibrated model to analyze the general equilibrium effects of RPS.

implementation. Section 3 sets out a model that identifies the channels through which integrating renewable generation can raise electricity costs. Section 4 outlines our data sources and presents summary statistics on the electricity sector prior to RPS passage. Section 5 describes the empirical strategy, and Section 6 presents and discusses the results. The paper then finishes with Interpretation and Conclusion sections.

2 Renewable Portfolio Standards

By 2009, 29 states and the District of Columbia had adopted mandatory portfolio standards, while an additional seven states had passed optional standards.[5] While only Iowa, Nevada, and Connecticut passed RPS between 1990 and 1998, 27 states followed suit over the next 11 years and these programs now cover 62% of electricity generation in the US.[6] Figure 1 contains a map of the United States that indicates which states have enacted RPS programs, with the colors indicating the years of enactment.

Figure 2 plots the number of RPS programs passed into law in each year (left y-axis) and the real national average retail electricity price (right y-axis). The plot shows that the majority of RPS programs were enacted after 2000, loosely corresponding with a break in the trend of national electricity prices, which declined from about 12 cents per kWh to 10 cents per kWh from 1990 through 2002 but returned to 12 cents per kWh by the end of the sample in 2015.[7] In the sections that follow, we will examine whether RPS policies contributed to this trend.

Most RPS programs require that retail electricity suppliers meet a percentage of demand with energy from renewable sources.[8] Once in place, the standard typically increases along a predefined schedule until a specified fraction of renewable generation is achieved. For example, California's policy specifies a goal of 33% retail sales from renewables by 2020, with interim targets of 20% by 2013 and 25% by 2016. While the standards sometimes exempt certain providers, most often smaller municipal or cooperative suppliers, they cover 82% of electric load in a state on average.[9]

The key feature of RPS programs is that compliance requires production from a set of designated technologies. In practice, the list always includes wind and solar, but the full list of tech-

[5] West Virginia also passed an *Alternative and Renewable Energy Portfolio Standard* in 2009 with characteristics similar to an RPS but which we do not consider. While renewables received some preference in this program, a much broader set of generation sources qualified, including "Advanced Coal Technology," and there was no guaranteed compliance from renewable sources. This program was also repealed before its first binding requirement came into effect.

[6] Iowa was the first state to establish a binding standard in 1991, requiring the states's two investor-owned utilities to build or contract for 105 MW of renewable capacity. Although Iowa originally enacted an *Alternative Energy Law* in 1983, the program wasn't given a concrete goal or made compulsory until a revision in 1991, so we consider that the first year of passage.

[7] All monetary figures are reported in January 2019 dollars.

[8] Our data classify qualifying generation as one of wind, solar, biomass, geothermal, landfill gas, or ocean power, with some states also allowing small hydroelectric.

[9] The statistic on load covered comes from the North Carolina Clean Energy Center's Database of State Incentives for Renewables & Efficiency (DSIRE).

nologies included differs from state to state. Electricity providers must demonstrate compliance with the program through possession of Renewable Energy Credits, or RECs, each of which certifies that a given unit of electricity production qualifies to meet a given standard. Most RECs are awarded by various regional authorities encompassing several states, which issue unique serial numbers for every megawatt-hour of generation produced by registered generators. The approximate coverage of these REC tracking systems is shown in Appendix Figure A.1. This independent tracking seeks to prevent double counting of generation used for RPS compliance. While there is some scope for transferring RECs between regional systems, in practice most RPS compliance occurs within a tracking region, a fact that we will return to later on when considering the impact of RPS on generation outcomes and emissions.

Once awarded, credits can be sold separately from the underlying electricity, enabling flexible transfer of the rights to environmental benefits and providing additional revenue to renewable suppliers.[10] In most cases, individual generators must be further approved by the state office administering the RPS to ensure that they comply with the specific requirements for generators set forth by that state. In restructured markets, retail providers then purchase RECs generated by these approved facilities, either via brokers or directly through individual contracts. In non-restructured markets, retail providers may also use RECs generated by their own renewable facilities. The serial numbers of the RECs obtained are filed for compliance and their retirement verified with the relevant tracking system. Depending on program rules, excess RECs may also be "banked" for use in later years, though there are typically vintage restrictions requiring that relatively recent credits be used. Therefore, REC prices reflect the marginal costs of *producing* electricity from one of the designated technologies, relative to the least expensive alternative, but they do not capture the systemwide costs of *supplying* that electricity, which additionally reflect the costs associated with intermittency, transmission, and compensating owners of stranded assets.

Most RPS programs enforce compliance using a system of Alternative Compliance Payments (ACPs), which effectively fine retail providers for failing to acquire sufficient RECs to cover their sales. These payments are large, averaging about $50 per MWh.[11] Such penalties are substantial, representing about half of the average revenue per MWh observed in 2011. In addition to a penalty, ACPs also provide an effective cost-ceiling for the REC market, as they provide an outside option for compliance. While in practice few retail suppliers fulfill their requirements through ACP payments, REC markets in some states have periodically traded at the ACP level, suggesting that marginal sources of compliance can be relatively high cost.

[10] A minority of RPS programs have the more stringent requirement that credits be "bundled" with electricity delivered into the state, as demonstrated by transmission to a state balancing authority.

[11] In the case of mandates for generation specifically from solar energy, they can climb even higher, sometimes exceeding $400 per MWh.

While statutory requirements like Maine's 29% target appear quite large, they often ramp up gradually from lower levels and may not reflect the amount of marginal generation actually mandated by RPS policies. Intuitively, if an RPS requirement were entirely covered by existing sources at its inception, in a competitive market we would expect producers to bid down the price of RECs to zero. Distinguishing the amount of new renewable generation required to comply with RPS policy is quite difficult in practice, since covered sources of generation vary from state to state even within narrowly defined categories. For instance, some states allow small-scale hydropower but not large-scale hydropower to qualify for their RPS. Further, six states, including Maine, explicitly mandate that part of their RPS be met using newly constructed renewable capacity. We measure the "net" requirement imposed by RPS policies using data from the Lawrence Berkeley National Laboratory (LBNL) compiled by Barbose (2018) that takes the gross MWh required for RPS compliance and subtracts existing generation from eligible sources in the year prior to RPS passage.

Figure 3 reports each state's total and net requirements as of seven years after passage of RPS legislation, ordering states by the calendar year in which they first adopted an RPS. While these numbers do not fully account for the complications described above, they do show a clear pattern of statutory requirements overstating the amount actually necessary to achieve compliance. For instance, seven event years after passage, the gross requirement in Michigan is 5.8%, but the net requirement after subtracting existing generation in the year of passage is only 2.2%. On average, seven event years after RPS passage, RPS states have a total requirement of 5.6%, but a substantially lower net requirement of 2.2%. In the remainder of the paper, we primarily focus on estimates of net requirements, described in greater detail in Section 4.1.

3 Conceptual Framework

Standard "levelized cost of electricity" (LCOE) estimates capturing the direct capital and maintenance costs of various generation sources provide an incomplete measure of the impact of transitioning electricity production to renewable sources on consumer prices. We set out a simplified model of the decision-making process of a retail electricity provider to illustrate the mechanisms through which renewable integration can affect system costs, and consequently retail prices. The model demonstrates how intermittency, transmission, and the displacement of existing capacity infrastructure interact to raise total costs. Notably, the model highlights the wide range of parameters and nontransparent data inputs that would be required to calculate these costs directly. The paper's empirical procedure sidesteps this difficulty by summarizing the aggregate effect of these mechanisms through the reduced-form impact of RPS programs on retail electricity prices.

For simplicity, the model assumes a vertically integrated setting with a single utility responsible for both power capacity and retail provision. The intuition from this framework translates straightforwardly to a deregulated setting with a retail provider purchasing electricity from competing generators, except for the assumption that ratepayers always pay the full cost of installed capacity. As discussed below, the extent to which owners of capital bear the losses from excess capacity stranded by integrating renewable sources is one factor that contributes to the overall effect on retail prices.

3.1 Representative Utility Model

A representative utility chooses capacity investments and daily generation sources to fulfill two requirements: ensuring that they meet the full electricity demand of their customers every hour and that their annual electricity production meets the RPS requirement. Utilities have three types of production capacity available with which to meet hourly electricity demand: renewables, R, baseload power, B, and dispatchable "peaker" plants, D, the latter two of which we assume come from non-renewable sources. Baseload generation produces a constant hourly amount, B_h, governed by annual capacity, B_t, and cannot be adjusted in response to hourly demand. Renewable generation is stochastic and drawn from a distribution $F(R)$, with mean, $\tilde{R}$, standard deviation, σ_R, and support $[\underline{R}, \overline{R}]$. $F(R)$ is a function of installed renewable capacity, R_t. The hourly demand for electricity is also drawn from a distribution, $G(E)$, with mean $\tilde{E}$, standard deviation σ_E, and support $[\underline{E}, \overline{E}]$. So given the available capacity of B_t, R_t, and D_t in year t, the utility observes the hourly draws of E_h and R_h and chooses the level of dispatchable power, D_h, to satisfy customer demand.

$$E_h = B_h + R_h + D_h, \tag{1}$$
$$E_h \sim G(E_t),\ R_h \sim F(R_t).$$

With knowledge of this hourly optimization problem, the utility chooses investment in new capacity at the beginning of each year. Total capacity of each type in period t consists of the depreciated capital from last period plus new investments in each of the three categories of electricity sources, denoted by I_B, I_R, and I_D. The equations of motion are as follows:

$$\begin{aligned} B_t &= B_{t-1}(1-\delta_B) + I_{Bt}, \\ R_t &= R_{t-1}(1-\delta_R) + I_{Rt}, \\ D_t &= D_{t-1}(1-\delta_D) + I_{Dt}. \end{aligned} \tag{2}$$

The utility chooses annual investments in new capacity to fulfill its two primary requirements. First, the RPS requirement dictates the proportion of annual electricity production that must come from renewables. For mandated renewable percentage, M, the utility must satisfy the following condition aggregated across all 8760 hours in a year:

$$\frac{\sum_{h=1}^{8760} R_h}{\sum_{h=1}^{8760} E_h} \geq M. \tag{3}$$

Under RPS requirements, failure to meet this condition will cost the utility a per-unit fine, f, for the amount by which renewable generation falls below the threshold. To avoid paying the fine, utilities must have enough installed renewable capacity, R_t, to produce enough electricity from renewables to meet this requirement. Determining what constitutes enough renewable capacity also may not be straightforward. If draws from the $F(R)$ distribution are correlated across days, simply ensuring that $\frac{E[R_h]}{E[E_h]} = M$ might not be sufficient to ensure compliance with the RPS mandate in a year with systematically low realizations for renewable generation. The utility will trade off the cost of increasing renewable capacity, R_t, with investments, I_R, against the fine for noncompliance when choosing the optimal R_t.

Second, the utility must ensure it can supply enough energy every hour of the year. We assume there is an infinite penalty for failing to meet demand. Since both energy demand and renewable production are stochastic, the utility must have enough dispatchable generation available to fill the largest possible hourly need. In particular, the utility chooses D_t such that it can meet total electricity needs in a hypothetical hour with the highest possible demand draw, $\overline{E}$, and the lowest possible renewable generation draw, $\underline{R}$.

$$D_t = \overline{E} - B_t - \underline{R} \tag{4}$$

In addition to choosing investment, the utility also has the option to prematurely retire capacity at the beginning of each year. The carrying costs of retired capacity are lower and for simplicity we assume that capacity that has not been retired will be run. Under certain conditions, they may choose to retire baseload capacity because too much baseload generation could prevent the utility from meeting the RPS requirement. If $\frac{B_t}{E[E_h]} > 1 - M$, for instance, then renewable production would be expected not to meet its mandate even without any dispatchable production. To ensure compliance with the RPS mandate, the utility must estimate the amount of dispatchable production necessary during the year and then scale back B_t such that the expected sum of baseload and dispatchable generation does not exceed $1 - M$ as a proportion of all production.

Total costs for the utility include the fixed costs of installed capacity, associated transmission and distribution requirements, and the variable costs associated with each type of power. The utility finances new investments such that they make a constant annual payment over a horizon of T years. The annualized prices of installed capacity, p_B, p_R, and p_D, incorporate differences in the cost per MWh for baseload, renewable, and dispatchable sources, as well as any differences in financing costs or investment tax incentives. New transmission investments in each period, which are also financed over a T-year horizon with annualized payment p_T, are a function of new installations across the three categories and depreciation of the existing transmission capital stock, with geographically dispersed renewable installations such as wind and solar likely having greater associated requirements. We represent these costs in the function, $Tr()$, that models transmission costs as a function of capacity investments. Since renewables require no fuel inputs, they incur no variable costs whereas baseload and dispatchable power have average costs ac_B and ac_D for each unit generated. For the purposes of this model, these average costs capture not only the cost of fuel inputs, but also any startup and shutdown costs associated with the operation of these generating sources. Thus, the utility's total costs in period t are as follows:

$$\begin{aligned} TC_t = & \sum_{k=t-T}^{t} p_{Bk} I_{Bk} + \sum_{k=t-T}^{t} p_{Dk} I_{Dk} + \sum_{k=t-T}^{t} p_{Rk} I_{Rk} \\ & + \sum_{k=t-T}^{t} p_{Tk} Tr(I_{Rk}, I_{Bk}, I_{Dk}) + 8760 B_t ac_B + \sum_{h=1}^{8760} D_h ac_D. \end{aligned} \tag{5}$$

The retail rate is given by total costs in year t divided by total kilowatt-hours of energy produced plus a markup, μ, assigned by the regulator. Thus:

$$\text{Retail Rate in Year } t = (1+\mu)\frac{TC_t}{\sum_{h=1}^{8760} E_{ht}}. \tag{6}$$

3.2 Empirical Requirements for Estimating the Full Costs of RPS

This framework illustrates the major practical difficulties involved in measuring the costs of RPS programs piece-by-piece. Specifically, even if renewable and non-renewable production have the same LCOE, defined by the prices of installed capacity and fuel inputs, transitioning a mature grid infrastructure could increase costs through a wide variety of channels. The list of excess costs includes:

- investments in new dispatchable capacity to protect against shortfalls of intermittent renewable generation,
- investments in new transmission infrastructure to accommodate the geographic locations of new renewable capacity,
- premature retirements of baseload capacity and/or transmission infrastructure that serves non-renewables to reduce non-renewable production to meet RPS mandates, which could also be achieved in some cases through further investments to convert baseload sources to dispatchable sources.

Note that the model does not explicitly incorporate the retirement decisions comprising this last category, though their importance is implied by need to meet the RPS mandate and reliably meet demand. Further, the incidence of this last category between ratepayers and owners of capital is unclear ex ante, although ratepayers seem more likely to bear the costs in traditionally regulated "cost-plus" markets, compared to restructured ones. However, it is worth noting that this last category differs from the others in two important ways. First, the social planner would not consider the continued need for financing irreversible past investments in a cost-benefit analysis since these are sunk costs at the time of policy implementation. Second, these costs are transitional in nature, while the first two are permanent features of increasing renewables' share of production.

It is instructive to consider the challenges with constructing a bottom-up or structural estimate of the costs of an RPS policy. First, it would require data or estimates of several moments from the distributions of hourly energy demand, $G(E_t)$, and hourly renewable generation, $F(R_t)$, the pre-existing level of installed capacity by generation type, B_t, D_t, R_t, the respective depreciation rates, investment prices, and fuel input prices for each of these three energy categories, and the transmission investments necessary to incorporate renewable capacity. Second, the estimates would need to make a series of assumptions for how utilities project electricity demand, renewable intermittency, and the need for dispatchable generation to protect against insufficient or excess supply, as well as decision criteria for retiring baseload generation. Third, estimating the model would require going beyond the representative utility setup and incorporating interactions between heterogeneous generators and retail providers in restructured and non-restructured markets. These interactions have proven to be quite complex to model as they also involve questions of market power. Fourth, the incidence of these costs between ratepayers, owners of capital, and even taxpayers, is also a complicated question and, as we noted above, is likely affected by the regulatory environment.

Recent work has made important progress on structurally estimating the indirect costs of renewable energy in specific settings. For instance, Gowrisankaran, Reynolds, and Samano (2016) use granular data on generating units and hourly load to estimate a model that quantifies the costs of intermittency for solar energy in southeastern Arizona. While this structural approach advances understanding, it examines just one of the channels through which RPS policies may influence electricity market equilibria in one location, leaving unanswered questions about the average costs and benefits of RPS policies. As an alternative, our empirical approach circumvents the complex interplay of underlying mechanisms with a reduced-form approach that captures costs borne by ratepayers due to all potential mechanisms, as well as the effect on CO_2 emissions.

4 Data Sources and Summary Statistics

In order to assess the impacts of RPS programs, we construct an annual state level panel from 1990 to 2015 with data on RPS programs, electricity prices, other electricity market and environmental policies, electricity generation, and emissions of CO_2 and other pollutants. We believe this is the most comprehensive data set ever compiled on RPS program characteristics, potential outcomes, and confounders. This section describes each data source and presents some summary statistics describing the context of the policy.

4.1 RPS Program Data

Since 1990, 29 states and the District of Columbia have adopted RPS programs. We construct indicators for the year in which rules for a mandatory RPS program were first adopted in each state, compiled using state legislative documents, state government websites, and summaries from the U.S. Department of Energy.[12] While there is typically a few years of lag between policy enactment and the onset of binding mandates for renewable generation, costs to electricity providers, and consequently customers, are likely to begin accruing when market participants start planning for and investing in the required future capacity. Data from the Lawrence Berkeley National Laboratory (LBNL) also include information about qualifying renewable sources under each program, including whether there are specific requirements for solar generation.

To better characterize each state's implementation, we also collect more detailed information on year-by-year requirements. Most RPS programs require an increasing percentage of electricity sales to come from renewable sources, leading to increased stringency over time. However, as mentioned earlier, the statutory percentage requirement may overstate the additional generation required if a large number of existing generators are eligible for compliance. To account for this, we use data from LBNL constructed by Barbose (2018) that calculates the RPS net requirement as the difference between statutory requirements and qualified pre-existing renewable generation. This measure of net requirements represents the total amount of new renewable generation necessary to comply with the policy, accounting for any regulations that require RPS compliance to be with new capacity and, where possible, for qualified pre-existing out-of-state generation that could be used to comply. Recall, Figure 3 highlights the substantial differences between the total and net requirements.

In addition to data on RPS programs, we also collect information on the presence of a wide variety of other programs and policies that may influence the amount of renewable generation and the retail price of electricity. In particular, we have data on the implementation dates of five types of electricity sector programs: electricity market restructuring, defined as retail market access for non-utility-owned generation plants, energy efficiency resource standards, which mandate utilities to achieve specified levels of energy savings through demand-side management programs, net metering, which pays consumers for electricity that they add to the grid with distributed generation such as solar PV, green power purchasing, which requires government-affiliated consumers to source a minimum amount of their power from renewables, and public benefits funds, which place a surcharge on retail electricity prices to fund programs such as research and development, energy education, and energy assistance for low-income households. The data on electricity market re-

[12] For example, Massachusetts passed legislation in 1997 creating a framework for establishing an RPS but did not adopt mandatory regulations until 2002. We use 2002 as our year of passage.

structuring comes from Fabrizio, Rose, and Wolfram (2007) and data for the other programs comes from the American Council for an Energy-Efficient Economy's State and Local Policy Database and the North Carolina Clean Energy Center's Database of State Incentives for Renewables & Efficiency (DSIRE) (Barnes, 2014). This data allows us to construct indicator variables for the presence of other programs as well as a continuous measure of energy efficiency expenditures. In addition to electricity market programs, we also collect information from the EPA on implementation dates for the Nitrogen Oxides Budget Program and the percentage of counties in each state designated as non-attainment under the Clean Air Act. We construct a state level control variable for the Clean Air Act attainment designation by taking the county level average of a binary measure of attainment versus non-attainment status across pollutants, and then averaging across counties to the state level weighting by county level fossil fuel capacity. We use this information on electricity market and environmental policies to control for the presence of potentially confounding programs.

4.2 Electricity Sector

Information on electricity sector variables is drawn from Energy Information Administration (EIA) survey forms. Electricity prices are computed from EIA Form 861, a mandatory census of retail sales by electric power industry participants.[13] Respondents report sales and revenues separately for commercial, industrial, and residential sectors. Price is then taken to be the average revenue per megawatt-hour sold for each category. This comprehensive measure should capture all direct and indirect costs associated with renewables, although their separate impacts cannot be isolated.

Electricity generation by state and fuel source is compiled from EIA Forms 906, 920, and 923, which concern power plant operations. This data is broken down by fuel type, ensuring plants with multiple fuel sources are accurately reflected in aggregate numbers. We also compile information on interstate and international electricity imports and exports as well as estimated electricity losses calculated by the EIA using Forms 111, 860, 861, and 923. In addition, we use data on electricity transmission and distribution capital, operations, and maintenance expenditures by investor-owned utilities from FERC Form 1, sourced from the data set in Fares and King (2017).

To measure CO_2 emissions, we use estimates derived by the EIA from power plant operations data taken from Forms 767, 906, and 923. Their estimation process involves converting fuel use to BTUs to provide a common comparison measure. Next, fuel uses that do not generate emissions are subtracted out. Finally, source-specific carbon emission coefficients are used to convert to metric tons of carbon.[14] The result is a yearly panel of state emissions from electricity generation.

[13] The 3,300 respondents cover essentially the universe of retail suppliers, including electric utilities, energy service providers, power marketers, and other electric power suppliers.

[14] More details on this process, including the conversion factors used, can be found in "Methodology and Sources" section of the *Monthly Electric Review* published by the EIA.

Finally, we collect information on the geographic boundaries of REC regions for RPS compliance by manually compiling information from the websites and documentation associated with each REC tracking system. This information allows us to account for cross-state spillovers in the impact of RPS caused by compliance through out-of-state REC purchases. Appendix Figure A.1 shows an approximate outline of the REC regions and Data Appendix Section 12.2 contains full details on the mapping of states to REC regions.

If RPS programs do in fact raise electricity prices, there may be downstream impacts on industries for which energy is a major input to production. To assess this, we construct a panel of employment in each state by industry code using data from the County Business Patterns (CBP) and calculate total and manufacturing employment for each state in each year. [15]

4.3 Summary Statistics

Before describing our empirical approach in detail, we briefly present some summary statistics from the data and report on some comparisons of treatment and control states in the year prior to RPS passage. Table 1 presents summary statistics for RPS states and control states. "Mean RPS" states in Column (1) refers to treatment states in the year prior to RPS legislation passage, "Mean Control" states in Column (2) covers the full set of control states, which consist of non-RPS states and RPS states that had not yet passed RPS by that year, and "Mean Non-RPS" states in Column (3) refers to the subset of control states that never pass RPS. The summary statistics for non-RPS states and control states are averaged across the set of states in each category corresponding to each RPS state's year of passage.

The statistics in Table 1 show some level differences between RPS states and control states in the year prior to legislation. RPS states tend to have more expensive electricity – 11.4 cents per kWh versus 9.4 in control states – larger populations, and better resources for producing solar and wind energy. The patterns are very similar when comparing RPS states to the full set of control states in Column (2) and to those that never adopt RPS in Column (3). The RPS states in our analysis are also more likely to have other simultaneous programs affecting electricity markets, including public benefits funds, net metering, green power purchasing programs, NO_x trading, and the percent of counties designated as non-attainment under the Clean Air Act. We control for the time-varying passage of these programs, along with energy efficiency resource standards and electricity market restructuring, at the state-by-year level in our analysis.

[15] One issue with these data is that employment statistics are often suppressed when the industry code and establishment size potentially disclose information about a specific business. Following previous papers, we apply an imputation procedure to estimate employment for these cells, using the national average for the industry in that cell size. To allow comparisons across years, we recode NAICS industry codes used in later years to SIC industry codes, redistributing employment proportionally based on concordances provided by the Census. For further details, and code used, see Autor et al. (2013) and the accompanying data files. For 2012 and 2013, where official concordances are unavailable, we allocate employment proportionally based on 2011 employment using the official code mapping 2012 to 2007 NAICS.

It is apparent that there are meaningful level differences between RPS adopters and non-adopters. These differences are not a source of bias in our difference-in-differences research design, but this design would be compromised by differences in trends. It is therefore reassuring that electricity prices rose by statistically equivalent amounts in all three sets of states in the 7 years preceeding adoption. Nevertheless, our main specification also adjusts the estimates for differences in pre-RPS trends in electricity prices.

5 Empirical Strategy

Our empirical approach begins with an event-study style equation:

$$y_{st} = \alpha + \sum_{\tau \in \{-19,\ldots,18\} \setminus \{-1\}} \sigma_\tau D_{\tau,st} + X_{st} + \gamma_s + \mu_t + \varepsilon_{st}, \tag{7}$$

where y_{st} is an outcome of interest in state s in year t. We include state fixed effects, γ_s, to control for any permanent, unobserved differences across states. Year fixed effects, μ_t, non-parametrically control for national trends in the outcome of interest. X_{st} includes time-varying indicators for the presence of energy efficiency resource standards, restructuring, net metering programs, green power purchasing programs, public benefits funds, and NO_x trading programs, along with the continuous control variable measuring the intensity of Clean Air Act regulation. The variables $D_{\tau,st}$ are separate indicators for each year τ relative to the passage of an RPS law, where τ is normalized to equal zero in the year that the program passed; they range from -19 through 18, which covers the full range of τ values.[16] For states that never adopt an RPS program, all $D_{\tau,st}$ are set equal to zero. As non-adopters, they do not play a role in the estimation of the σ_τ's but they aid in the estimation of the year fixed effects, μ_t, as well as the constant, α.

The σ_τ's are the parameters of interest as they report the annual mean of the outcome variable in event time, after adjusting for state and year fixed effects, and the wide set of controls. An appealing feature of this design is that, because states passed RPS programs into law in different calendar years, it is possible to separately identify the σ_τ's and the year fixed effects μ_t. In the remainder of the analysis, we will particularly focus on the σ_τ's that range from -7 through 6. This is the maximum range for which the σ_τ's can all be estimated from all 30 RPS states.[17] Restricting the treatment period in this way holds the advantage of eliminating questions about the role played by differences in the composition of states identifying the various σ_τ's.

We will present event-study figures that plot the estimated σ_τ's against τ. These figures provide an opportunity to visually assess whether there are differential trends in the outcome variables prior

[16] Iowa adopted an RPS in 1991, which means that only one pre-RPS year is available. Consequently, we drop Iowa from the primary sample although its inclusion does not alter the qualitative findings.

[17] This range is determined by Nevada, which passed its law in 1997 on one side of the range, and Kansas, which passed its law in 2009 on the other side of the range.

to RPS passage, which helps to assess the validity of the difference-in-differences identification strategy. The event-study figures also demonstrate whether any impact on the outcome emerges immediately or over time, which informs the choice of specification to summarize the average effect of RPS policies.

Given that most RPS programs have requirements that increase gradually over time after legislation is passed, it is likely that the impact on electricity prices and other outcomes will increase correspondingly. Therefore, we summarize the event study estimates using a trend-break model that allows the effect of RPS programs to grow over time. A further appeal of this model is that detrended difference-in-differences specifications that allow for the possibility of differences in pre-adoption trends require weaker assumptions to produce valid estimates of the impact of RPS programs. For these reasons, we fit the following equation that allows for differential trends before and after RPS program passage:

$$\begin{aligned} y_{st} = {} & (\delta_0 + \beta_0 \tau_{st}) + (\delta_1 + \beta_1 \tau_{st}) * \mathbb{1}(-19 \leq \tau \leq -8)_{st} * \mathbb{1}(\text{RPS} = 1)_s \\ & + (\delta_2 + \beta_2 \tau_{st}) * \mathbb{1}(7 \leq \tau \leq 18)_{st} * \mathbb{1}(\text{RPS} = 1)_s \\ & + (\delta_3 + \beta_3 \tau_{st}) * \mathbb{1}(0 \leq \tau \leq 6)_{st} * \mathbb{1}(\text{RPS} = 1)_s \\ & + X_{st} + \gamma_s + \mu_t + \varepsilon_{st}. \end{aligned} \tag{8}$$

To summarize the policy's effects, we calculate and report the impact seven years after RPS passage, which is given by $\delta_3 + 6\beta_3$. This is the longest period for which our data contains a balanced sample. To allow for the possibility that the longer term effects of RPS differ, we will also estimate a version of this equation that allows for estimating the effect of RPS 12 years after passage, though this can only be done with an unbalanced sample as only 16 states had a RPS policy in place for 12 years by 2015. In these specifications we adjust Equation (8) correspondingly, so that δ_3 and β_3 apply to the period from $\tau = 0$ to $\tau = 11$ and comparison is between prices in the 12 years after passage with the same 7 years prior to passage. Finally, we report standard errors that are clustered by state from the estimation of Equation (8) to allow for correlation in the errors within state over time.

6 Results

6.1 Net RPS Requirements and Retail Electricity Prices

We begin with an examination of the net RPS requirements. Figure 4a plots the event year means of net RPS requirements against τ. Event time is normalized so that the program passage year occurs at $\tau = 0$ and the vertical line at $\tau = -1$ indicates the last year before program passage. It is apparent that the RPS programs' passage into law leads to increases in the required use of renewable technologies that begin almost immediately and continue over time. Seven years after passage, the average RPS state's net requirement is 2.2 percentage points of sales. It is noteworthy that this is substantially smaller than the increase in the total gross requirement, which is 5.6% through the end of the balanced sample (at $\tau = 6$).

Figure 4b reports on the estimation of Equation (7) for average retail price, where prices are normalized so that they equal zero at $\tau = -1$. Recall, the estimated σ_τ's are adjusted for state and year fixed effects and a wide variety of other policies that might influence retail rates. There are two primary points that emerge. First, there is no evidence of a meaningful difference in price trends, either upwards or downwards, among adopting states in the six years preceding RPS program passages, from $\tau = -7$ to $\tau = -1$. Thus, for example, there doesn't appear to be any evidence that prior to RPS passage, adopting states were differentially passing unobserved policies that influence electricity prices positively or negatively or facing differential cost shocks. More broadly, this figure supports the validity of the difference-in-differences research design.

Second, it is apparent that retail prices increased after program passages, but not all at once; the figure suggests that a model that allows for a trend-break describes the data well. It is striking that the trend in prices appears to very closely shadow the trend in net RPS requirements.

Column (1) in Panel A of Table 2 presents results from the estimation of Equation (8) that confirms the visual impression that retail electricity prices increase after RPS program passage. The estimates indicate that retail prices are higher in RPS states post-passage, and rise by roughly 0.14 cents each year, with statistically insignificant pre-trends.[18] We focus on the effect seven years after RPS passage, which is calculated as the combination of the mean-shift and trend-break coefficients, $\delta_3 + 6\beta_3$.

Overall, the estimates from this regression suggest that RPS policies have increased retail electricity prices by about 1.2 cents per kWh seven years after passage. This increase is statistically significant and economically substantial, representing an increase of about 11% over the mean retail price at $\tau = -1$. Such a large increase in the retail price of electricity is striking, given the modest net requirements 7 years after passage. Further, these estimates are much larger than LCOE differences alone would indicate, suggesting that the indirect costs of RPS mandates are an important component of their total costs. Overall, multiplying the estimated impact of RPS on prices by the total amount of electricity consumed in RPS states suggests that the policies increased total costs to consumers by about $30 billion in the seventh year after passage, or approximately $140 per person in additional annual electricity costs.

The appeal of the Panel A results is that there is a balanced sample for all event years, but this sample restriction limits the number of post-years. In Panel B, we extend the post-period

[18] We estimate a β_0 of -0.006 with a standard error of 0.06.

through $\tau = 11$ which allows us to estimate the effect of the RPS programs through 12 years after passage. The Panel B Column (1) results tell much the same story of prices increasing over time. As RPS programs are in force for longer here, their net requirements increase and their impact on electricity prices increases. The Column (1b) estimates indicate that at twelve years after passage, the average retail price has increased by 1.9 cents per kWh, or 17%, for a 5.0 percentage point net RPS requirement at that point (gross or total RPS requirements are higher at 10.7 percentage points).

6.2 Robustness

Columns (2)-(7) of Table 2 explore the robustness of the main results from Column (1) to a variety of changes in Equation (8). In Column (2) we replace the binary measure of the presence of a state level energy efficiency program with a continuous measure of energy efficiency expenditures reported by utilities. In Column (3) we drop Hawaii due to its unique geography. The estimates in these two columns are qualitatively unchanged from the baseline specification for the balanced sample, and somewhat smaller, though still statistically significant and economically meaningful, for the longer event window in Panel B.

The next two columns adjust for the possibility of local shocks to electricity prices that might confound the adoption of RPS programs. Specifically, Columns (4) and (5) include Census region by year and Census division by year fixed effects, respectively. There are four Census regions and nine Census divisions. The estimated increases in electricity prices are modestly smaller here than in Column (1), but these differences seem statistically unimportant in light of the standard errors. These specifications suggest that the estimated effects of RPS on prices are not driven by time-varying regional differences, such as changes in local fuel prices (i.e., shale gas) caused by the fracking revolution. Overall, we conclude that flexibly controlling for local shocks leaves the qualitative findings unchanged.

Next, we seek to test for the possibility of spillovers in the costs of RPS by aggregating retail price observations to the wholesale market level. To do so, we sum the utility level data on revenues and sales to the level of each balancing authority (BA) listed in the EIA Form 861 data set. For example, an Indepedendent System Operator such as PJM or MISO counts as one balancing authority unit, with each covering multiple states in this specification. Price is calculated as revenue divided by sales at the BA level and the RPS indicator is calculated as the weighted average of whether RPS was in effect in each state in the BA where the weights are the MWh of sales in that state. This approach seeks to account for the fact that electricity is traded across state borders and that RPS policies in one state can affect the costs faced by consumers in neighboring states with common electricity markets. We chose the balancing authority as the unit of analysis because that is the level at which markets clear and wholesale market auctions take place, ensuring scope for substantial tradability of electricity within each grouping of utilities.[19]

Columns (6) and (7) of Table 2 report the results for the effects of the RPS policy at the wholesale market (i.e. BA) level under two different weighting schemes. In Column (6), we weight each BA by sales and in Column (7), we weight by each BA's number of states such that the result can be interpreted as the effect on the average state, in line with how we interpret our main specification.[20] The Panel A results show that the positive, statistically and economically significant effect of RPS on retail prices seven years after passage is robust to accounting for wholesale market spillovers under either weighting scheme. The point estimates in Panel B for the unbalanced sample 12 years after passage are qualitatively similar, though with larger standard errors. To assess whether the spillovers on neighboring states within a wholesale market are positive or negative on net, we can compare the coefficients in Columns (6) and (7) to that of the main result in Column (1), which shows that prices increased by 1.2 cents per kWh seven years after RPS passage. The similarity of the (6) and (7) point estimates with that of Column (1) suggest that any cross-state impacts on prices are modest in magnitude, though we lack the precision to draw definitive conclusions.

As a further robustness check, we employ a synthetic controls estimator to compare RPS states to non-adopting states with similar ex ante characteristics. While the trend break model in our main specification controls for both level differences across states and differences in pre-trends, the synthetic controls approach helps further correct for selection into the policy based on factors that may be correlated with future changes in electricity prices. In particular, we reproduce the difference-in-differences analysis using a control group comprised of a weighted average of non-RPS states, constructed to match RPS states as closely as possible in terms of electricity prices, solar and wind potential, electricity sector CO_2 intensity, the percent of preexisting RPS-eligible generation, and the percent of coal and natural gas generation. Appendix Table A.1 shows that the control group in this specification resembles RPS states more closely along these dimensions in levels than the original control group of states shown in Table 1.

Figure 5a displays the results for the estimation of the primary synthetic controls specification. The "Pooled" specification weights control states to minimize the pre-treatment imbalance for the average of the treated units, whereas "Separate" estimates weights for the control states to separately minimize the pre-treatment imbalance for each treated unit. The "Partially Pooled" speci-

[19] In practice, multi-state ISOs such as MISO have expanded greatly over the period covered by our sample. We assign utilities to the balancing authority listed in the final year of the sample, 2015, since ISOs often formed across regions that were already trading electricity prior to the formal designation. We choose the balancing authority rather than the North American Electric Reliability Corporation (NERC) region as the unit of analysis, because utilities in a shared NERC region coordinate on developing regulatory standards, rather than any particular mechanism for trading electricity.

[20] In Column (7) of Table 2 we sum observations for multiple balancing authorities within the same state to the state level. For multi-state BAs that cover only parts of some states, the state count variable sums that BA's proportion of state level sales in each state. So a BA that covered all of Indiana and 30% of the sales in Illinois would receive a weight of 1.3.

fication minimizes a weighted average of the two imbalances, as recommended by Ben-Michael, Feller, and Rothstein (2021).[21]

Figure 5a finds that the results from the synthetic control estimation approaches are very similar to those from the main specification in Figure 4b, though the standard errors in this approach are modestly larger. Further, Figure A.2 reports on a series of alternative synthetic control approaches and they too are generally similar to the results from the paper's main specification, providing further support for a causal interpretation of the results from the estimation of Equation (8).

Finally, we note that difference-in-differences models with staggered treatment timing face a potential challenge due to endogeneity arising from heterogeneity in treatment effects across periods. As an additional robustness check, we reproduce the event-study style analysis using the interaction-weighted estimator recommended by Abraham and Sun (2019) to address this concern. Specifically, this approach takes the event study specification from Equation (7) and fully interacts the σ_τ's with indicators for each cohort-year of RPS adoption. This provides a separate estimate of $\sigma_{\tau,e}$ for each cohort of RPS states that pass the policy in year e, and σ_τ's are calculated as the weighted average across $\sigma_{\tau,e}$'s, where the weights are the number of states in each passage year cohort. Figure 5b reports the results from this estimation, which are also very similar to those from the main specification.

6.3 Mechanisms

This section tests for evidence of the three mechanisms proposed in Section 3 by which RPS can increase systemwide costs in the electricity sector – transmission, intermittency, and excess capacity. We start by examining the impact of RPS on utility level transmission and distribution expenditures. Panel A of Table 3 displays the results from estimating Equation (8) with annual capital, operations, and maintenance costs for transmission, distribution, and the sum of the two, as the dependent variables.

The estimates suggest that RPS led to a large increase in transmission and distribution expenditures. The point estimate in Column (1) of Panel A indicates a large increase in transmission costs of 70 log points seven years after RPS passage that would be judged statistically significant at the 10% level. The result for the sum of transmission and distribution costs in Panel A Column (3) is modestly less precise, but the point estimate indicates a 47 log point increase or 0.9 cents

[21] In addition, Figure A.2 reproduces the synthetic control results under a variety of different specifications. The top two panels labeled "Balancing on Dependent Variable" construct a control group to match only the dependent variable, retail electricity prices, in the pre-policy period, whereas the panels labeled "Balancing on Dependent Variable and Independent Variables" use a control group constructed as described above. The left two panels of Figure A.2 exclude the fixed effects in the specification that control for remaining level differences between RPS states and their synthetic controls. The bottom right panel of Figure A.2 reproduces the primary synthetic control specification from Figure 5a that balances on both the dependent variable and the chosen independent variables and includes fixed effects.

per kWh on a baseline average of 1.7 cents per kWh in the year before RPS passage. Overall, we conclude that these results are consistent with the conventional wisdom that renewables require higher transmissions and distribution costs and that these costs explain a meaingful portion of the increase in electricity prices in RPS states that was documented in Table 2.

Next, we consider the effects of RPS on capacity and generation. The model in Section 3 shows that mandated increases in renewable generation and the increased availability of readily dispatchable generation they require can cause the early retirement or decreased utilization of existing baseload generation. Although we do not have data on the many forms of opaque payments to the owners of displaced generation that can ultimately be passed on to consumers, we can examine the effects of RPS on capacity directly.

Table 3 Panel B Column (1) displays the results from estimating Equation (8) with total state level nameplate capacity across all sources as the dependent variable. The estimate indicates a noisy, but large, 8 log point increase in total GW available. It is striking, then, that Panel B Column (2) finds little evidence of a change in capacity factor (generation divided by capacity), with the imprecise point estimate actually suggesting an increase. This seeming mystery is explained by Column (3), which reveals that the capacity factor did not fall in RPS states because generation rose along with capacity; the point estimate suggests a 20 log point increase seven years after RPS passage. Finally, Panel B Column (4) documents that there was no impact of RPS on electricity sales, consistent with inelastic demand for electricity.

The Panel B Column (3) – (4) results are puzzling. Generation increased in RPS states but sales remained constant, implying that RPS policies led states to produce more electricity without consuming more electricity. Panel C provides a potential explanation: Column (1) shows that excess generation (i.e. the difference between generation and sales divided by sales) increased by about 9.4 percentage points and Column (2) suggests that the entire increase in excess generation is explained by sales to other states and countries (i.e. Canada or Mexico), though both estimates are imprecise.[22] Together, the Panel B and C results suggest that RPS policies led to capacity expansions, generation increases, and exporting of the additional electricity to other states and countries.

The possibility that RPS policies affected non-RPS states would complicate our difference-in-differences strategy. This concern appears not to be a meaningful problem with respect to the price regressions, because the balancing authority level regressions give similar results to the state level ones. However, the possibility that non-RPS states were affected will be a focus of our efforts to estimate the impacts of RPS on CO_2 emissions.

[22] The corresponding event study graph in Appendix Figure A.7 visually confirms the substantial increase in excess generation after RPS passage, with no discernible pre-trend.

The final mechanism we proposed for RPS costs, intermittency, is difficult to test directly. One way to accommodate increased intermittency is to construct additional natural gas peaker plants that are able to ramp production up and down quickly. While we cannot observe generation from peaker plants specifically, we can observe total generation from both peaker and non-peaker natural gas plants. Appendix Table A.5 reveals some evidence of an increase in natural gas generation in Column (4), though this result is sensitive to specification.

6.4 Heterogeneity in RPS Price Effects and Impacts on Economic Activity

Appendix Table A.2 considers whether RPS policies exhibit heterogeneous effects, by the category of customer. The EIA divides retail sales among three sectors: residential, commercial, and industrial, that together account for total retail sales. According to the EIA, the residential sector covers "living quarters for private households," the commercial sector covers "service-providing facilities and equipment of businesses; Federal, State, and local governments; and other private and public organizations," and the industrial sector covers "all facilities and equipment used for producing, processing, or assembling goods."[23] Residential is the largest sector for most years in our data, comprising about 37% of sales in 2015, while commercial and industrial account for 36% and 26% in that year.[24] As noted in Table 1, retail rates also vary among these groups, with residential customers paying the highest rates while industrial customers pay the lowest. This differentiated pricing may reflect demand elasticities that are correlated with usage, leading utilities to price discriminate by charging lower prices to their most intensive, and therefore price sensitive, customers (Bjørner et al., 2001).

The event-study figures derived from the fitting of Equation (7) for these outcomes are presented in Appendix Figure A.4. There is little evidence of difference in trends between adopting and non-adopting states prior to RPS passage. Industrial prices appear to shift upward substantially in the first year after passage, while the commercial and residential sectors adjust more gradually. Overall, changes by sector track closely with net requirement changes, though perhaps with a slight lag. The statistical sectoral price analyses from estimating Equation (8) for the balanced sample are reported in Columns (2) through (4) of Panel A in Table A.2. In all three sectors, the point estimates represent substantial price increases in the first 7 years after RPS passage; they are 11.2% for residential, 7.8% for commercial, and 10.5% for industrial.

Appendix Table A.3 tests for heterogeneity in the effect of RPS on electricity prices across different groups of states. In particular, these estimates take the main specification (i.e., Equation (8)) and fully interact it with an indicator for membership in a subsample of interest. The results in Table A.3 report the main estimate for RPS states not in the given subsample, and a second

[23]For complete definitions, see the EIA's Electric Power Monthly.
[24]Authors' calculation, from the EIA Electricity Data Browser.

coefficient that measures whether the seven year effect differs in the subgroup of interest. The full effect for the subgroup is the sum of the two reported estimates.

It is apparent that splitting the RPS states in these ways is demanding of the data. The results in Panel A show little evidence that the impact of RPS differed for those states that adopted the policy after 2004, the median year of passage in the data. Thus, the declines in renewables' cost of generation do not appear to reduce the costs of RPS, perhaps a further indication that the indirect costs are the primary drivers. The estimates in Panels B, C, and D suggest that the costs of RPS were lower in states that restructured their electricity market, higher in states that set specific requirements for solar generation, and higher in states with above median percentage of coal generation, though all these results are imprecise.

Since the estimates suggest that RPS programs lead to substantial increases in electricity prices, it is natural to examine whether there are impacts on the real economy. Appendix Table A.4 reports results for estimating Equation (8) for total employment and manufacturing employment. Energy costs are a relatively high share of total costs in manufacturing. There is little evidence of a decline in overall employment as would be expected. In the case of manufacturing employment, the point estimate suggests a 4% decline, but it would not be judged statistically significant by standard criteria.

6.5 Emissions

This section examines the impact of RPS on CO_2 emissions. We start by estimating the main specification from Equation (8) with state level log CO_2 emissions as the dependent variable. This estimate, displayed in Table 4 Panel A Column (1a), suggests that RPS caused only a modest and imprecisely estimated 3 log point reduction in emissions seven years after passage, qualitatively consistent with the findings of other work in the literature such as Upton and Snyder (2017).

However, the remainder of this subsection demonstrates that this specification leads to the wrong conclusion about the impact of RPS on emissions because it fails to account for two types of cross-state spillovers, both of which suggest the need for alternative specifications that address possible violations of SUTVA. First, most RPS states allow compliance through out-of-state REC purchases, thus diverting some of the emissions reductions to nearby states within the same REC region. This complication can be handled in a straightforward way: we account for the purchase of out-of-state RECs by aggregating our data to the REC region level. In practice, we calculate REC region level electricity generation and emissions as the sum across all states within a REC region and whether an RPS program was in force as the weighted average of the state level RPS indicators, where the weight is the state level MWh of generation in the year before RPS was first passed in any state in a given region.[25]

Second, the results presented in Table 3 suggest that RPS states increased net electricity exports to non-RPS states in response to the policy. This finding implies that increased generation in RPS states displaced production in neighboring states, creating spillover effects on emissions in non-RPS states and causing RPS states to record increased emissions associated with exports, rather than local consumption. We previously accounted for such wholesale market spillovers in our estimates of RPS effects on electricity prices by aggregating our data to the balancing authority level. Those results, presented in Columns (6) and (7) of Table 2, show an effect of RPS on prices that is qualitatively similar to the state level specification. However, such a strategy is not available to us in the case of emissions for two reasons. First, about 32% of the balancing authorities in our data cross over REC region boundaries, eliminating any possibility of an aggregation that captures both dimensions of spillovers.[26] Second, our data contains information on emissions only at the state level, which does not allow us to aggregate this variable by balancing authority since balancing authorities frequently cover incomplete portions of states.

With these challenges in mind, we motivate our choice of specifications by first defining the ideal measure of RPS policies' effect on total national emissions in the presence of cross-state spillovers. Let total emissions, E, be the product of electricity generation, G, and emissions intensity, I, in RPS states and their geographic neighbors (denoted by RPS-N):

$$E = G^{RPS} \times I^{RPS} + G^{RPS-N} \times I^{RPS-N} \tag{9}$$

We are interested in measuring the impact of RPS on national emissions, $\Delta E = E_{R=1} - E_{R=0}$, where R represents the RPS policy applied in RPS states. Taking the difference of Equation (9) and rearranging generates the following decomposition of the elements of ΔE :

$$\begin{aligned}\Delta E = & \underbrace{\Delta I^{RPS}\left(G^{RPS} + \Delta G^{RPS}\right)}_{1} + \underbrace{I^{RPS} \times \Delta G^{RPS}}_{2} \\ & + \underbrace{\Delta G^{RPS-N}\left(I^{RPS-N} + \Delta I^{RPS-N}\right)}_{3} + \underbrace{G^{RPS-N} \times \Delta I^{RPS-N}}_{4}\end{aligned} \tag{10}$$

where $\Delta G = G_{R=1} - G_{R=0}$ and $\Delta I = I_{R=1} - I_{R=0}$.

The four terms in Equation (10) represent distinct channels through which an RPS policy could

[25] For REC regions that never pass REC policies, we use 1990 MWh of generation to weight states. An approximate outline of REC region borders is shown in Appendix Figure A.1 and Data Appendix Section 12.2 details the full allocation of states to REC regions. Appendix Table A.7 shows that our CO_2 results are robust to alternative classifications of states with multiple or partial REC region affiliations.

[26] For balancing authorities that span multiple REC regions, any aggregation that captures the full balancing authority region in an observation will include multiple REC regions, and any aggregation that correctly defines REC region boundaries will split the balancing authority. Thus, there is no set of boundaries that can capture both types of spillovers.

affect national emissions. Term (1) captures the primary direct effect of RPS on emissions in RPS states. RPS policies require the use of renewable technologies, likely reducing the emissions intensity in participating states (ΔI^{RPS}). Multiplying this change in emissions intensity by total generation in RPS states captures the tons reduced by RPS requirements for cleaner production in RPS states. Term (2) captures the change in emissions due to changes in generation in RPS states evaluated with the pre-RPS emissions intensity. Term (3) represents changes in RPS-neighbor state emissions caused by changes in their generation. If RPS policies cause implementing states to export more electricity, as suggested by Table 3, then we expect that term (2) will be positive and term (3) will be negative as the policy shifts production and corresponding emissions from neighboring states to RPS states. Since the increase in RPS regions must be offset by generation reductions in non-RPS states (except for international imports/exports), these two terms will approximately cancel each other out if the emissions intensity is equal in RPS regions and non-RPS states and emissions intensities in non-RPS states are unaffected by RPS adoption. The data fail to contradict the former condition and without data on the "merit order" in non-adopting states the latter is difficult to sign, though seems likely to be small.[27] Finally, term (4) represents any potential change in emissions due to changes in emissions intensity in neighboring states evaluated at the pre-RPS generation level, which we noted is of uncertain sign and seems likely to be small.

Guided by the framework laid out in Equation (10), we estimate two specifications for the impact of RPS on REC region level emissions and characterize the assumptions under which each allows us to recover the true effect on national emissions, ΔE. First, in Column (1a) of Table 4 Panel B, we report the estimated impact of RPS on the log of CO_2 emissions. In Column (1b) we calculate the reduction in CO_2 emissions implied by this specification, which represents the sum of terms (1) and (2) at the REC region level and can be interpreted as the true impact on national emissions if terms (3) and (4) sum to zero. A sufficient condition for this assumption to hold would be that all cross-state spillovers take place within REC regions so that RPS causes no changes in generation or emissions intensity outside of REC regions. If this assumption fails to hold then the sign of the bias is unclear.

In our second specification in Column (2a) of Panel B, CO_2 intensity is the dependent variable. This allows us to calculate the value of term (1) from Equation (10) at the REC region level, which equals ΔE under the assumption that terms (2), (3), and (4) collectively sum to zero. Column (2b) provides an estimate of the change in CO_2 emissions calculated as the product of the estimated impact in (2a) and the relevant year's generation. As we noted above, it seems plausible that terms (2) and (3) cancel each other out and term (4) is small in magnitude, but it remains difficult to judge whether this assumption holds in practice.

[27]The relevant summary statistic in Table 1 shows that emissions intensity in control states the year before RPS passage is only 0.2% higher than that of RPS states (p-value = 0.98).

The results in Table 4 suggest that RPS caused substantial declines in national emissions that are much larger than implied by specifications that fail to account for cross-state spillovers. The estimates in Panel B Column (1a) show large declines in CO_2 emissions of 10 to 15 log points seven years after a state's passage of an RPS. The estimates for twelve years after passage are more than twice as large, and would be judged statistically significant at conventional levels.

Table 4 Panel B reports estimates derived from REC region level regressions for both an unweighted regression and a version that weights observations by the number of states in a REC region. The case for the unweighted regression is that the data generating process takes place at the REC region level, whereas the case for weighting by the number of states is that the result can be interpreted as the effect on the average state, analogous to the main specification for the impact of RPS on prices. Column (1b) of Panel B shows that these specifications imply that RPS policies reduced emissions by 141 to 213 million metric tons (10-14%) across the 29 participating states in the seventh year after passage, compared with only 38 million in the state level specification.

In Column (2a) of Table 4 Panel B, we present results for the impact of RPS on CO_2 intensity. Depending on weighting scheme, the estimates suggest that RPS passage reduced emissions intensity by 82 to 170 metric tons per GWh. This effect is larger (175 to 267 metric tons per GWh) 12 years after RPS passage. Column (2b) suggests that total emissions were 203 to 419 million metric tons (14-25%) lower in RPS states in the seventh year after passage, a substantially larger decrease than the corresponding estimates for the log CO_2 specification in Column (1b).[28]

An important feature of the results is that the magnitude of the measured reductions in CO_2 is large relative to the scale of the policy. While we previously reported that RPS raised the net requirement for renewables by 2.2 percentage points seven years after passage, the results in Table 4 indicate that the policies reduced emissions by 10-25% in the same time frame, depending on specification. For context, if the estimated 2.2 percentage point renewable net requirement had one-for-one displaced coal generation in RPS states the reduction in emissions would have been about 4%, making our estimated reduction in emissions two to six times larger than the direct effect of the policy.

While our reduced form estimates do not allow for a full accounting of the mechanisms by which RPS reduced emissions, we explore whether the integration of additional renewable generation affected the relative utilization of fossil fuels with differing fuel intensities. Appendix Table A.5 details the estimated impact of RPS on various forms of generation using REC region level versions of Equation (8), just as in Panel B of Table 4. The striking result here is that RPS adoption is associated with sharp declines in the share of generation from coal and petroleum with

[28] Figure A.8 reveals that there is a relative upward pre-trend in CO_2 emissions in adopting states, underscoring the importance of the trend break specification for this outcome.

some evidence of increases in natural gas, which has about half the carbon intensity of both coal and petroleum. These results suggest that RPS policies have a general equilibrium-style influence by affecting the broader "merit order," which is determined by sources' cost functions (including start-up and shutdown costs) and ultimately dictates which sources operate, even in periods when renewables are not operating.

Given the findings on CO_2 emissions, it is natural to examine whether RPS also had an impact on other pollutants. Table A.6 reports the impact of RPS on several measures of local air pollution using the same specifications as the CO_2 regressions in Table 4. The results show some evidence that RPS reduced SO_2 emissions and emissions intensity. However, there is little evidence of a change in $PM_{2.5}$ concentrations, which is the primary mechanism through which local air pollution affects human health; the results for the monitor and satellite measures of $PM_{2.5}$ concentrations (see Columns (1a) and (1b) respectively) are of opposite sign and neither would be judged statistically significant by conventional criteria.

7 Interpretation

Our estimates suggest that RPS programs have had substantial effects on both electricity prices and CO_2 emissions. To make this concrete, we calculate the implied total costs to consumers and avoided CO_2 emissions in the 29 RPS states in the seventh year after passage. We calculate the increase in electricity payments by consumers as the product of the estimated increase in prices (from the fitting of Equation (8)) and total electricity consumption in the 29 RPS states in the analysis and the reduction in CO_2 emissions using the results from the log CO_2 emissions and CO_2 intensity specifications as described in Section 6.5.

A natural summary statistic of RPS programs' efficacy is the cost per metric ton of CO_2 abated. Figure 6 uses this paper's estimates to develop a range of estimates of this measure. We have presented several specifications of the effect of RPS on both prices and CO_2 emissions that differ in terms of the level of aggregation and the weighting scheme: REC region (weighted and unweighted) estimates of log CO_2 emissions and CO_2 intensity for emissions, and balancing authority (weighted and unweighted) and state level estimates for electricity prices. To avoid imposing any arbitrary choices on the results, we show the cost per ton for all permutations of specifications of the price and emissions regressions in Figure 6.

The point estimates for the cost per ton abated range from \$58 to \$298.[29] Depending on the chosen specification, the estimates suggest that RPS programs reduced emissions by 142 to 419 million metric tons at a total cost to consumers of \$14 to \$34 billion in the seventh year after passage. To characterize the range of uncertainty around the cost per ton estimates, we employ a

[29] Appendix Figure A.9 shows the corresponding estimates of cost per ton for the 12th year after passage.

seemingly unrelated regressions estimation approach by "stacking" and fully interacting the price and CO_2 emissions regressions. This approach allows us to use the delta method to calculate the variance of the ratio of the impact of RPS on costs to consumers and on emissions reductions. Specifically, we use the coefficients from the stacked regression to calculate the impact of RPS on prices, as in Table 2, and the impact on CO_2 emissions, as in Table 4, and then plot the interquartile range of the cost per ton in Figure 6. The uncertainty around these estimates reflects the challenge inherent in taking the ratio of two functions of coefficients from different regressions estimated at different spatial units.

It is useful to put the estimated abatement costs in context by comparing them to a range of other climate policies, and to the estimated benefits of emissions mitigation. Our point estimates for the cost per ton of CO_2 abatement from RPS are substantially higher than the price of a permit to emit a ton of CO_2 in major carbon markets. For example, the current prices in the California/Quebec, Regional Greenhouse Gas Initiative, and European Union ETS markets are about \$18, \$8, and \$63, respectively. On the other hand, other studies have found that abatement costs from policies such as home weatherization investments or low-carbon fuel standards can be several hundred dollars per ton of CO_2 (Fowlie, Greenstone, and Wolfram, 2018; Holland, Hughes, and Knittel, 2009). In terms of comparing the costs of abatement from RPS to the benefits of emissions reductions, it is also worth noting that the Obama Administration (and the Biden Administration on an interim basis) set the social cost of carbon (i.e., the monetized damages from the release of an additional ton of CO_2) at \$51 per ton, although it was estimated at \$125 per ton in recent work (Greenstone, Kopits, and Wolverton, 2013; Carleton and Greenstone, 2021). These estimates of the benefits of carbon mitigation are generally at the lower end of the range of point estimates of the abatement costs of RPS, though again we note the imprecision which makes definitive statements about net benefits challenging.

There are several caveats and implications of the paper's results that bear noting. First, the analysis is "reduced form" so we cannot assign precise shares of the RPS programs' full costs to differences in generation costs, intermittency, transmission, and stranded assets. Furthermore, it seems reasonable to assume that these shares vary over time and in ways that further complicate attempts to get at their magnitudes. For example, it seems plausible that any stranded asset costs decline over time while intermittency costs increase as net requirements grow. Similarly, the data requirements necessary to unpack the sources of RPS' impacts on costs with a structural analysis are extraordinary, starting with the cost functions of all current and potential electricity generators, their current and potential locations, and the resulting merit orders at each pricing node within the relevant balancing authorities and REC regions; we are unaware of the availability of such a data set.

Second, it is often claimed that renewable policies provide an external benefit by reducing the costs of future renewable generation in a way that is generic (e.g., learning-by-doing) and cannot be fully appropriated by the firm undertaking the activities. If there are such spillovers or positive externalities that occur outside our data, then our estimates of the costs per metric ton of abatement will be systematically too high because they do not account for the benefits received by future customers. In principle, these benefits could be global and thus quite substantial. The coincidence of the global proliferation of policies that support renewable energy and the decline in solar and wind prices over the last decade is consistent with the possibility of such spillovers. However, research that isolates the magnitude of any such spillovers from other factors is probably best described as emerging, making this a rich area for future research (Gillingham and Stock, 2018).

Third, more broadly, a randomized controlled trial is unavailable here, so we cannot rule out the possibility of a form of unobserved heterogeneity that explains the results without RPS programs playing a causal role. This is a particular challenge for inference on policies that apply at states or higher levels of aggregation as RPS programs do.

8 Conclusion

This paper has provided the first comprehensive evaluation of the impacts of RPS programs, which are the most popular and prevalent carbon policy in the United States, and has several main findings. First, these programs mandate increases in renewable generation that are often smaller than advertised. Seven years after passage, RPS programs require a 2.2 percentage point increase in renewables' share of generation, and 12 years after they require a 5.0 percentage point increase. Second, RPS program passage leads to substantial increases in electricity prices that mirror the program's increasing stringency over time. Seven years after passage, we estimate that average retail prices are 1.2 cents per kWh, or 11%, higher than they otherwise would be, with over half the increase due to increased transmission and distribution costs. The corresponding effect twelve years after passage is 1.9 cents per kWh, or 17%, higher. Third, the estimates indicate that RPS programs lead to CO_2 emissions reductions of 10% to 25% seven years after passage (23% to 36% 12 years after passage). Putting the results together, the cost per metric ton of CO_2 abated in the seventh year after RPS passage ranges from $60-$300 with confidence intervals that cannot rule out substantially smaller or larger abatement costs.

A particularly striking finding is that RPS programs meaningfully alter electricity market equilibria. This effect, which has not been possible to comprehensively measure to date, appears to account for the majority of RPS program costs and benefits. A recent study suggests that the direct costs of RPS increase retail electricity prices by 2% (Barbose, 2018), which is substantially smaller than our estimates that prices are about 11% higher seven years after passage. Although there are several differences between these two studies, it seems likely that the indirect costs, including intermittency, transmission, and stranded asset payments, account for a substantial fraction of RPS program costs. This finding means that caution is warranted in extrapolating declines in the direct generation costs of renewable energy to its overall impact on electricity prices. Further, it raises the possibility that indirect costs associated with grid integration could represent the more important barrier to substantially increasing renewables' share of generation.

Similarly, the estimated reductions in carbon emissions are larger than the effect of swapping increased renewable generation for even the most carbon intensive forms of electricity generation production like coal and petroleum. This finding underscores that projecting the carbon impacts of the coming years' legally mandated increases in RPS stringency will require projecting the resulting "merit orders" at all pricing nodes in the relevant balancing authorities and REC regions.

Renewable Portfolio Standards have been the most prevalent form of climate policy in the U.S. to date. Existing legislation requires these policies to continue expanding in scale and reach unprecedented levels of stringency in the coming years. Any projection of the effects of future policy will require uncertain assumptions about factors that go beyond what can be learned from historical data, such as the pace of technological innovation or the effects of renewable energy integration at levels of penetration beyond the range of past experience. Perhaps this paper's central contribution to projecting the costs and benefits of future policy is to highlight the importance of understanding the indirect effects of renewable energy and the viability of mechanisms to facilitate their grid integration. These are important topics for future research.

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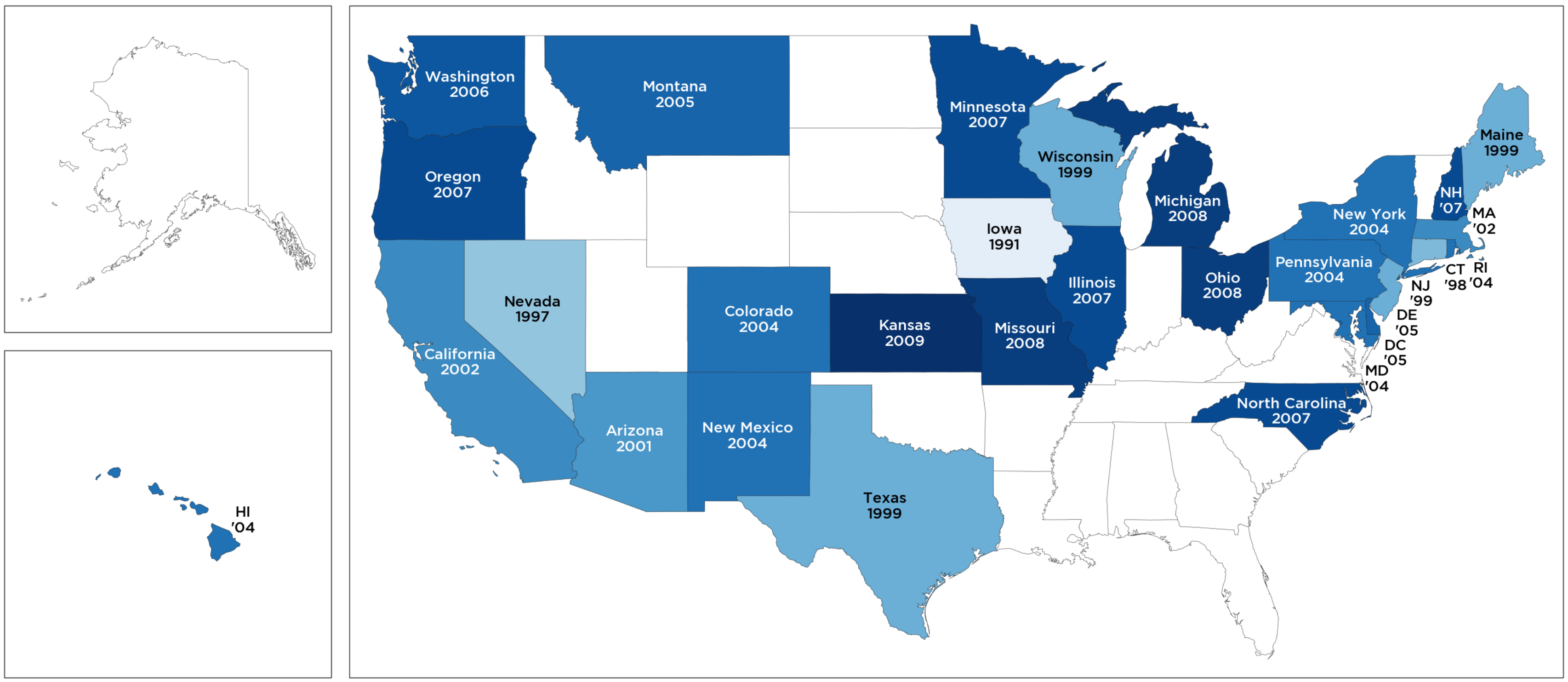
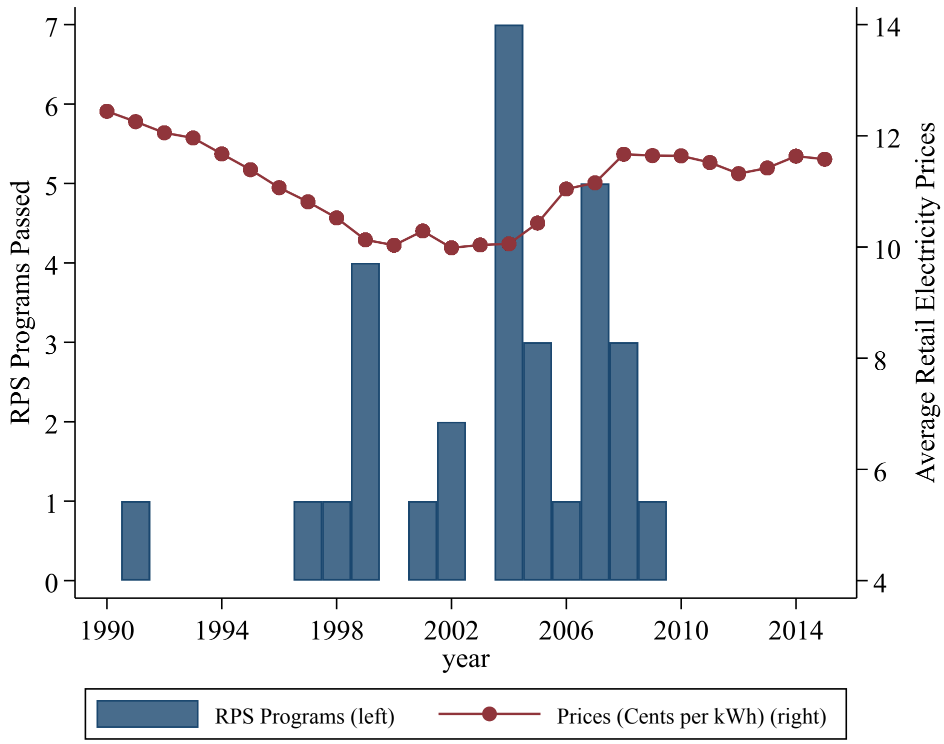
9 Figures

Figure 1: RPS Passage by State



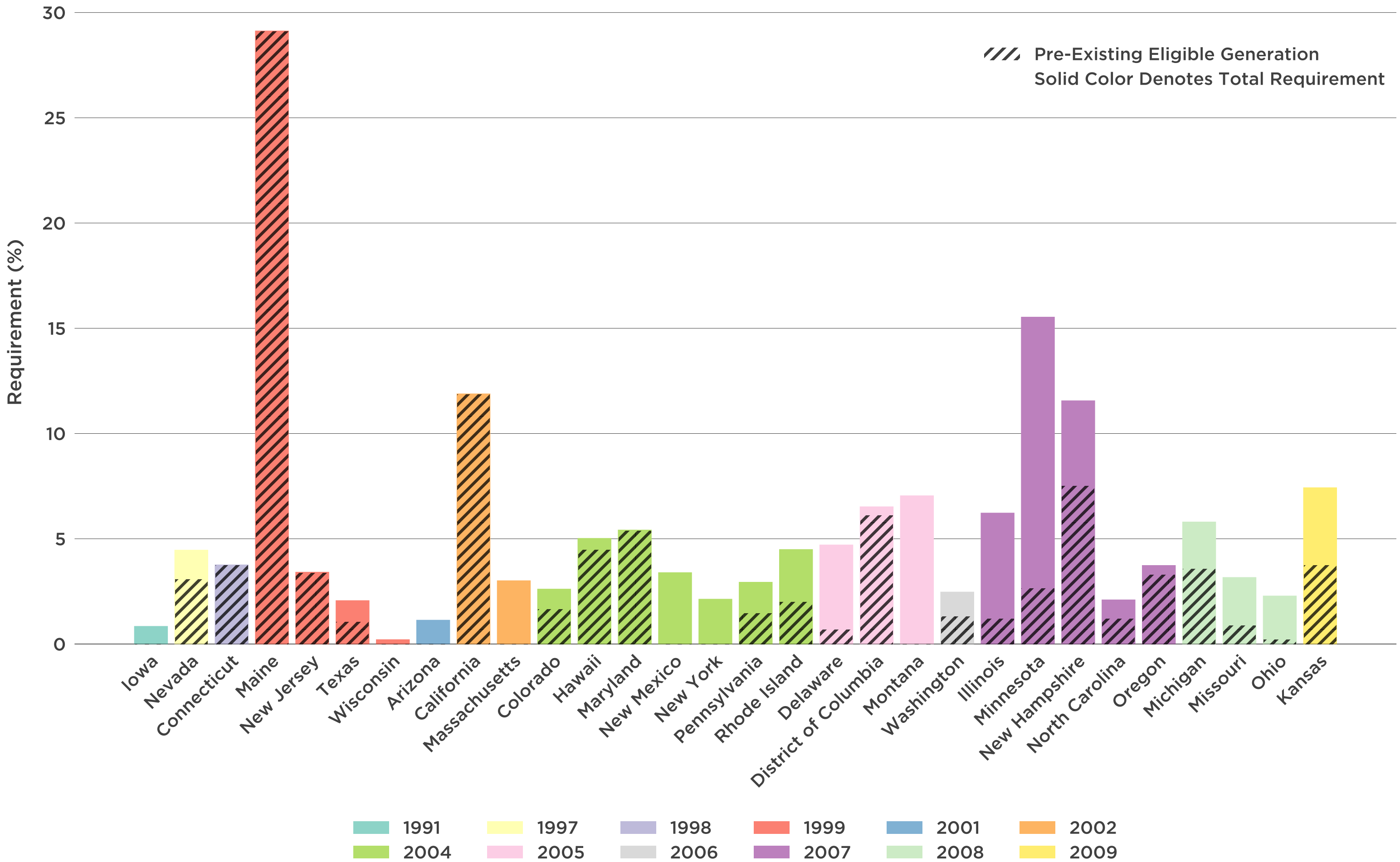
Notes: States that have adopted any RPS policy are colored according to the year in which the RPS legislation was first passed. We gather this information from a combination of state legislative documents, state government websites, and summaries from the U.S. Department of Energy.

Figure 2: Number of RPS Programs Newly Passed into Law, by Year



Notes: Average national retail electricity prices are shown in constant 2019 dollars and taken from the EIA. We construct data on new RPS legislation passage from a combination of state legislative documents, state government websites, and summaries from the U.S. Department of Energy.

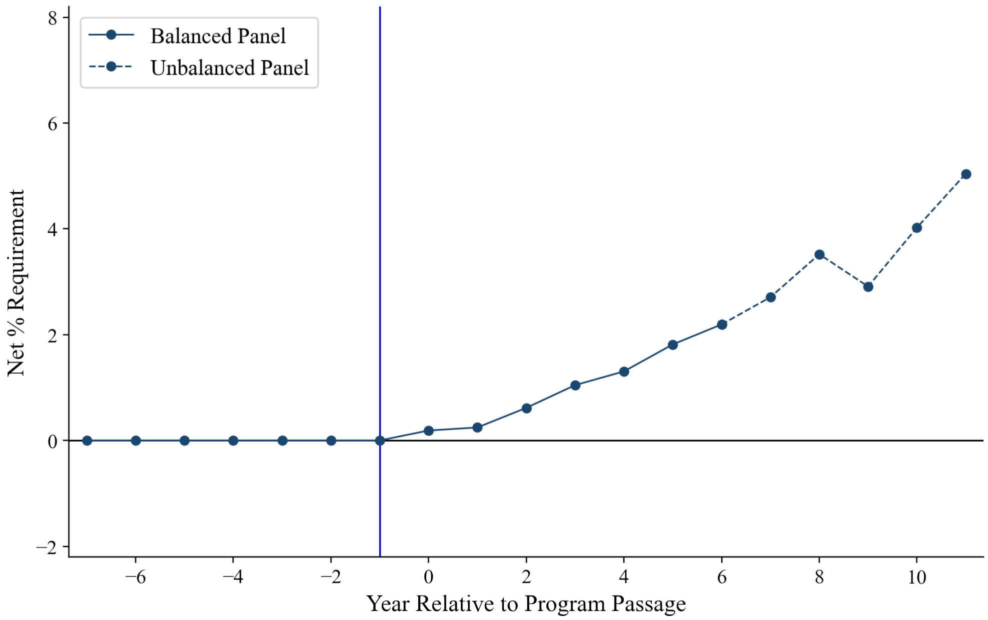
Figure 3: RPS Total and Net Requirements, by State



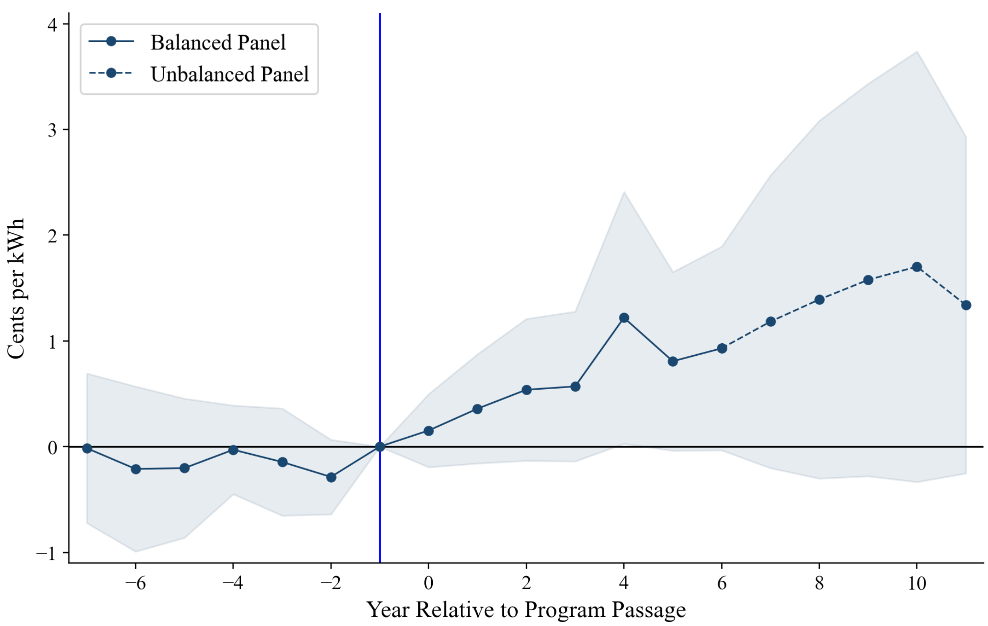
Notes: States are sorted by the year in which their RPS policies were first passed. The bars are colored according to RPS passage year. The total height of each bar denotes the gross RPS requirement in the seventh year after RPS passage at $\tau = 6$; the non-patterned portion of each bar denotes the net requirement at $\tau = 6$. The data for gross and net RPS requirements are from the LBNL, in MWh, and are converted to percentages by dividing by contemporary generation at $\tau = 6$. RPS program passage dates are from a combination of state legislative documents, state government websites, and summaries from the U.S. Department of Energy.

Figure 4: Estimated Effects of RPS Programs on Net Renewable Requirements and Retail Electricity Prices

(a) Net RPS Requirements



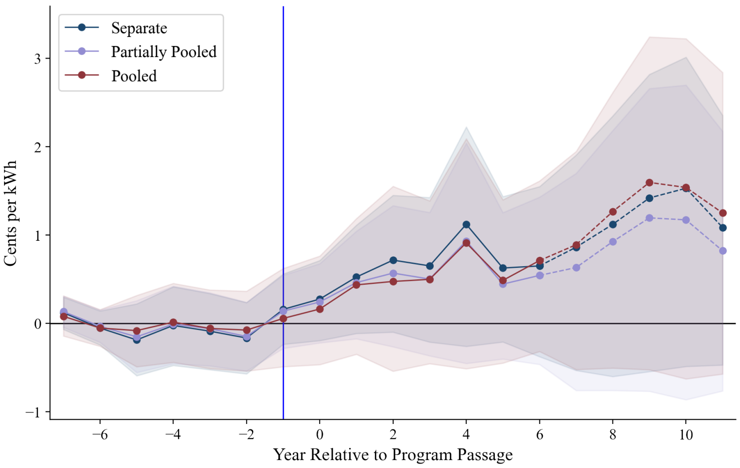
(b) Retail Prices



Notes: Graph (a) shows the mean net RPS requirement percentage for event years τ = -7 to τ = 11. Graph (b) shows coefficients for σ_τ for τ = -7 to τ = 11 from the event study specification in Equation (7) for retail electricity prices regressed on indicator variables for years relative to program passage, controlling for state and year fixed effects, and indicators for other programs listed in Table 1. Blue lines show the point estimates and shaded areas represent the 95% confidence intervals. We take net RPS requirement data from the LBNL as constructed by Barbose (2018). Electricity price data are from the EIA. RPS program passage dates are from a combination of state legislative documents, state government websites, and summaries from the U.S. Department of Energy. Standard errors are clustered at the state level.

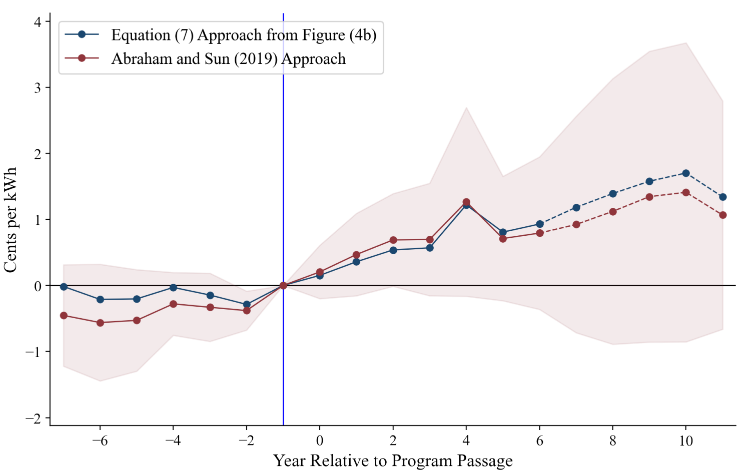
Figure 5: Estimated Effects of RPS Programs on Retail Electricity Prices, Robustness Checks

(a) Synthetic Control Method



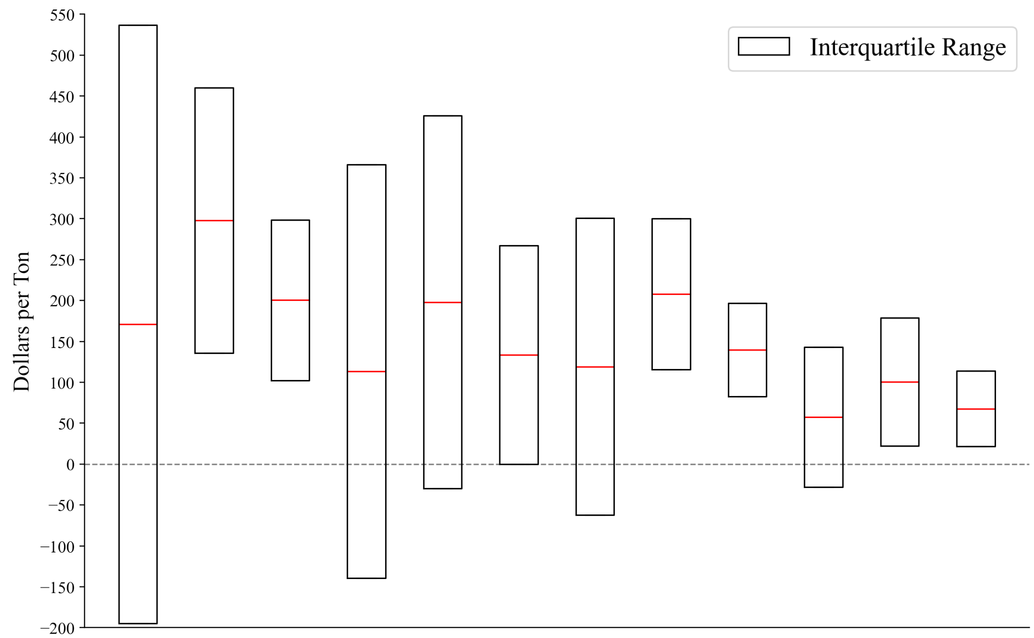
Notes: Lines show estimates from synthetic control method specifications as recommended by Ben-Michael, Feller, and Rothstein (2021) for event years τ = -7 to τ = 11, and shaded area represent 95% confidence intervals. Each specification includes state fixed-effects and balances on electricity price as the dependent variable, and solar and wind potential, CO_2 intensity, percent RPS-eligible generation, and percent coal and natural gas generation as independent variables. Appendix Table A.1 shows summary statistics for the weighted sample of synthetic control states, as compared to RPS states and control states in the main specification. Appendix Table A.2 shows additional synthetic control method specifications.

(b) Comparing Baseline and Abraham and Sun (2019) Approach



Notes: The red line displays coefficients for an alternative specification that uses an "interaction-weighted" estimator proposed by Abraham and Sun (2019) for difference-in-differences estimation with staggered treatment timing, while the blue line displays coefficients from the event study specification as shown in Figure 4b. The red line corresponds to σ_τ for τ = -7 to τ = 11 with a modified version of the event study specification in Equation (7) that allows for cohort-year interactions with the σ_τ's. More specifically, the estimating equation is: $y_{st} = \alpha + \sum_e \sum_\tau \sigma_{\tau,e \in E} * \mathbf{I}\{E_s = e\} * D_{\tau,st} + X_{st} + \gamma_s + \mu_t + \varepsilon_{st}$, where E_s denotes the RPS passage year of state s and E denotes the set of all years in which at least one state passed an RPS program. To aggregate the $\sigma_{\tau,e}$'s to σ_τ, we take a weighted average across cohort-years. For example, given τ = 1, suppose we have a total of 3 observations in our data set, of which 2 are for states whose RPS was passed in 1998 and 1 is for a state whose RPS was passed in 2001. Then $\sigma_{\tau=1} = \frac{2}{3} * \sigma_{\tau=1,e=1998} + \frac{1}{3} * \sigma_{\tau=1,e=2001}$. The shaded area represents the 95% confidence interval. Electricity price data are from the EIA. RPS program passage dates are from a combination of state legislative documents, state government websites, and summaries from the U.S. Department of Energy. Standard errors are clustered at the state level.

Figure 6: Cost per Ton of CO_2 Abatement



Price Specification												
BA Aggregation (Sales Weighted)	✓			✓			✓			✓		
BA Aggregation (State-Count Weighted)		✓			✓			✓			✓	
State			✓			✓			✓			✓
CO_2 Specification												
$\log(CO_2)$	✓	✓	✓	✓	✓	✓						
CO_2 Intensity							✓	✓	✓	✓	✓	✓
REC Region Aggregation (Unweighted)	✓	✓	✓				✓	✓	✓			
REC Region Aggregation (State-Count Weighted)				✓	✓	✓				✓	✓	✓

Notes: Each red line displays the cost per ton of CO_2 corresponding to a particular combination of specifications for estimating the impact of RPS on CO_2 reductions and retail electricity costs in the 7th year post RPS passage. For example, the second column value of $298 corresponds to using a REC region regression with no regression weight for measuring CO_2 reductions and using a balancing authority level regression with state count regression weights for measuring price changes. The "State" specification for price comes from Column (1) of Table 2. The "BA Aggregation (Sales Weighted)" specification for price comes from Column (6) of Table 2. The "BA Aggregation (State-Count Weighted)" specification for price comes from Column (7) of Table 2. The "$\log(CO_2)$" specification for CO_2 comes from Column (1a) of Table 4 Panel B. The "CO_2 Intensity" specification for CO_2 comes from Column (2a) of Table 4 Panel B. We calculate standard errors by stacking the specifications using a seemingly unrelated regressions procedure, and the black boxes display the interquartile range of the estimates.

10 Tables

Table 1: Summary Statistics

	Mean RPS (1)	Mean Control (2)	Mean Non-RPS (3)	P-value RPS vs Control (4)	P-value RPS vs Non-RPS (5)
Price (2018 Cents/kWh)					
Total	11.4	9.4	8.9	0.00	0.00
Residential	13.4	11.3	10.8	0.01	0.00
Commercial	11.8	9.8	9.4	0.00	0.00
Industrial	8.5	6.9	6.5	0.01	0.00
Price Change in 7 Years Preceding RPS Adoption	-0.6	-0.6	-0.5	0.89	0.62
Total Sales (TWh)	76.2	64.3	59.4	0.39	0.23
Population (Millions)	7.0	4.7	3.9	0.11	0.03
CO_2 Emissions (Million mt)	48.0	49.2	49.0	0.90	0.91
CO_2 Emissions Intensity (mt per GWh)	654.5	655.9	655.8	0.98	0.98
Renewable Potential (PWh)					
Solar	9.1	6.6	6.2	0.34	0.26
Wind	1.1	0.9	0.8	0.40	0.19
Generation					
Total (TWh)	80.5	73.3	70.0	0.64	0.49
RPS Eligible (TWh)	8.9	5.9	4.0	0.37	0.13
RPS Eligible (% of Total)	13.5	13.0	12.9	0.89	0.87
Generating Capacity					
Total (GW)	20.3	18.4	17.4	0.60	0.43
RPS Eligible (GW)	2.5	1.6	1.2	0.36	0.16
RPS Eligible (% of Total)	14.2	14.3	14.2	0.99	1.00
Other Programs (%)					
Public Benefits Fund	0.66	0.45	0.40	0.03	0.01
Net Metering	0.07	0.02	0.00	0.30	0.16
Green Power Purchasing	0.03	0.03	0.04	0.91	0.89
Energy Efficiency	0.59	0.25	0.12	0.00	0.00
Has Restructured	0.38	0.18	0.16	0.03	0.02
Has NO_x Trading	0.15	0.06	0.03	0.00	0.00
% of Counties Clean Air Act Non-Attainment	0.07	0.03	0.02	0.02	0.01
Energy Efficiency Expenditure (2018 Cents/kWh)	0.41	0.11	0.02	0.00	0.00
Number of Observations	29	29	29		

Notes: "Mean RPS" refers to RPS states in the year prior to RPS passage. A control is defined for each RPS state as the mean across non-RPS states and RPS states that have yet to pass RPS in the year prior to the reference RPS state's RPS passage. "Mean Control" is the average across these controls. "Mean Non-RPS" refers to the corresponding average restricting to the subset of control states that never implement RPS. Column (4) reports p-values from a paired two-sample t-test between Columns (1) and (2) that allows for unequal variances across groups. Iowa is excluded from these summary statistics due to the particularly early passage of its RPS that precludes pre-passage data availability.

Table 2: RPS Impact on Retail Electricity Prices

	Dependent Variable: Retail Electricity Prices						
						Balancing Authority Aggregation	
	Base Specification	Continuous control for energy efficiency	Exclude Hawaii	Year-Region Fixed Effect	Year-Division Fixed Effect	Sales-weighted	State-count-weighted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: 7 Post-Passage Years, Balanced Sample							
Mean Shift (δ_3)	0.36	0.39*	0.28	0.49*	0.43	0.51	0.32
	(0.23)	(0.22)	(0.24)	(0.25)	(0.26)	(0.62)	(0.59)
Trend Break (β_3)	0.14*	0.16*	0.16*	0.10	0.09	0.09	0.25*
	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.16)	(0.14)
Effect of RPS 7 years after passage	1.22**	1.37**	1.23*	1.11**	0.99*	1.04*	1.82**
($6\beta_3 + \delta_3$)	(0.58)	(0.60)	(0.61)	(0.51)	(0.52)	(0.56)	(0.89)
Panel B: 12 Post-Passage Years, Unbalanced Sample							
Mean Shift (δ_3)	0.39	0.42	0.38	0.50*	0.34	0.61	0.48
	(0.28)	(0.27)	(0.30)	(0.28)	(0.27)	(0.52)	(0.51)
Trend Break (β_3)	0.14**	0.16**	0.12**	0.11*	0.14	0.03	0.17*
	(0.07)	(0.07)	(0.06)	(0.06)	(0.09)	(0.11)	(0.09)
Effect of RPS 12 years after passage	1.91**	1.38***	1.08**	1.14**	1.18**	0.97	2.38*
($11\beta_3 + \delta_3$)	(0.77)	(0.49)	(0.46)	(0.46)	(0.54)	(0.83)	(1.19)
Other Programs	X		X	X	X	X	X
Other Programs and Energy Eff. Expenditures		X					
Exclude Hawaii			X				
State Fixed Effect	X	X	X	X	X		
Balancing Authority Fixed Effect						X	X
Year Fixed Effect	X	X	X			X	X
Year-Census Region Fixed Effect				X			
Year-Census Division Fixed Effect					X		
Number of Observations	1300	1200	1274	1300	1300	1558	1558

Notes: The columns report estimates for the impact of RPS on retail electricity prices using the specification from Equation (8). All specifications control for year and either state or balancing authority fixed effects, as well as indicators for the other programs listed in Table 1. Column (1) is our base specification. Column (2) replaces the indicator variable for energy efficiency programs with a continuous measure for energy efficiency program costs in the set of controls. Our continuous measure of energy efficiency expenditures is not available before 1992 so this specification covers a slightly reduced sample of years. Running our main specification with an energy efficiency indicator on this modified sample produces an estimate that RPS raises costs by 1.37 cents 7 years after passage, identical to the 1.37 cents estimate shown here with the continuous energy efficiency control. Column (3) excludes Hawaii due to its geographic isolation. Columns (4) and (5) add more stringent fixed effects to control for regional shocks such as differential fuel price changes and local economic fluctuations. There are four Census regions and nine Census divisions. Columns (6) and (7) account for cross-state wholesale market spillovers by aggregating observations to the balancing authority level using data from EIA Form 861. More details on this procedure can be found in the Data Appendix 12.1. Standard errors are clustered at either the state level or the balancing authority level with statistical significance indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Mechanisms

Panel A: Transmission and Distribution Costs

	log(Transmission Costs)	log(Distribution Costs)	log(Transmission and Distribution Costs)
	(1)	(2)	(3)
Mean Shift (δ_3)	0.32*	0.14	0.24*
	(0.18)	(0.09)	(0.14)
Trend Break (β_3)	0.06	0.02	0.04
	(0.04)	(0.02)	(0.03)
Effect of RPS 7 years after passage	0.70*	0.27	0.47
($6\beta_3+\delta_3$)	(0.40)	(0.19)	(0.31)
Implied Change in Costs	0.52 ¢/kWh	0.34 ¢/kWh	0.91 ¢/kWh
Mean at $\tau=-1$	0.5 ¢/kWh	1.2 ¢/kWh	1.7 ¢/kWh
State Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Other Programs	Yes	Yes	Yes
Number of Observations	1060	1059	1060

Panel B: Electricity Production and Consumption

	log(Capacity)	Capacity Factor	log(Generation)	log(Sales)
	(1)	(2)	(3)	(4)
Mean Shift (δ_3)	0.02	0.97	0.08**	0.00
	(0.02)	(0.82)	(0.04)	(0.01)
Trend Break (β_3)	0.01	0.27	0.02	0.00
	(0.01)	(0.47)	(0.02)	(0.00)
Effect of RPS 7 years after passage	0.08	2.57	0.20	0.01
($6\beta_3+\delta_3$)	(0.06)	(3.32)	(0.12)	(0.04)
Mean at $\tau=-1$	20.3 GW	42.9	80.5 TWh	76.2 TWh
State Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Other Programs	Yes	Yes	Yes	Yes
Number of Observations	1300	1300	1300	1300

Panel C: Excess Generation Accounting

	Excess Generation	Electricity Net Exports
	(1)	(2)
Mean Shift (δ_3)	3.67	3.98
	(2.76)	(2.75)
Trend Break (β_3)	0.96	0.99
	(1.18)	(1.19)
Effect of RPS 7 years after passage	9.42	9.93
($6\beta_3+\delta_3$)	(9.17)	(9.21)
Mean at $\tau=-1$	5.8 pp	-5.1 pp
State Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Other Programs	Yes	Yes
Number of Observations	1300	1300

Notes: Each column in each panel shows an estimate using Equation (8) for the given dependent variable. Panel A and B columns are in logs, except for capacity factor which is shown in percentage points. Data on transmission and distribution costs come from FERC Form 1 as compiled by Fares and King (2017). This data has fewer observations because it begins in 1994 and does not include Nebraska, which has no investor-owned utilities. In addition, taking logs results in dropping a small number of observations listed as zero, which we interpret as missing data since it is not feasible for transmission and distribution infrastructure to require no operating and maintenance costs for a full year. Data on capacity, capacity factor, generation, sales, and electricity net exports come from EIA Forms 860, 861, 867, 906, 920, and 923. Using Equation (8) notation, the effect of RPS 7 years after passage is $6\beta_3+\delta_3$. All specifications control for state and year fixed effects, and indicators for the other programs listed in Table 1. Standard errors are clustered at the state level with statistical significance indicated by $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table 4: Estimates of RPS Impact on CO_2 Emissions

Panel A: State-Level Observations

	log(CO_2 Emissions)	
	Regression Estimates from Equation (8) (1a)	Implied Change in CO_2 Emissions (Million mt) (1b)
7 Post-Passage Years		
Mean Shift (δ_3)	0.04	
	(0.03)	
Trend Break (β_3)	−0.01	
	(0.01)	
Effect of RPS 7 years after passage	−0.03	−1.3
	(0.11)	
12 Post-Passage Years		
Mean Shift (δ_3)	0.05	
	(0.04)	
Trend Break (β_3)	−0.02	
	(0.01)	
Effect of RPS 12 years after passage	−0.13	−3.2
	(0.14)	
Mean at $\tau = -1$	48.0 Million mt	
State Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Other Programs	Yes	Yes
Number of Observations	1300	1300

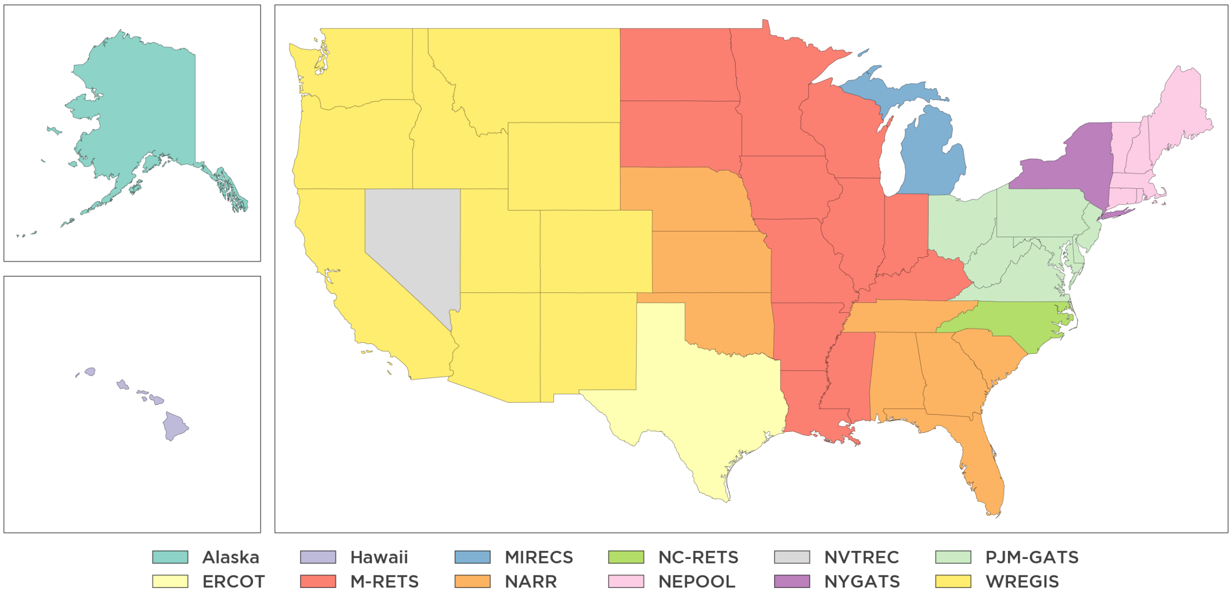
Panel B: REC Region-Level Observations

	log(CO_2 Emissions)		CO_2 Intensity (mt/GWh)	
	Regression Estimates from Equation (8) (1a)	Implied Change in CO_2 Emissions (Million mt) (1b)	Regression Estimates from Equation (8) (2a)	Implied Change in CO_2 Emissions (Million mt) (2b)
Unweighted (7 Post-Passage Years)				
Mean Shift (δ_3)	0.04		13.2	
	(0.04)		(17.7)	
Trend Break (β_3)	-0.02^{**}		-15.9^{***}	
	(0.01)		(4.3)	
Effect of RPS 7 years after passage	−0.10	−4.9	-82.1^{*}	−7.0
	(0.06)		(37.9)	
Weighted (7 Post-Passage Years)				
Mean Shift (δ_3)	−0.02		−26.7	
	(0.05)		(22.5)	
Trend Break (β_3)	-0.02^{**}		-23.8^{**}	
	(0.01)		(8.9)	
Effect of RPS 7 years after passage	−0.15	−7.3	-169.5^{**}	−14.4
	(0.09)		(71.8)	
Unweighted (12 Post-Passage Years)				
Mean Shift (δ_3)	0.05		19.3	
	(0.04)		(20.1)	
Trend Break (β_3)	-0.03^{***}		-17.6^{***}	
	(0.01)		(4.3)	
Effect of RPS 12 years after passage	-0.26^{**}	−7.0	-174.8^{**}	−8.8
	(0.11)		(56.8)	
Weighted (12 Post-Passage Years)				
Mean Shift (δ_3)	0.00		−31.0	
	(0.07)		(28.6)	
Trend Break (β_3)	-0.03^{**}		-21.5^{**}	
	(0.01)		(7.2)	
Effect of RPS 12 years after passage	-0.32^{**}	−8.9	-267.2^{**}	−13.5
	(0.12)		(98.9)	
Mean at $\tau = -1$	95.3 Million mt		596.0 mt/GWh	
Region Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Other Programs	Yes	Yes	Yes	Yes
Number of Observations	312	312	312	312

Notes: (a)-columns display estimates from Equation (8), while (b)-columns display the corresponding implied changes in CO_2 emissions on average for RPS states. Using Equation (8) notation, the effect of RPS 7 years after passage is $6\beta_3 + \delta_3$, and the effect of RPS 12 years after passage is $11\beta_3 + \delta_3$. Panel A contains state level regressions. Panel B contains specifications run at the REC region level aggregating observations using the generation-weighted average of states in the region; the weighted specification further weights each observation by the count of states in the region. All specifications control for state (or REC region) and year fixed effects, and indicators for the other programs listed in Table 1. Standard errors are clustered at either the state level or the REC region level with statistical significance indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

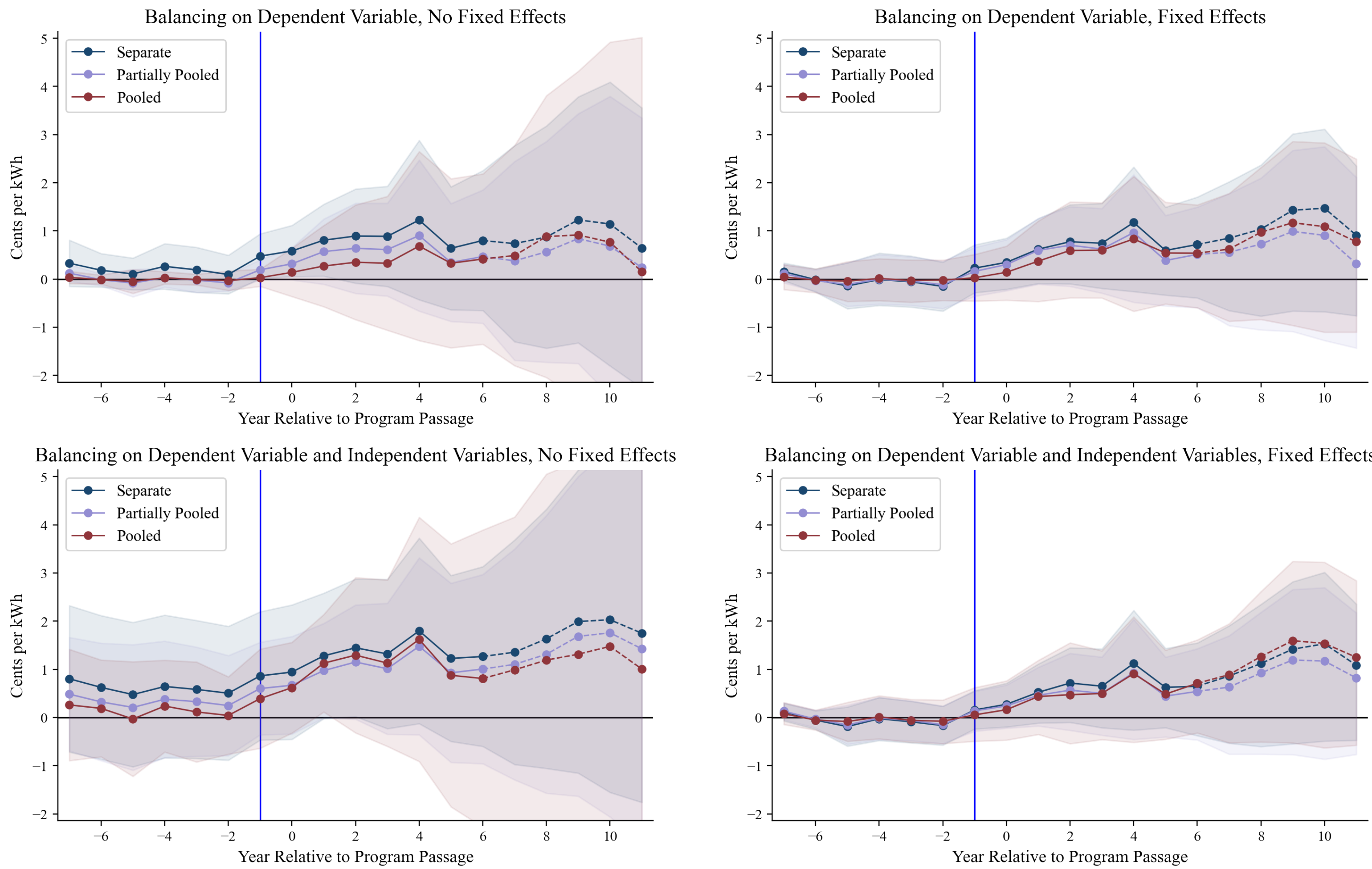
11 Appendix (For Online Publication)

Figure A.1: REC Tracking Markets



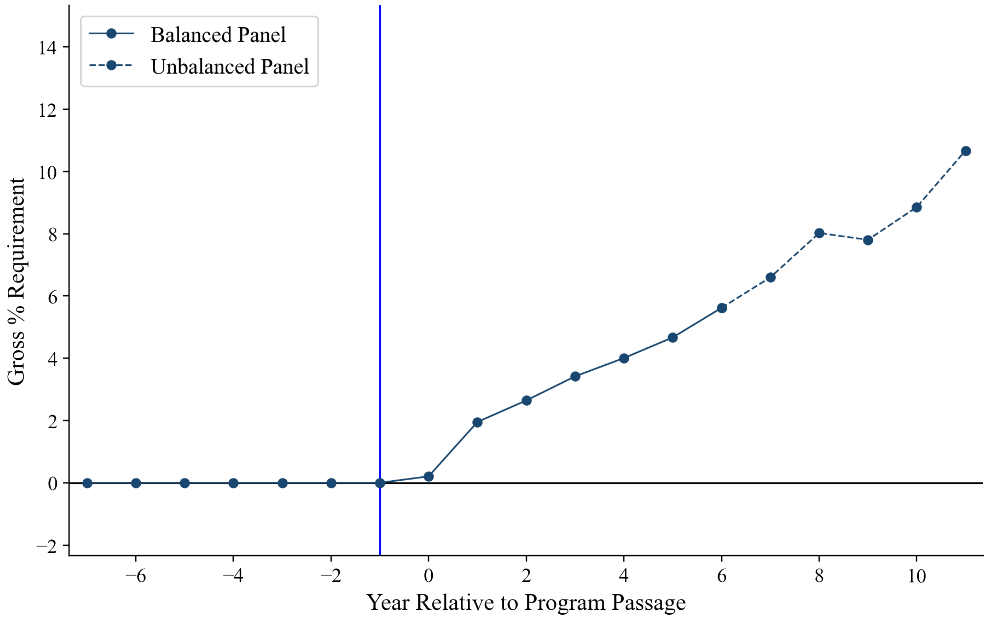
Notes: We compile these boundaries using REC region tracking system websites. Portions of some states qualify for multiple REC regions. We show robustness of our main CO_2 results to alternative classifications for these few states in Appendix Table A.7.

Figure A.2: Estimated Effects of RPS Programs on Retail Electricity Prices, Synthetic Control Method



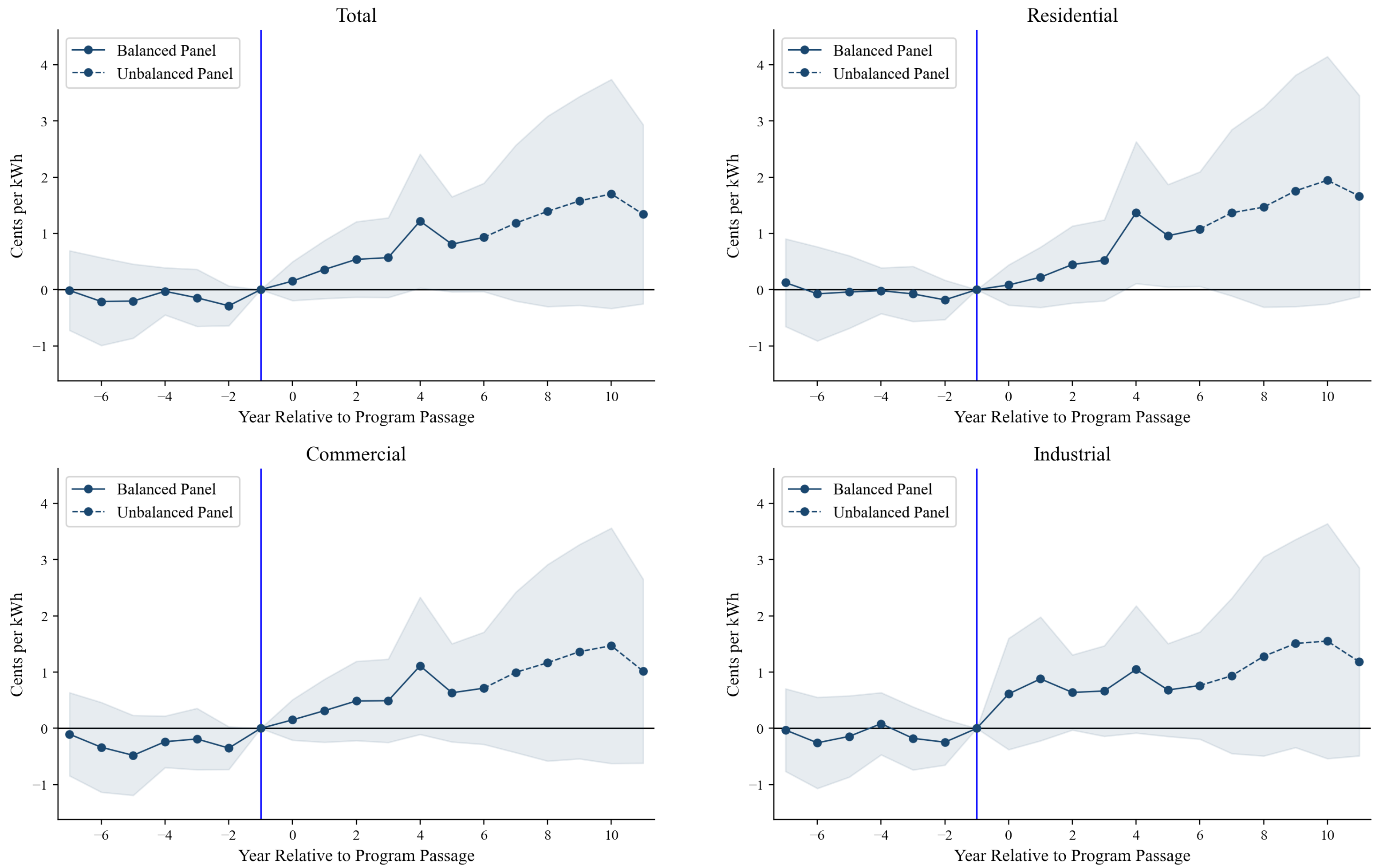
Notes: Graphs show estimates from a range of specifications employing synthetic controls methods, as recommended by Ben-Michael, Feller, and Rothstein (2021) for event years τ = -7 to τ = 11. For specifications that construct synthetic controls by targeting balance on independent variables, we use solar and wind potential, CO_2 intensity, percent RPS-eligible generation, and percent coal and natural gas generation as the independent variables of interest. Appendix Table A.1 shows summary statistics for the weighted sample of synthetic control states, as compared to RPS states and control states in the main specification. Electricity price data are from the EIA. RPS program passage dates are from a combination of state legislative documents, state government websites, and summaries from the U.S. Department of Energy. Standard errors are clustered at the state level.

Figure A.3: Estimated Effects of RPS Programs on **Gross** Renewable Requirements (Extended Post Period)



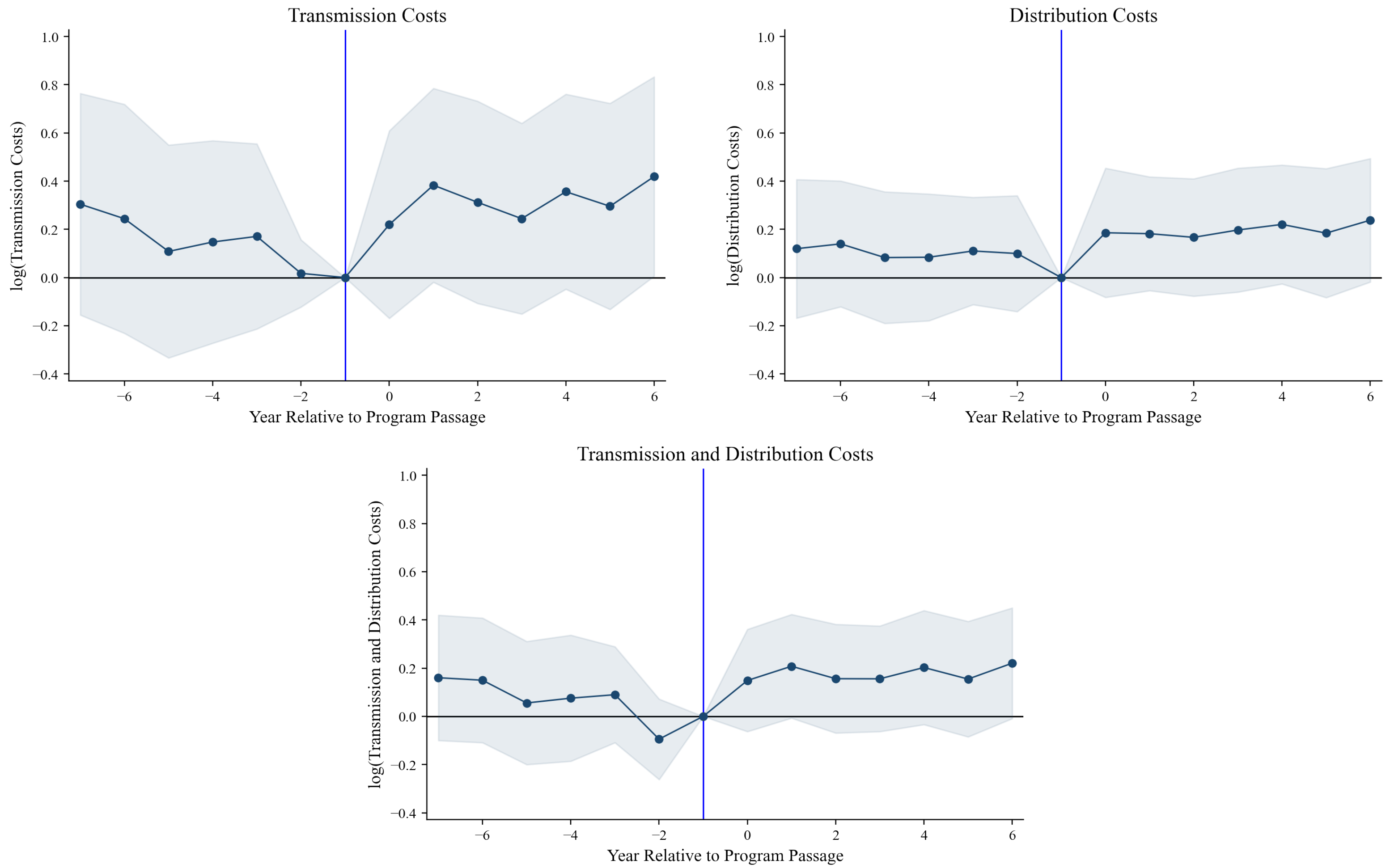
Notes: The graph shows the mean gross RPS requirement percentage for event years τ = -7 to τ = 11. We take gross RPS requirement data from the LBNL as constructed by Barbose (2018). Electricity price data are from the EIA. RPS program passage dates and requirements are from a combination of state legislative documents, state government websites, and summaries from the U.S. Department of Energy.

Figure A.4: Electricity Prices Before and After RPS Passage, by Sector



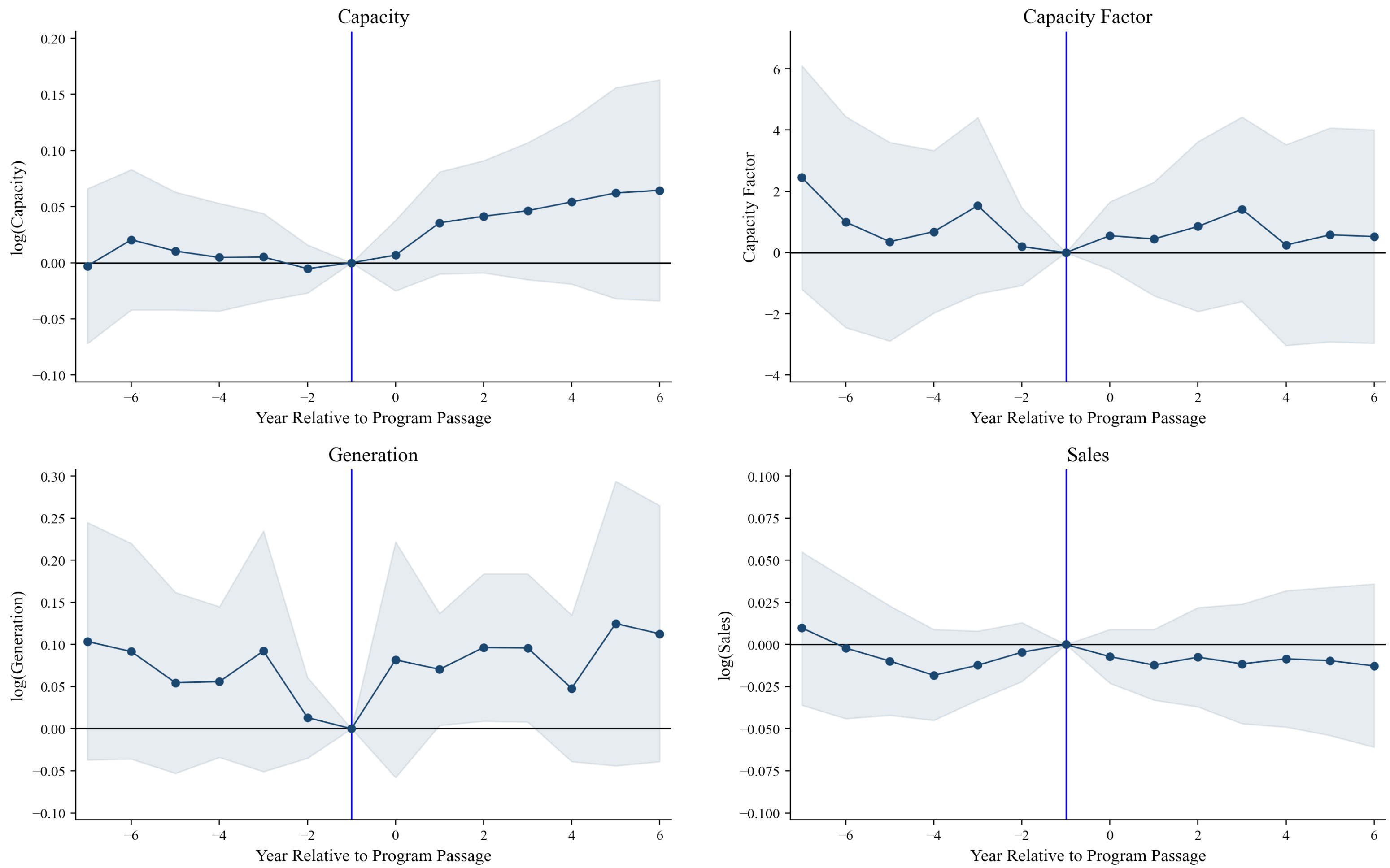
Notes: Graphs show coefficients for σ_τ for τ = -7 to τ = 11 from the event study specification in Equation (7) that regresses the dependent variable - retail electricity prices - on indicator variables for years relative to program passage, controlling for state and year fixed effects, and indicators for the other programs listed in Table 1. Blue lines show the point estimates and shaded areas represent the 95% confidence intervals. Sectoral electricity price data are from the EIA. RPS program passage dates are from a combination of state legislative documents, state government websites, and summaries from the U.S. Department of Energy. Standard errors are clustered at the state level.

Figure A.5: Transmission and Distribution Costs Before and After RPS Passage



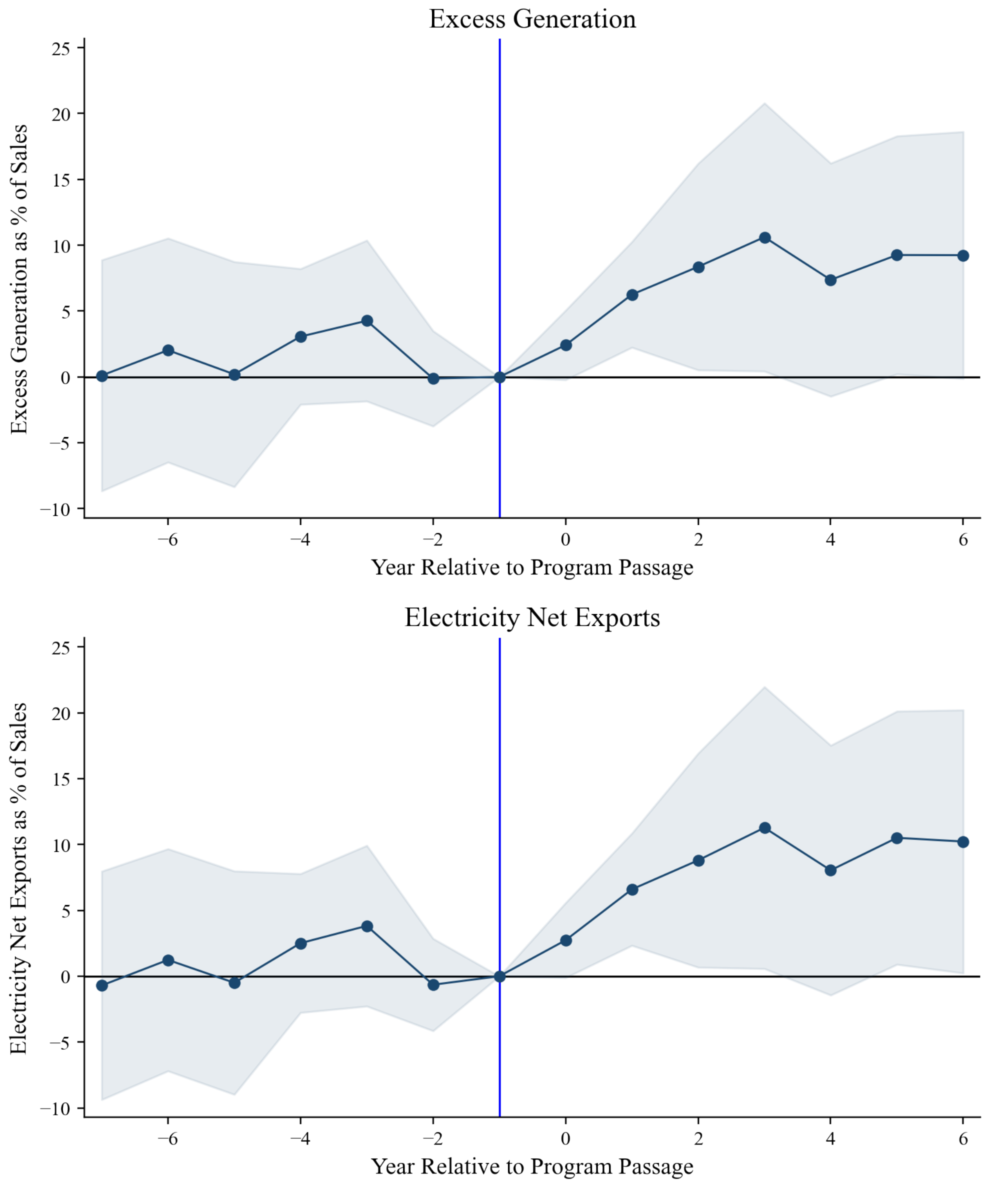
Notes: Graphs show coefficients for σ_τ for τ = -7 to τ = 6 from the event study specification in Equation (7) that regresses the dependent variable - transmission and distribution costs - on indicator variables for years relative to program passage, controlling for state and year fixed effects, and indicators for the other programs listed in Table 1. Blue lines show the point estimates and shaded areas represent the 95% confidence intervals. Data on transmission and distribution costs are from the FERC. RPS program passage dates are from a combination of state legislative documents, state government websites, and summaries from the U.S. Department of Energy. Standard errors are clustered at the state level.

Figure A.6: Electricity Production and Consumption Before and After RPS Passage



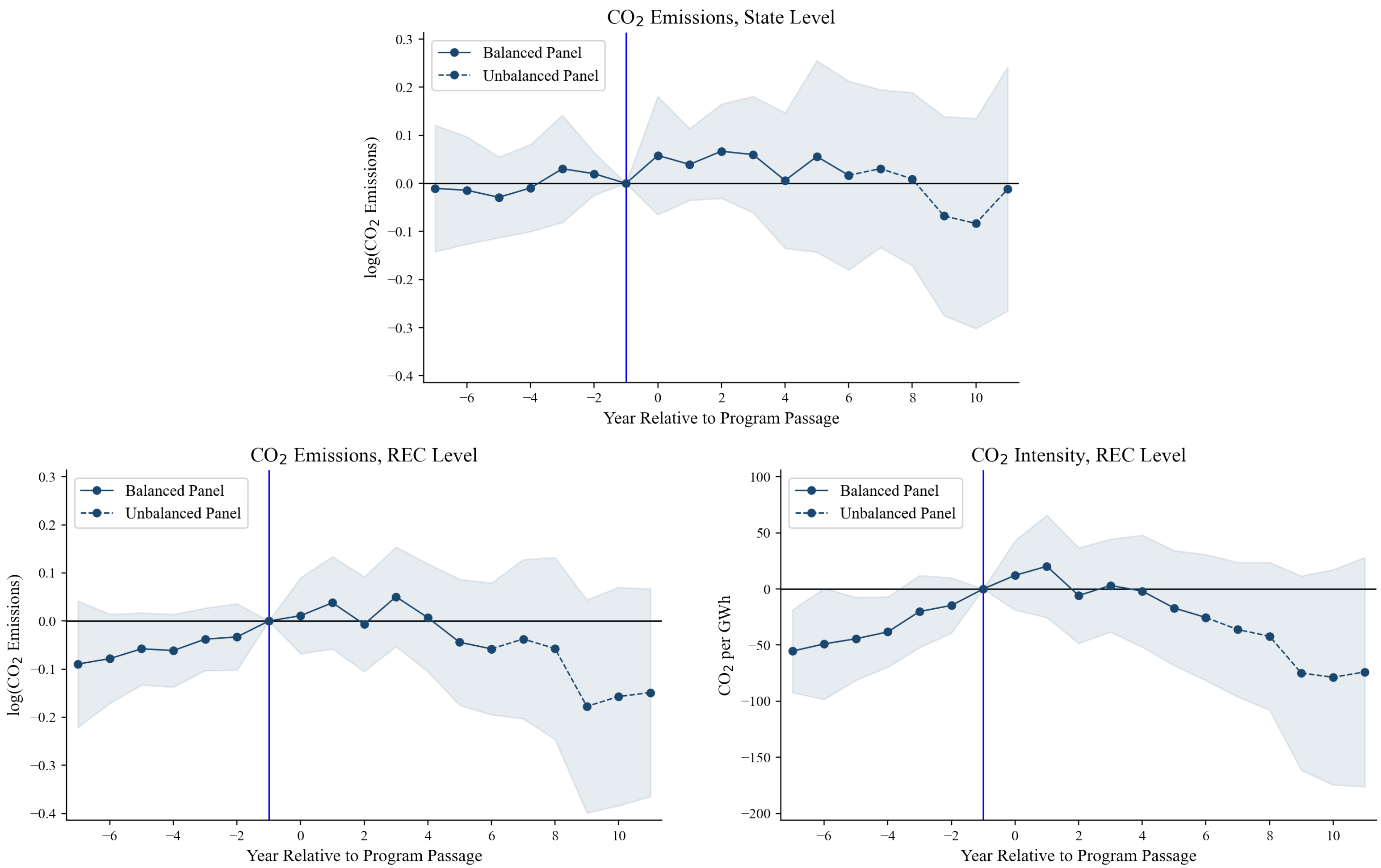
Notes: Graphs show coefficients for σ_τ for τ = -7 to τ = 6 from the event study specification in Equation (7) that regresses the dependent variable - capacity, capacity factor, generation, and sales - on indicator variables for years relative to program passage, controlling for state and year fixed effects, and indicators for the other programs listed in Table 1. Blue lines show the point estimates and shaded areas represent the 95% confidence intervals. Data on capacity, capacity factor, generation, and sales are from the EIA. RPS program passage dates are from a combination of state legislative documents, state government websites, and summaries from the U.S. Department of Energy. Standard errors are clustered at the state level.

Figure A.7: Excess Generation Before and After RPS Passage



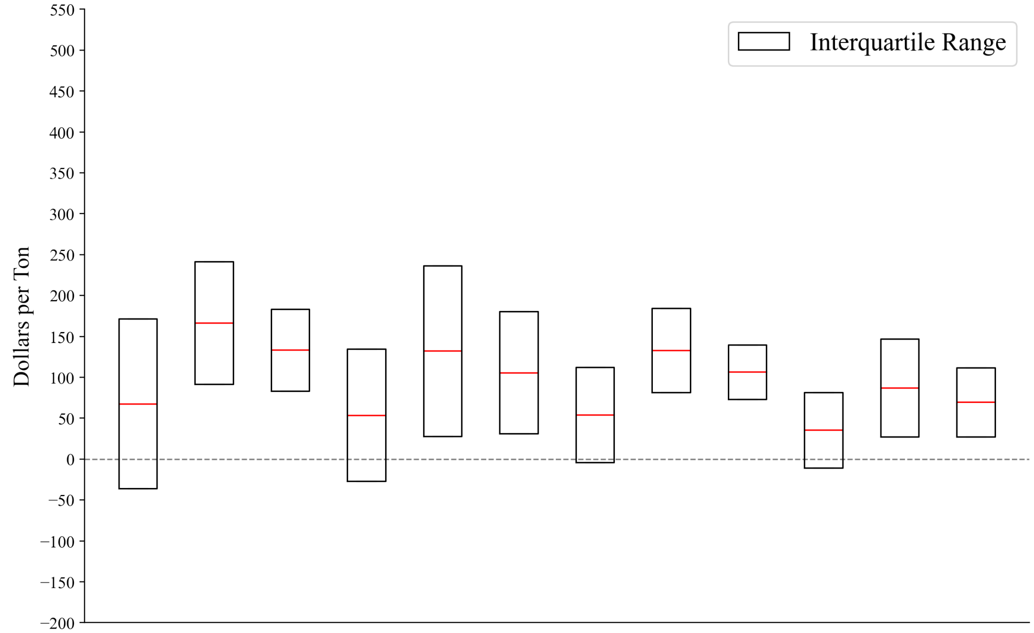
Notes: Graphs show coefficients for σ_τ for τ = -7 to τ = 6 from the event study specification in Equation (7) that regresses the dependent variable - excess generation and electricity net exports - on indicator variables for years relative to program passage, controlling for state and year fixed effects, and indicators for the other programs listed in Table 1. Blue lines show the point estimates and shaded areas represent the 95% confidence intervals. Data on excess generation and electricity net exports are from the EIA. RPS program passage dates are from a combination of state legislative documents, state government websites, and summaries from the U.S. Department of Energy. Standard errors are clustered at the state level.

Figure A.8: CO_2 Emissions Before and After RPS Passage



Notes: Graphs show coefficients for σ_τ for τ = -7 to τ = 6 from the event study specification in Equation (7) that regresses the dependent variable - CO_2 emissions and CO_2 intensity - on indicator variables for years relative to program passage, controlling for state and year fixed effects, and indicators for the other programs listed in Table 1. Blue lines show the point estimates and shaded areas represent the 95% confidence intervals. Data on CO_2 emissions and CO_2 intensity are from the EIA. RPS program passage dates are from a combination of state legislative documents, state government websites, and summaries from the U.S. Department of Energy. Standard errors are clustered at the state level.

Figure A.9: Cost per Ton of CO_2 Abatement, 12 Years Post-Passage



Price Specification												
BA Aggregation (Sales Weighted)	✓			✓			✓			✓		
BA Aggregation (State-Count Weighted)		✓			✓			✓			✓	
State			✓			✓			✓			✓
CO_2 Specification												
log(CO_2)	✓	✓	✓	✓	✓	✓						
CO_2 Intensity							✓	✓	✓	✓	✓	✓
REC Region Aggregation (Unweighted)	✓	✓	✓				✓	✓	✓			
REC Region Aggregation (State-Count Weighted)				✓	✓	✓				✓	✓	✓

Notes: Each red line displays the cost per ton of CO_2 corresponding to a particular combination of specifications for estimating the impact of RPS on CO_2 reductions and retail electricity costs, in the 12th year post RPS passage. For example, the second column value of $167 corresponds to using a REC region regression with no regression weight for measuring CO_2 reductions and using a balancing authority level regression with state count regression weights for measuring price changes. The "State" specification for price comes from Column (1) of Table 2. The "BA Aggregation (Sales Weighted)" specification for price comes from Column (6) of Table 2. The "BA Aggregation (State-Count Weighted)" specification for price comes from Column (7) of Table 2. The "log(CO_2)" specification for CO_2 comes from Column (1a) of Table 4 Panel B. The "CO_2 Intensity" specification for CO_2 comes from Column (2a) of Table 4 Panel B. We calculate standard errors by stacking the specifications using a seemingly unrelated regressions procedure, and the black boxes display the interquartile range of the estimates.

Table A.1: Summary Statistics, Synthetic Control Method

	Mean RPS (1)	Mean SCM Control (2)	P-value RPS vs SCM Control (3)
Price (2018 Cents/kWh)			
Total	11.4	9.7	0.00
Residential	13.4	11.6	0.00
Commercial	11.8	9.8	0.00
Industrial	8.5	7.1	0.00
Price Change in 7 Years Preceding RPS Adoption	-0.6	-0.6	0.97
Total Sales (TWh)	76.2	57.3	0.27
Population (Millions)	7.0	4.3	0.11
CO_2 Emissions (Million mt)	48.0	42.3	0.62
CO_2 Emissions Intensity (mt per GWh)	654.5	611.3	0.30
Renewable Potential (PWh)			
Solar	9.1	8.5	0.80
Wind	1.1	1.1	0.96
Generation			
Total (TWh)	80.5	61.9	0.31
RPS Eligible (TWh)	8.9	3.0	0.06
RPS Eligible (% of Total)	13.5	14.4	0.55
Generating Capacity			
Total (GW)	20.3	15.8	0.32
RPS Eligible (GW)	2.5	0.9	0.07
RPS Eligible (% of Total)	14.2	15.5	0.47
Other Programs (%)			
Public Benefits Fund	0.66	0.41	0.04
Net Metering	0.07	0.00	0.16
Green Power Purchasing	0.03	0.07	0.36
Energy Efficiency	0.59	0.14	0.00
Has Restructured	0.38	0.03	0.00
Has NO_x Trading	0.15	0.03	0.00
% of Counties Clean Air Act Non-Attainment	0.07	0.03	0.02
Energy Efficiency Expenditure (2018 Cents/kWh)	0.41	0.04	0.00
Number of Observations	29	29	

Notes: "Mean RPS" is for RPS states in the year prior to RPS passage. A SCM control is defined for each RPS state as the synthetic control weighted average across non-RPS states, in the year prior to the reference RPS state's RPS passage. "Mean SCM Control" is the average across these controls. Column (3) reports p-values from a paired two-sample t-test between Columns (1) and (2) that allows for unequal variances across groups. Iowa is excluded from these summary statistics due to the particularly early passage of its RPS that precludes pre-passage data availability.

Table A.2: Estimates of RPS Impact on Retail Electricity Prices

	Dependent Variable: Sectoral Retail Electricity Price			
	Total (1)	Residential (2)	Commercial (3)	Industrial (4)
Panel A: 7 Post-Passage Years, Balanced Sample				
Mean Shift (δ_3)	0.36	0.21	0.39*	0.80*
	(0.23)	(0.23)	(0.22)	(0.46)
Trend Break (β_3)	0.14*	0.22**	0.09	0.01
	(0.09)	(0.09)	(0.09)	(0.09)
Effect of RPS 7 years after passage	1.22**	1.51**	0.92	0.89*
($6\beta_3 + \delta_3$)	(0.58)	(0.62)	(0.60)	(0.49)
Panel B: 12 Post-Passage Years, Unbalanced Sample				
Mean Shift (δ_3)	0.39	0.27	0.40	0.68*
	(0.28)	(0.28)	(0.27)	(0.40)
Trend Break (β_3)	0.14**	0.19**	0.09	0.07
	(0.07)	(0.07)	(0.08)	(0.08)
Effect of RPS 12 years after passage	1.91**	2.41***	1.39	1.46*
($11\beta_3 + \delta_3$)	(0.77)	(0.87)	(0.87)	(0.80)
Mean at $\tau = -1$	11.4	13.4	11.8	8.5
State Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Other Programs	Yes	Yes	Yes	Yes
Number of Observations	1300	1300	1300	1300

Notes: Columns (1) through (4) show estimates from Equation (8), with total retail electricity price and sector-specific retail electricity prices as the dependent variables. Using Equation (8) notation, the effect of RPS 7 years after passage is $6\beta_3 + \delta_3$, and the effect of RPS 12 years after passage is $11\beta_3 + \delta_3$. All specifications control for state and year fixed effects, and indicators for the other programs listed in Table 1. Standard errors are clustered at the state level with statistical significance indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.3: Heterogeneous Effects of RPS Programs on Retail Electricity Prices

	Dependent Variable: Sectoral Retail Electricity Price	
	Total	Residential
Panel A: Late Adopters		
Mean Shift (δ_3)	0.45	0.23
	(0.35)	(0.35)
Trend Break (β_3)	0.11	0.18
	(0.12)	(0.13)
Effect of RPS 7 years after passage ($6\beta_3 + \delta_3$)	1.13	1.33
	(0.75)	(0.86)
(Effect of RPS 7 years after passage) * (Late)	-0.10	0.25
	(1.42)	(1.43)
Panel B: Ever Restructured		
Mean Shift (δ_3)	0.19	0.20
	(0.37)	(0.40)
Trend Break (β_3)	0.30^{**}	0.35^{**}
	(0.14)	(0.14)
Effect of RPS 7 years after passage ($6\beta_3 + \delta_3$)	1.98^{*}	2.31^{*}
	(1.12)	(1.16)
(Effect of RPS 7 years after passage) * (Restructured)	-0.82	-0.80
	(1.33)	(1.40)
Panel C: Has Solar Set-Aside		
Mean Shift (δ_3)	0.47	0.37
	(0.33)	(0.33)
Trend Break (β_3)	0.06	0.13
	(0.10)	(0.12)
Effect of RPS 7 years after passage ($6\beta_3 + \delta_3$)	0.85	1.13
	(0.77)	(0.95)
(Effect of RPS 7 years after passage) * (Solar Set-Aside)	1.06	1.13
	(1.23)	(1.26)
Panel D: Heavy Coal States		
Mean Shift (δ_3)	0.61	0.42
	(0.41)	(0.40)
Trend Break (β_3)	0.04	0.14
	(0.11)	(0.13)
Effect of RPS 7 years after passage ($6\beta_3 + \delta_3$)	0.85	1.26
	(0.86)	(1.00)
(Effect of RPS 7 years after passage) * (Heavy Coal)	0.77	0.59
	(1.27)	(1.36)
State Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Other Programs	Yes	Yes
Number of Observations	1300	1300

Notes: The coefficients give the aggregate effect of RPS programs on total and residential retail prices 7 years after passage estimated from the trend-break model in Equation (8). The top row in each panel shows the coefficient for the subset of states *not* in the given category and the bottom row shows the difference in the coefficient for the given subset. Using Equation (8) notation, the effect of RPS 7 years after passage is $6\beta_3 + \delta_3$. All specifications control for state and year fixed effects, and indicators for the other programs listed in Table 1. Standard errors are clustered at the state level with statistical significance indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.4: RPS Impact on Employment

	Employment	
	Total	Manufacturing
	(1)	(2)
Mean Shift (δ_3)	0.003	-0.008
	(0.008)	(0.014)
Trend Break (β_3)	0.003	-0.006
	(0.003)	(0.005)
Effect of RPS 7 years after passage	0.023	-0.043
($6\beta_3 + \delta_3$)	(0.024)	(0.037)
State Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Other Programs	Yes	Yes
Number of Observations	1200	1200

Notes: The dependent variable in Column (1) is the log of total employment in each state; in Column (2) it is log manufacturing employment. Columns report estimates from the trend-break model given by Equation (8). Using Equation (8) notation, the effect of RPS 7 years after passage is $6\beta_3 + \delta_3$. All specifications control for state and year fixed effects, and indicators for the other programs listed in Table 1. Standard errors are clustered at the state level with statistical significance indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.5: RPS Impact on Generation

	Generation			
	Renewables	Hydro & Nuclear	Coal & Petroleum	Natural Gas
	(1)	(2)	(3)	(4)
Unweighted (7 Post-Passage Years)				
Mean Shift (δ_3)	-0.17	0.12	3.46	-3.45
	(0.46)	(1.60)	(3.97)	(4.29)
Trend Break (β_3)	-0.19	0.24	-3.08^{***}	3.10^{***}
	(0.22)	(0.46)	(0.64)	(0.78)
Effect of RPS 7 years after passage	-1.32	1.58	-15.03^{**}	15.15^{**}
($6\beta_3 + \delta_3$)	(1.61)	(3.63)	(6.73)	(6.25)
Weighted (7 Post-Passage Years)				
Mean Shift (δ_3)	-0.71	2.01	-2.93	1.36
	(0.59)	(2.10)	(3.28)	(3.42)
Trend Break (β_3)	-0.27	2.23^{*}	-2.41^{***}	0.45
	(0.24)	(1.09)	(0.77)	(1.18)
Effect of RPS 7 years after passage	-2.30	15.36^{*}	-17.37^{**}	4.03
($6\beta_3 + \delta_3$)	(1.86)	(7.96)	(6.09)	(6.79)
Unweighted (12 Post-Passage Years)				
Mean Shift (δ_3)	-0.40	0.28	3.89	-3.90
	(0.50)	(1.46)	(5.11)	(5.54)
Trend Break (β_3)	-0.14	0.15	-3.20^{***}	3.28^{***}
	(0.20)	(0.46)	(0.62)	(0.90)
Effect of RPS 12 years after passage	-1.95	1.94	-31.26^{***}	32.22^{***}
($11\beta_3 + \delta_3$)	(2.62)	(5.80)	(8.14)	(8.81)
Weighted (12 Post-Passage Years)				
Mean Shift (δ_3)	-1.14	2.33	-3.66	2.13
	(0.77)	(2.40)	(4.37)	(4.23)
Trend Break (β_3)	-0.11	2.04^{*}	-2.05^{*}	0.15
	(0.21)	(0.97)	(0.95)	(1.54)
Effect of RPS 12 years after passage	-2.39	24.72^{*}	-26.21^{**}	3.82
($11\beta_3 + \delta_3$)	(2.78)	(12.16)	(9.79)	(15.00)
Mean at $\tau = -1$	2.35	30.27	47.73	19.25
Region Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Other Programs	Yes	Yes	Yes	Yes
Number of Observations	312	312	312	312

Notes: Columns (1) through (4) show estimates from the trend-break specification Equation (8), each with a specific generation source (in units of percentage points of total generation). "Renewables" includes wind, solar, geothermal, other biomass, wood, and wood-derived fuels. Using Equation (8) notation, the effect of RPS 7 years after passage is $6\beta_3 + \delta_3$. The unweighted specification is run at the REC region level aggregating observations using the generation-weighted average of states in the region; the weighted specification further weights each observation by the count of states in the region. All specifications control for REC region and year fixed effects, and indicators for the other programs listed in Table 1. Standard errors are clustered at the REC region level with statistical significance indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.6: RPS Impact on Other Pollutants

	Monitor $PM_{2.5}$ Concentration (1a)	Satellite $PM_{2.5}$ Concentration (1b)	$\log(SO_2$ Emissions) (2a)	SO_2 Intensity (2b)	$\log(NO_x$ Emissions) (3a)	NO_x Intensity (3b)
Unweighted (7 Post-Passage Years)						
Mean Shift (δ_3)	0.61	−0.21	0.03	−0.15	0.03	0.09
	(1.38)	(0.55)	(0.13)	(0.27)	(0.20)	(0.25)
Trend Break (β_3)	0.48	−0.34	-0.12^{**}	−0.23	−0.06	−0.05
	(0.58)	(0.21)	(0.05)	(0.14)	(0.03)	(0.06)
Effect of RPS 7 years after passage	3.47	−2.23	-0.66^{*}	-1.55^{*}	−0.31	−0.23
($6\beta_3 + \delta_3$)	(4.66)	(1.31)	(0.34)	(0.86)	(0.31)	(0.56)
Weighted (7 Post-Passage Years)						
Mean Shift (δ_3)	0.84	−0.01	−0.16	−0.11	−0.04	0.04
	(0.87)	(0.50)	(0.13)	(0.42)	(0.13)	(0.12)
Trend Break (β_3)	0.25	−0.13	−0.03	-0.38^{*}	-0.05^{*}	-0.13^{*}
	(0.47)	(0.34)	(0.05)	(0.19)	(0.03)	(0.06)
Effect of RPS 7 years after passage	2.35	−0.80	−0.34	-2.42^{**}	−0.34	−0.74
($6\beta_3 + \delta_3$)	(3.49)	(1.95)	(0.30)	(1.03)	(0.19)	(0.45)
Unweighted (12 Post-Passage Years)						
Mean Shift (δ_3)	0.92	−0.31	0.09	−0.23	0.03	0.10
	(1.63)	(0.62)	(0.19)	(0.31)	(0.18)	(0.25)
Trend Break (β_3)	0.34	−0.31	-0.14^{***}	−0.21	-0.05^{*}	−0.06
	(0.48)	(0.21)	(0.04)	(0.12)	(0.03)	(0.05)
Effect of RPS 12 years after passage	4.67	−3.75	-1.43^{**}	-2.56^{*}	−0.57	−0.51
($11\beta_3 + \delta_3$)	(6.67)	(2.27)	(0.48)	(1.39)	(0.45)	(0.79)
Weighted (12 Post-Passage Years)						
Mean Shift (δ_3)	0.74	−0.07	−0.13	−0.29	−0.10	−0.02
	(1.09)	(0.55)	(0.18)	(0.44)	(0.13)	(0.13)
Trend Break (β_3)	0.27	−0.12	−0.04	−0.32	−0.02	-0.10^{*}
	(0.38)	(0.29)	(0.07)	(0.19)	(0.02)	(0.05)
Effect of RPS 12 years after passage	3.69	−1.36	−0.60	-3.77^{*}	−0.35	−1.14
($11\beta_3 + \delta_3$)	(4.98)	(3.14)	(0.67)	(1.93)	(0.26)	(0.67)
Mean at $\tau = -1$	11.64	11.71	12.20	2.39	11.65	1.05
Region Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Other Programs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	311	216	312	312	312	312

Notes: Each column shows the estimated impact of RPS on a different measure of pollution, shown in units of metric tons per GWh for SO_2 Intensity and NO_x Intensity, and micrograms per cubic meter for $PM_{2.5}$ Concentration. Using Equation (8) notation, the effect of RPS 7 years after passage is $6\beta_3 + \delta_3$, and the effect of RPS 12 years after passage is $11\beta_3 + \delta_3$. The unweighted specification is run at the REC region level aggregating observations using the generation-weighted average of states in the region; the weighted specification further weights each observation by the count of states in the region. All specifications control for REC region and year fixed effects, and indicators for the other programs listed in Table 1. Standard errors are clustered at the REC region level with statistical significance indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.7: Robustness Checks for RPS Impact on CO_2 Emissions

	Robust 1 (Trend Break)		Robust 2 (Trend Break)		Robust 3 (Trend Break)		Robust 4 (Trend Break)		Robust 5 (Trend Break)	
	log(CO_2 Emissions)	CO_2 Intensity	log(CO_2 Emissions)	CO_2 Intensity	log(CO_2 Emissions)	CO_2 Intensity	log(CO_2 Emissions)	CO_2 Intensity	log(CO_2 Emissions)	CO_2 Intensity
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
Unweighted (7 Post-Passage Years)										
Mean Shift (δ_3)	0.04	15.2	0.05	14.8	0.04	13.2	0.07	21.8	0.04	10.1
	(0.04)	(17.1)	(0.04)	(17.6)	(0.04)	(17.8)	(0.06)	(24.3)	(0.03)	(12.7)
Trend Break (β_3)	-0.02^{***}	-15.2^{***}	-0.03^{**}	-14.6^{***}	-0.02^{**}	-15.9^{***}	-0.03^{**}	-15.4^{**}	-0.01^{*}	-7.7^{*}
	(0.01)	(4.4)	(0.01)	(4.6)	(0.01)	(4.4)	(0.01)	(5.8)	(0.01)	(4.2)
Effect of RPS 7 years after passage ($6\beta_3 + \delta_3$)	-0.11	-76.1^{*}	-0.11	-72.8^{*}	-0.10	-82.5^{*}	-0.11	-70.8	-0.03	-36.2
	(0.06)	(38.1)	(0.07)	(39.3)	(0.06)	(38.1)	(0.09)	(51.1)	(0.05)	(33.7)
Weighted (7 Post-Passage Years)										
Mean Shift (δ_3)	-0.01	-14.8	-0.00	-20.5	-0.02	-26.7	-0.02	-36.2	-0.01	-22.1
	(0.04)	(19.5)	(0.06)	(20.9)	(0.05)	(22.7)	(0.07)	(26.9)	(0.04)	(17.4)
Trend Break (β_3)	-0.02^{**}	-21.6^{**}	-0.02^{**}	-19.4^{**}	-0.02^{**}	-24.5^{**}	-0.03^{***}	-26.0^{**}	-0.02^{**}	-20.6^{**}
	(0.01)	(8.2)	(0.01)	(8.8)	(0.01)	(9.3)	(0.01)	(10.0)	(0.01)	(7.9)
Effect of RPS 7 years after passage ($6\beta_3 + \delta_3$)	-0.15^{*}	-144.3^{**}	-0.12	-137.1^{*}	-0.16	-173.9^{**}	-0.18^{*}	-192.2^{**}	-0.13	-145.7^{**}
	(0.08)	(65.0)	(0.09)	(69.4)	(0.09)	(74.0)	(0.10)	(82.7)	(0.08)	(61.9)
Unweighted (12 Post-Passage Years)										
Mean Shift (δ_3)	0.05	21.5	0.06	20.6	0.05	19.4	0.08	26.2	0.05	8.0
	(0.04)	(19.7)	(0.04)	(20.1)	(0.04)	(20.1)	(0.06)	(28.3)	(0.03)	(16.9)
Trend Break (β_3)	-0.03^{***}	-17.1^{***}	-0.03^{**}	-16.4^{***}	-0.03^{***}	-17.8^{***}	-0.03^{***}	-17.1^{***}	-0.01	-6.7
	(0.01)	(4.2)	(0.01)	(4.5)	(0.01)	(4.3)	(0.01)	(4.7)	(0.01)	(4.2)
Effect of RPS 12 years after passage ($11\beta_3 + \delta_3$)	-0.26^{**}	-166.7^{**}	-0.27^{**}	-159.4^{**}	-0.26^{**}	-176.0^{**}	-0.30^{*}	-162.0^{**}	-0.10	-65.4
	(0.10)	(56.4)	(0.12)	(59.5)	(0.11)	(57.1)	(0.14)	(67.7)	(0.09)	(50.3)
Weighted (12 Post-Passage Years)										
Mean Shift (δ_3)	0.01	-17.6	0.02	-25.7	-0.00	-31.0	-0.00	-42.9	0.00	-30.4
	(0.06)	(26.1)	(0.08)	(28.9)	(0.07)	(28.7)	(0.09)	(35.3)	(0.06)	(22.8)
Trend Break (β_3)	-0.03^{**}	-19.9^{**}	-0.03^{**}	-17.3^{**}	-0.03^{**}	-22.2^{**}	-0.03^{***}	-22.9^{**}	-0.02^{**}	-17.0^{**}
	(0.01)	(6.5)	(0.01)	(6.4)	(0.01)	(7.5)	(0.01)	(7.4)	(0.01)	(6.3)
Effect of RPS 12 years after passage ($11\beta_3 + \delta_3$)	-0.31^{**}	-236.9^{**}	-0.28^{**}	-215.8^{**}	-0.32^{**}	-275.2^{**}	-0.37^{***}	-295.1^{**}	-0.27^{**}	-217.3^{**}
	(0.11)	(88.9)	(0.11)	(91.9)	(0.12)	(103.0)	(0.09)	(107.1)	(0.10)	(86.9)
Mean at $\tau = -1$	19.2	641.0	19.2	644.2	19.2	643.4	19.4	638.3	18.6	655.0
Region Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Programs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	312	312	312	312	312	312	260	260	494	494

Notes: The (a)-columns show the impact of RPS on log(CO_2 emissions) while the (b)-columns show the impact of RPS on CO_2 emissions intensity in units of metric tons per GWh. Using Equation (8) notation, the effect of RPS 7 years after passage is $6\beta_3 + \delta_3$. The unweighted specification is run at the REC region level aggregating observations using the generation-weighted average of states in the region; the weighted specification further weights each observation by the count of states in the region. Each pair of columns differs in terms of how states are assigned to REC regions, relative to our preferred specification in Table 4. Robust 1 assigns Ohio to M-RETS. Robust 2 assigns Illinois, Indiana, and Kentucky to PJM. Robust 3 assigns South Dakota to WREGIS. Robust 4 assigns Alaska and Hawaii to NARR. Robust 5 assigns all states that are assigned to NARR in our preferred specification to its own region. More details on REC region construction can be found in the Data Appendix 12.2. Standard errors are clustered at the REC region level with statistical significance indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

12 Data Appendix

12.1 Balancing Authority Data Set Construction

We construct a version of our electricity price data set at the balancing authority (BA) level to test whether state level RPS policies have spillover effects on out-of-state consumers in wholesale markets that cross state boundaries. The results from this estimation are shown in Table 2, Column (6) and (7). We assemble this data as follows. First, we assign utilities to BAs using EIA Form 861 data. The most recent data reports sales at the utility-BA level, allowing us to apportion utilities that operate across multiple BAs by their share of sales in each. For utilities that do not appear in the most recent year of data, we use the latest year of data in which their BA mapping is reported. Prior to aggregating utility level sales and revenue to the BA level, we drop non-utility observations and account for mergers and acquisitions using a manually compiled data set. If a utility is acquired by another utility during our sample period, we recode the former to the latter for all years for consistency of measurement. After making these adjustments, we sum reported utility level sales and revenues to the BA level (apportioning utility revenues across multiple BAs by each one's share of sales). Electricity price is given by revenue divided by sales. Note that other state level variables, such as our indicators for RPS or other programs, are also aggregated to the BA level using sales weighting. For example, if a BA has 40% of its sales in Indiana and 60% in Illinois, then its value for the RPS indicator variable will be 0.4 * 1{RPS in Illinois}+ 0.6 * 1{RPS in Illinois}.

12.2 REC Region Data Set Construction

We construct a version of our data set at the REC region level to account for interstate purchases of Renewable Energy Credits to comply with RPS. We use the REC region level data to estimate the effects of RPS on pollution in Table 4 and Appendix Tables A.6 and A.7, and on generation in Appendix Table A.5. We assign states to REC regions by manually compiling information on included entities from the website and documentation associated with each tracking system. Once assigned, we take the generation weighted average of the state level variables to aggregate to the REC region. Portions of some states qualify for multiple REC regions, though our data for these dependent variables is only at the state level. In our baseline specification, we assign the state to that REC region which contains the largest share of its sales. For several states, we also show robustness to an alternative classification. Using 2015 sales, about 20.4% of Indiana, 29.1% of Kentucky, and 46.4% of Illinois qualify for the PJM REC Region, and 24.5% of South Dakota qualifies for the WREGIS REC Region. In addition, the state of Ohio fully qualifies in both M-RETS and PJM.

Our main specification assigns states to REC regions as follows:

- WREGIS – Arizona, California, Colorado, Idaho, Montana, New Mexico, Oregon, Utah, Washington, Wyoming
- M-RETS – Arkansas, Illinois, Indiana, Iowa, Kentucky, Louisiana, Minnesota, Mississippi, Missouri, North Dakota, South Dakota, Wisconsin
- NE-POOL – Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
- PJM – Delaware, District of Columbia, Maryland, New Jersey, Ohio, Pennsylvania, Virginia, West Virginia
- ERCOT – Texas
- MIRECS – Michigan
- NC-RETS – North Carolina
- NYGATS – New York
- NVTREC – Nevada
- NARR – Alabama, Florida, Georgia, Kansas, Nebraska, Oklahoma, South Carolina, Tennessee

Our robustness checks make the following adjustments to the main classifications:

Table A.8: Robustness Check of REC Definitions

States	Base	Robustness 1	Robustness 2	Robustness 3	Robustness 4	Robustness 5
Ohio	PJM	M-RETS	No change	No change	No change	No change
Illinois	M-RETS	No change	PJM	No change	No change	No change
Indiana	M-RETS	No change	PJM	No change	No change	No change
Kentucky	M-RETS	No change	PJM	No change	No change	No change
South Dakota	M-RETS	No change	No change	WREGIS	No change	Own region
Hawaii	Own region	No change	No change	No change	NARR	No change
Alaska	Own region	No change	No change	No change	NARR	No change
NARR States	NARR	No change	No change	No change	No change	Own region

12.3 Continuous Control for Energy Efficiency Expenditures

In addition to our binary control variable for energy efficiency resource standards in our main specification, we also run a robustness check controlling for a continuous measure of utility investments in energy efficiency. We construct this measure using data from EIA Form 861 on utility level expenditures on energy efficiency. We aggregate from the utility to the state level apportioning expenditures for multi-state utilities by each state's share of that utility's sales, as with the balancing authority aggregation. In addition, the data reporting format for energy efficiency expenditures changes across years in our sample. We standardize this data across years by isolating the energy efficiency component of reported demand side management expenditures.

12.4 Transmission and Distribution Expenditures Data Set Construction

To construct a measure of transmission and distribution expenditures, we use data compiled by the UT Austin Energy Institute (https://openei.org/datasets/dataset/ferc-form-1-electric-utility-cost-energy-sales-peak-demand-and-customer-count-data-1994-2016). This data contains expenditures on capital, operations, and maintenance costs for transmission and distribution data for over 200 investor-owned utilities from their FERC Form 1 submissions for 1994-2016. We use our EIA Form 861 data to manually map each utility to the set of states in which it operates (again using sales to apportion) using the most recent year in which the mapping exists. For a small subset of utilities that we could not map using EIA 861 data (which only contains this mapping for the later years in our sample), we manually looked up the utility's information. If the utility predominantly or entirely operates in a single state, we map it to that state; otherwise, we drop it from the data set rather than risk mistaken state mapping. Note also that Nebraska does not have any investor-owned utilities and thus does not enter this data set. Overall, investor-owned utilities accounted for 72% of US electricity sales in 2017 according to the EIA, allowing us to interpret these results as broadly representative.