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

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Abstract

The most prevalent climate policies in the U.S. are Renewable Portfolio Standards (RPS), which mandate a specified share of electricity come from sources such as wind and solar. 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 11-24% lower. Point estimates suggest that the cost per ton of CO_2 abatement ranges from \$80-\$210 in preferred specifications. We also find suggestive evidence that the cost of each increment of mandated renewable generation has declined over time as the costs of renewable energy sources have fallen.

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1 Introduction

The United States has had great difficulty developing significant and enduring climate policy. One major exception have been Renewable Portfolio Standards (RPS), which require a specified 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 by 2015 RPS policies had been enacted in 29 states and the District of Columbia.[1] These programs play a central role in existing U.S. climate policy, covering 21% of US CO_2 emissions compared to 7.1% for state and regional cap-and-trade programs in 2015. 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 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, which 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 provides what we believe is the most comprehensive evaluation of RPS programs to date. A key part of any evaluation is the impact of RPS programs on electricity prices. The analysis begins with a conceptual framework that shows that simply comparing

[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.

the cost of electricity generation between renewable and other sources will not capture the full costs of these programs. A key challenge is that renewables are generally intermittent, so their installation must be accompanied by sources that generate electricity when the renewables are unavailable (e.g., when the sun isn't shining or wind isn't blowing). Additionally, they tend to be located away from population centers and cause the displacement of existing sources, both of which also introduce system wide costs. Specifically, we set out a simplified model of a retail electricity provider's optimal decision to illustrate the "indirect" mechanisms through which renewable generation can affect system costs, beyond any differences in generation costs. This model also makes clear the wide range of parameters and data inputs that would be required to conduct a complete "bottom up" assessment of the costs that RPS programs impose.

The heart of the paper is an empirical reduced-form evaluation of the aggregate costs and benefits of RPS programs that sidesteps the challenges associated with the "bottom up" approach. Its core is a difference-in-differences analysis that compares states that did and did not adopt RPS policies before and after implementation 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 adopting and non-adopting states. Additionally, we analyze the effects of RPS programs on state-level CO_2 emissions and renewables generation. Importantly, we collected data that allow us to control for a wide range of potentially confounding electricity and environmental policies and market trends, including energy efficiency programs and investments, fuel prices, electricity market restructuring, net metering, green power purchasing programs, public benefits funds, participation in CO_2 and nitrous oxide emissions trading programs (Deschênes, Greenstone, and Shapiro, 2017), and nonattainment designations under the Clean Air Act that restrict emissions (Greenstone, 2002). This approach stands in contrast to the seemingly impossible task of a *complete* bottom up approach that separately measures each of the indirect mechanisms through which renewables affect total system costs in heterogeneous states, in addition to the direct differences in generation costs between renewables and other sources of electricity.[3]

There are three key findings. First, electricity prices increase substantially after RPS adoption. The estimates indicate that in the 7th year after passage, average retail electricity prices are 1.4 cents per kWh or 11% higher, totaling about $31 billion of annual additional costs to consumers in RPS states. Twelve years later they are 2.3 cents, or 17%, higher.

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

These estimates are statistically significant at conventional levels and robust to a variety of specification checks including: controlling for state-level prices for coal, oil, and natural gas, employing specifications with region-by-year fixed effects that compare states to only their closest geographic neighbors, 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 heterogeneous treatment effects. Further, RPS adoption leads to a roughly 50% increase in transmission and distribution costs, which accounts for a majority of the increase in electricity prices in RPS states, though this evidence borders on statistical significance. Finally, we find suggestive evidence that the cost of RPS per percentage point of *net* required renewable generation decreased substantially in the later sample years (i.e., after 2009).[4]

Second, RPS programs substantially reduce carbon emissions. Depending on the specification, we find that CO_2 emissions fall by 11-24% in the seventh year after RPS passage, and 25-41% in the 12th year after passage. Importantly, these estimates are obtained from specifications that attempt to account for cross-state spillovers in generation, both through the trade of credits for compliance with RPS and through the trade of electricity.

Third, putting together the findings on electricity prices and emissions, the estimates suggest that the cost to consumers per metric ton of CO_2 abated ranges from \$80 to \$210 in the preferred specifications in 2022 dollars, though confidence intervals include substantially lower and 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 further context, the Biden Administration recently set the social cost of carbon (i.e., the monetized damages from the release of an additional metric ton of CO_2) at \$216 per metric ton in 2022 dollars, which suggests that RPS policies may have social benefits (i.e, reduced climate damages) that exceed their costs. It is also worth noting that these cost per ton of CO_2 estimates use the average effects estimated in the sample and do not incorporate the suggestive evidence that the policies have become less costly over time, which could mean that future RPS implementation is less costly than observed in the past. Finally, it is often argued that RPS

[4]We calculate the *net* required renewable generation of RPS policies by taking the difference between the statutorily required percentage of generation from renewables and the percentage of 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, we calculated its net requirement as 4.0% in this year. In the sample, we estimate that 7 years after adoption the average adopting state's net requirement was 2.2% of generation and 12 years after it was 4.5%.

policies cause technical progress, which reduces the costs of renewables and facilitates future abatement. If these effects, which we do not measure, exist in practice that would also mean that the cost per ton estimates are too high.

This paper builds on a collection of other papers on the costs and benefits of RPS policies that use a variety of techniques. On the cost side, research on the effects of RPS on electricity prices includes qualitative evaluations (Fischer, 2010; Schmalensee, 2012) and prospective evaluations, some of which have been commissioned by states considering adoption (Chen, Wiser, and Bolinger, 2007). There are also ex-post evaluations that have largely taken place outside peer-reviewed journals and focused on the direct costs of renewable energy, which find that RPS adoption increases electricity prices by roughly 2-4% (Heeter et al., 2014; Tuerck et al., 2013). Johnson (2014) contributes to this literature by estimating the price elasticity of supply of renewable electricity generation (among other findings). Further, there is a developing literature that estimates the various indirect costs associated with the integration of renewables into the grid (Denholm and Margolis, 2007; Borenstein, 2008; Lamont, 2008; Joskow, 2011; Milligan et al., 2011; Cullen, 2013; Jacobson et al., 2015; Gowrisankaran et al., 2016). Finally, work by Lyon and Yin (2010) considers the political economy of RPS, examining state-level variables that are correlated with RPS passage. We use the results from that paper to inform our choice of control variables in all specifications and matching variables in the synthetic controls specification.

A second line of research estimates the benefits of RPS policies, focusing especially on their impact on renewable generation and capacity, and carbon emissions. Recent work by Deschenes et al. (2023) finds that RPS has effects on capacity and generation from wind, but little effect on solar. Earlier work by Yin and Powers (2010) estimates that RPS increases renewables investment when accounting for the net requirements imposed by the policy, and Maguire and Munasib (2016) finds great heterogeneity in the impact on renewable generation across states, with especially large impacts on renewable capacity in Texas. Additionally, Carley et al. (2018) show that RPS stringency leads to increases in renewable generation and capacity.[5] Finally, Bento, Garg, and Kaffine (2018) take an innovative approach by developing and calibrating a general equilibrium model of an RPS policy that suggests that they can either deliver large resource booms or large emissions savings but not both.

Upton and Snyder (2017) is the most similar to this paper in estimating both the costs and benefits of RPS policies. They use a difference-in-differences synthetic controls approach

[5] Barbose et al. (2016) is broader in scope in assessing RPS impacts by estimating their effect on CO_2 emissions, conventional air pollution, water withdrawals, and employment/economic activity. Hollingsworth and Rudik (2019) also broadens the scope on estimating the benefits of RPS by examining their effects on renewable generation in neighboring states.

and find that RPS programs raise electricity prices, as well as weak evidence of CO_2 emissions reductions and no impact on renewable generation. In contrast, our paper's approach allows for the price effects to differ over time because RPS policies tend to become stricter after initial passage and finds that they are about 60% larger when capturing these temporal dynamics. [6] Additionally, we find large effects of RPS on national emissions because, in contrast to Upton and Snyder, we use specifications that account for cross-state spillovers from electricity trade and renewable energy credits. Further, we demonstrate that the emissions reductions are driven by increases in renewable generation that are similar in magnitude to the net requirements. Putting these estimates together, our paper's results suggest that RPS was much more cost-effective in reducing emissions than the previous literature suggests.

The paper proceeds as follows. Section 2 provides background on RPS policies and their typical 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.[7] 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.[8] 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.

[6] Appendix Table A.2 replicates the results from Upton and Snyder (2017) for the effects of RPS on prices in Column (1), and shows how adjusting the specification, sample, and controls leads to the differences with our primary specification that is reported in Column (10). The most direct comparison is between the Column (7) and Column (10) estimates, which compare that paper and this paper's preferred specifications using the same sample with the same control variables. Our preferred specification that allows for a trend-break finds an effect on prices that is over 60% larger than the result that Upton and Snyder emphasize (i.e. 1.4 cents per kWh compared with 0.9 cents per kWh). This table additionally shows that our results are robust to controlling for a wide range of potentially confounding policies.

[7] 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.

[8] Iowa was the first state to establish a binding standard in 1991, requiring the state'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.

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 14 cents per kWh to 12 cents per kWh from 1990 through 2002 but returned to 14 cents per kWh by the end of the sample in 2015.[9] 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.[10] 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 specified 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.[11]

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 technologies 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.[12] In most cases, individual generators must be further approved

[9] All monetary figures are reported in January 2022 dollars.

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

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

[12] 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.

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.[13] 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.

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. The LBNL

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

data makes a variety of state-specific adjustments for covered subcategories of generation and pre-planned capacity expansions. We also show results for an alternative unadjusted definition of net requirement, similar to that used by Yin and Powers (2010), that takes the gross statutory requirement and subtracts generation from the EIA's standard nationwide definition of renewable sources in the year prior to policy implementation.

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 $\frac{E[R_h]}{E[E_h]} = M$ holds 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:

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

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:

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

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 pol-

icy 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. This would also require accounting for the compensation structure regulators offer utilities, which typically differentiates between fixed and variable costs. 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.[14] 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, for state-specific inclusion of subcategories of generation, and, where possible, for qualified pre-existing out-of-state generation that could be used to comply. As mentioned above, since the LBNL measure of net requirements includes a number of hidden adjustments that cannot be observed directly we also include for transparency a second measure of net requirements that consists of the simple difference between the statutory requirement and the EIA's uniform national definition of renewable generation in the period prior to policy passage. 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

[14] 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.

dates of six types of electricity sector programs: carbon markets such as California's cap-and-trade program and the Regional Greenhouse Gas Initiative (RGGI), 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 restructuring 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).[15] 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 nonattainment 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 nonattainment 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.

In addition to contemporaneous electricity market policies, trends and fluctuations in fossil fuel markets also play an important role in electricity prices and emissions. To the extent that changes occurring during the period of our sample, such as technological progress in hydraulic fracturing techniques that reduced the cost of natural gas, varied geographically, these developments could also potentially confound the estimated effects of RPS. Thus, we compile a state-by-year panel of coal, natural gas, and oil fuel prices paid by power producers using data from the EIA's State Energy Data System. This data is missing for a small number of state-by-year observations, most of which occur in states that have little to no usage of the fuel for which the price is missing.[16] We impute the missing observations using a variety of techniques and test robustness to imputation methods when including fuel prices as a

[15] We also show robustness to controlling for definitions of electricity market restructuring that come from Cicala (2014) and Cicala (2014).

[16] Specifically, 170 out of 3900, or 4.4%, of state-by-year-by-fuel observations are missing. 10.5% of state-by-year observations are missing data for at least one fuel.

control variable.

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.[17] 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.[18] The result is a yearly panel of state emissions from electricity generation.

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

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

[18] 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.

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. [19]

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. As an alternative measure, Appendix Table A.1 also shows the full set of contemporaneous summary statistics for all RPS and non-RPS states in 1997, prior to the first year of implementation in RPS states.

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 – 13.3 cents per kWh versus 10.9 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 nonattainment 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.

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

[19] 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.

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 preceding 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:

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

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.[20] 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.[21] 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

[20] 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.

[21] 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.

outcome variables prior 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:

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

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 an 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.

Equations (7) and (8) produce estimates that treat the implementation of RPS as a binary variable. However, we note that Figure 3 shows that there is substantial heterogeneity in the net requirement imposed across states. To measure the effects of this additional source of variation, we estimate the following specification that allows the effects of RPS to vary with the stringency of the policy:

$$
\begin{aligned}
y_{st} =& \delta_0 + \delta_1 \mathbb{1}(-19 \leq \tau_{st} \leq -8) * \mathbb{1}(RPS = 1)_s \\
&+ \delta_2 \mathbb{1}(0 \leq \tau_{st} \leq 6) * D_{st} + \delta_3 \mathbb{1}(7 \leq \tau_{st} \leq 18) * \mathbb{1}(RPS = 1)_s \\
&+ X_{st}\alpha + \gamma_s + \mu_t + \varepsilon_{st}
\end{aligned} \tag{9}
$$

We also consider a version of this specification that allows the effects of each unit of RPS net requirements to differ in the early and latter parts of the sample by interacting the net requirement measure with an indicator for whether the year is before 2010, the 7th year after RPS passage for the median state in the sample. This specification is as follows:

$$
\begin{aligned}
y_{st} =& \delta_0 + \delta_1 \mathbb{1}(-19 \leq \tau_{st} \leq -8) * \mathbb{1}(RPS = 1)_s \\
&+ \delta_{2,t<2010} \mathbb{1}(0 \leq \tau_{st} \leq 6) * D_{st} + \delta_{2,t\geq 2010} \mathbb{1}(0 \leq \tau_{st} \leq 6) * D_{st} \\
&+ \delta_{3,t<2010} \mathbb{1}(7 \leq \tau_{st} \leq 18) * \mathbb{1}(RPS = 1)_s + \delta_{3,t\geq 2010} \mathbb{1}(7 \leq \tau_{st} \leq 18) * \mathbb{1}(RPS = 1)_s \\
&+ X_{st}\alpha + \gamma_s + \mu_t + \varepsilon_{st}
\end{aligned} \tag{10}
$$

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, using both the LBNL measure that makes state-specific adjustments and the unadjusted uniform measure, 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 using the LBNL measure, and 2.0 percentage points using the unadjusted measure. 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 $\tau = 6$). Twelve years after passage, the net requirement is about 4 to 4.5 percentage points, depending on the measure.

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 0.17 cents each year, with statistically insignificant pre-trends.[22] 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 1.43 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 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

[22] We estimate a β_0 of .02 with a standard error of 0.08.

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 2.25 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. Column (3) adds controls for state-level prices of coal, oil, and natural gas. In Column (4) we drop Hawaii due to its unique geography. The estimates in these three columns are very similar to the baseline specification. Note that the specification for fuel prices includes a small number of observations for which fuel prices are imputed, but the results in the table are identical to the second decimal place across a range of three imputation procedures we consider that are detailed in the Data Appendix. In Appendix Table A.10 we show robustness to using definitions of state electricity market restructuring from Cicala (2014) and MacKay and Mercadal (2021) instead of Fabrizio et al. (2007).

The next two columns adjust for the possibility of local shocks to electricity prices that might confound the adoption of RPS programs. Specifically, Columns (5) and (6) 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 the differences across specifications are not statistically significant. These specifications suggest that the estimated effects of RPS on prices are not driven by time-varying regional differences. 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 Independent 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.[23]

Columns (7) and (8) 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 (7), we weight each BA by sales and in Column (8), 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.[24] The Panel A results show that the positive 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, though the standard errors are much larger in the specification in Column (8). 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 (7) and (8) to that of the main result in Column (1), which shows that prices increased by 1.43 cents per kWh seven years after RPS passage. The point estimates for the effects of RPS in Columns (7) and (8) are generally larger than in Column (1) suggesting positive cross-state impacts on prices, 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, the percent of coal and natural gas generation, the unemployment rate, the rate of population growth, and the

[23] 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.

[24] In Column (8) 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.

presence of a Democratic state legislature.[25] We use the analysis of the political economy of RPS in Lyon and Yin (2010) in part to inform the choice of matching variables. 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" specification minimizes a weighted average of the two imbalances, as recommended by Ben-Michael, Feller, and Rothstein (2021).[26]

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 heterogeneity in treatment effects and panel units that switch between the treatment and control groups 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

[25] Note that including a time-varying measure of Democratic control of the state legislature as an additional control variable in the baseline specification from Column (1) of Table 2 changes the effect of RPS 7 years after passage from 1.43 cents per kWh to 1.27 cents per kWh. We do not include this control in the primary analysis because it is not defined for Washington D.C., which does not have a state legislature, and Nebraska, which has a nonpartisan legislature.

[26] 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.

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 system wide 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 1.06 cents per kWh on a baseline average of 1.94 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 meaningful 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.[27] 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.

6.4 Heterogeneity in RPS Effects and Impacts on Economic Activity

Appendix Table A.3 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."[28] 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.[29] 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

[27] 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.

[28] For complete definitions, see the EIA's Electric Power Monthly.

[29] Authors' calculation, from the EIA Electricity Data Browser.

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.3. 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.4 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.4 report the main estimate for RPS states not in the given subsample, and a second 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. 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.5 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 subsection develops estimates of the national CO_2 emissions reductions resulting from the state-level RPS policies. In the case of emissions, there are two potential cross-state spillovers that mean that RPS policies potentially influence emissions in non-RPS states.

These spillovers make it difficult to interpret estimates from difference-in-differences designs that compare states that do and do not adopt RPS and non-RPS policies, yet such designs are the conventional approach in the empirical literature (e.g., Upton and Snyder (2017)). Here, we describe the spillovers and set out an approach that has the potential to recover the effect of RPS policies on national emissions in their presence. We conclude by reporting estimates from this new approach, as well as from the more conventional one that does not account for the spillovers.

The first spillover is that most RPS states allow compliance through REC purchases that occur in other states within the same REC region. The consequence is that an RPS policy can reduce emissions throughout a REC region, even within states without an RPS in force.[30] If this were the only spillover, it would be straightforward to handle this complication by following the same style of solution that we used to account for wholesale market spillovers in the estimation of the effects of RPS on retail electricity prices.[31] Specifically, it is possible to account for the purchase of out-of-state RECs by aggregating the data to the REC region level.

In the case of emissions, there is evidence of a second spillover that comes from the finding in Table 3, which suggests that RPS states increased net electricity exports to non-RPS states. This spillover is more challenging to accommodate. Exports from RPS states to non-RPS states reduce emissions and generation in non-RPS states and cause higher emissions in RPS states associated with exported electricity, rather than local consumption. Unfortunately, the potential solution of aggregating to the balancing authority level (as we did for retail electricity prices) is not appealing here, because about 32% of the balancing authorities cross REC region boundaries, eliminating the possibility of an aggregation that captures both dimensions of spillovers.[32] Below, we show results from estimation approaches with both state-by-year and REC region-by-year as the unit of observation, noting that neither approach perfectly accommodates these two forms of spillovers.

We make the case that estimating regressions using emissions intensity (i.e., CO_2 emissions per GWh) as the dependent variable, instead of the conventional approach of using CO_2 emissions, has the potential to address the challenge of estimating the effect of RPS policies on national emissions in a way that accounts for possible spillovers to non-RPS states. To examine the assumptions under which each choice of dependent variable provides an accurate

[30] Data Appendix Section 12.2 details the full allocation of states to the 10 REC regions in the analysis. Appendix Figure A.1 provides an approximate outline of the REC region borders

[31] Recall, Columns (7) and (8) of Table 2.

[32] 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.

estimate of the full effects of RPS, we start by developing an expression for the change in national emissions due to state-level RPS policies in the presence of cross-state spillovers. Let national emissions, E, be the product of electricity generation, G, and emissions intensity, I, in RPS states (denoted by the "RPS" superscript) and the states that do not adopt an RPS (denoted by the "No RPS" superscript):

$$E = G^{RPS} \times I^{RPS} + G^{No\,RPS} \times I^{No\,RPS} \tag{11}$$

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 (11) and rearranging generates the following decomposition of the elements of ΔE into four terms:

$$\begin{aligned}\Delta E = &\underbrace{\Delta I^{RPS}\left(G^{RPS} + \Delta G^{RPS}\right)}_{1} + \underbrace{\Delta G^{RPS} \times I^{RPS}}_{2} \\ &+ \underbrace{\Delta G^{No\,RPS}\left(I^{No\,RPS} + \Delta I^{No\,RPS}\right)}_{3} + \underbrace{\Delta I^{No\,RPS} \times G^{No\,RPS}}_{4}\end{aligned} \tag{12}$$

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

The four terms in Equation (11) represent distinct channels through which state RPS policies that potentially cause spillovers can affect national emissions. Term (1) is the product of the change in emissions intensity in RPS states and total generation in those states, which represents the primary direct effect of RPS on emissions in RPS states. It is reasonable to expect this term to be negative because RPS policies require the use of zero carbon renewable technologies that reduce the emissions intensity in participating states (ΔI^{RPS}).

The next three terms capture the effects of RPS-induced changes on generation in RPS and non-RPS states. Specifically, term (2) represents the change in emissions due to changes in generation in RPS states evaluated with the pre-RPS emissions intensity, and term (3) represents changes in non-RPS state emissions caused by changes in the level of their generation. The results in Table 3 suggest that term (2) is positive and term (3) is negative as RPS causes implementing states to raise their generation and export more electricity to neighboring states. Since the increase in RPS states from exported electricity is offset by generation reductions in non-RPS states (except for international imports/exports), these two terms will approximately cancel each other out subject to two assumptions. The first

is that the emissions intensity is equal in RPS and non-RPS states (i.e., $I^{RPS} = I^{No\,RPS}$). Recall, Table 1 documented that the emission intensities in RPS states (see Column (1)) and non-RPS states (see Columns (2) and (3)) are virtually identical, lending some support to this assumption. The second is that the emissions intensities in non-RPS states are unaffected by their neighbors' adoption of RPS programs (i.e., $\Delta I^{No\,RPS} = 0$). Even if this assumption does not hold exactly, the impact on non RPS states' emissions intensity (i.e., $\Delta I^{No\,RPS}$) is of indeterminate sign and likely to be relatively small since the estimated increase in exports from RPS states is 10% of their generation (recall 3). Overall, our judgment is that it is plausible to assume that terms (2) and (3) approximately sum to zero, but this cannot be tested directly. Finally, term (4) represents any potential change in emissions due to changes in emissions intensity in non-RPS states (i.e., $\Delta I^{No\,RPS}$) evaluated at the pre-RPS generation level. As we noted, it is difficult to predict the sign of $\Delta I^{No\,RPS}$, but we expect that it is small.

The possibility of electricity generation spillovers and this decomposition of the national change in CO_2 emissions lead us to report two sets of estimates of the national effect of RPS policies on national CO_2 emissions. The first takes estimates of the effect of RPS policies on CO_2 intensity and multiplies them by total generation in RPS states to estimate the change in national CO_2 emissions. This object is an estimate of term (1), and it is the true impact on national emissions if terms (2), (3), and (4) sum to zero. The second approach is the conventional one and it takes estimates of RPS policies on ln CO_2 emissions and sums them across all RPS states (i.e., the sum of terms (1) and (2)). It does not account for the possibility of electricity generation spillovers, and it is necessary to assume that the sum of terms (3) and (4) equals zero for this object to recover the national change in CO_2 emissions. Intuitively, this approach penalizes RPS states for increases in emissions associated with exporting electricity to non-RPS states, but does not capture the corresponding decrease in emissions in non-RPS states. It is this failure to account for the full effect of RPS-induced exporting of electricity, which was documented in Table 3, that causes us to conclude that the conventional approach requires stronger assumptions to produce a valid estimate of the national change in emissions. Consequently, we emphasize the results from the new approach that uses regressions with emissions intensity as the dependent variable.

Table 4 reports on our efforts to estimate the effect of the state-level RPS policies on annual national CO_2 emissions. Columns (1a) - (1c) report results from estimating versions of Equation (8) with CO_2 intensity as the dependent variable.. In each panel, the first two rows report the mean shift and trend break coefficients from the 7 and 12 year versions of Equation (8). Below the regression results, the table details the following measures of the effects of RPS policies: the change in predicted CO_2 intensity (or log(CO_2) in Columns (2a)

- (2c)), the implied national change in emissions measured in millions of metric tons (Mmt) from all 29 RPS states 7 (12 in panel B) years after passage of RPS policies, which does not correspond to a single calendar year because the RPS policies were implemented in a range of years (recall Figure 2), and this national change in emissions expressed as a percentage of 2010 national power sector emissions. The unit of observation is a state by year in Column (1a) and a REC region by year in Columns (1b) and (1c). The observations are weighted by the number of states in each REC in the (b) columns and unweighted in the (c) columns.[33] For completeness, Columns (2a) - (2c) report the analogous results from the conventional approach where the dependent variable is the log of CO_2 emissions.

The results in Columns (1a) - (1c) all indicate that RPS policies lead to significant reductions in CO_2 intensity. The large trend break coefficient means that the magnitude of the emissions reductions is increasing in the number of years since passage,[34] which explains why the effect ranges from a decline in carbon intensity of 11.4% - 18.6% at 7 years after passage and rises to 25.1% - 41.0% by 12 years after passage.[35] Due to weighting by the number of states in Column (1b), this REC-level specification is conceptually most similar to the Column (1a) specification where the unit of observation is a state by year. It is striking that the Column (1b) effect on CO_2 intensity is roughly double the Column (1a) estimated effects 7 and 12 years after passage, suggesting an important role for cross-state spillovers through REC trading. It is also noteworthy that the Column (2a) estimates that most closely resemble the previous literature's approach (i.e., $\ln(CO_2)$ as the dependent variable and state by year observation) suggest no change in emissions at 7 years and a statistically insignificant 6 ln points decline at 12 years, both of which are qualitatively consistent with the findings of other work in the literature such as Upton and Snyder (2017).[36]

The ultimate goal from these regressions is to infer the national change in CO_2 emissions. The entries suggest national emissions declines of 69-302 Mmt of CO_2 or 2.9% - 12.9% of 2010 power sector emissions 7 years after passage. This effect increases to 7.2% - 22.5% of power sector emission 12 years after passage. Finally, the estimated decline in emissions is generally much smaller in the less preferred Columns (2a) - (2c), presumably because it

[33] We note that there is a case for both the unweighted and weighted versions of the REC region level regressions in Table 4. 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.

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

[35] Appendix Table A.8 shows that our CO_2 results are robust to alternative classifications of states with multiple or partial REC region affiliations.

[36] With the $\ln(CO_2)$ dependent variable, both REC-level regressions indicate larger declines in the outcome variable than when the unit of observation is a state by year. Thus, these results are similar to those in Columns (1a) - (1c) in also suggesting that cross-state spillovers through REC trading make the state-level regressions difficult to interpret.

includes emissions associated with the RPS-induced increase in generation that is exported from RPS states to non-RPS states (as discussed above). The remainder of the paper will focus on the preferred CO_2 intensity results, while also reporting results based on ln CO_2 emissions in the appendix for completeness.

Given the findings on CO_2 emissions, it is natural to examine whether RPS also had an impact on other pollutants. Table 5 reports the impact of RPS on several measures of local air pollution emissions from power plants, as well as ambient concentrations, 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.

6.6 RPS Effects Per Unit of Net Requirement

While the results to this point have focused on measuring the effects of RPS as a binary treatment variable, this section examines results from the specifications in Equations (11) and (12) that use the measure of treatment intensity as the independent variable. Specifically, Table 6 shows the effects of RPS per percentage point of net requirement on a range of outcomes. Panel A shows estimates that use the LBNL measure of net requirement that make a variety of adjustments for source inclusion by state policy and subcategory of generation. Panel B reports estimates that use the unadjusted difference between the statutory requirement and the EIA's uniform national definition of renewable generation in the period prior to policy passage.

The Column (1) estimates indicate that RPS states with larger net requirements have modestly larger price increases, although they are not determined precisely. In the case of the effects of RPS on price, one notable correlation is that the average stringency of RPS increased over time as the costs of renewable energy have fallen. Figure (A.12) shows that the average net requirement conditional on having RPS rose from close to zero in the year 2000 to 3.8% in 2015, using the LBNL adjusted measure. Thus, the coefficient on D_{st} potentially captures the net effect of both rising stringency and falling costs over time.

Column (2) of Table 5 aims to disentangle these competing effects by testing whether the cost per unit of net requirement differs in the earlier and later parts of the sample. The results show that the relationship between the costs of RPS and policy stringency appear to have differed sharply before and after 2010, which is seven years after passage for the median

RPS state. Prior to 2010, each unit of net requirement was associated with approximately a 0.21 cent increase in electricity price when using the LBNL measure of net requirement, and a 0.51 cent increase when using the unadjusted measure. In contrast, after 2010 there is no detectable relationship between electricity prices and either measure of net requirements. These findings are consistent with the per-unit costs of RPS compliance falling over this period due to the secular downward trend in the cost of renewable energy technologies that has been widely documented elsewhere.

Column (3) measures the heterogeneous effects of RPS per unit of net requirement on CO_2 intensity. Unsurprisingly, states with greater net requirements saw larger drops in CO_2 intensity.

Column (4) shows the effects of RPS on renewable generation. We find that each percentage point of RPS net requirement was associated with about a 0.86. percentage point increase in renewables using the LBNL measure and a 0.67 percentage point increase using the unadjusted measure. This is consistent with the majority of policy compliance taking place within-state and some compliance coming through traded REC permits from out-of-state generation, though the confidence intervals do not rule out that compliance occurred fully within state.[37]

Columns (5) - (12) measure the association between net requirements and generation from a range of sources. The dependent variable in each of these columns is expressed in terms of percentage points of total generation. The Column (5) results suggest that RPS compliance occurred primarily through wind generation, with Column (7) showing some suggestive evidence of hydroelectric power responding as well. In contrast, Column (6) shows no association between net requirements and increases in solar generation, consistent with recent work by Deschenes et al. (2023). Finally, Column (10) shows suggestive evidence that the increase in RPS mandates displaced generation from coal, though the magnitude and precision of the effect is sensitive to the choice of the net requirement measure.

7 Interpretation

The paper's estimates suggest that RPS programs have had substantial effects on both electricity prices and national CO_2 emissions, so it is natural to calculate their cost per metric ton of CO_2 abated. This statistic is a standard measure of mitigation program efficiency, facilitating comparisons with alternative mitigation programs. To make this concrete, we calculate the implied total costs to consumers in the 29 RPS states in the seventh year after

[37]Note that the pattern in Appendix Table A.6 shows that the effects on renewable generation are not detectable when using the binary RPS treatment variable that does not adjust for treatment intensity across states.

passage. The increase in the cost of electricity is then calculated as the product of the estimated increase in prices (from the fitting of Equation (8)) and total electricity consumption in the RPS states. Additionally, we estimate the national change in CO_2 emissions using the results from the preferred CO_2 intensity specifications as described in Section 6.5.

Figure 6 uses the paper's estimates of RPS effects on electricity prices and national CO_2 emissions to report on the resulting range of estimated cost per metric ton of CO_2 abated due to RPS policies. Recall, the paper presented results from several specifications of the effect of RPS on both prices and national CO_2 emissions that differ in terms of the level of aggregation and the weighting scheme: state level and balancing authority level regressions for prices, and state and REC region (weighted and unweighted) level estimates of CO_2 intensity for emissions. Figure 6 reports on the full range of the results by displaying the cost per ton for all permutations of specifications of the price and emissions regressions. Showing the range of permutations avoids imposing potentially arbitrary assumptions or choices about the right specification.[38].[39] The uncertainty in these estimates is captured by the boxes that reflect the interquartile range.

The point estimates for the cost per metric ton abated in the 7th year after passage range from \$81 to \$210 across all combinations of specifications.[40] These estimates of the costs per metric ton are the ratio of estimated RPS induced reductions in national CO_2 emissions of 68 to 301 million metric tons and a total cost to consumers of \$14 to \$63 billion in the seventh year after passage. To characterize the range of uncertainty around the cost per ton estimates, we employ a seemingly unrelated regressions estimation approach by "stacking" and fully interacting the price and CO_2 emissions regressions. We then 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 impacts of RPS on prices, as in Table 2 and on CO_2 emissions, as in Table 4, and then plot the interquartile range of the cost per ton in Figure 6. In some instances, the resulting interquartile range is substantial, reflecting the challenge 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 higher than the price of a

[38] For completeness, Appendix Figure A.9 reports results based on the ln CO_2 regressions that have conceptual shortcomings described in Section 6.5.

[39] We omit the balancing authority price regression with state-count weighting from Column (8) of Table (2) because the standard errors are sufficiently large that this estimate lacks empirical content.

[40] Appendix Figure A.10 details the corresponding estimates of cost per metric ton of $CO_2$for the 12th year after passage.

permit to emit a ton of CO_2 in major carbon markets. For example, the May 2024 prices in the California/Quebec carbon cap and trade, Regional Greenhouse Gas Initiative, and European Union ETS markets are about \$41, \$16, and \$82.35, respectively. On the other hand, 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 Biden Administration recently set the social cost of carbon (i.e. the monetized damages from the release of an additional ton of CO_2) at \$225 per ton in 2023 dollars and \$216 in 2022 dollars, which suggests that there is substantial probability that RPS policies would pass a cost-benefit test at the updated social cost of carbon (although not at the previous one that was approximately \$50).

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 is reasonable to assume that these shares vary over time and in ways that further complicate attempts to recover 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 difficult to predict the cost of future RPS policies or the coming increase in stringency among many existing ones. On the one hand, the paper demonstrates that the costs of RPS per unit of net requirement decline over time within the sample. This decline means that the average cost estimates from implementation of past policies as in Figure 6 may overstate the cost of future policies implemented in a context with improved technology. Thus, the cost-effectiveness of new policies may be greater than what is implied by the calculation of the average cost per ton in the figure. On the other hand the costs of intermittency are likely to increase as renewables' share increases.

Third, it is often claimed that policies encouraging renewable energy deployment contribute themselves to reducing the cost of future renewable generation through learning-by-doing externalities that 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 (e.g., China's production subsidies and Germany's embrace of renewable generation) 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).

Fourth, a randomized controlled trial is unavailable here, so we cannot rule out the possibility of omitted variables beyond the extensive set we control for that could explain 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. The paper 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. Seven years after passage, we estimate that average retail prices are 1.4 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 2.3 cents per kWh, or 17%, higher. We show, however, that the increase in costs per unit of net requirement is larger earlier in the sample than later in the sample, suggesting that the improvements in the efficiency of renewable technologies is reducing the costs of RPS policies. Third, the estimates indicate that RPS programs lead to CO_2 emissions reductions of 2.9% to 12.9% seven years after passage (7.2% to 22.5% 12 years after passage). Putting the results together, point estimates suggest that the cost per metric ton of CO_2 abated in the seventh year after RPS passage ranges from \$81-\$210 in preferred specifications.

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 raises the possibility that indirect costs associated with grid integration could represent the more important barrier to substantially increasing renewables' share of generation than the direct cost of renewable energy.

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 costs 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.

References

Abraham, S. and L. Sun (2019). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Working paper*. 1, 6.2, 5

Autor, D., D. Dorn, and G. Hanson (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review 103*(6), 2121–2168. 19

Barbose, G. (2018). U.s. renewable portfolio standards: 2018 annual status report. *Lawrence Berkeley National Lab (LBNL), Berkeley, CA*. 1, 2, 4.1, 8, 4, A.3, A.12

Barbose, G., R. Wiser, J. Heeter, T. Mai, L. Bird, M. Bolinger, A. Carpenter, G. Heath, D. Keyser, J. Macknick, et al. (2016). A retrospective analysis of benefits and impacts of us renewable portfolio standards. *Energy Policy 96*, 645–660. 5

Barnes, J. (2014). Dsire dataset on renewable portfolio standards. *Database of State incentives for Renewables & Efficiency (DSIRE), North Carolina State University, Raleigh, NC*. 4.1

Ben-Michael, E., A. Feller, and J. Rothstein (2021). The augmented synthetic control method. *Journal of the American Statistical Association* (just-accepted), 1–34. 1, 6.2, 5, A.2

Bento, A. M., T. Garg, and D. Kaffine (2018). Emissions reductions or green booms? general equilibrium effects of a renewable portfolio standard. *Journal of Environmental Economics and Management 90*, 78–100. 1

Bjørner, T., M. Togeby, and H. Jensen (2001). Industrial Companies' Demand for Electricity: Evidence From a Micropanel. *Energy Economics 23*(5), 595–617. 6.4

Borenstein, S. (2008). The Market Value and Cost of Solar Photovoltaic Electricity Production. Working Paper. 1

Carley, S., L. L. Davies, D. B. Spence, and N. Zirogiannis (2018). Empirical evaluation of the stringency and design of renewable portfolio standards. *Nature Energy 3*(9), 754–763. 1

Chen, C., R. Wiser, and M. Bolinger (2007). Weighing the Costs and Benefits of State Renewables Portfolio Standards: A Comparative Analysis of State-Level Policy Impact Projections. Technical Report 61580, LBNL. 1

Cicala, S. (2014, May). When Does Regulation Distort Costs? Lessons from Fuel Procurement in U.S. Electricity Generation. Technical Report w20109, National Bureau of Economic Research, Cambridge, MA. 15, 6.2

Cullen, J. (2013). Measuring the environmental benefits of wind-generated electricity. *American Economic Journal: Economic Policy 5*(4), 107–133. 1

Denholm, P. and R. M. Margolis (2007). Evaluating the limits of solar photovoltaics (pv) in traditional electric power systems. *Energy policy 35*(5), 2852–2861. 1

Deschenes, O., C. Malloy, and G. McDonald (2023, August). Causal Effects of Renewable Portfolio Standards on Renewable Investments and Generation: The Role of Heterogeneity and Dynamics. Technical Report w31568, National Bureau of Economic Research, Cambridge, MA. 1, 6.6

Deschênes, O., M. Greenstone, and J. S. Shapiro (2017, October). Defensive Investments and the Demand for Air Quality: Evidence from the NOx Budget Program. *American Economic Review 107*(10), 2958–89. 1

Fabrizio, K., N. Rose, and C. Wolfram (2007). Do Markets Reduce Costs? Assessing the Impact of Regulatory Restructuring on US Electric Generation Efficiency. *American Economic Review 97*(4), 1250–1277. ISBN: 00028282. 4.1, 6.2

Fares, R. L. and C. W. King (2017). Trends in transmission, distribution, and administration costs for us investor-owned electric utilities. *Energy Policy 105*, 354–362. 4.2, 3

Fischer, C. (2010). Renewable Portfolio Standards: When Do They Lower Energy Prices? *Energy Journal 31*(1), 101–120. 1

Fowlie, M., M. Greenstone, and C. Wolfram (2018, 01). Do Energy Efficiency Investments Deliver? Evidence from the Weatherization Assistance Program*. *The Quarterly Journal of Economics 133*(3), 1597–1644. 1, 7

Gillingham, K. and J. Stock (2018). The cost of reducing greenhouse gas emissions. *Journal of Economic Perspectives 32*(4), 53–72. 1, 7

Gowrisankaran, G., S. S. Reynolds, and M. Samano (2016). Intermittency and the value of renewable energy. *Journal of Political Economy 124*(4), 1187–1234. Publisher: University of Chicago Press Chicago, IL. 3, 1, 3.2

Greenstone, M. (2002). The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures. *Journal of Political Economy 110*(6), 1175–1219. Publisher: The University of Chicago Press. 1

Heeter, J., G. Barbose, L. Bird, S. Weaver, F. Flores-Espino, K. Kuskova-Burns, and R. Wiser (2014). A Survey of State-Level Cost and Benefit Estimates of Renewable Portfolio Standards. Technical Report 6A20-61042, NREL/TP. 1

Holland, S. P., J. E. Hughes, and C. R. Knittel (2009, February). Greenhouse gas reductions under low carbon fuel standards? *American Economic Journal: Economic Policy 1*(1), 106–46. 1, 7

Hollingsworth, A. and I. Rudik (2019). External impacts of local energy policy: The case of renewable portfolio standards. *Journal of the Association of Environmental and Resource Economists 6*(1), 187–213. 5

Jacobson, M. Z., M. A. Delucchi, M. A. Cameron, and B. A. Frew (2015). Low-cost solution to the grid reliability problem with 100% penetration of intermittent wind, water, and solar

for all purposes. *Proceedings of the National Academy of Sciences 112*(49), 15060–15065. 1

Johnson, E. P. (2014). The cost of carbon dioxide abatement from state renewable portfolio standards. *Resource and Energy Economics 36*(2), 332–350. 1

Joskow, P. L. (2011). Comparing the costs of intermittent and dispatchable electricity generating technologies. *The American Economic Review 101*(3), 238–241. 1

Lamont, A. D. (2008). Assessing the long-term system value of intermittent electric generation technologies. *Energy Economics 30*(3), 1208–1231. 1

Lyon, T. and H. Yin (2010). Why Do States Adopt Renewable Portfolio Standards?: An Empirical Investigation. *31*(3), 131–156. 1, 6.2

MacKay, A. and I. Mercadal (2021). Deregulation, Market Power, and Prices: Evidence from the Electricity Sector. *SSRN Electronic Journal*. 6.2

Maguire, K. and A. Munasib (2016, August). The Disparate Influence of State Renewable Portfolio Standards on Renewable Electricity Generation Capacity. *Land Economics 92*(3), 468–490. 1

Milligan, M., E. Ela, B.-M. Hodge, B. Kirby, D. Lew, C. Clark, J. DeCesaro, and K. Lynn (2011). Integration of variable generation, cost-causation, and integration costs. *The Electricity Journal 24*(9), 51–63. 1

Mills, A., R. Wiser, and K. Porter (2009). The cost of transmission for wind energy: A review of transmission planning studies. *Lawrence Berkeley National Lab (LBNL), Berkeley, CA*. 1

Schmalensee, R. (2012). Evaluating Policies to Increase Electricity Generation from Renewable Energy. *Review of Environmental Economics and Policy 6*(1), 45–64. 1

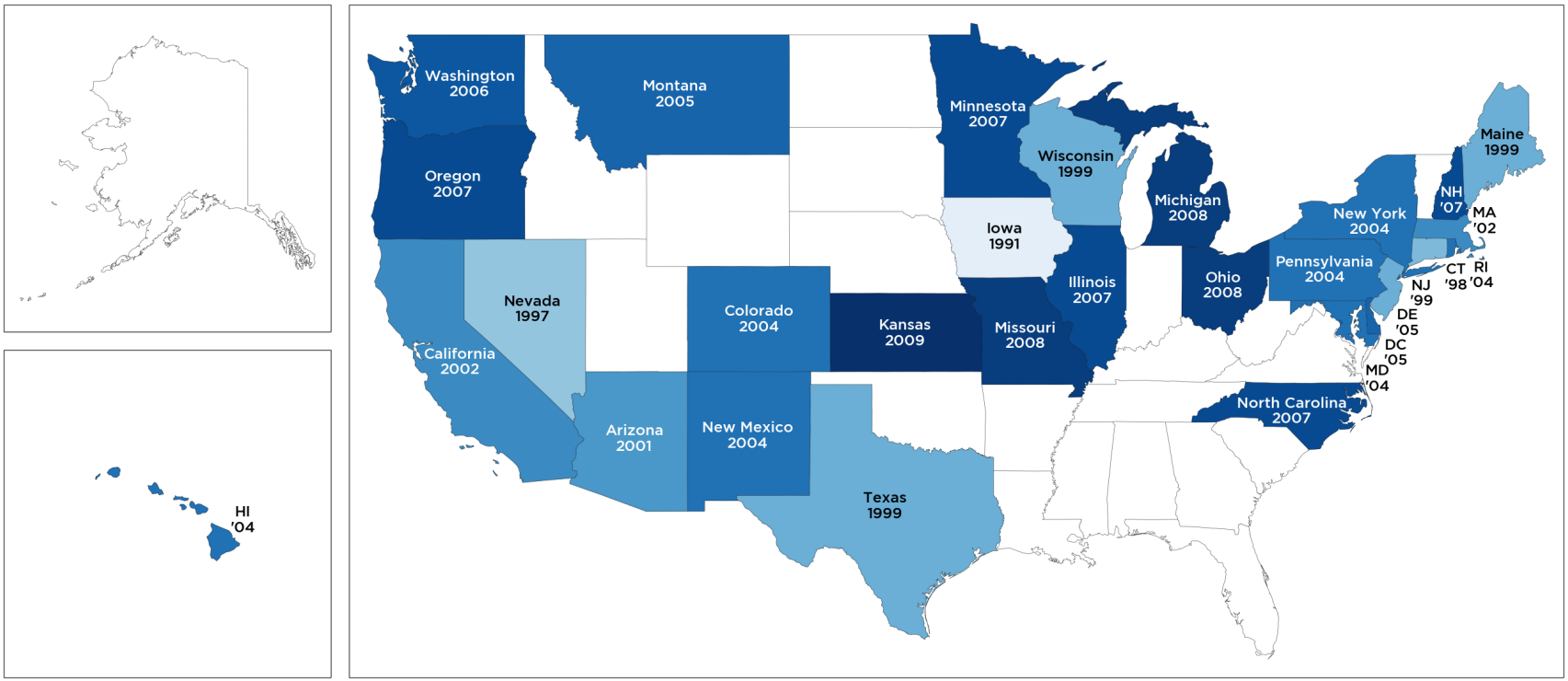
Tuerck, D., P. Bachman, and M. Head (2013). The Economic Impact of Wisconsin's Renewable Portfolio Standard. *26*(4). 1

Upton, G. and B. Snyder (2017). Funding renewable energy: An analysis of renewable portfolio standards. *Energy Economics 66*, 205–216. 1, 6, 6.5, 6.5

Yin, H. and N. Powers (2010). Do State Renewable Portfolio Standards Promote In-State Renewable Generation? *Energy Policy 38*(2), 1140–1149. 1, 2

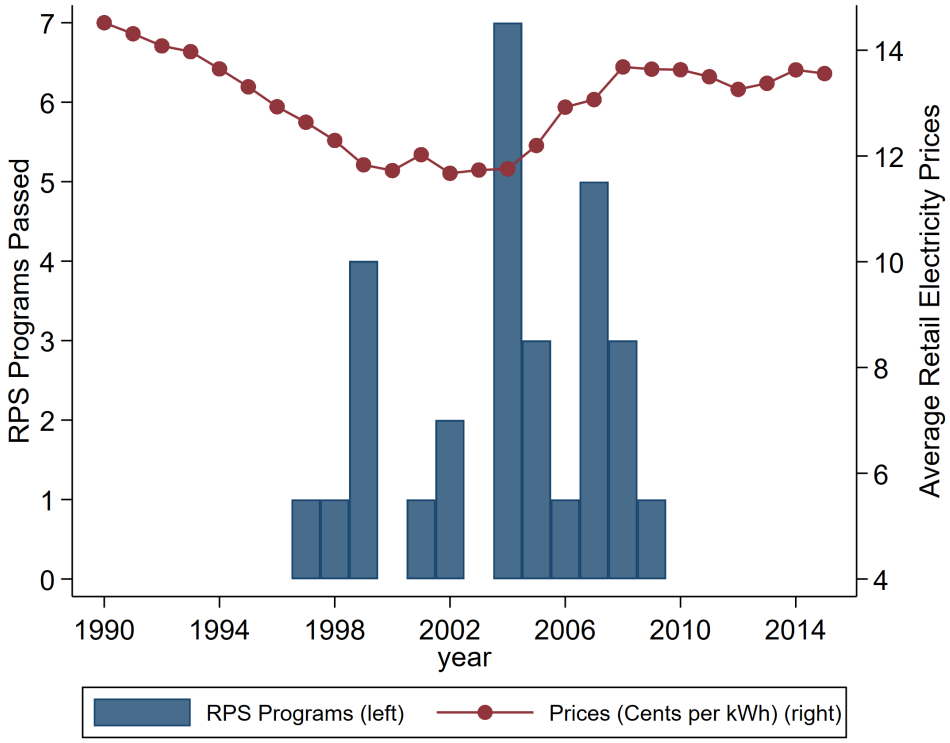
9 Figures

Figure 1: RPS Passage by State



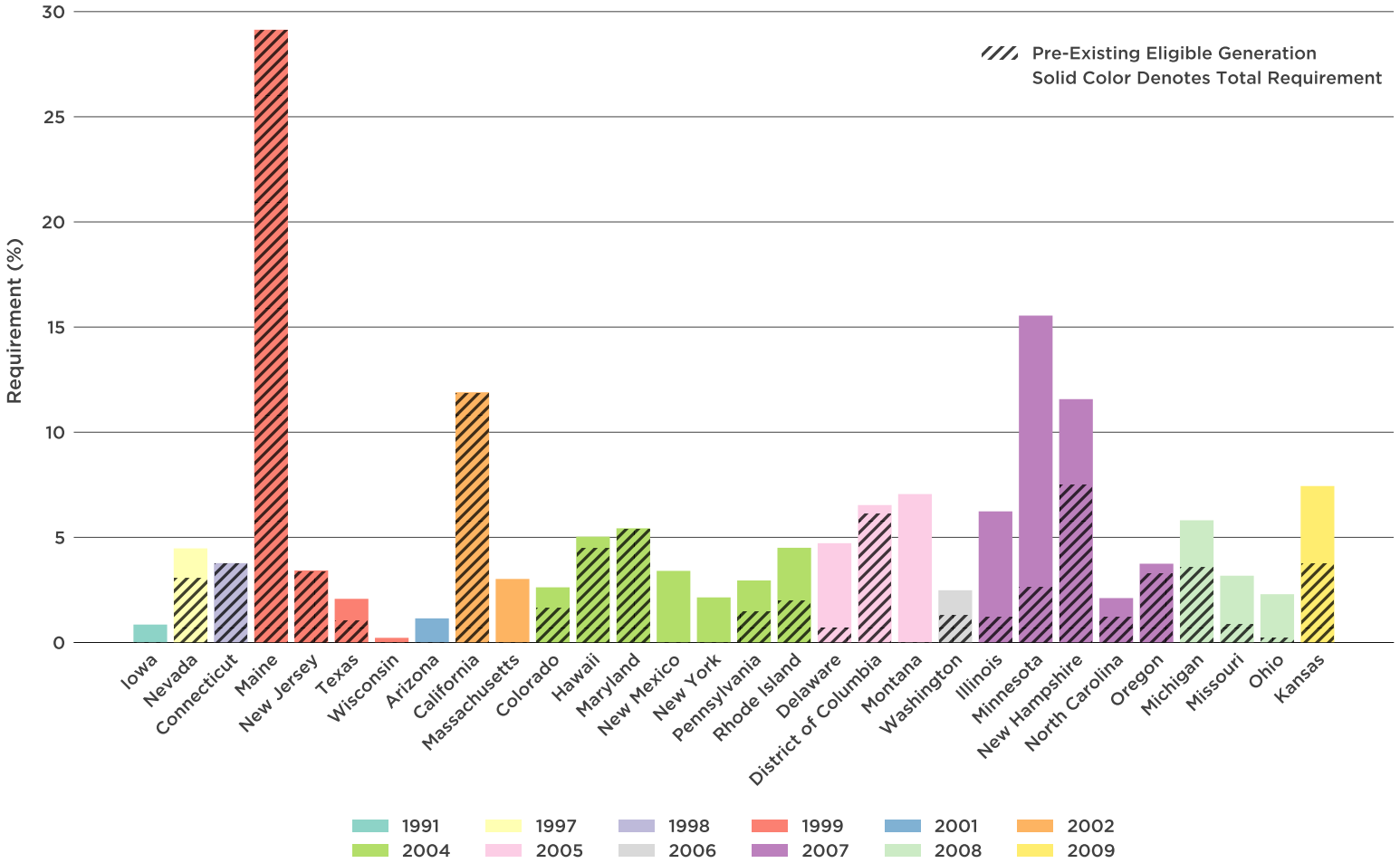
Notes: States that have adopted any RPS policy are colored according to the year in which the RPS legislation was first passed. We gather this information from a combination of state legislative documents, state government websites, and summaries from the U.S. Department of Energy.

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



Notes: Average national retail electricity prices are shown in constant 2022 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.

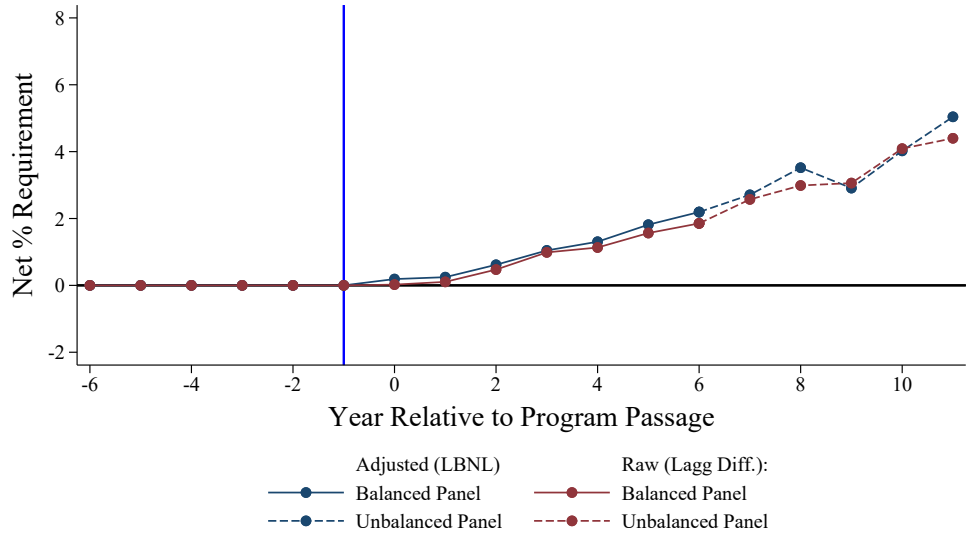
Figure 3: RPS Total and Net Requirements, by State



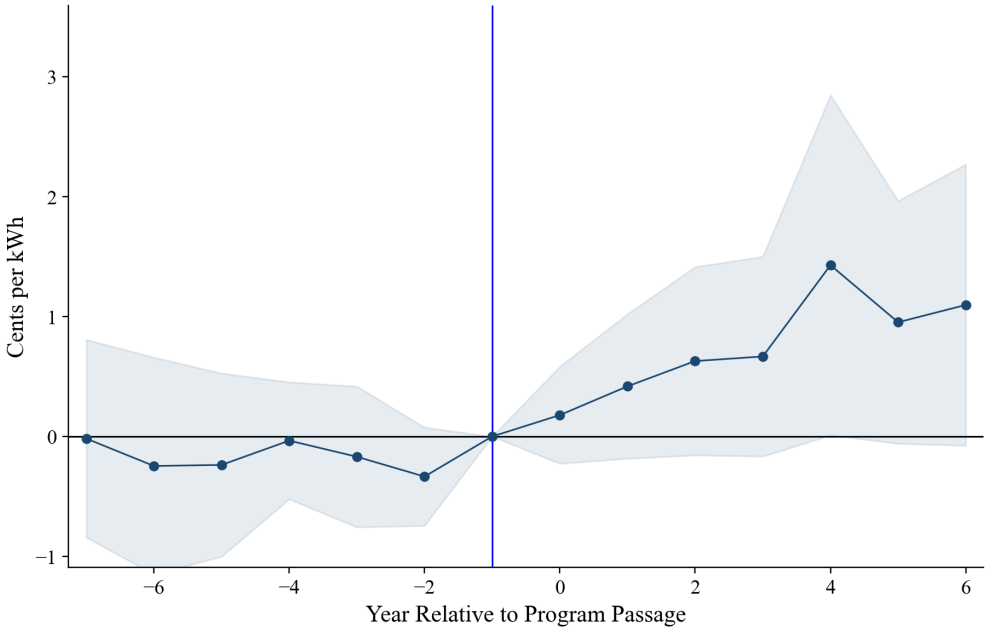
Notes: States are sorted by the year in which their RPS policies were first passed. The bars are colored according to RPS passage year. The total height of each bar denotes the gross RPS requirement in the seventh year after RPS passage at $\tau = 6$; the non-patterned portion of each bar denotes the 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



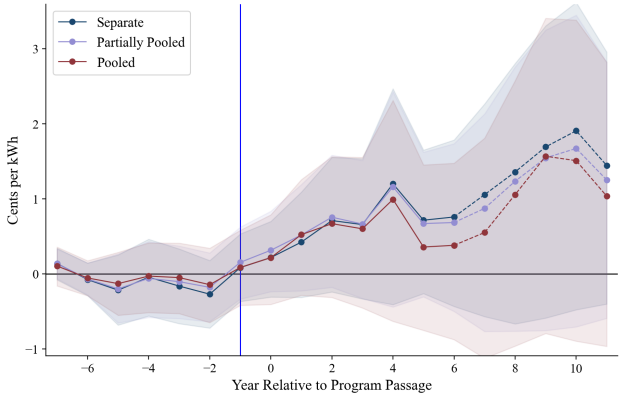
(b) Retail Prices



Notes: Graph (a) shows the mean net RPS requirement percentage for event years τ = -6 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.

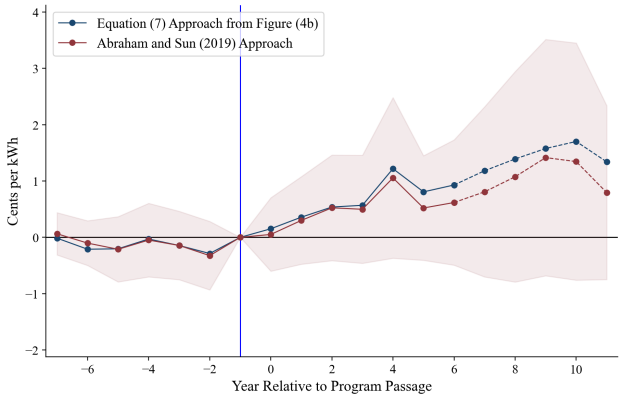
Figure 5: Estimated Effects of RPS Programs on Retail Electricity Prices, Robustness Checks

(a) Synthetic Control Method



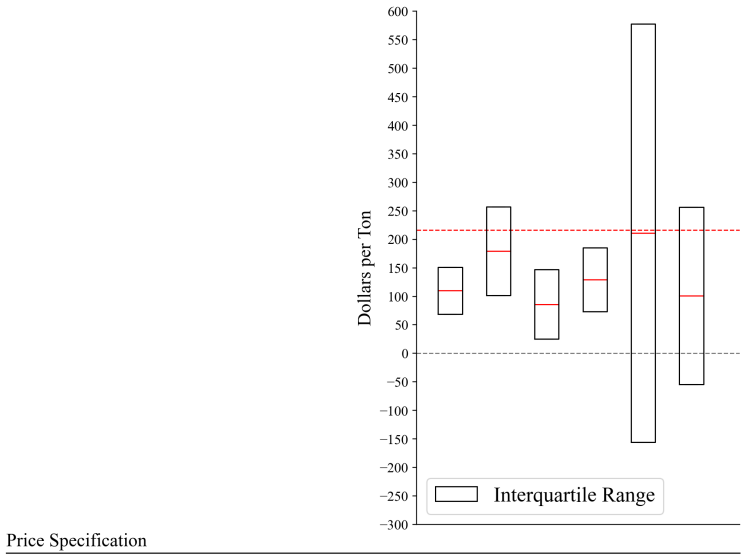
Notes: Lines show estimates from synthetic control method specifications as recommended by Ben-Michael, Feller, and Rothstein (2021) for event years τ = -7 to τ = 11, and shaded area represent 95% confidence intervals. Each specification includes state fixed-effects and balances on electricity price as the dependent variable, and solar and wind potential, CO_2 intensity, percent RPS-eligible generation, Democratic control of the state legislature, population growth, unemployment rate 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 $\tau = 11$ 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: $y_{st} = \alpha + \sum_e \sum_\tau \sigma_{\tau,e \in E} * \mathbf{I}\{E_s = e\} * D_{\tau,st} + X_{st} + \gamma_s + \mu_t + \epsilon_{st}$, 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 $\tau = 1$, 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)				✓	✓	✓
State	✓	✓	✓			
CO_2 Specification						
REC CO_2 Intensity		✓	✓		✓	✓
REC Region Aggregation (Unweighted)		✓				✓
REC Region Aggregation (State-Count Weighted)			✓		✓	
State CO_2 Intensity	✓			✓		

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 \$179 corresponds to using a REC region regression with no regression weight for measuring CO_2 reductions. The "State" specification for price comes from Column (1) of Table 2. The "BA Aggregation (Sales Weighted)" specification for price comes from Column (7) of Table 2. The "CO_2 Intensity" specification for CO_2 comes from Column (2a) of Table 4 Panel B. The dotted red line demarks the social cost of carbon $225 in 2023 dollars$(216 in 2022 dollars). 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	Mean Control	Mean Non-RPS	P-value RPS vs Control	P-value RPS vs Non-RPS
	(1)	(2)	(3)	(4)	(5)
Price (2018 Cents/kWh)					
Total	13.3	10.9	10.4	0.00	0.00
Residential	15.6	13.2	12.6	0.01	0.00
Commercial	13.8	11.4	11.0	0.00	0.00
Industrial	9.9	8.0	7.6	0.01	0.00
Price Change in 7 Years Preceding RPS Adoption	-0.7	-0.7	-0.6	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 Restructuring	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	0.09	0.04	0.02	0.02	0.01
Has Regional Greenhouse Gas Initiative	0.00	0.00	0.00	.	.
Has Carbon Cap and Trade Program	0.00	0.00	0.00	.	.
Additional Controls					
Democratic Control of State Legislature	0.48	0.29	0.34	0.07	0.16
Population Growth	1.19	0.93	0.97	0.28	0.36
Unemployment Rate	4.99	4.88	4.71	0.56	0.14
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

	State-level Aggregation						Balancing Authority Aggregation	
	(1) Base Specification	(2) Continuous Control for Energy Efficiency	(3) Fuel Price Controls	(4) Exclude Hawaii	(5) Year-Region Fixed Effects	(6) Year-Division Fixed Effects	(7) Sales-weighted	(8) State-count-weighted
Panel A. 7 Post-Passage Years, Balanced Sample								
Regression Estimates								
Mean Shift (δ_3)	0.42	0.46*	0.41	0.33	0.59**	0.52*	0.86	0.21
	(0.26)	(0.24)	(0.25)	(0.28)	(0.29)	(0.30)	(0.66)	(0.56)
Trend Break (β_3)	0.17*	0.19*	0.16	0.18*	0.11	0.10	0.16	0.37
	(0.10)	(0.10)	(0.10)	(0.10)	(0.08)	(0.09)	(0.18)	(0.29)
Effect of RPS 7 years after passage	1.43**	1.60**	1.37*	1.40*	1.23**	1.10*	1.83**	2.41
($6\beta_3 + \delta_3$)	(0.67)	(0.68)	(0.70)	(0.70)	(0.58)	(0.58)	(0.74)	(2.19)
Panel B. 12 Post-Passage Years, Unbalanced Sample								
Regression Estimates								
Mean Shift (δ_3)	0.45	0.48	0.45	0.45	0.59*	0.40	1.10*	0.54
	(0.31)	(0.30)	(0.30)	(0.34)	(0.32)	(0.31)	(0.57)	(0.84)
Trend Break (β_3)	0.16**	0.19**	0.15*	0.13*	0.11	0.15	0.06	0.26
	(0.08)	(0.08)	(0.09)	(0.06)	(0.07)	(0.10)	(0.14)	(0.18)
Effect of RPS 12 years after passage	2.25**	2.54***	2.11**	1.86**	1.85**	2.10*	1.70	3.35
($11\beta_3 + \delta_3$)	(0.91)	(0.92)	(1.03)	(0.79)	(0.84)	(1.05)	(1.15)	(2.70)
Other programs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Energy Efficiency Expenditures		Yes						
Fuel Prices			Yes					
Exclude Hawaii				Yes				
Balancing Authority FE							Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes		
Year FE	Yes	Yes	Yes	Yes			Yes	Yes
Year × Census Region FE					Yes			
Year × Census Division FE						Yes		
Observations	1300	1200	1300	1274	1300	1300	1586	1586

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 1.60 cents 7 years after passage, identical to the 1.60 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

	Transmission and Distribution Costs		
	(1) log(Transmission Costs)	(2) log(Distribution Costs)	(3) log(Transmission and Distribution Costs)
	Panel A. 7 Post-Passage Years, Balanced Sample		
Regression Estimates			
Mean Shift (δ_3)	0.32*	0.14*	0.24*
	(0.18)	(0.08)	(0.13)
Trend Break (β_3)	0.07	0.02	0.04
	(0.04)	(0.02)	(0.03)
Effect of RPS 7 years after passage	0.71*	0.27	0.47
$(6\beta_3 + \delta_3)$	(0.40)	(0.19)	(0.30)
Implied Change in Costs (¢/kWh)	0.61	0.38	1.06
Mean at $\tau = -1$	0.59 ¢/kWh	1.35 ¢/kWh	1.94 ¢/kWh
Other Programs	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1060	1059	1060

	Electricity Production and Consumption			
	(1) log(Capacity)	(2) Capacity Factor	(3) log(Generation)	(4) log(Sales)
	Panel B. 7 Post-Passage Years, Balanced Sample			
Regression Estimates				
Mean Shift (δ_3)	0.02	0.97	0.07**	0.00
	(0.02)	(0.80)	(0.04)	(0.01)
Trend Break (β_3)	0.01	0.24	0.02	0.00
	(0.01)	(0.47)	(0.01)	(0.00)
Effect of RPS 7 years after passage	0.08	2.40	0.21*	0.01
$(6\beta_3 + \delta_3)$	(0.06)	(3.32)	(0.11)	(0.03)
Mean at $\tau = -1$	20.26GW	42.89	80.46TWh	76.20TWh
Other Programs	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1300	1300	1300	1300

	Excess Generation Accounting	
	(1) Electricity Net Exports (%)	(2) Excess Generation (%)
	Panel C. 7 Post-Passage Years, Balanced Sample	
Regression Estimates		
Mean Shift (δ_3)	3.95	3.65
	(2.61)	(2.66)
Trend Break (β_3)	1.02	0.97
	(1.20)	(1.17)
Effect of RPS 7 years after passage	10.09	9.49
$(6\beta_3 + \delta_3)$	(9.22)	(9.11)
Mean at $\tau = -1$	-5.14pp	5.76pp
Other Programs	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes
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

	Dependent Variable: CO_2 Intensity			Dependent Variable: log(CO_2)		
	(1a) State-Level	(1b) Weighted REC-Level	(1c) Unweighted REC-Level	(2a) State-Level	(2b) Weighted REC-Level	(2c) Unweighted REC-Level
			Panel A. 7 Post-Passage Years, Balanced Sample			
Regression Estimates						
Mean Shift (δ_3)	-24.88**	-23.26	14.15	0.03	-0.02	0.04
	(9.64)	(21.86)	(17.30)	(0.03)	(0.05)	(0.04)
Trend Break (β_3)	-16.19***	-22.10**	-14.82***	-0.01	-0.01	-0.01*
	(5.09)	(8.19)	(4.38)	(0.01)	(0.01)	(0.01)
Effect of RPS 7 years after passage						
Change in Predicted CO_2 Intensity log(CO_2) ($6\beta_3 + \delta_3$)	-122.04***	-155.89**	-74.80*	-0.00	-0.10	-0.05
	(37.24)	(67.10)	(38.73)	(0.09)	(0.08)	(0.06)
Change in National CO_2 Emissions (Mmt)	-301.7	-191.4	-68.9	-3.1	-71.7	-27.2
Change in National CO_2 Emissions relative to 2010 Power Sector Emissions	-12.9%	-8.2%	-2.9%	-0.1%	-3.1%	-1.2%
			Panel B. 12 Post-Passage Years, Unbalanced Sample			
Regression Estimates						
Mean Shift (δ_3)	-25.83**	-22.01	21.01	0.04	0.00	0.05
	(10.19)	(25.85)	(20.57)	(0.04)	(0.05)	(0.04)
Trend Break (β_3)	-15.74***	-22.46**	-16.92***	-0.01	-0.02*	-0.02**
	(4.92)	(7.61)	(4.47)	(0.01)	(0.01)	(0.01)
Effect **of RPS 12 years after passage**						
Change in Predicted CO_2 Intensity log(CO_2) ($11\beta_3 + \delta_3$)	-199.00***	-269.11**	-165.13**	-0.06	-0.24*	-0.16
	(61.02)	(101.02)	(58.04)	(0.12)	(0.13)	(0.09)
Change in National CO_2 Emissions (Mmt)	-526.8	-273.2	-167.7	-78.7	-140.98	-0.1
Change in National CO_2 Emissions relative to 2010 Power Sector Emissions	-22.5%	-11.7%	-7.2%	-3.4%	-6.0%	-0.0%
REC-Level Mean at $\tau = -1$		656.7 mt/GWh	656.7 mt/GWh		81.5 Mmt	81.5 Mmt
State-Level Mean at $\tau = -1$	654.5 mt/GWh			48.0 Mmt		
Other programs	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes			Yes		
REC FE		Yes	Yes		Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1300	312	312	1300	312	312

Notes: Columns (2a)-(2b) display log(CO_2) emissions estimates from Equation (8), while Columns (1a)-(1b) display CO_2 intensity. Columns (1a) and (2a) contain state level regressions. Columns (1b)-(1c) and (2b)-(2c) contain specifications run at the REC region level. Columns (1c) and (2c) aggregate observations using the generation-weighted average of states in the region. Columns (1b) and (2b) further weight each observation by the count of states in the region. Using Equation (8) notation, the change in CO_2 intensity/log(CO_2) from RPS 7 years after passage is $6\beta_3 + \delta_3$, and the change in CO_2 intensity/log(CO_2) from RPS 12 years after passage is $11\beta_3 + \delta_3$. CO_2 is in metric tons and CO_2 intensity is in gigawatt hours per metric ton. Change in national CO_2 emissions is calculated using mean electricity generation and the estimated change in CO_2 intensity for columns (1a)-(1c), and mean CO_2 emissions and the estimated change in log(CO_2) emissions in columns (2a)-(2c). Each number is then multiplied by the proportion of RPS states/RPS REC region emissions in order to obtain national estimates. Change in national CO_2 emissions as a percentage of 2010 power sector emissions is calculated by dividing relative implied change estimates by total national CO_2 emissions combined with our estimated implied change and displayed as a percentage. 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 $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: RPS Impact on Other Pollutants

	(1) log(SO_2)	(2) SO_2 Intensity	(3) log(NOx)	(4) NOx Intensity	(5) Monitor PM2.5	(6) Satelite PM2.5
	Panel A. 7 Post-Passage Years, Balanced Sample; Unweighted					
Regression Estimates						
Mean Shift (δ_3)	0.04	-0.16	0.03	0.08	0.42	0.01
	(0.14)	(0.27)	(0.20)	(0.25)	(0.65)	(0.12)
Trend Break (β_3)	-0.10*	-0.25*	-0.06*	-0.07	0.25	-0.12*
	(0.05)	(0.13)	(0.03)	(0.05)	(0.22)	(0.06)
Effect of RPS 7 years after passage	-0.57	-1.65*	-0.34	-0.35	1.91	-0.73*
($6\beta_3 + \delta_3$)	(0.37)	(0.83)	(0.30)	(0.51)	(1.83)	(0.38)
	Panel B. 12 Post-Passage Years, Unbalanced Sample; Weighted					
Regression Estimates						
Mean Shift (δ_3)	-0.14	-0.15	-0.06	-0.01	0.70	0.09
	(0.14)	(0.39)	(0.14)	(0.13)	(0.51)	(0.14)
Trend Break (β_3)	-0.02	-0.36*	-0.05*	-0.14**	0.18	-0.06
	(0.05)	(0.16)	(0.03)	(0.05)	(0.15)	(0.05)
Effect of RPS 7 years after passage	-0.28	-2.31**	-0.35	-0.83*	1.76	-0.28
($6\beta_3 + \delta_3$)	(0.32)	(0.82)	(0.20)	(0.38)	(1.22)	(0.24)
Mean at $\tau = -1$						
Other programs	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	312	312	312	312	311	216

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 $6\beta_3 + \delta_3$. 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 $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

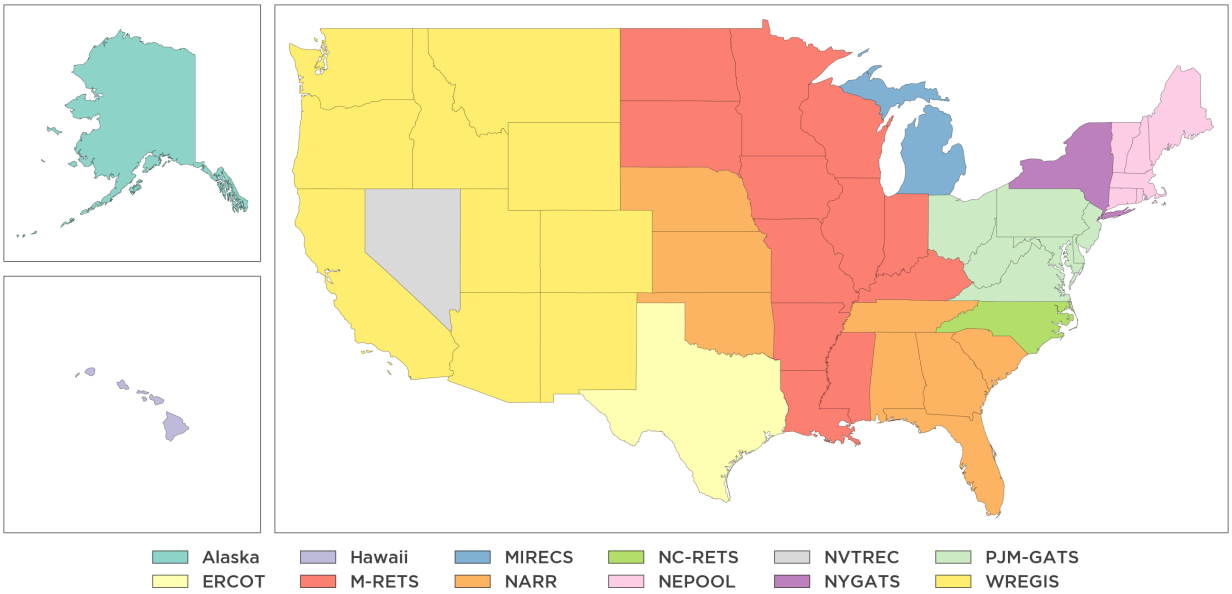
Table 6: RPS Impact Per Unit of Net Requirement

	Price		CO_2 Intensity	Renewables	Wind	Solar	Hydro	Geothermal	Natural Gas	Coal	Biomass	Wood
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Dst = Adjusted Net Requirement (LBNL)												
Regression Estimates												
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st}$	0.05	0.21	-8.83***	0.86***	0.57**	-0.01	0.23	-0.01	0.01	-0.68**	0.05	0.03
	(0.07)	(0.22)	(2.88)	(0.25)	(0.23)	(0.01)	(0.17)	(0.02)	(0.42)	(0.29)	(0.04)	(0.03)
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st} \times$ Year$\geq$ 2010		-0.23										
		(0.23)										
Panel B. Dst = Raw Net Requirement (Lag Diff.)												
Regression Estimates												
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st}$	0.16	0.51**	-10.29***	0.67*	0.49*	-0.00	0.18	-0.00	-0.68	-0.28	-0.03	0.03
	(0.13)	(0.22)	(3.79)	(0.33)	(0.27)	(0.01)	(0.16)	(0.01)	(0.58)	(0.38)	(0.10)	(0.03)
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st} \times$ Year$\geq$ 2010		-0.46**										
		(0.18)										
Mean at τ = -1	13.33	13.33	654.50	13.55	0.44	0.01	9.98	0.48	16.83	42.29	1.26	1.38
Other Programs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1300	1300	1300	1300	1300	1300	1300	1300	1300	1300	1300	1300

Notes: Column (2) displays estimates from Equation (10). All other columns display estimates from Equation (9). Panel A contains the LBNL measure of net requirement while Panel B utilizes the lag difference measure. All specifications control for state and year fixed effects, and indicators for the other programs listed in Table 1. Standard errors are clustered at either the state level with statistical significance indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

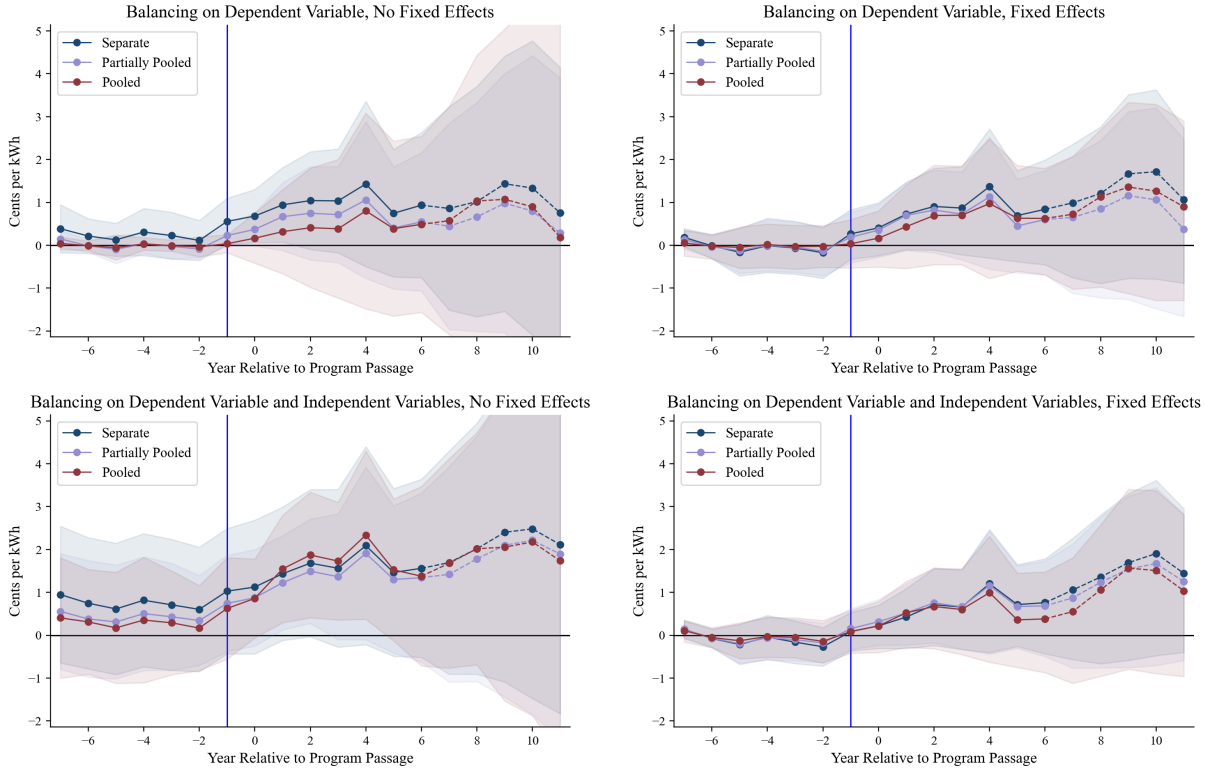
11 Appendix (For Online Publication)

Figure A.1: REC Tracking Markets



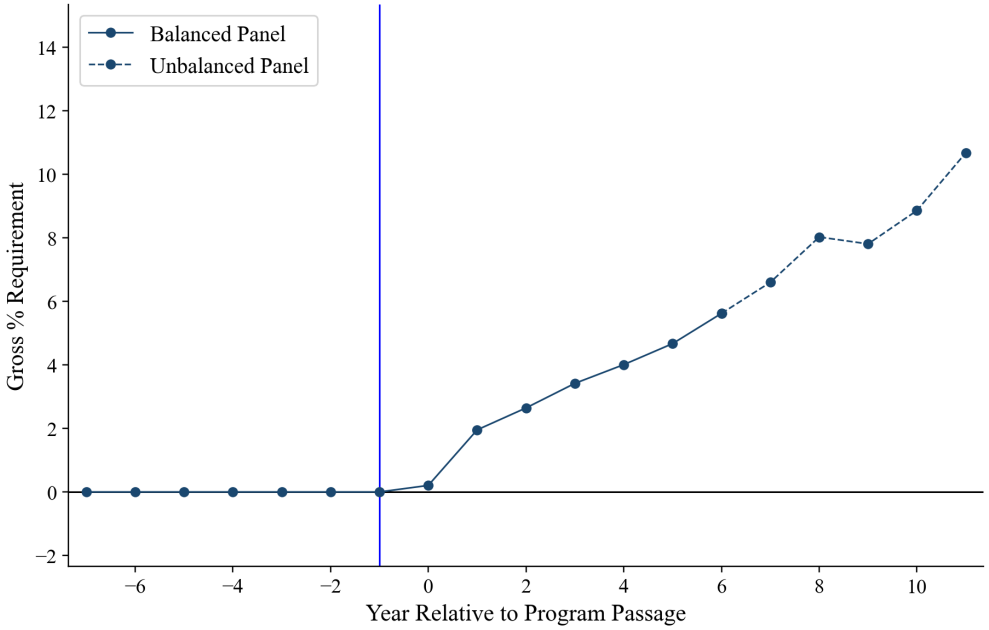
Notes: We compile these boundaries using REC region tracking system websites. Portions of some states qualify for multiple REC regions. We show robustness of our main CO_2 results to alternative classifications for these few states in Appendix Table A.8.

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



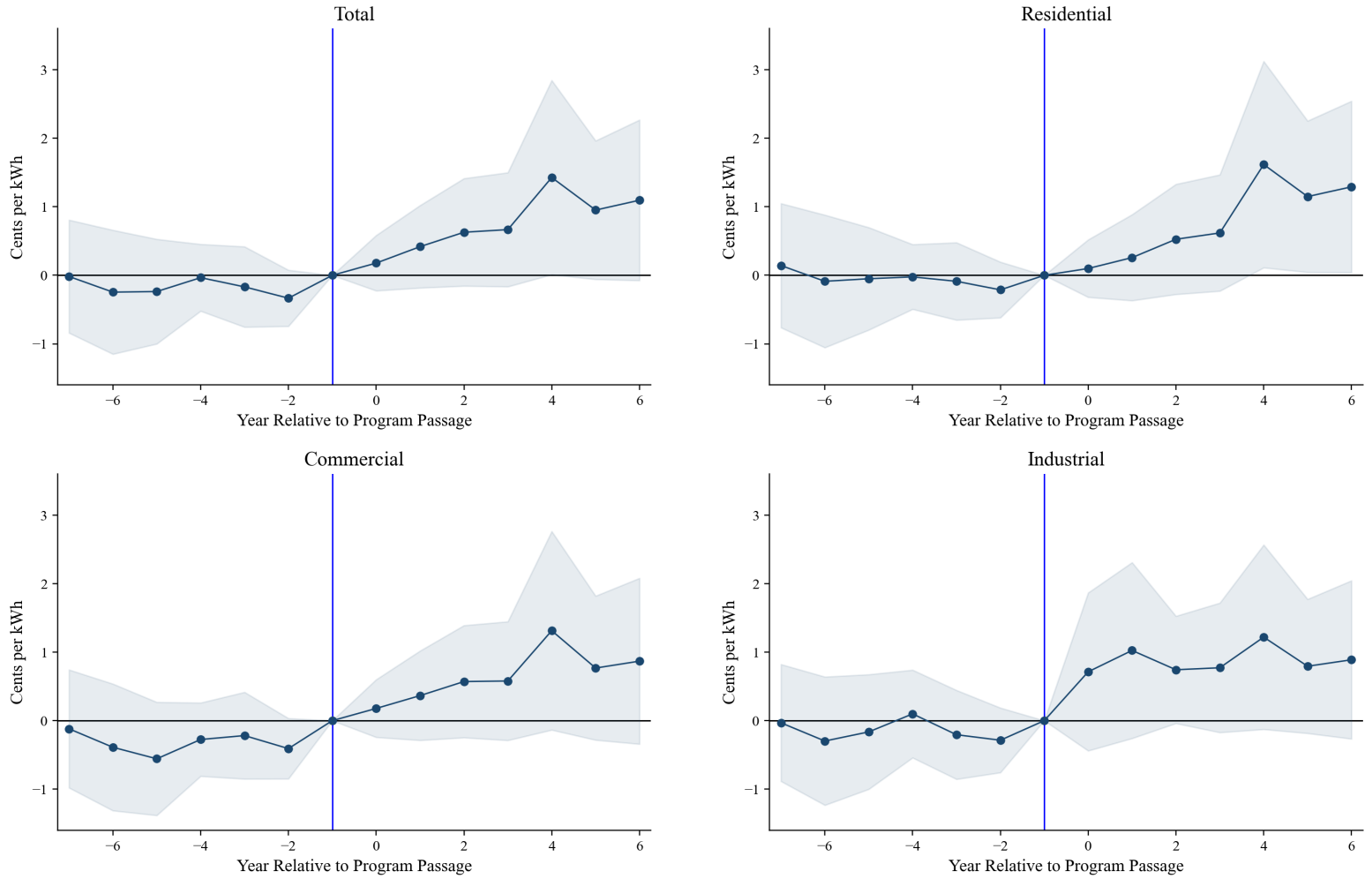
Notes: Graphs show estimates from a range of specifications employing synthetic controls methods, as recommended by Ben-Michael, Feller, and Rothstein (2021) for event years τ = -7 to τ = 11. For specifications that construct synthetic controls by targeting balance on independent variables, we use solar and wind potential, CO_2 intensity, percent RPS-eligible generation, percent coal and natural gas generation, Democratic control of state legislature, unemployment rate and population growth 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)



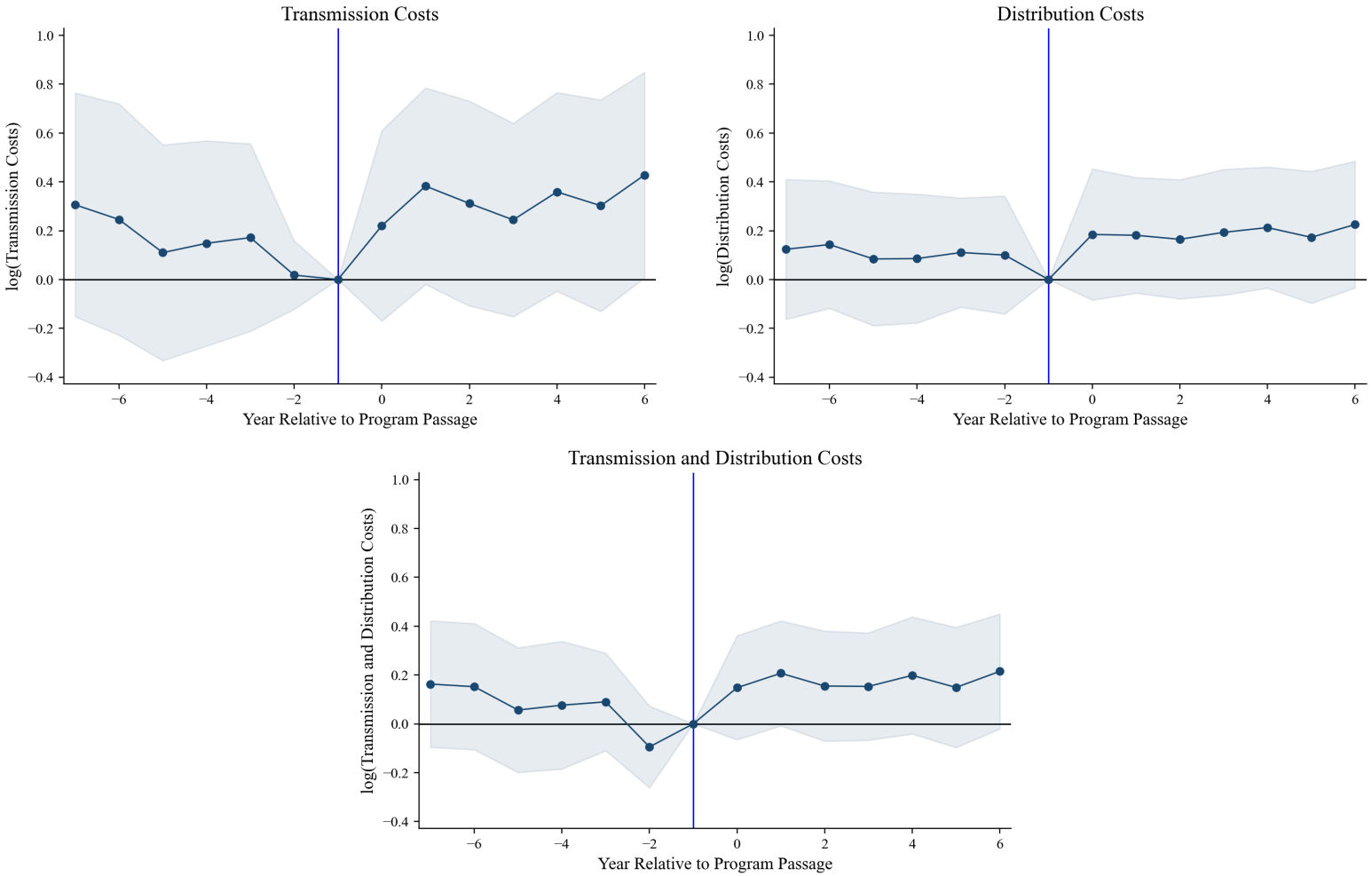
Notes: The graph shows the mean gross RPS requirement percentage for event years τ = -7 to τ = 11. We take gross RPS requirement data from the LBNL as constructed by Barbose (2018). Electricity price data are from the EIA. RPS program passage dates and requirements are from a combination of state legislative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



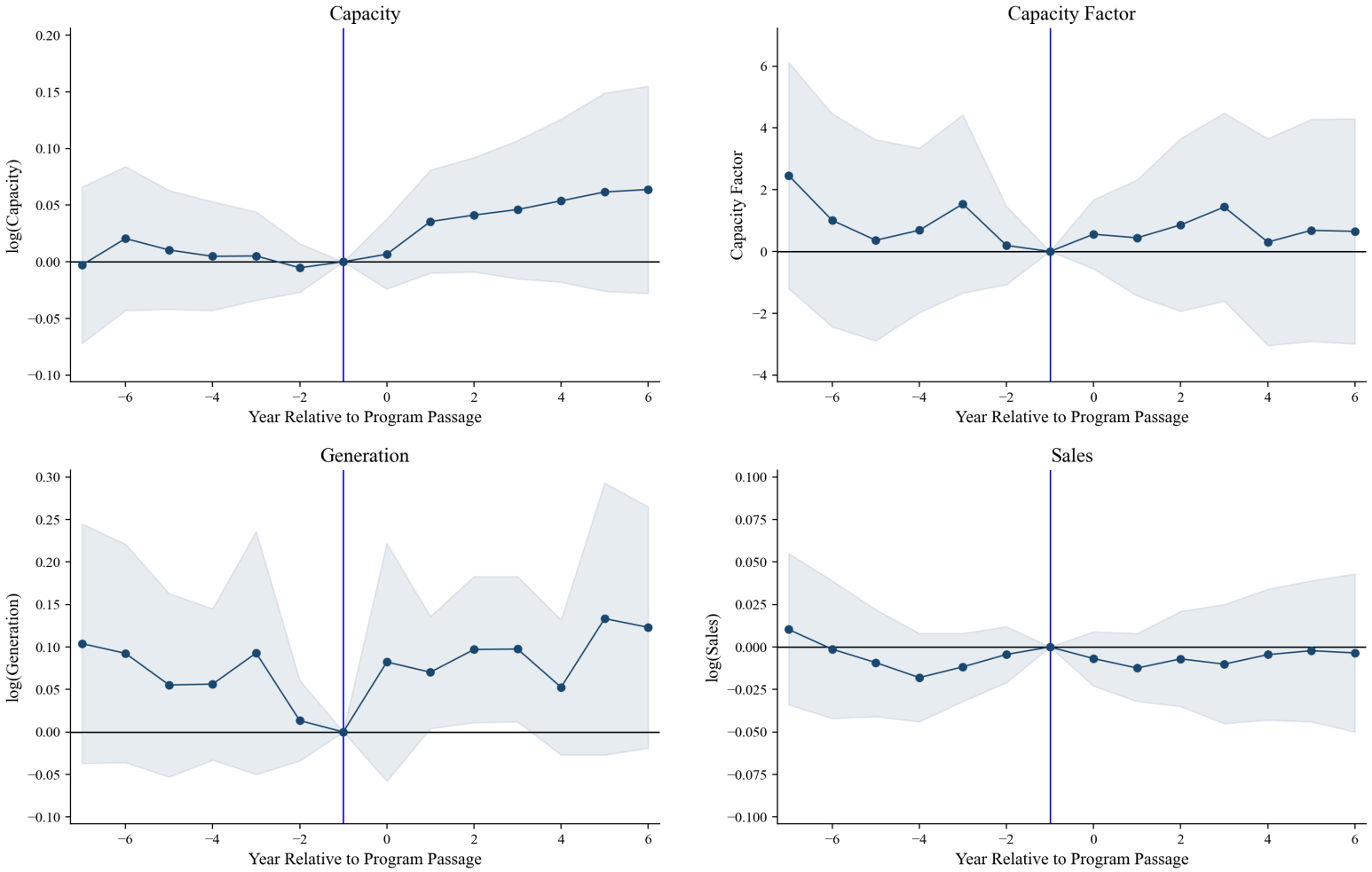
Notes: Graphs show coefficients for σ_τ for τ = -7 to τ = 11 from the event study specification in Equation (7) that regresses the dependent variable - retail electricity prices - on indicator variables for years relative to program passage, controlling for state and year fixed effects, and indicators 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



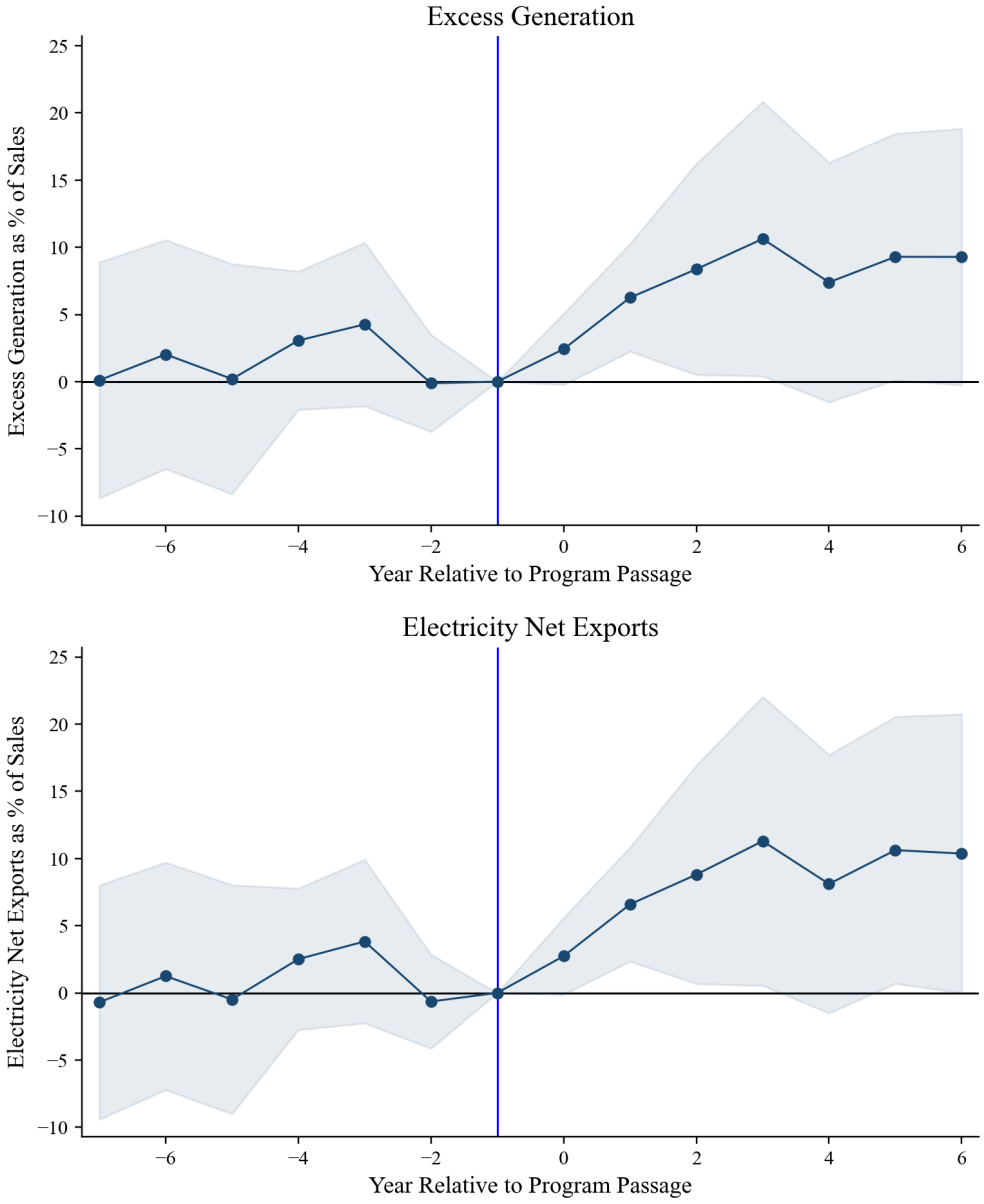
Notes: Graphs show coefficients for σ_τ for τ = -7 to τ = 6 from the event study specification in Equation (7) that regresses the dependent variable - transmission and distribution costs - on indicator variables for years relative to program passage, controlling for state and year fixed effects, and 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



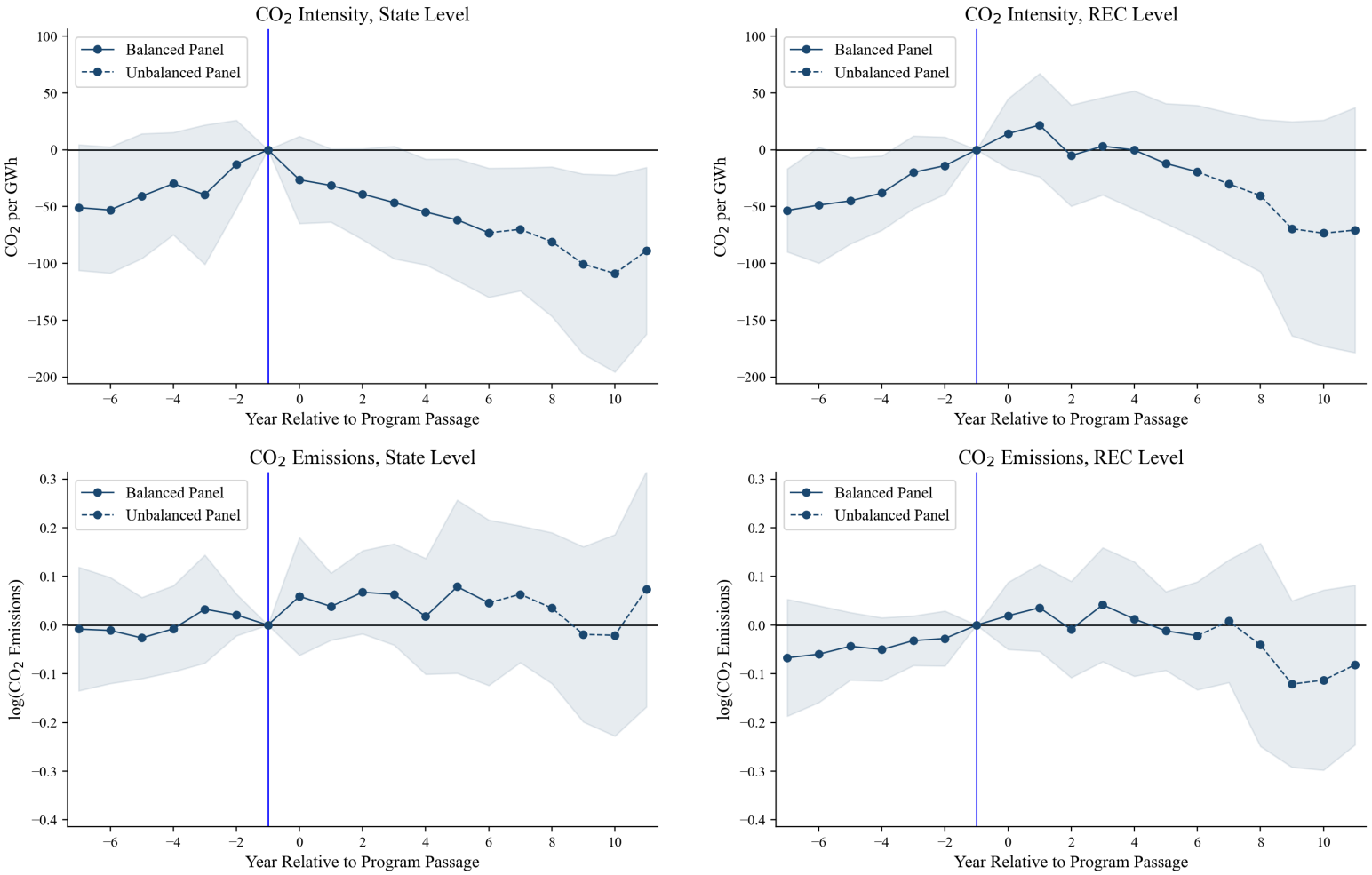
Notes: Graphs show coefficients for σ_τ for τ = -7 to $\tau = 6$ from the event study specification in Equation (7) that regresses the dependent variable - capacity, capacity factor, generation, and sales - on indicator variables for years relative to program passage, controlling for state and year fixed 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



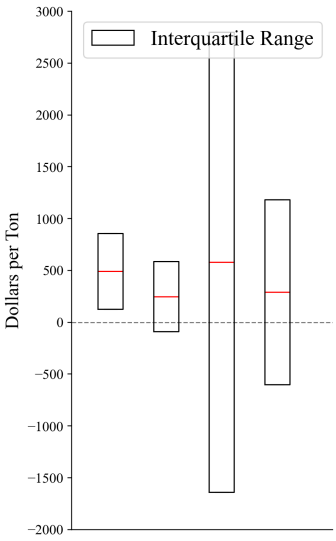
Notes: Graphs show coefficients for σ_τ for τ = -7 to τ = 6 from the event study specification in Equation (7) that regresses the dependent variable - excess generation and electricity net exports - on indicator variables for years relative to program passage, controlling for state and year fixed effects, 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.

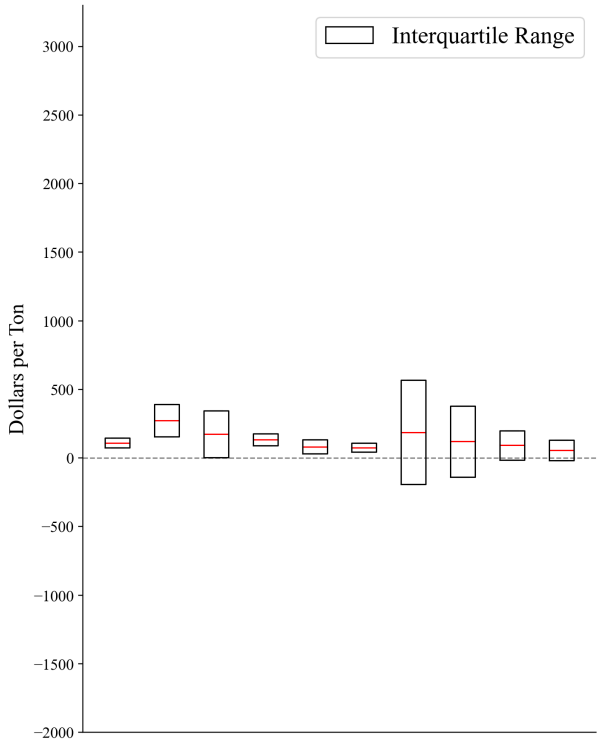
Figure A.9: Cost per Ton of CO_2 Abatement



Price Specification				
BA Aggregation (Sales Weighted)			✓	✓
State	✓	✓		
CO_2 Specification				
REC log(CO_2)	✓	✓	✓	✓
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 \$248 corresponds to using a REC region regression with state count regression weights measuring log(CO_2) reductions. The "State" specification for price comes from Column (1) of Table 2. The "BA Aggregation (Sales 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. 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.

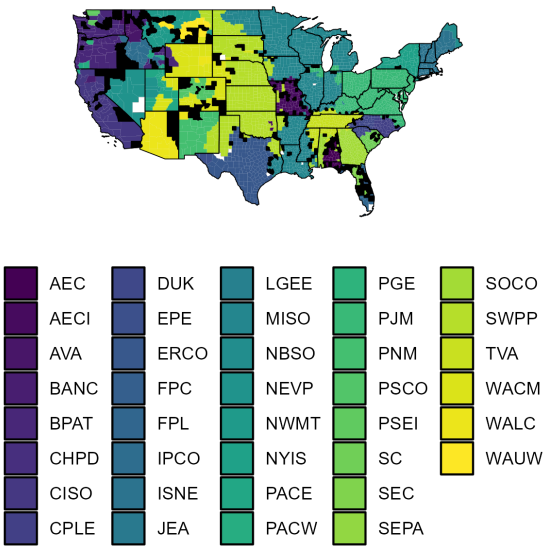
Figure A.10: Cost per Ton of CO_2 Abatement, 12 Years Post-Passage



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

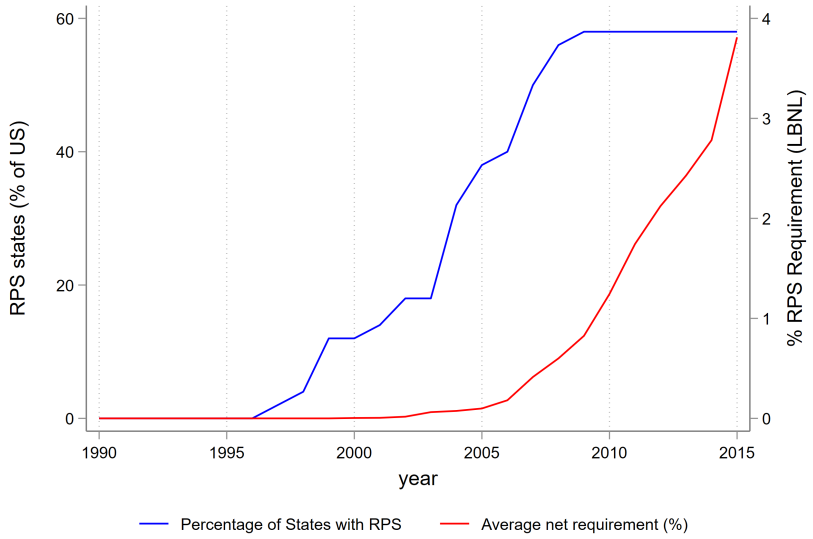
Notes: Each red line displays the cost per ton of CO_2 corresponding to a particular combination of specifications for estimating the impact of RPS on CO_2 reductions and retail electricity costs, in the 12th year post RPS passage. For example, the second column value of \$272 corresponds to using a REC region regression with no regression weight for measuring CO_2 reductions. The "State" specification for price comes from Column (1) of Table 2. The "BA Aggregation (Sales 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.

Figure A.11: Map of Balancing Authorities



Notes: We compile these boundaries using the EIA-861 county level data and aggregating to the balance authority level. Portions of some counties qualify for multiple balancing authorities. These mixed regions are filled in black.

Figure A.12: RPS requirements and Retail Time Series



Notes: This graph shows two relevant characteristics across our panel: the percentage of states in the U.S. with and RPS requirement and the average requirement in those states. We take RPS requirement data from the LBNL as constructed by Barbose (2018). 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.

Table A.1: Summary Statistics, Synthetic Control Method and Pre-RPS Period

	Mean RPS (1)	Mean SCM Control (2)	P-value RPS vs SCM Control (3)	Mean RPS (1997) (4)	Mean Non-RPS (1997) (5)
Price (2018 Cents/kWh)					
Total	13.3	10.6	0.00	14.0	10.8
Residential	15.6	12.8	0.00	17.1	13.2
Commercial	13.8	11.0	0.00	14.6	11.7
Industrial	9.9	7.8	0.00	10.0	7.7
Price Change in 7 Years Preceding RPS Adoption	-0.7	-0.7	0.93	-1.5	-2.0
Total Sales (TWh)	76.2	36.1	0.01	69.7	51.8
Population (Millions)	7.0	2.4	0.00	6.6	3.6
CO_2 Emissions (Million mt)	48.0	34.5	0.17	43.9	45.3
CO_2 Emissions Intensity (mt per GWh)	654.5	631.5	0.55	655.4	652.2
Renewable Potential (PWh)					
Solar	9.1	8.0	0.62	9.1	6.2
Wind	1.1	1.0	0.72	1.1	0.8
Generation					
Total (TWh)	80.5	48.1	0.05	73.4	63.3
RPS Eligible (TWh)	8.9	2.9	0.05	11.4	4.9
RPS Eligible (% of Total)	13.5	14.7	0.50	16.5	15.1
Generating Capacity					
Total (GW)	20.3	11.7	0.03	18.0	14.2
RPS Eligible (GW)	2.5	0.8	0.06	2.4	1.2
RPS Eligible (% of Total)	14.2	15.5	0.48	14.5	15.4
Other Programs (%)					
Public Benefits Fund	0.66	0.39	0.02	0.38	0.10
Net Metering	0.07	0.00	0.16	0.00	0.00
Green Power Purchasing	0.03	0.05	0.75	0.00	0.00
Energy Efficiency	0.59	0.19	0.00	0.34	0.05
Has Restructuring	0.38	0.08	0.00	0.00	0.00
Has NO_x Trading	0.15	0.03	0.00	0.14	0.03
Has Regional Greenhouse Gas Initiative	0.09	0.02	0.00	0.11	0.03
Has Carbon Cap and Trade Program	0.00	0.00	.	0.00	0.00
% of Counties Clean Air Act Non-Attainment	0.00	0.00	.	0.00	0.00
Additional Controls					
Democratic Control of State Legislature	0.48	0.43	0.59	0.38	0.43
Population Growth	1.19	0.97	0.26	0.88	0.82
Unemployment Rate	4.99	4.70	0.20	4.87	4.62
Energy Efficiency Expenditure (2018 Cents/kWh)	0.41	0.02	0.00	0.03	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. Columns (4) and (5) are summarized over eventual RPS and non-RPS states in 1997, prior to RPS passage in all states but Iowa. 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: Comparison Table With Upton and Snyder (2017)

	U&S Main		G&N Without Controls		U&S With G&N Controls	G&N With Controls		U&S with G&N	G&N Main	
	(1) Includes Iowa	(2) Restricted	(3) Restricted	(4) Unrestricted	(5) Restricted	(6) Restricted	(7) Unrestricted	(8) Restricted	(9) Restricted	(10) Unrestricted
Regression Estimates										
RPS × Post	0.91**	0.88**	0.66	0.66	0.80	0.88	0.89			
	(0.38)	(0.38)	(0.47)	(0.47)	(0.49)	(0.63)	(0.61)			
Mean Shift (δ_3)								0.24	0.33	0.42
								(0.16)	(0.25)	(0.26)
Trend Break (β_3)								0.13**	0.17*	0.17*
								(0.06)	(0.10)	(0.10)
Effect of RPS 7 years after passage ($6\beta_3 + \delta_3$)								1.05**	1.36**	1.43**
								(0.40)	(0.67)	(0.67)
Average Price	7.87	7.90	12.83	13.04	7.90	12.83	13.04	7.90	12.83	13.04
Data	U&S	U&S	G&N	G&N	U&S	G&N	G&N	U&S	G&N	G&N
Estimation	TWFE	TWFE	TWFE	TWFE	TWFE	TWFE	TWFE	MSTB	MSTB	MSTB
Controls	N	N	N	N	Y	Y	Y	Y	Y	Y
Sample Restriction	N	Y	Y	N	Y	Y	N	Y	Y	N
Years	1990-2013	1990-2013	1990-2013	1990-2015	1990-2013	1990-2013	1990-2015	1990-2013	1990-2013	1990-2015
States	49	48	48	50	48	48	50	48	48	50
Observations	1176	1152	1152	1300	1152	1152	1300	1152	1152	1300

Notes: Moving across the table, Columns (1) and (2) show estimates using U&S data and their main TWFE specification. They exclude Alaska and D.C. As we exclude Iowa in our main specification, columns denoted "restricted" with U&S data add Iowa to their excluded states. Columns (3) and (4) replicate Columns (1) and (2) with our data. Columns (5)-(7) are all U&S main specification with added controls: Public Benefit Funds, net metering, Green Power Policy, Energy Efficiency Standards, deregulation, NOx trading, nonattainment, RGGI, and carbon cap and trade. Columns (9) and (10) are our main specification and our data. In Column (9) we restrict our sample to the years and states that U&S include. Columns using G&N data use 2022 dollars. Columns using U&S data do not adjust for differences in price levels across years. 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: 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)	0.39	0.25	0.39	0.84
	(0.28)	(0.28)	(0.27)	(0.53)
Trend Break (β_3)	0.19*	0.31***	0.12	0.02
	(0.10)	(0.11)	(0.10)	(0.12)
Effect of RPS 7 years after passage	1.54**	2.09***	1.11	0.97*
($6\beta_3 + \delta_3$)	(0.70)	(0.77)	(0.71)	(0.55)
Panel B: 12 Post-Passage Years, Unbalanced Sample				
Mean Shift (δ_3)	0.46	0.37	0.44	0.72
	(0.36)	(0.36)	(0.35)	(0.46)
Trend Break (β_3)	0.17**	0.26***	0.11	0.08
	(0.08)	(0.08)	(0.09)	(0.10)
Effect of RPS 12 years after passage	2.34**	3.25***	1.63	1.58
($11\beta_3 + \delta_3$)	(0.94)	(1.02)	(1.03)	(0.97)
Mean at $\tau = -1$	13.3	15.6	13.8	9.9
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.4: 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)	0.52	0.27
	(0.41)	(0.40)
Trend Break (β_3)	0.13	0.21
	(0.13)	(0.15)
Effect of RPS 7 years after passage ($6\beta_3 + \delta_3$)	1.32	1.55
	(0.88)	(1.00)
(Effect of RPS 7 years after passage) * (Late)	−0.11	0.29
	(1.65)	(1.67)
Panel B: Ever Restructured		
Mean Shift (δ_3)	0.22	0.23
	(0.43)	(0.47)
Trend Break (β_3)	0.35**	0.41**
	(0.16)	(0.16)
Effect of RPS 7 years after passage ($6\beta_3 + \delta_3$)	2.31*	2.69*
	(1.30)	(1.36)
(Effect of RPS 7 years after passage) * (Restructured)	−0.96	−0.94
	(1.55)	(1.63)
Panel C: Has Solar Set-Aside		
Mean Shift (δ_3)	0.55	0.44
	(0.39)	(0.39)
Trend Break (β_3)	0.07	0.15
	(0.12)	(0.14)
Effect of RPS 7 years after passage ($6\beta_3 + \delta_3$)	0.99	1.32
	(0.90)	(1.11)
(Effect of RPS 7 years after passage) * (Solar Set-Aside)	1.23	1.31
	(1.44)	(1.47)
Panel D: Heavy Coal States		
Mean Shift (δ_3)	0.71	0.49
	(0.48)	(0.46)
Trend Break (β_3)	0.05	0.16
	(0.13)	(0.15)
Effect of RPS 7 years after passage ($6\beta_3 + \delta_3$)	0.99	1.46
	(1.00)	(1.16)
(Effect of RPS 7 years after passage) * (Heavy Coal)	0.89	0.68
	(1.48)	(1.59)
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.5: RPS Impact on Employment

	Employment	
	Total (1)	Manufacturing (2)
7 Post-Passage Years, Balanced Sample		
Mean Shift (δ_3)	0.00	−0.01
	(0.01)	(0.01)
Trend Break (β_3)	0.00	−0.00
	(0.00)	(0.00)
Effect of RPS 7 years after passage	0.03	−0.02
$(6\beta_3 + \delta_3)$	(0.02)	(0.03)
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.6: RPS Impact on Generation

	REC-Region Generation				State-level Generation			
	(1) Renewables	(2) Hydro and Nuclear	(3) Coal and Petroleum	(4) Natural Gas	(5) Renewables	(6) Hydro and Nuclear	(7) Coal and Petroleum	(8) Natural Gas
Panel A. 7 Post-Passage Years, Balanced Sample; Unweighted								
Regression Estimates								
Mean Shift (δ_3)	-0.15	0.35	3.77	-4.00	-0.21	0.91	-1.18	0.27
	(0.41)	(1.56)	(3.98)	(4.35)	(0.49)	(1.25)	(0.90)	(1.77)
Trend Break (β_3)	-0.16	0.07	-2.97***	3.12***	-0.24	0.81*	-1.55**	0.98
	(0.22)	(0.44)	(0.67)	(0.82)	(0.21)	(0.45)	(0.61)	(0.68)
Effect of RPS 7 years after passage	-1.08	0.77	-14.04*	14.72*	-1.63	5.77	-10.50**	6.16
$(6\beta_3 + \delta_3)$	(1.51)	(3.49)	(7.03)	(6.84)	(1.66)	(3.57)	(4.13)	(5.40)
Panel B. 7 Post-Passage Years, Balanced Sample; Weighted								
Regression Estimates								
Mean Shift (δ_3)	-0.63	2.48	-2.05	-0.02				
	(0.56)	(2.24)	(3.15)	(3.15)				
Trend Break (β_3)	-0.25	1.90*	-2.19**	0.51				
	(0.21)	(0.95)	(0.75)	(1.16)				
Effect of RPS 7 years after passage	-2.11	13.89*	-15.20**	3.05				
$(6\beta_3 + \delta_3)$	(1.65)	(7.33)	(5.81)	(6.77)				
Panel B. 12 Post-Passage Years, Balanced Sample; Unweighted								
Regression Estimates								
Mean Shift (δ_3)	-0.35	0.41	4.28	-4.47	-0.06	0.57	-0.93	0.20
	(0.45)	(1.42)	(5.20)	(5.62)	(0.73)	(1.39)	(1.50)	(2.28)
Trend Break (β_3)	-0.12	0.02	-3.13***	3.32***	-0.32*	0.95**	-1.72***	1.09
	(0.20)	(0.45)	(0.65)	(0.91)	(0.19)	(0.39)	(0.64)	(0.68)
Effect of RPS 7 years after passage	-1.67	0.68	-30.11***	32.02***	-3.56	10.99**	-19.81***	12.15
$(6\beta_3 + \delta_3)$	(2.52)	(5.68)	(8.49)	(9.38)	(2.29)	(5.17)	(7.05)	(8.31)
Panel B. 12 Post-Passage Years, Balanced Sample; Weighted								
Regression Estimates								
Mean Shift (δ_3)	-0.92	2.11	-2.24	0.70				
	(0.68)	(2.12)	(4.43)	(4.58)				
Trend Break (β_3)	-0.17	2.03*	-2.12**	0.27				
	(0.20)	(1.00)	(0.94)	(1.54)				
Effect of RPS 12 years after passage	-2.79	24.47*	-25.52**	3.68				
$(11\beta_3 + \delta_3)$	(2.55)	(12.43)	(9.25)	(14.57)				
Mean at $\tau = -1$	2.7	21.7	56.7	18.4	3.6	25.7	53.5	16.8
Other programs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	No	No	No	No
State FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	312	312	312	312	1300	1300	1300	1300

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 and state level. The REC level estimates are created by aggregating observations using the generation-weighted average of states in the region; the weighted specification further weights each REC level observation by the count of states in the region. All specifications control for REC region or State and year fixed effects, and indicators for the other programs listed in Table 1. Standard errors are clustered at the REC region level and state level respectively with statistical significance indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.7: RPS Impact on Other Pollutants

	(1) log(SO_2)	(2) SO_2 Intensity	(3) log(NOx)	(4) NOx Intensity	(5) Monitor PM2.5	(6) Satelite PM2.5
	Panel A. 12 Post-Passage Years, Unbalanced Sample; Unweighted					
Regression Estimates						
Mean Shift (δ_3)	0.09	-0.22	0.02	0.09	0.61	-0.05
	(0.20)	(0.31)	(0.18)	(0.23)	(0.65)	(0.16)
Trend Break (β_3)	-0.12***	-0.24*	-0.06*	-0.07	0.18	-0.11**
	(0.04)	(0.13)	(0.03)	(0.05)	(0.20)	(0.04)
Effect of RPS 12 years after passage ($11\beta_3 + \delta_3$)	-1.24**	-2.81*	-0.61	-0.73	2.60	-1.23**
	(0.48)	(1.40)	(0.43)	(0.73)	(2.76)	(0.52)
	Panel B. 12 Post-Passage Years, Unbalanced Sample, Weighted					
Regression Estimates						
Mean Shift (δ_3)	0.75	0.03	-0.10	-0.19	-0.10	-0.05
	(0.49)	(0.13)	(0.18)	(0.45)	(0.14)	(0.14)
Trend Break (β_3)	0.16	-0.04	-0.04	-0.35*	-0.03	-0.12**
	(0.13)	(0.04)	(0.06)	(0.19)	(0.02)	(0.04)
Effect of RPS 12 years after passage ($11\beta_3 + \delta_3$)	2.49	-0.45	-0.52	-4.04**	-0.41	-1.37**
	(1.83)	(0.34)	(0.62)	(1.79)	(0.27)	(0.56)
Mean at $\tau = -1$	14.1	8.4	12.1	2.4	11.5	1.4
Other programs	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
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 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.8: Robustness Checks for RPS Impact on CO_2 Emissions

	Robust 1		Robust 2		Robust 3		Robust 4		Robust 5	
	(1) log(CO_2 Emissions)	(2) CO_2 Intensity	(3) log(CO_2 Emissions)	(4) CO_2 Intensity	(5) log(CO_2 Emissions)	(6) CO_2 Intensity	(7) log(CO_2 Emissions)	(8) CO_2 Intensity	(9) log(CO_2 Emissions)	(10) CO_2 Intensity
Panel A. 7 Post-Passage Years, Balanced Sample; Unweighted										
Regression Estimates										
Mean Shift (δ_3)	0.03	15.59	0.04	15.69	0.04	14.13	0.07	24.37	0.03	10.73
	(0.04)	(16.73)	(0.04)	(17.53)	(0.04)	(17.33)	(0.06)	(24.90)	(0.03)	(11.84)
Trend Break (β_3)	-0.02*	-14.08***	-0.02*	-13.52**	-0.01*	-14.87***	-0.02	-13.76**	-0.01	-7.05
	(0.01)	(4.47)	(0.01)	(4.65)	(0.01)	(4.42)	(0.01)	(5.82)	(0.01)	(4.13)
Effect of RPS 7 years after passage ($6\beta_3 + \delta_3$)	-0.06	-68.87	-0.06	-65.42	-0.05	-75.12*	-0.02	-58.19	0.00	-31.55
	(0.06)	(38.92)	(0.07)	(40.45)	(0.06)	(38.91)	(0.07)	(53.29)	(0.05)	(32.78)
Panel B. 7 Post-Passage Years, Balanced Sample; Weighted										
Regression Estimates										
Mean Shift (δ_3)	-0.02	-14.59	-0.01	-18.91	-0.02	-23.12	-0.02	-31.99	-0.01	-19.53
	(0.04)	(19.43)	(0.05)	(22.13)	(0.05)	(22.06)	(0.06)	(27.82)	(0.04)	(16.83)
Trend Break (β_3)	-0.01	-20.03**	-0.01*	-18.58**	-0.01	-22.70**	-0.01*	-23.31**	-0.01	-18.77**
	(0.01)	(7.61)	(0.01)	(8.25)	(0.01)	(8.49)	(0.01)	(8.93)	(0.01)	(7.00)
Effect of RPS 7 years after passage ($6\beta_3 + \delta_3$)	-0.10	-134.78*	-0.10	-130.38*	-0.10	-159.34**	-0.11	-171.82*	-0.08	-132.16**
	(0.07)	(61.93)	(0.08)	(68.39)	(0.08)	(68.85)	(0.09)	(76.96)	(0.06)	(56.75)
Panel C. 12 Post-Passage Years, Unbalanced Sample; Unweighted										
Regression Estimates										
Mean Shift (δ_3)	0.05	22.44	0.05	22.14	0.05	21.13	0.09	30.16	0.04	9.84
	(0.04)	(20.30)	(0.05)	(21.08)	(0.04)	(20.53)	(0.06)	(29.06)	(0.04)	(16.49)
Trend Break (β_3)	-0.02**	-16.23***	-0.02**	-15.54***	-0.02**	-17.02***	-0.02**	-16.06***	-0.01	-6.53
	(0.01)	(4.33)	(0.01)	(4.64)	(0.01)	(4.50)	(0.01)	(4.88)	(0.01)	(4.40)
Effect of RPS 7 years after passage ($11\beta_3 + \delta_3$)	-0.16*	-156.12**	-0.18	-148.82**	-0.16	-166.08**	-0.15	-146.45*	-0.04	-62.02
	(0.09)	(57.08)	(0.10)	(60.40)	(0.09)	(58.41)	(0.11)	(70.69)	(0.08)	(51.07)
Panel C. 12 Post-Passage Years, Unbalanced Sample; Weighted										
Regression Estimates										
Mean Shift (δ_3)	0.00	-13.52	0.01	-18.87	0.00	-21.71	0.01	-31.41	0.01	-22.02
	(0.04)	(23.84)	(0.06)	(27.62)	(0.05)	(25.75)	(0.07)	(32.57)	(0.04)	(19.77)
Trend Break (β_3)	-0.02**	-20.34**	-0.02*	-18.49**	-0.02*	-23.13**	-0.02**	-23.56**	-0.02**	-17.72**
	(0.01)	(6.71)	(0.01)	(7.00)	(0.01)	(7.96)	(0.01)	(7.82)	(0.01)	(6.71)
Effect of RPS 12 years after passage ($11\beta_3 + \delta_3$)	-0.23*	-237.29**	-0.24*	-222.27**	-0.24*	-276.10**	-0.26**	-290.62**	-0.19*	-216.93**
	(0.11)	(90.24)	(0.13)	(96.86)	(0.13)	(104.83)	(0.12)	(109.75)	(0.10)	(88.03)
Mean at $\tau = -1$	17.7	656.7	17.7	656.7	17.7	656.7	18.1	628.6	17.7	677.2
Other programs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	312	312	312	312	312	312	260	260	494	494

Notes: The odd-columns show the impact of RPS on log(CO_2 emissions) while the even-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 $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.9: RPS Impact Per Unit of Net Requirement (REC Region Level)

	Price		log(CO_2)	CO_2 Intensity	Renewables	Wind	Solar	Hydro	Geothermal	Natural Gas	Coal	Biomass	Wood
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Panel A. Dst = Adjusted Net Requirement (LBNL); Unweighted													
Regression Estimates													
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st}$	0.71***		-0.01	-10.60	0.28	0.40*	-0.02	-0.01	-0.20	0.82	-0.62	0.11	0.02
	(0.21)		(0.01)	(7.76)	(0.52)	(0.22)	(0.08)	(0.39)	(0.16)	(1.37)	(1.00)	(0.10)	(0.04)
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st} \times$ Year<2010		0.92**											
		(0.37)											
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st} \times$ Year≥ 2010		0.47											
		(0.60)											
Effect 7 years after passage	0.96		-0.01	-14.35	0.38	0.54	-0.03	-0.02	-0.27	1.11	-0.83	0.14	0.03
Panel B. Dst = Raw Net Requirement (Lag Diff.); Unweighted													
Regression Estimates													
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st}$	0.10		0.03	1.82	-0.27	-0.11	-0.11	0.03	-0.16	1.20	-0.56	-0.08	0.02
	(0.48)		(0.03)	(7.87)	(0.38)	(0.46)	(0.09)	(0.36)	(0.16)	(1.73)	(1.11)	(0.17)	(0.04)
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st} \times$ Year<2010		0.44											
		(0.63)											
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st} \times$ Year≥ 2010		-0.06											
		(0.56)											
Effect 7 years after passage	0.07		0.02	1.23	-0.19	-0.07	-0.08	0.02	-0.11	0.81	-0.38	-0.05	0.02
Other Programs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
REC Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	312	312	312	312	312	312	312	312	312	312	312	312	312

	Price		log(CO_2)	CO_2 Intensity	Renewables	Wind	Solar	Hydro	Geothermal	Natural Gas	Coal	Biomass	Wood
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Panel A. Dst = Adjusted Net Requirement (LBNL); Weighted													
Regression Estimates													
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st}$	0.27		0.02	-1.04	0.39	0.77**	-0.05	0.30	-0.25	-1.86	2.48	-0.09	-0.03
	(0.55)		(0.03)	(12.48)	(0.57)	(0.32)	(0.08)	(0.44)	(0.18)	(2.67)	(2.11)	(0.21)	(0.04)
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st} \times$ Year<2010		1.22**											
		(0.52)											
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st} \times$ Year≥ 2010		-0.71											
		(0.69)											
Effect 7 years after passage	0.37		0.03	-1.41	0.53	1.04	-0.07	0.41	-0.34	-2.52	3.35	-0.13	-0.04
Panel B. Dst = Raw Net Requirement (Lag Diff.); Weighted													
Regression Estimates													
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st}$	-0.27		0.06	7.83	0.16	0.14	-0.02	0.13	-0.16	-2.32	1.11	0.10	0.02
	(0.47)		(0.04)	(10.91)	(0.48)	(0.44)	(0.12)	(0.47)	(0.15)	(2.63)	(1.68)	(0.19)	(0.04)
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st} \times$ Year<2010		0.69											
		(0.47)											
$\mathbf{1}[0 \leq \tau \leq 6] \cdot D_{st} \times$ Year≥ 2010		-0.76											
		(0.66)											
Effect 7 years after passage	-0.18		0.04	5.31	0.11	0.09	-0.01	0.09	-0.11	-1.57	0.75	0.07	0.01
Other Programs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
REC Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	312	312	312	312	312	312	312	312	312	312	312	312	312

Notes: Column (2) displays estimates from Equation (10). All other columns display estimates from Equation (9) on the REC region level. Panel A contains the LBNL measure of net requirement while Panel B utilizes the lag difference measure. Subtable 1 "unweighted", aggregates observations using the generation-weighted average of states in the region. Subtable 2 "weighted", 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 REC region level with statistical significance indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.10: RPS Impact on Electricity Prices with Alternative Restructuring Definitions

	State-level Aggregation			Balancing Authority Aggregation					
	(1) Base Specification	(2) Cicala	(3) Mercadal	(4) Sales-weighted	(5) State-count-weighted	(6) Sales-weighted	(7) State-count-weighted	(8) Sales-weighted	(9) State-count-weighted
Panel A. 7 Post-Passage Years, Balanced Sample; Unweighted									
Regression Estimates									
Mean Shift (δ_3)	0.36	0.28	0.30	0.73	0.23	0.63	0.26	0.71	0.17
	(0.22)	(0.27)	(0.22)	(0.57)	(0.53)	(0.49)	(0.55)	(0.57)	(0.51)
Trend Break (β_3)	0.14*	0.16	0.14*	0.14	0.35	0.18	0.49	0.13	0.39
	(0.08)	(0.12)	(0.08)	(0.16)	(0.29)	(0.19)	(0.40)	(0.16)	(0.29)
Effect of RPS 7 years after passage	1.23**	1.25	1.15**	1.59**	2.35	1.69**	3.17	1.51**	2.51
($6\beta_3 + \delta_3$)	(0.57)	(0.78)	(0.57)	(0.63)	(2.21)	(0.82)	(2.89)	(0.64)	(2.19)
Panel B. 12 Post-Passage Years, Unbalanced Sample; Unweighted									
Regression Estimates									
Mean Shift (δ_3)	0.38	0.11	0.34	0.93*	0.55	0.58	0.02	0.90*	0.50
	(0.27)	(0.32)	(0.28)	(0.49)	(0.81)	(0.58)	(0.61)	(0.48)	(0.80)
Trend Break (β_3)	0.14**	0.25***	0.13*	0.06	0.24	0.25*	0.62	0.05	0.28
	(0.07)	(0.07)	(0.07)	(0.12)	(0.18)	(0.13)	(0.41)	(0.12)	(0.19)
Effect of RPS 12 years after passage	1.93**	2.81***	1.77**	1.53	3.23	3.29***	6.89	1.43	3.57
($11\beta_3 + \delta_3$)	(0.78)	(0.87)	(0.79)	(0.99)	(2.72)	(1.04)	(4.94)	(0.97)	(2.71)
Other programs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cicala Restructuring		Yes				Yes	Yes		
Mercadal Restructuring			Yes					Yes	Yes
Balancing Authority FE				Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Census Region FE									
Year × Census Division FE									
Observations	1300	947	1300	1584	1584	1158	1158	1584	1584

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 our indicator variable for restructuring with a restructuring variable constructed in Cicala (2015). The Cicala (2015) indicator for restructuring is not available after 2010 so this specification covers a slightly reduced sample of years. Column (3) uses the Mercadal et al(2012) restructuring indicator. Columns (4) thorugh (9) 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. Alternate columns use different restructuring indicators. Standard errors are clustered at either the state level or the balancing authority level with statistical significance indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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 5 and A.8, and on generation in Appendix Table A.6. 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.11: 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.

12.5 Fuel Energy Prices

Fuel prices for utilities are obtained from the State Energy Data Systems (SEDS) from the EIA. SEDS provieds annual energy price and expenditure estimates for all energy sources by major economic sectors for the 50 states and the District of Columbia. All SEDS price estimates are in current dollars per million Btu to facilitate comparison across energy sources. EIA uses gross heat content values to convert prices in physical units to prices in million Btu. There is no adjustment for general inflation overtime, however, we adjust for inflation in our dataset. There is some missing data, notably, Vermont, Rhode Island, Idaho, and DC are missing fuel prices for coal, and Georgia and DC (except for one year) are missing data

for natural gas. However, these states have nearly zero generation from the source for which the data is missing with the exception of DC, which is missing most of the data for natural gas but has significant generation in later years.

We impute missing values by taking an equal-weighted average of neighboring states and years for which the data is available. If a state is missing prices for a given fuel source for all years, we impute using global average across time so that these states do not contribute to estimation of the coefficient for the respective fuel type. To check robustness we also implemented two other imputation rules: i) predicted values from a regression on fuel prices on year and state fixed effects and ii) predicted values from a regression on neighboring states' fuel prices. In addition to different imputation rules, we also tried restricting the sample away from states that are missing data for all years for any given source (in combination with all three imputation rules). Regression results are robust to alternative imputation rules and sample restrictions.