Indirect Effects of Renewable Portfolio Standards on Carbon Emissions

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Abstract

Renewable Portfolio Standards (RPS) are a popular class of state-level renewable energy policies in the United States. I analyze how existing electricity generation markets adjust to the introduction of RPS policies, and the implications of this adjustment for carbon emissions. I estimate the effect of RPS policies on total carbon emissions from generation, decomposed into: (1) change in demand for electricity, (2) changes in the utilization shares of different fuels in generation, and (3) changes in the carbon intensity of generation by fuel type. I find that, while RPS policies do increase renewable generation, the carbon implications of this change are small compared to those of the indirect effects of RPS policies. In particular: decreased quantity of electricity generated (carbon-negative), increased coal generation relative to natural gas (carbon-positive), and increased carbon intensity of fuel generation (carbon-positive). These effects appear to cancel out somewhat, and I do not find a statistically significant net effect of RPS policies on carbon emissions.

1 Introduction

In recent years, concerns about carbon emissions and climate change have led many state governments to pass regulations encouraging renewable generation. The most popular of these are Renewable Portfolio Standards (RPS), versions of which are currently in effect in 31 states and Washington, DC.

Renewable portfolio standards are a class of policies that encourage renewable generation by mandating that some proportion α of a state's energy generation[1] come from eligible renewable sources by a target year $\bar{t}$. These eligible sources typically only include wind and solar. I refer to α as the "nominal requirement." RPS policies enforce this mandate by introducing tradable Renewable Energy Credits (RECs). An RPS enacted in year $\underline{t}$ mandates that, each year beginning with the target year $\bar{t}$, (generally several years after $\underline{t}$) eligible renewable generators will receive RECs for each MWh of energy produced that year. All generators must then trade

[1] Or, occasionally, consumption. See next paragraph.

RECs until each generator owns RECs equal to α times the total quantity of electricity it generated that year.

I analyze how existing electricity generation markets adjust to the introduction of RPS policies, and the implications of this adjustment on carbon emissions. I do this by first using panel data at the state-year level from 1997 to 2013 to estimate the effect of RPS policies on per capita generation and carbon emissions intensity for each of the following energy sources: coal, natural gas ("gas"), combined wind and solar, and other. Next, I perform a counterfactual exercise in which I compare all treated states in 2013 with an untreated counterfactual. I compare the difference in total emissions between the data and the counterfactual, and decompose this difference into: (1) change in total per capita generation, (2) change in the relative utilization of energy sources in generation, and (3) change in the average carbon intensity of generation by energy source.

Our estimate of the effect on total emissions is positive but not highly significant. More interestingly, I find that coal generation tended to increase relative to natural gas in response to RPS policies, which increases total carbon emissions, and that the carbon emissions intensity of fuel (coal and gas) generation also tended to increase. However, I also find that total generation quantities tended to decrease in response to RPS policies, which decreases carbon emissions. Previous literature suggests that these indirect effects of RPS policies are largely due to the intermittent nature of wind and solar generation, and the ways in which existing generation must adjust to accommodate it.[2]

While an increased renewable share of generation *per se* reduces emissions, this decomposition suggests that, in terms of its impact on carbon emissions, this effect of RPS policies is dwarfed by the indirect channels described above. That is: reduction in total generation quantities (carbon-negative), increased coal share relative to natural gas (carbon-positive), and increased carbon intensity of fuel generation (carbon-positive). These channels cancel out somewhat, and I do not find a statistically significant overall effect of RPS policies on total carbon emissions. However, the errors on this estimate on total carbon emissions is an order of magnitude larger than the estimated effect of increased renewable share, and the error thereof.

I reiterate that I only estimate the effect of RPS policies on 2013 emissions within the state that passed the RPS. Thus, I do not take into account effects materializing after 2013, even though all but eight of the policies I study have target years after 2013. High fixed costs of entry might also lead to slow adjustment and a delayed materialization of the full effect. Furthermore, I do not consider these policies' role in accelerating innovation in renewable energy, an effect which could catalyze or hasten widespread adoption of renewables. Finally, I do not consider the effect of RPS policies passed in one state on its surrounding states, though these effects are likely important.

Section 2 describes existing research on RPS policies. Section 3 describes my data sources and the construction of the stringency measure. Section 4 discusses emissions and the power mix. In it I present summary statistics on U.S. power mix, explicitly define the decomposition I

[2]See Section 4.3

outline above, and discuss the economics of these channels in relation to RPS policies. Section 5 describes my two-stage empirical approach. Section 6 presents the results of this analysis. Section 7 concludes.

2 Previous Work

2.1 Renewable Portfolio Standards

Theoretical and simulation-based work on RPS policies have the longest history. Palmer and Burtraw, 2005 simulate a national RPS and find that it would increase renewable capacity and energy prices, decrease demand, and that renewables would disproportionately displace gas over coal. Fischer, 2010 finds that we might expect RPS policies to lower electricity prices in the short run, but that prices would rise if the policy were sufficiently stringent.

As RPS policies have been enacted, research has begun to study their effects ex post. They have, to varying degrees, encountered certain empirical challenges. First, RPS policies are highly heterogeneous in their implementation. Wiser and Bolinger, 2007 describe many dimensions of RPS heterogeneity, which I discuss in section 3.1.

Second, the adoption of an RPS policy is an endogenous event. Lyon and Yin, 2010 analyze the factors leading states to adopt an RPS, arguing that they are popular because they are perceived as advancing multiple political goals simultaneously. They also find that the adoption of an RPS is driven by, *inter alia*, the left/right political leaning of the state legislature, low gas generation, and high state solar and wind potential. Thus, the presence of unobserved pro-renewable trends or policies could be correlated with the adoption of an RPS. However, in general these findings have the opposite sign from what one would expect if other carbon-targeting regulations passed in RPS states were driving these findings.

Third, states are heterogeneous in many ways that could affect the impact of an RPS, including in existing renewable capacity, which is taken into account in the analysis of Yin and Powers, 2010. States also vary in their solar potential, wind potential, and the size of their mining and manufacturing sectors. These are taken into account in the analysis of Upton and Snyder, 2017.

Due in part to these complicating factors, estimates of the effects of a state-level RPS remain broadly dispersed. Early papers, such as Menz and Vachon, 2006 and Adelaja et al., 2010 use a cross-sectional approach and a binary variable for the existence of an RPS and find that renewable development is greater in states with an RPS. Shrimali and Kniefel, 2011 use a panel data approach and differentiate between RPS policies based on their nominal requirement, finding that RPS policies based on generation do not increase renewable capacity. Tackling the issue of deeper RPS heterogeneity, Yin and Powers, 2010 develop a measure of the effective stringency of an RPS. They find that RPS policies do induce an increase in the renewable share of generation capacity, but only as a function of the shortfall between the renewable share present when the policy is enacted and the share actually mandated by the policy.[3] With a binary RPS variable taking no heterogeneity into account, they find no effect on renewable share. When interacting this binary variable with the nominal requirement of the RPS, the effect has a positive sign. Also approaching the issue of deeper RPS heterogeneity, Carley and Miller, 2012 develop a simple, one-dimensional, time-invariant measure of the stringency of an RPS, which I also adopt. Tackling the issue of state heterogeneity, Upton and Snyder, 2017 use the method of synthetic controls to generate composite control observations: linear combinations of actual (non-treated) states into control states that most closely resemble treated states. Furthermore, they study the effect of RPS policies on renewable generation and electricity demand and are the first to empirically study the effect of RPS policies on electricity prices. They also study the effect of RPS policies on state-level carbon emissions from fuel generation, but do not decompose this effect.

Greenstone and Nath, 2019 study the effect of RPS policies on generation by fuel type and on emissions, as I do, as well as on total generation. They similarly emphasize that indirect costs of RPS policies–costs of the adjustments they necessitate in the state's electricity market–are the main component of total welfare costs. They do examine the effect of RPS policies on generation by energy source and overall emissions intensity. However, they stop at estimating the effect of RPS policies on these quantities, and do not quantitatively analyze the implications of these estimated effects for carbon emissions, as I do. Neither do they examine emissions intensity by energy source, a necessary component of the decomposition I estimate. Indeed, to the best of my knowledge, this study is the first to estimate a decomposition of the effects of RPS policies on carbon emissions.

2.2 Heterogeneous Externalities by Fuel

A key driver of my analysis is that some fuels are more carbon intensive than others. However, production of carbon dioxide by combustion is not the only externality associated with using fuel to generate electricity, even with regard to climate change.

Fuel extraction can have complex and extensive environmental costs. Jenner and Lamadrid, 2013 perform a study of negative externalities of coal and gas generation, such as nitrogen oxide and sulfur dioxide emissions from coal generation, which contribute to respiratory illnesses and acid rain; leakage of methane, a greenhouse gas thirty times more potent than CO2, from gas extraction; and groundwater contamination from shale gas extraction via hydraulic fracturing ("fracking"). They find that coal has greater negative externalities on public health, worker safety, local environmental protection, and carbon emissions, but that the relative effect of coal and gas on total greenhouse gas emissions depends on the rate of methane leakage in gas extraction. Fuel supply chains are also responsible for carbon emissions through energy consumption, estimated at 10.5% of generation emissions for coal by Wu et al., 2016.

CO2 emissions are the only externality I directly address. However, my results about the effects of RPS policies on fuel mix have direct welfare implications whenever externalities of

[3]For a more detailed discussion of this shortfall measure, see Section 3.1.

generation differ by fuel type.

3 Data

I perform my primary analysis at the state-year level from 1997 to 2013. I include every continental U.S. state with nonzero gas and coal generation throughout the sample period, leaving 46 states.[4] I use state-year level data from the Energy Information Administration (EIA) on total generation and total emissions by energy source. To put variables in per capita form, I use population estimates from the United States Census Bureau.

3.1 Stringency

RPS policies are highly heterogeneous along a number of dimensions. Wiser and Bolinger, 2007 document that state RPS policies vary in, among other things, the nominal requirement, the target year, whether they regulate energy production or consumption, whether they permit RECs to be traded across state lines, which renewable technologies are eligible, penalties for noncompliance, and exclusions for generators. This final dimension is a complex one. RPSs often exclude or differentially regulate different classes of generators: investor-owned, consumer-owned, or publicly-owned; urban or rural; or generators whose annual generation exceeds a threshold quantity. Some RPSs also exclude specific generators by name.

In order to account for this heterogeneity, some empirical papers have introduced one-dimensional measures of the stringency of an RPS, where a stringency of zero is equivalent to the absence of an RPS.

I use a measure of RPS stringency introduced by Carley and Miller, 2012, who compute this measure from 1997 through 2008. I use the extended set of values computed by Upton and Snyder, 2017 through 2013. The measure is defined as the annualized increase in the mandated proportion of renewable generation in a state s and year t, as described in Equation 1.

$$AS_{st} \equiv \text{annualized stringency} = AS(R_{st}) = \frac{\alpha_{\text{final}}(R_{st}) - \alpha_{\text{starting}}(R_{st})}{\text{year}_{\text{final}}(R_{st}) - \text{year}_{\text{starting}}(R_{st})} \cdot \text{Coverage}(R_{st}) \cdot 100 \tag{1}$$

Here, R_{st} refers to the RPS policy in effect in state s in year t. The variable $\alpha_{\text{initial}}(R_{st})$ refers to the nominal requirement in effect prior to the passage of the current RPS R_{st}. Unless R_{st} replaced a preexisting RPS, this value will be zero. The variable $\alpha_{\text{final}}(R_{st})$ refers to the nominal requirement of R_{st}. The year that R_{st} was passed is $\text{year}_{\text{starting}}(R_{st})$, and the target year of R_{st} is $\text{year}_{\text{final}}(R_{st})$. Finally, $\text{Coverage}(R_{st})$ refers to the proportion of generation covered by R_{st}. Note that all heterogeneity in coverage (due for example to exemptions or differential requirements for different classes of generators) is thus accounted for in $\text{Coverage}(R_{st})$.

[4]Excluded are Alaska, Hawaii, Vermont and Rhode Island.

This measure can be thought of as a linear interpolation of the RPS mandate between the start and end year of the policy. In their analysis, Upton and Snyder, 2017 use as their independent variable the interaction between "annualized stringency" AS_{st} and the number of years that an RPS has been in effect:

$$\mathrm{RPS}_{st} = t - \mathrm{year}_{\mathrm{starting}}(R_{st}).$$

This product variable essentially linearly interpolates the renewable generation requirement of the RPS between the start and end year of the policy. That is, at the start year, their regressor is equal to

$$AS_{st} \cdot \mathrm{RPS}_{st} = AS_{st} = 0$$

and at the target year equal to

$$AS_{st} \cdot \mathrm{RPS}_{st} = (\alpha_{\mathrm{final}}(R_{st}) - \alpha_{\mathrm{starting}}(R_{st})) \cdot \mathrm{Coverage}(R_{st}) \cdot 100.$$

I do something very similar, except that I wish to account for preexisting RPS policies and revisions to policies. I will therefore define a regressor S_{st} with the property that at the start year of a policy

$$S_{st} = \alpha_{\mathrm{starting}} \cdot \mathrm{Coverage}(R_{st}^{\mathrm{previous}}) \cdot 100$$

and at the end year of a policy

$$S_{st} = \alpha_{\mathrm{final}} \cdot \mathrm{Coverage}(R_{st}) \cdot 100.$$

I desire the regressor to have the following property: when a policy is revised between its start year and end year, the current year's S_{st} should be unaffected, but the values of S_{st} between the current year and end year should linearly interpolate between the current value and the new value of $\alpha_{\mathrm{final}} \cdot \mathrm{Coverage}(R_{st}) \cdot 100$. To achieve these properties, I define this regressor as follows.

$$S_{st} = (\text{interpolated stringency})_{st} = \sum_{\tau=-\infty}^{t} AS_{s\tau}. \tag{2}$$

Because revisions to RPS policies are rare in this panel, this regressor usually matches up with the regressor of Upton and Snyder, 2017. In cases where it differs, I believe mine to be a slightly more reasonable reflection of a state's total exposure to RPS legislation.

The measure of Carley and Miller, 2012, upon which I base this regressor, does not take into account existing generation. In particular, if a state already fulfills the requirement when the policy is passed, I would expect it to have no effect. However, this measure would consider the policy equivalent to an identical policy in a state with preexisting renewable capacity. For an alternative measure of RPS stringency which does take into account existing generation, see Yin and Powers, 2010.

4 Emissions and Power Mix

Total carbon emissions arise as the dot product of total generation by energy source and average carbon intensity by energy source. Since energy sources vary significantly in their carbon intensity, the power mix–the relative use of different energy sources in generation–is a key determinant of total emissions. In this section, I first describe summary statistics of levels and trends in generation and carbon intensity data by energy source. I then define a decomposition of a change in net emissions into (1) effects of changes in the total quantity of electricity generated, (2) effect of changes in the utilization shares of different fuels in generation, and (3) effects of changes in the carbon intensity of generation by fuel type. Finally, I describe different mechanisms by which electricity generation markets might respond to RPS policies, and how these mechanisms might affect carbon emissions through different channels of the decomposition I define.

4.1 Power Mix: Summary Statistics

Coal and gas together accounted for approximately two-thirds of total U.S. electricity generation throughout my panel, from 1997 to 2013. Within that two-thirds, gas gradually began to supplant coal, a trend which continues to the present. The majority of the remaining generation is nuclear and hydroelectric, whose levels have remained largely stable. Wind and solar have gained a small foothold in recent years, but levels remained negligible until near the end of the panel. Figure 1 shows trends in total generation by fuel source and Figure 2 shows trends in relative utilization. Table 1 reports relative utilization by power source in a few snapshot years.

While my main analysis will show a positive coefficient on coal generation, new coal capacity is actually rare. Figure 3 shows newly-activated coal capacity in the U.S.–capacity active in a given year but inactive the previous year–as a proportion of existing capacity, by year. This is divided into reactivated capacity–capacity which has been utilized at some point in the past–and new capacity, which has not. Together, they average just under 0.2% of total coal capacity per year over 14 years. Our main analysis then largely indicates that RPS policies cause states' coal generation to decline more slowly, rather than to actually increase.

The carbon intensities of different fuel types have also been experiencing differing trends. The average carbon intensity of coal used in electricity generation is higher than gas and has been stable in the 1000 kg/MWh range. The average carbon intensity of gas trended downwards from the 620 kg/MWh range to the 470kg/MWh range over the duration of the panel. The carbon intensity of average U.S. electricity generation, slightly higher, trended downward from the 650 kg/MWh range to the 550 kg/MWh range throughout the panel. Annual values are presented graphically in Figure 4.

4.2 Decomposition

Let $\vec{q}$ denote the vector of total electricity generation by energy source (for some region, over some time period), and let $\vec{b}$ denote the vector of average carbon intensities of generation by energy source. Then total carbon emissions are given by

$$\text{Total Carbon Emissions} = \vec{q} \cdot \vec{b} = q_1 b_1 + q_2 b_2 + \cdots + q_n b_n.$$

Now suppose that $\vec{q}^p$ and $\vec{b}^p$ refer to generation and carbon intensity if some policy were to be implemented, and $\vec{q}^u, \vec{b}^u$ to generation and carbon intensity in the absence of such a policy. Then the net effect of the policy on total carbon emissions is given by

$$\vec{q}^p \cdot \vec{b}^p - \vec{q}^u \cdot \vec{b}^u.$$

I wish to decompose this effect.

4.2.1 Coarse Decomposition

I begin by decomposing into three broad channels:

1. **Total generation quantity.** The effect of a change in total electricity generated.
2. **Power mix.** The effect of changes in the relative utilization of different energy sources for generation.
3. **Carbon intensity.** The effect of changes in average carbon intensitiy of generation by fuel type.

Let C_i denote the contribution of Channel i. Channel 1 is given by simply scaling total emissions by the change in total generation, where $|\cdot|$ denotes the sum.

$$C_1 = \frac{|\vec{q}^p|}{|\vec{q}^u|}\vec{q}^u \cdot \vec{b}^u - \vec{q}^u \cdot \vec{b}^u$$

Channel 2 is given as the effect of the change in the vector of quantities $\vec{q}^p$ (while keeping carbon intensities constant at $\vec{b}^u$), minus the contribution of Channel 1.

$$C_2 = \vec{q}^p \cdot \vec{b}^u - \frac{|\vec{q}^p|}{|\vec{q}^u|}\vec{q}^u \cdot \vec{b}^u$$

Finally, Channel 3 is given by the effect of the change in the vector of carbon intensities, given the new vector of quantities.

$$C_3 = \vec{q}^p \cdot \vec{b}^p - \vec{q}^p \cdot \vec{b}^u.$$

4.2.2 Fine Decomposition

I can also perform a finer decomposition, in which I look at the contribution from changes in each component of $\vec{q}$ and $\vec{b}$. That is, total generation and carbon intensity for each energy source. In my analysis, I divide energy sources into the following four categories: (1) coal, (2) gas, (3) combined wind and solar, and (4) other (which I signify by c, g, r, and o respectively) so that

$$\begin{aligned} \vec{q} &= [q_c, q_g, q_r, q_o] \\ \text{and} \quad \vec{b} &= [b_c, b_g, b_r, b_o] \,. \end{aligned}$$

Suppose again that the treated and untreated states are $(\vec{q}^p, \vec{b}^p)$ and $(\vec{q}^u, \vec{b}^u)$, respectively, as before. Channel 1 is still given by

$$C_1 = \frac{|\vec{q}^p|}{|\vec{q}^u|}\vec{q}^u \cdot \vec{b}^u - \vec{q}^u \cdot \vec{b}^u.$$

Channel 2 is decomposed into three subchannels corresponding to the change in wind and solar generation relative to everything else, the change in "other" generation relative to coal and gas, and the change in coal generation relative to gas. These subchannels, denoted by C_{2r}, C_{2o}, and C_{2c}, are given by

$$\begin{aligned} C_{2r} &= \frac{q_c^p + q_g^p + q_o^p}{q_c^u + q_g^u + q_o^u}(q_c^u b_c^u + q_g^u b_g^u + q_o^u b_o^u) + q_r^p b_r^u - \frac{|\vec{q}^p|}{|\vec{q}^u|}\vec{q}^u \cdot \vec{b}^u \\ &= \frac{q_c^p + q_g^p + q_o^p}{q_c^u + q_g^u + q_o^u}\vec{q}^u \cdot \vec{b}^u - \frac{|\vec{q}^p|}{|\vec{q}^u|}\vec{q}^u \cdot \vec{b}^u \qquad \text{(since } b_r^p = b_r^u = 0\text{)} \\ C_{2o} &= \frac{q_c^p + q_g^p}{q_c^u + q_g^u}(q_c^u b_c^u + q_g^u b_g^u) + q_o^p b_o^u - \frac{q_c^p + q_g^p + q_o^p}{q_c^u + q_g^u + q_o^u}\vec{q}^u \cdot \vec{b}^u \\ C_{2c} &= q_c^p b_c^u + q_g^p b_g^u - \frac{q_c^p + q_g^p}{q_c^u + q_g^u}(q_c^u b_c^u + q_g^u b_g^u) \end{aligned}$$

Intuitively, for each energy source e, its subchannel is computed by comparing total emissions computed using a measure of carbon intensities which considers e separately to one which lumps e together with other energy sources.

Channel 3 is further decomposed into three channels, corresponding to the change in carbon intensity of generation using coal, gas, and "other," respectively.[5] These subchannels, respectively denoted by C_{3o}, C_{3g}, and C_{3c}, are given by

$$\begin{aligned} C_{3o} &= q_o^p b_o^p - q_o^p b_o^u \\ C_{3g} &= q_g^p b_g^p - q_g^p b_g^u \\ C_{3c} &= q_c^p b_c^p - q_c^p b_c^u. \end{aligned}$$

[5] I do not include a subchannel for wind and solar, as these always have zero carbon intensity of generation.

Thus, the entire difference in carbon emissions between the treated and untreated states is given by these channels:

$$\begin{aligned}\vec{q}^p \cdot \vec{b}^p - \vec{q}^u \cdot \vec{b}^u &= C_1 + C_2 + C_3 \\ C_2 &= C_{2r} + C_{2o} + C_{2c} \\ C_3 &= C_{3o} + C_{3g} + C_{3c}.\end{aligned}$$

4.3 Power Mix and Renewable Portfolio Standards

To understand the net effect of RPS policies on carbon emissions, I must look at all of the channels detailed above. By contrast, previous work has focused on the effect of RPS policies on renewable generation, essentially only considering only (sub-)Channel C_{2r}. Exceptions to this are Upton and Snyder, 2017 who consider the effect of RPS policies on prices and total generation quantities and total emissions; and Greenstone and Nath, 2019, who study the effect of RPS policies on generation by energy source as well as on total emissions. However, while they report on the effects of RPS policies on generation by energy source, they do not quantify the implications of these changes for carbon emissions.

By analyzing the effect of RPS policies on the determinants of carbon emissions, I can gain insight into how electricity generation markets adapt to RPS policies. Different mechanisms by which an electricity generation market might adjust to the introduction of an RPS policy will affect carbon emissions through different channels of this decomposition. Thus, examining the estimated magnitudes of these channels can provide evidence for or against the existence of possible adjustment mechanisms. Furthermore, this decomposition allows us to study the magnitude of these adjustments in terms of their relative effect on carbon emissions. In the following, I relate the channels I have defined to the market adjustments that may contribute to them, and the economics of how RPS policies might induce these adjustments.

4.3.1 Channel 1: Total generation quantity

When total generation quantity decreases *ceteris paribus*, emissions also decrease. The most likely explanation for a decrease in total generation quantity is an increase in prices caused by, in broad terms, an inward shift of the supply curve. Indeed, Upton and Snyder, 2017 and Greenstone and Nath, 2019 find that RPS policies increase retail electricity prices. Economically, prices likely increase because the adjustments made by the generation market to RPS policies decrease their efficiency.

4.3.2 Channel 2: Power Mix

Wind and Solar

Channel C_{2r}, the effect of a change in the market share of wind and solar generation, is the channel that has received the most attention in the literature thus far. Its mechanism is clear and direct. An RPS induces cross-subsidization of wind and solar by other energy sources, decreasing the effective cost of wind and solar generation while increasing the cost of other generation. This subchannel is the focus of earlier empirical work such as Yin and Powers, 2010 and Nicolini and Tavoni, 2017.

Coal, Gas, and Other

Because different fuel types have different carbon intensities, a change in the relative shares of coal and gas, for example, affects emissions. Coal, for instance, is approximately twice as carbon-intensive as gas.

Broadly speaking, the question of how an RPS policy affects relative fuel shares is probably a matter of substitutability. If coal and gas have similar price elasticities of supply, an RPS should affect them similarly. Relative changes in their shares, then, are probably the result of differential substitutability with wind and solar. The RPS increases wind and solar shares, and whichever energy source is more substitutable with them will experience a greater decline.

At a finer level, this differential substitutability is likely due to the different roles that different energy sources play in generation. Some–particularly nuclear, hydroelectric, and coal–are relatively costly to cycle on and off. These therefore tend to operate continuously as "baseload" capacity. Other energy sources, such as gas, are more flexible, and often operate only when needed, as "load-following" or "peak" capacity. Wind and solar generation, unlike fuel sources of energy, are highly intermittent, their output determined by transient natural conditions. It is generally accepted (Smith, 2019, Marrero and Ramos-Real, 2010) that intermittent renewables require more residual (i.e. not wind or solar) capacity to be load-following, to take over when renewables exogenously stop producing.

The question of which energy sources are more or less substitutable with renewables, however, is still open. For coal and natural gas, for instance, some, such as Marrero and Ramos-Real, 2010, argue that gas is more substitutable with intermittent renewables than coal is, while others such as Palmer and Burtraw, 2005 predict via simulation that gas would be displaced more than coal. While I focus on coal and gas shares in this analysis, lumping together all other sources as "other," these concerns certainly apply to these "other" sources as well, and a more complete treatment of how RPS policies affect them is an avenue for future work.

One important thing which I do not take into account is that power mix is largely governed by investment dynamics and slow adjustment. Large fixed costs of investment in new generating capacity can cause one type of generation to remain economical to use long past the point it is not economical to build more of it.[6] Due to this, I may significantly underestimate the effect of RPS policies. If RPS policies act to render new investment in some forms of conventional generation uneconomical, then they could precipitate a slow but long-term decline in the usage of those energy sources.

[6] For example, as I describe in Section 4.1, coal generation in the U.S. has been slowly declining for decades, and new coal capacity is rare. However, coal continues to be widely used for generation, accounting for over a quarter of electricity generation in 2018.

4.3.3 Channel 3: Carbon Intensity

When the average carbon intensity of an energy source increases *ceteris paribus*, total emissions increase. This change in average carbon intensity, however, might be driven by what might be termed the "extensive" or the "intensive" margins, i.e., which plants are used for generation and how those plants are used, respectively.

At the "extensive" margin, within a given energy source, an RPS can affect the composition of generating capacity by inducing entry or exit. If entering plants are less (more) carbon-intensive than average, or exiting plants more (less) carbon-intensive than average, then I would expect entry and exit to decrease (increase) average carbon-intensity. I might expect older, less efficient plants to generally exit first, while plants that enter use more modern and cleaner-than-average technologies. That is, I might expect the effect of an RPS through this "extensive" margin to decrease average carbon intensities.

At the "intensive" margin, an RPS can affect how existing plants operate. Smith, 2019 finds a tendency for coal plants to transition from baseload to load-following operation in recent years. As I have mentioned, intermittent renewable generation necessitates more load-following generation in its market. Smith, 2018 finds that baseload plants transitioning to load-following operation operate less efficiently and with higher carbon intensity. Thus, the introduction of intermittent renewables may increase the carbon intensity of existing capacity.

If these suppositions hold, then a decrease in carbon intensities of generation associated with RPS policies provides suggestive evidence that the "extensive" margin effect is larger, while an increase in carbon intensities suggest that the "intensive" margin effect is larger, in terms of its effect on carbon emissions.

5 Methodology

5.1 First Stage

I use the data described in Section 3 to estimate the following difference-in-differences model.

$$y_{st} = \delta_1 S_{st} + \delta_2 S_{st}^2 + \alpha_s + \alpha_t + \varepsilon_{st} \tag{3}$$

Here, y_{st} is the endogenous variable of interest, α_s and α_t are state and time fixed effects respectively, ε_{st} is an error term, S_{st} is the "interpolated stringency" as described in Equation 2 of Section 3.1, reproduced below, and S_{st}^2 is the square of S_{st}.

$$S_{st} = (\text{interpolated stringency})_{st} = \sum_{\tau=-\infty}^{t} AS_{s\tau}. \tag{2}$$

I use panel data on 46 states between 1997 and 2013. The model is estimated via weighted least squares (WLS) weighting by total generation in each state-year. Standard errors are computed via bootstrap at the state level. The bootstrap procedure is as follows: I split the panel of 46 states into a set of 46 time series, one per state. I then select from that set of time series 46 times, with replacement. I then reintegrate this sample of 46 states into a panel, and re-run the analysis on this panel, generating a new set of estimates. I repeat this process 2000 times, yielding 2000 estimates for each parameter. For each parameter, I obtain standard errors as the sample standard deviation of the bootstrap estimates, p-values as the proportion of bootstrap estimates with the opposite sign as the main estimate. The use of a full set of year and state dummies supercedes any strictly time-based or state-based controls, such as business cycle controls or any dimension of state heterogeneity. The use of the bootstrap standard error also means that serial correlation between regressors will not lead to inaccurately precise results.

The endogenous variables of interest I examine are per capita generation (MWh per capita) and average carbon intensity of generation (kg/kWh) for each of the following: coal, gas, combined wind and solar, and other.

5.2 Second Stage

I use the estimates from the first stage to generate counterfactual data for generation and carbon intensity in 2013, had no RPS policies been passed. That is, for each state s with an RPS, having obtained estimates in the first stage for the determinants of the endogenous variable,

$$y_{st} = \hat{\delta}_1 S_{st} + \hat{\delta}_2 S_{st}^2 + \hat{\alpha}_s + \hat{\alpha}_t + \hat{\varepsilon}_{st},$$

I compute the counterfactual variable as

$$\bar{y}_{st} = \hat{\alpha}_s + \hat{\alpha}_t + \hat{\varepsilon}_{st}, \tag{4}$$

representing the counterfactual values for what per capita generation and average carbon intensity would have been had no RPS policies been passed, by energy source. I multiply per capita generation by state population to obtain total generation by energy source, giving the vectors of total generation and average carbon intensity by energy source for both observed and counterfactual data, $(\vec{q}^p, \vec{b}^p)$ and $(\vec{q}^u, \vec{b}^u)$, as described in Section 4.2.

I then decompose the difference between total counterfactual and observed emissions in 2013, as described in Section 4.2. I first perform a coarse decomposition into the three channels (C_1, C_2, C_3), then further decompose C_2 into subchannels (C_{2r}, C_{2o}, C_{2c}) and decompose C_3 into subchannels (C_{3o}, C_{3g}, C_{3c}).

To obtain p-values and bounds on the C_i variables, I generate bootstrap panels exactly as in the first stage. For each bootstrap panel, I re-estimate each C_i variable. 95% confidence intervals are given as the range between the 2.5% and 97.5% quantiles of the bootstrap estimates, and p-values are given as the proportion of bootstrap estimates with the opposite sign as the main estimate.

6 Results

6.1 First Stage

Our results are summarized in Tables 2 and 3. The coefficient on S_{st} can be interpreted as the linear component of the difference between the observed value of the endogenous variable, and the value that it would have taken if the interpolated stringency S_{st} was 1pp weaker in year t. Similarly, the coefficient S_{st}^2 refers to the quadratic component of that effect.

I grant that the construction of S_{st} and the inclusion of the squared term make the interpretation of these coefficients somewhat opaque. Therefore, to give a sense of the magnitude of these effects, in Table 4 I present the estimates of the combined effect of all pre-2013 RPS policies on total generation and average carbon intensity across all 26 treated states in 2013, by energy source. That is, for each of these aggregate quantities, I report its observed value and the counterfactual value computed by setting $S_{st} = 0$ as described in Equation 4.

The most statistically significant effect is a decrease in gas generation, corresponding to a 29% decrease from the counterfactual in treated states in 2013. The estimated effect on combined wind and solar generation is large but only significant at the $p < .11$ level, corresponding to a 40% increase over the counterfactual in treated states in 2013. When the endogenous variable is carbon intensity, for both coal and gas the signs on S_{st} and S_{st}^2 do not match. However, the positive effect is in each case the larger and more statistically significant one (although significance is still low in either case). Indeed, in each case I estimate the RPS to have caused an increase in average carbon intensity, in treated states in 2013, of 8% in the case of coal and 36% in the case of gas.

6.2 Second Stage

I decompose the effect of the RPS policy on total emissions in treated states in 2013, as described in Section 4.2. First, I perform a decomposition into three channels: total generation quantity (C_1), power mix (C_2), and carbon intensity (C_3). I report results numerically in Table 5 and graphically in Figure 5. In Table 5, I report the decomposition both in absolute terms, and as a percent of total emissions in treated states in 2013.

I estimate that RPS policies led to a decrease in total quantity of electricity generation, but an increase in emissions through both the power mix and carbon intensity channels. The estimate for the carbon intensity channel C_3, however, is larger and much more statistically significant. With $p < .11$, I estimate that the net effect of the policies was to increase carbon emissions.

Second, I perform a further decomposition of the power mix channel C_2 into the effects of changes in wind and solar generation (C_{2r}), other generation (C_{2o}), and coal generation relative to gas (C_{2c}). I report results numerically in Table 6 and graphically in Figure 6. I find that, within the power mix channel (C_2), the usually-emphasized channel of increased renewable share (C_{2r}) is dominated by the effect of an increase in coal generation relative to gas (C_{2c}). The latter estimated carbon-positive effect C_{2c}, is highly significant and an order of magnitude greater than the estimated carbon-negative effect, and error thereof, of a relative increase in wind and solar generation (C_{2r}). Nevertheless, I do find a small but statistically significant carbon-negative effect of a relative increase in wind and solar generation.

Finally, I perform a further decomposition of the carbon intensity channel C_3 into the effects of changes in carbon intensity of generation using "other" sources (C_{3o}), gas (C_{3g}), and coal (C_{3c}). I report results numerically in Table 7 and graphically in Figure 7. I find that the estimated effect of an increase in carbon intensity of gas generation (C_{3g}), is large and carbon-positive, with $p < .05$. I also find that the effect of an increase in carbon intensity of coal generation (C_{3c}) is carbon-positive, and about half the magnitude of C_{3g}.

Figure 8 shows the full decomposition into seven channels. The largest components are C_{2c} and C_{3g}, although demand reduction, C_1, reduced relative use of "other" generation, C_{2o}, and increased carbon intensity of coal generation, C_{3c}, could also play a significant role.

7 Conclusion

Broadly speaking I find that, when looking at the carbon abatement effect of RPS policies, the channel of increased renewable generation is almost negligible compared to other channels, in particular: decreased total generation, increased coal generation relative to gas, and increased carbon intensity of fuel generation. Although balanced out to some degree by reduced quantity of generation, the overall effect of RPS policies on treated states in 2013 is likely carbon-positive.

Our finding that RPS policies likely reduce quantities demanded is in line with recent literature such as Greenstone and Nath, 2019 and Upton and Snyder, 2017, who find that RPS policies increase electricity prices and decrease quantities. Our inability to find a statistically significant net effect of RPS policies on emissions is also in line with these two papers, who do find a small or statistically insignificant such effect. However, a decomposition of this apparent non-effect reveals that it arises as the combination of more clearly signed components that cancel out somewhat.

I find that RPS policies likely increase coal generation relative to natural gas generation. This favors the prediction of Palmer and Burtraw, 2005–that intermittent renewables are more substitutable with gas than they are with coal–over the prediction of Marrero and Ramos-Real, 2010 that the opposite is true. If these findings are true, than this carbon-gas power mix channel is much larger than the direct effect of increasing renewable generation, and could make the net effect of RPS policies carbon positive.

I also find that RPS policies may cause the carbon intensity of fuel generation to increase significantly. This is consistent with Smith, 2018, who finds that increased renewable shares cause fuel generation to switch from baseload to load-following operation, and that this makes them more carbon-intensive. I discuss next steps necessary to further understand this phenomenon below.

What these results make clear is that, in terms of carbon abatement, the indirect effects of an RPS policy on a state's electricity generation market are apparently much larger than what might be viewed as the direct effect: an increase in renewable generation. While a deeper understanding of the substitutability of different sources of energy and the dynamics of investment in generation capacity are beyond the scope of this paper, these results nevertheless suggest that to understand the net effect of RPS policies on carbon emissions, I must widen my view from renewable generation *per se*.

Nevertheless, these results are contingent on my empirical design, which is far from ideal. The stringency measure that I use does not account for renewable capacity that exists when an RPS policy is passed. Thus, if identical RPS policies are imposed on states with different preexisting stocks of renewable capacity, this measure assigns them the same stringency. Of course, I would expect the state with more preexisting renewable capacity to be affected less.

As studied in Lyon and Yin, 2010, the passage of an RPS policy is a highly endogenous event, depending on state political climate, wind and solar potential, and the relative power of different interest groups. Upton and Snyder, 2017, for example, control for political climate, the size of the state's mining and manufacturing sectors, and wind and solar potential. I control for none of these things, putting the magnitudes of these estimates in question. However, if I suspected that RPS policies were being introduced in states that were already trending toward lower emissions, I would expect the opposite sign on the coal generation and carbon intensity channels I estimate, ruling that particular story out as a driving factor.

I study the within-state effects of RPS policies and, in the decomposition, attempt to measure these effects as manifested in 2013. However, whereas a theme of this paper is the need for a broader scope in accounting for an RPS policy's overall effects, the analysis is still in many ways too narrow. For instance, I do not capture cross-state, global, and long-term/future effects of RPS policies.

Electricity markets cross state lines, and RPS policies and increased renewable generation in one state certainly affects states with which it shares a border. It is conceivable, for instance, that RPS policies induce planned renewable projects out-of-state to simply relocate in-state, having in these cases zero net effect. Similarly, it is also possible that RPS policies also cause in-state fuel generation to relocate out-of-state, although measured increases in retail electricity prices (Upton and Snyder, 2017, Greenstone and Nath, 2019) seem to indicate that generation quantities actually do go down.

I also fail to account for global or public-good externalities of renewable investment, such as induced technical change or proof of viability. Increasing demand for renewables incentivizes innovation in renewables. Also, inducing increased renewable generation in markets forces generators to learn how to most efficiently adapt: lessons which could be used to introduce renewables more efficiently in the future. The creation of these intellectual public goods may dwarf even the large indirect effects I estimate.

I emphasize also that I can only report on the effects of RPS policies as manifested in

2013, and that the panel usually only includes a few years after an RPS was introduced.[7] It is possible that RPS policies only start to have an effect close to their target years, in which case we would not observe most of them.[8] It is also possible that, in their early years, RPS policies lay the groundwork for deeper long-term structural change which we cannot see. For example, as I argue in Section 4.3.2, the slow decline of coal generation over decades and dearth of new coal capacity suggest that generation continues to operate long past the point when it has been made "obsolete," in the sense that it is no longer economical to build more of it.

Some of these findings are intriguing seem deserving of deeper analysis. For one, I do not examine the nature of changes in average carbon intensities. Do individual generators increase their carbon intensities–the "intensive" margin–or is the change driven by entry of more carbon-intensive generators and exit of less carbon-intensive ones? If we believe that entering generators are unlikely to be more carbon-intensive than average, and exiting generators unlikely to be less, then the "intensive" margin story seems more plausible. Answering this question with actual data is the next step toward understanding the carbon intensivity channel.

Though my main analysis consists of a decomposition of changes to carbon emissions, this approach could in principle be applied to any externality of generation that varies by energy source.[9] A full cost-benefit analysis of RPS policies should consider a larger set of the externalities of generation.

For simplicity, I grouped together all generation except for wind, solar, coal, and natural gas as "other." Our summary statistics show that this mostly consists of hydroelectric and nuclear. I find that the net effect of RPS policies on "other" generation, and the carbon intensity thereof, is of indeterminate sign. A further disaggregation of this quantity, even just into renewable and non-renewable components, would be informative, as could a treatment of wind and solar generation separately.

Finally, aforementioned factors such as cross-state effects, investment dynamics, and complex patterns of substitutability, not only by fuel type but also geographically, suggest that any reduced-form approach to the question of how RPS policies affect electricity markets and carbon emissions will ultimately be inadequate. In the data, I observe equilibria of the electricity market, but in my analysis I do not model these as explicitly arising as equilibria, instead making strong assumptions about the reduced-form effects of these policies. A model built around the understanding of observed data as equilibria, in other words a structural model, is essential to credibly predicting counterfactual effects of RPS policies, or their absence. That is, such a model is essential to predicting what other equilibria could prevail.

While it is good for renewable capacity to increase *ceteris paribus*, carbon abatement only occurs when traditional fuel generation, or the carbon intensity thereof, decreases. In evaluating RPS policies, therefore, it is insufficient to score them by their effect on renewable generation. Indeed, it is possible for a policy to increase renewable generation, and even

[7]The median RPS in the panel is 7.5 years old in 2013.
[8]All but eight of the RPS policies in the panel have target years after 2013.
[9]Examples of such externalities are listed in Section 2.2.

to decrease non-renewable generation, while having no significant abating effect on carbon emissions. Our results suggest that this may not be far from the truth.

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Appendix: Figures

Figure 1: Total U.S. Power Generation By Source

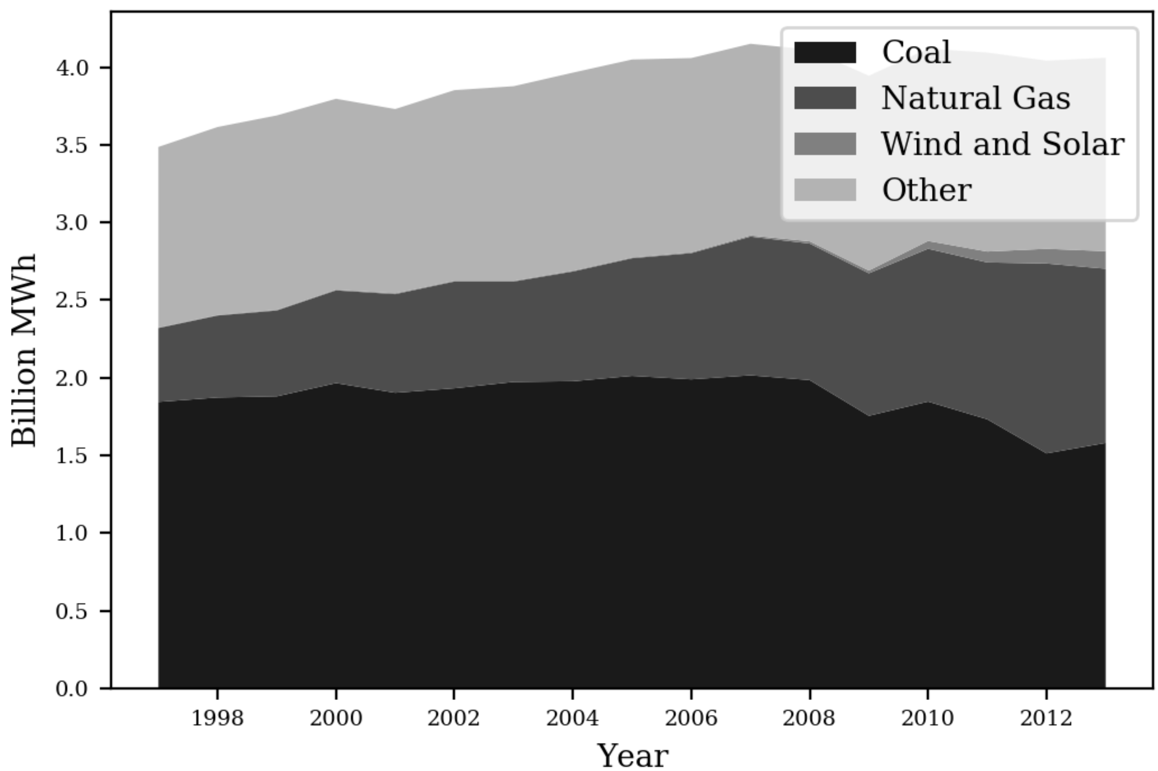

Table 1: Snapshots of U.S. Power Mix

	Share of Total U.S. Generation (%)						
Year	Coal	Gas	Nuclear	Hydroelectric	Wind	Solar	Other
1997	52.8	13.7	18.0	10.2	0.094	0.015	5.14
2003	50.8	16.7	19.7	7.10	0.29	0.014	5.36
2007	48.5	21.6	19.4	5.95	0.83	0.015	3.72
2013	38.9	27.7	19.4	6.61	4.13	0.22	3.31
2018	27.5	35.2	19.4	7.01	6.54	1.53	4.41

Figure 2: Total U.S. Power Generation By Source (% of Total)

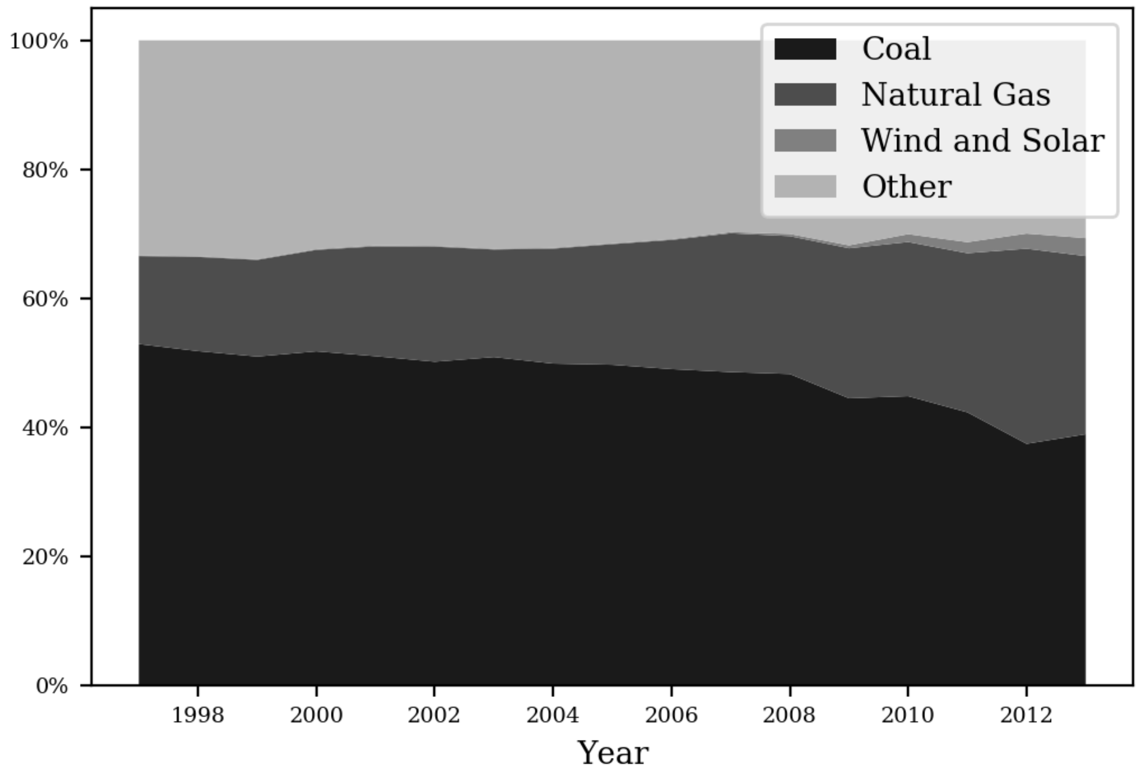

Figure 3: U.S. New and Reactivated Coal Capacity (% of Total Coal Capacity)

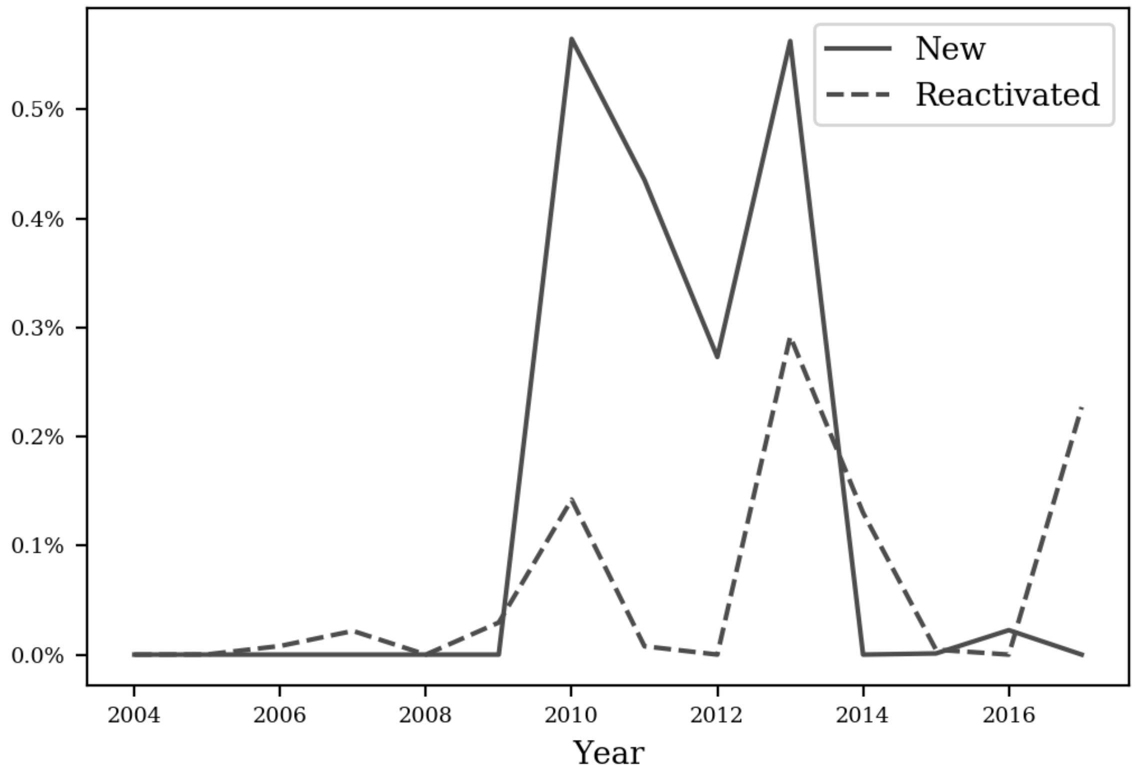

Figure 4: Average Carbon Intensity of U.S. Electricity Generation by Source

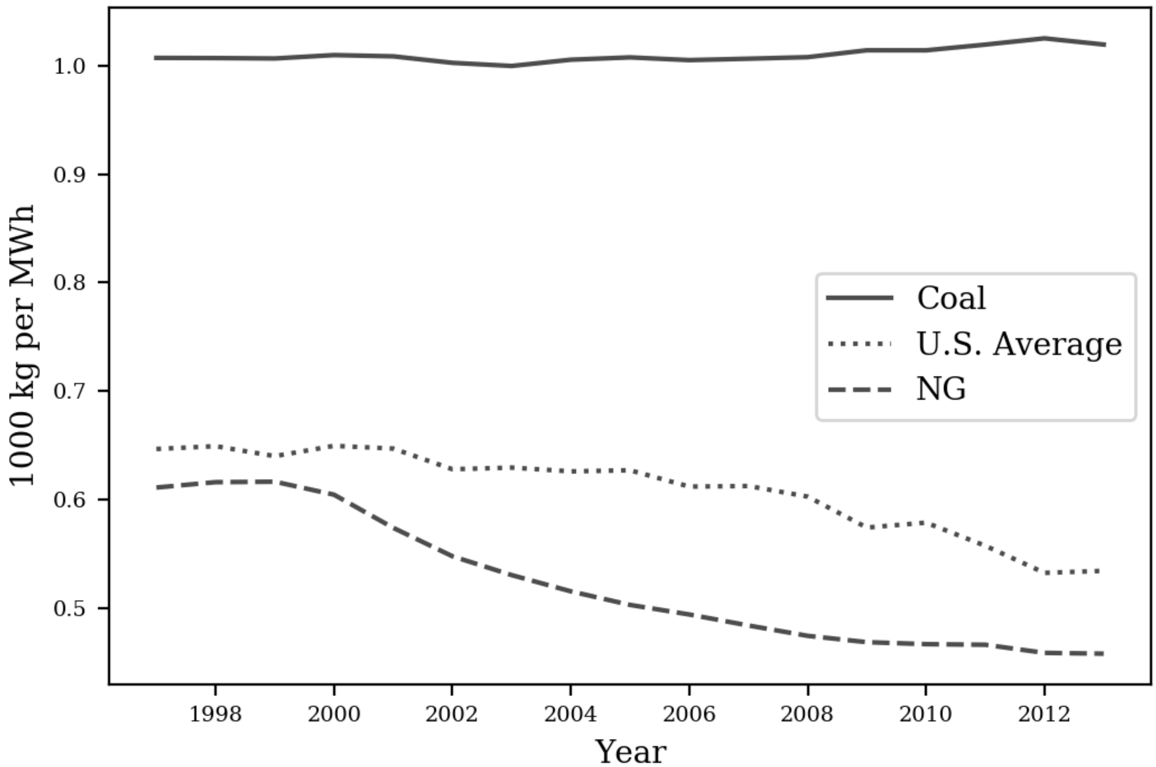

Table 2: Per Capita Generation by Energy Source (MWh per capita)

	Coal	Gas	Wind+Solar	Other
S_{st}	0.935	-3.33^{**}	0.460	0.337
	(1.468)	(1.538)	(0.409)	(1.133)
	$p < .27$	$p < .012$	$p < .11$	$p < .31$
S_{st}^2	9.38×10^{-4}	1.72×10^{-3}	-2.20×10^{-4}	$-8.57 \times 10^{-4*}$
	(2.05×10^{-3})	(1.80×10^{-3})	(6.96×10^{-4})	(9.03×10^{-4})
	$p < .27$	$p < .15$	$p < .27$	$p < .09$

Effect of an increase of 1pp in S_{st} (1pp^2 in S_{st}) on per capita generation by energy source. Estimated via WLS weighted by total state generation. Standard errors by bootstrap at the state level. *, **, and *** refer to significance at the 10%, 5%, and 1% levels.

Table 3: Average Carbon Intensity by Energy Source (kg/kWh)

	Coal	Gas	Other
S_{st}	-4.15×10^{-5}	2.20×10^{-4}	7.77×10^{-5}
	(1.65×10^{-4})	(2.12×10^{-4})	(9.87×10^{-5})
	$p < .35$	$p < .17$	$p < .31$
S_{st}^2	2.73×10^{-7}	-5.79×10^{-9}	-9.06×10^{-8}
	(1.82×10^{-7})	(1.82×10^{-7})	(1.03×10^{-7})
	$p < .104$	$p < .53$	$p < .24$

Effect of an increase of 1pp in S_{st} (1pp^2 in S_{st}) on average carbon intensity by energy source. Estimated via WLS weighted by total state generation. Standard errors by bootstrap at the state level. *, **, and *** refer to significance at the 10%, 5%, and 1% levels.

Table 4: Observed Data and Counterfactual in Treated States, 2013

	Total Generation (Million MWh)				Average Carbon Intensity (kg/kWh)		
	Coal	Gas	Wind+Solar	Other	Coal	Gas	Other
Data	899.0	698.0	108.1	798.7	1.146	0.476	0.053
Counterfactual	779.3	985.8	77.4	834.0	1.061	0.350	0.047
Difference	119.7	-287.8	30.67	-35.3	0.085	0.126	0.006

Combined effect of all extant RPS policies on total generation and average carbon intensity, by energy source, across all 26 treated states in 2013. “Data” refers to values observed in the data, “Counterfactual” to values constructed as described in Section 5.

Figure 5: Coarse Decomposition of RPS Effect

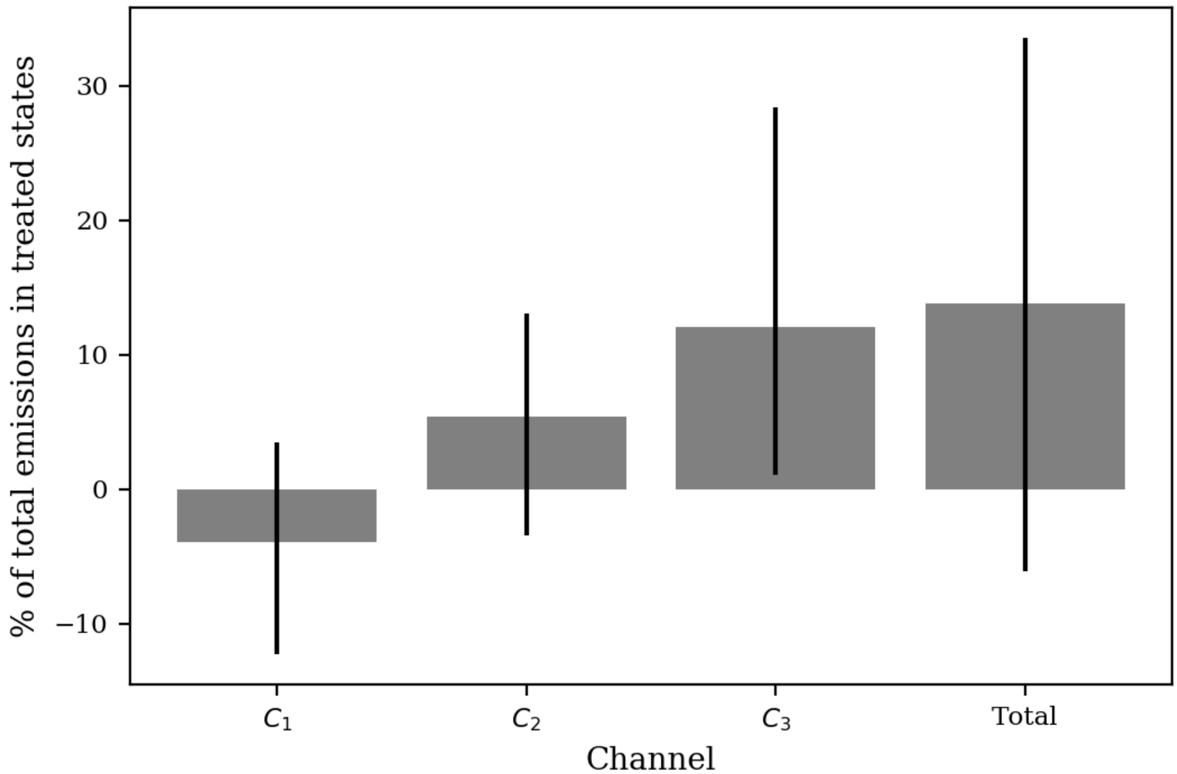

Table 5: Coarse Decomposition

	Absolute Size (Billion Tons)			Share of Total (%)	
	Estimate	95% CI	p value	Estimate	95% CI
C_1 (tot. gen. quantity)	-49.13	[-155.08, 35.59]	.1175	-3.92	[-12.37, 2.84]
C_2 (power mix)	67.18	[-50.02, 160.52]	.1155	5.36	[-3.99, 12.81]
C_3 (carbon intensity)	151.23	[4.61, 373.77]	.0175	12.06	[0.37, 29.82]
Total	173.37	[-77.08, 420.50]	.107	13.83	[-6.15, 33.55]

Decomposition of combined effect of all extant RPS policies on total emissions across all 26 treated states in 2013, as described in Section 4.2. "Absolute Size" refers to the absolute size of the channel. "Share of Total" is the size of the channel divided by total 2013 emissions in the treated states.

Figure 6: Further Decomposition of Channel C_2

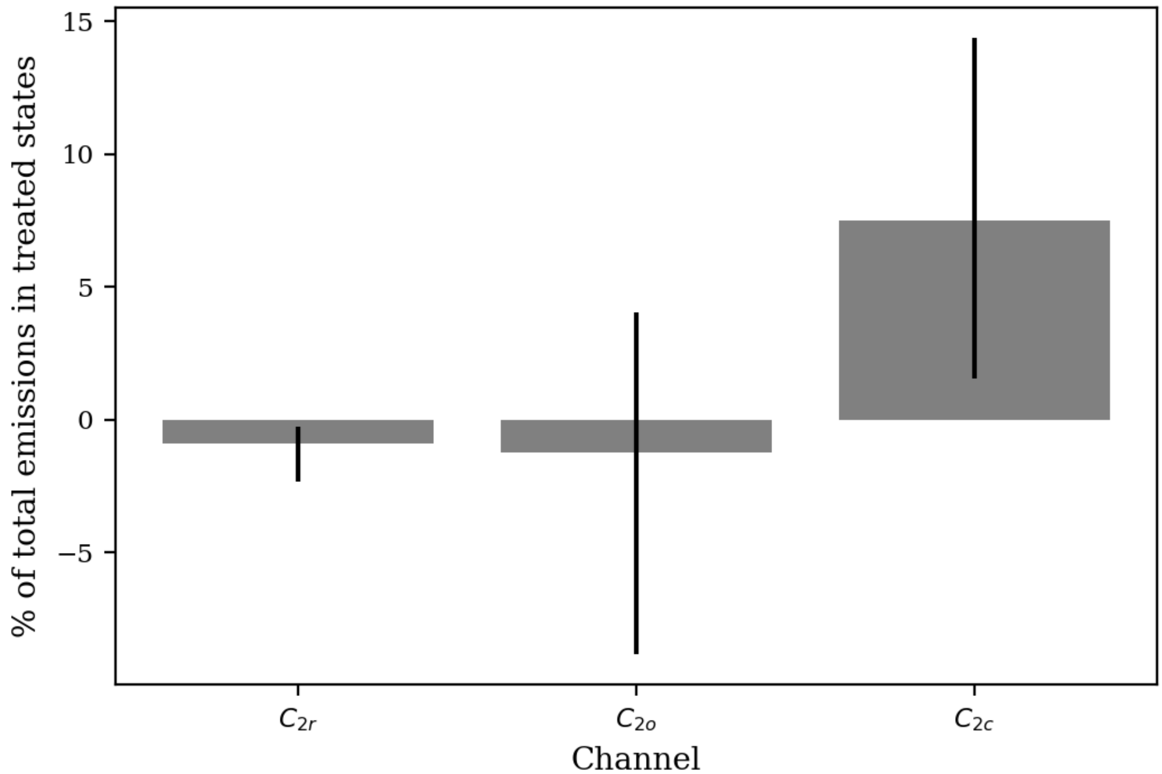

Table 6: Further Decomposition of Power Mix Channel C_2

	Absolute Size (Billion Tons)			Share of Total (%)	
	Estimate	95% CI	p value	Estimate	95% CI
C_{2r} (wind+solar share)	-11.23	[-28.96, -3.63]	.0015	-0.90	[-2.31, -0.29]
C_{2o} (other share)	-15.36	[-113.38, 49.33]	.36	-1.22	[-9.04, 3.94]
C_{2c} (coal vs. gas share)	93.77	[17.78, 173.11]	.0095	7.48	[1.42, 13.81]

Decomposition of C_2 into the effect of changes in generation shares by energy source, as described in Section 4.2. “Absolute Size” refers to the absolute size of the channel. “Share of Total” is the size of the channel divided by total 2013 emissions in the treated states.

Figure 7: Further Decomposition of Channel C_3

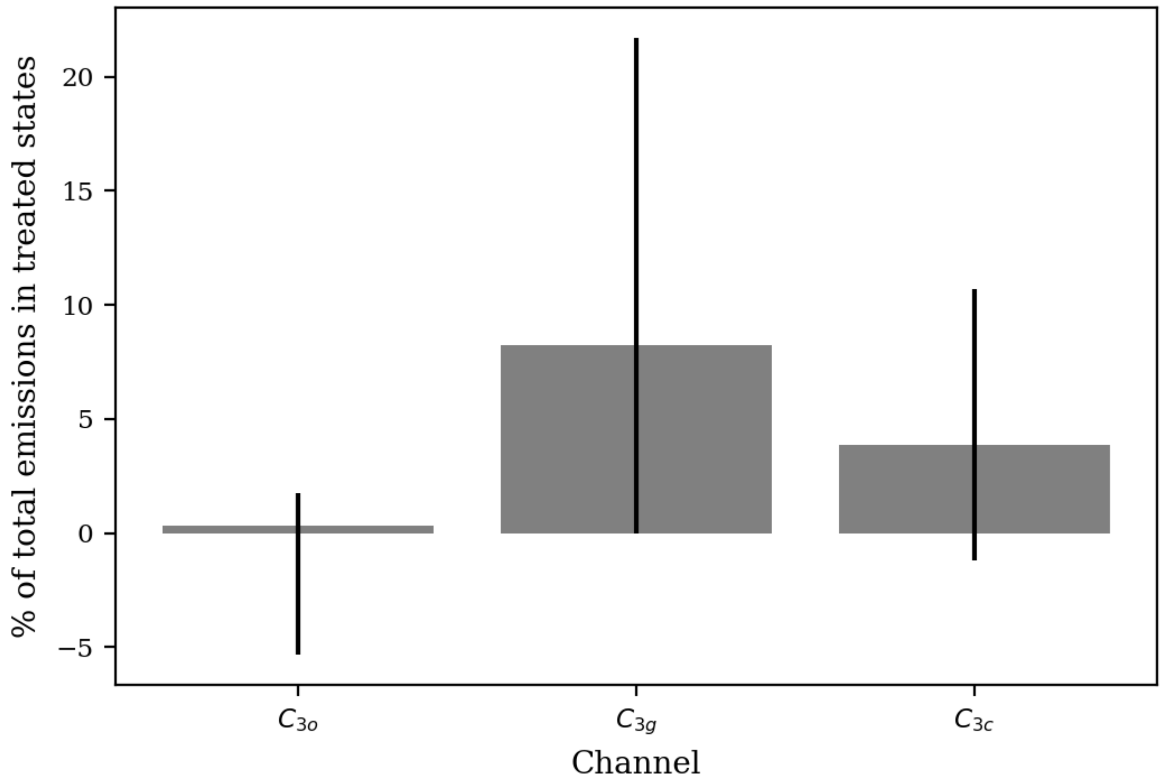

Table 7: Further Decomposition of Carbon Intensity Channel C_3

	Absolute Size (Billion Tons)			Share of Total (%)	
	Estimate	95% CI	p value	Estimate	95% CI
C_{3o} ("other")	4.10	[-64.53, 20.32]	.50	0.33	[-5.15, 1.62]
C_{3g} (gas)	103.04	[-3.80, 294.85]	.034	8.22	[-0.30, 23.52]
C_{3c} (coal)	48.18	[-13.13, 127.82]	.094	3.84	[-1.05, 10.20]

Decomposition of C_3 into the effect of changes in average carbon intensity by energy source, as described in Section 4.2. "Absolute Size" refers to the absolute size of the channel. "Share of Total" is the size of the channel divided by total 2013 emissions in the treated states.

Figure 8: Full Decomposition of RPS Effect