Effects of Tightening Renewable Energy Standards:
General Equilibrium Analytical Model and Empirical Tests

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Abstract

Our analytical general equilibrium model is used to explain why tightening a state's Renewable Portfolio Standard (RPS) unambiguously reduces carbon dioxide emissions but has ambiguous effects on renewable energy development. Second, it shows how the direction and magnitude of the effects of tightening the RPS on both carbon emissions and renewable deployment depend on key factors such as the state's endowment of intermittent resources like wind and solar potential as well as non-intermittent resources like geothermal or hydropower potential. Results also depend on actual renewable energy intermittency, transmission constraints, the pre-existing renewable energy requirement, each cost share parameter, and each elasticity of substitution. We use the model to generate testable hypotheses, and we use U.S. state-level data from 1990 to 2015 to test these hypotheses.

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Renewable Portfolio Standards generally require a minimum percentage of electricity supplied by electric utilities to come from eligible renewable sources. These standards are among the most popular incentive programs for renewable energy in the U.S. and are mandatory in twenty-nine states, Washington, D.C., and three territories. Through various channels, these programs can have major impacts on renewable energy use and on environmental quality. Empirical studies find mixed evidence of the impacts of these programs on renewable development but seem to agree on their environmental benefits.[1] This paper investigates the key factors that determine both the sign and the magnitude of these impacts, information useful to state policymakers eager to determine whether their own state has the key factors that would make these standards successful.

Theoretical partial equilibrium (PE) models shed light on ambiguous impacts of a Renewable Portfolio Standard (RPS) on energy sources, prices, emissions, and total energy consumption.[2] The PE approach does not account for economy-wide resource constraints, however, and it does not allow price adjustments in all markets. Since electricity is an input to production of most other goods, however, an RPS in the electricity sector could significantly affect other output prices. Complex engineering and computational general equilibrium (GE) models can calculate the many impacts of the RPS, but these models often do not focus on the mechanisms.[3] A recent paper by Bento *et al.* (2018) employs an analytical GE model and numerical calibration to study the trade-off between impacts of the RPS on emission reductions and on local booms (increases in rents from renewable energy endowments). Unlike Bento *et al*., this paper focuses on examining factors that determine the cost of the policy and its effectiveness in an analytical general equilibrium framework with testable hypotheses.

Our tractable GE model considers cost differences between fossil fuel and renewable technologies, and it distinguishes renewable sources based on intermittency. Traditional fossil fuel power plants use long-developed technologies with a storable fuel supply. Renewable technologies, however, have not been fully developed and have relied on intermittent sources with storage limitations. In addition, some renewable sources like wind and solar are highly

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[1] For example, Menz and Vachon (2006), Delmas and Montes-Sancho (2011), Yin and Powers (2010), Hitaj (2013), Upton and Snyder (2017), Yi (2015), and Lyon (2016).

[2] For example, Fischer and Newell (2008); Holland *et al.* (2009); Fischer (2010).

[3] For example, Logan *et al*. (2009); Rausch and Mowers (2014); Ryan *et al*. (2016).

intermittent but others are not (e.g., hydro and biomass). The intermittency of renewables has important implications for the cost of renewable electricity and for policy. By incorporating all these elements in a tractable GE model, we can (1) derive closed-form solutions for effects of an RPS on energy sources, consumption, prices, and emissions; (2) decompose the total effect on emissions and on renewable energy use into interpretable components; (3) pinpoint exactly the key parameters that determine the signs and magnitudes of these effects; and (4) derive testable hypotheses.

Using our analytical model, we find that an increase in stringency of the RPS unambiguously reduces carbon dioxide emissions but has an ambiguous effect on renewable energy development. We also find that the direction and magnitude of the effects of RPS on both carbon emissions and renewable deployment depend in particular ways on the endowments and intermittency of renewable resources, transmission constraints, the production cost of renewable electricity, the pre-existing renewable energy requirement, each cost share parameter, and each elasticity of substitution.

Our empirical results support these analytical findings. The endowment of intermittent versus non-intermittent renewable resources and the degree of intermittency prove to be key determinants of the impacts of RPS on both carbon emissions and renewable electricity generation. In states with lower degree of renewable energy intermittency, RPS policies are found to have a larger impact on increasing renewable electricity generation but a smaller impact on reducing emissions. Empirical results also show the different effects of an RPS on renewable electricity generation and emissions reduction in states with greater intermittent renewable potential versus greater non-intermittent renewable potential.

Below, Section 1 describes our basic analytical model and analytical results. Section 2 discusses extensions to the analytical model, and Section 3 provides empirical predictions. Section 4 discusses the empirical framework, challenges, data, and results. Section 5 concludes. All appendices are included below, but later will be online only.

1. Analytical General Equilibrium Model

1.1. Setup

State Renewable Portfolio Standards generally set a minimum renewable electricity generation requirement as a fraction of total generation, but those requirements differ by size and timing. For example, Missouri requires 15% of generation must be from renewables by 2021, while New York requires 29% by 2015, and Hawaii requires 100% by 2045. Other RPS design features can also vary across states such as geographical and technological eligibility and the definition of renewable energy. For example, Illinois does not count geothermal energy as an eligible renewable source, while most other states do. Colorado sets no restriction on geographic eligibility, while Hawaii and Iowa prefer in-state projects. Some states set one target for all types of renewables, while other states set a target for each type of renewable or “tier”. Nearly half of states use a credit multiplier that gives more credit for a preferred technology toward meeting the overall RPS target. Some states set a cost cap to protect ratepayers from higher costs associated with RPS implementation, whiles states like Minnesota and Pennsylvania set no cost caps.

Our main objective here is to design a GE model that is analytically tractable and yet can study key impacts of an RPS on emissions, renewable energy, prices, and welfare. To keep the model tractable, we abstract from many details of various RPS design features and other policies such as government expenditures, other mandates, and taxes on inputs and outputs. We focus on the RPS policy’s key feature, the percentage requirement for renewable electricity. The essential function of government modeled here is to mandate a minimum renewable electricity generation, R, as a fraction of total electricity, E, where this total E is the sum of R plus fossil-fuel electricity F. Specifically, government sets a policy scalar η and requires that $R/E \geq \eta$. Assuming the standard is binding, we have:

$$\frac{R}{E} \equiv \frac{R}{R+F} = \eta \tag{1}$$

For a simple model of equilibrium outcomes and economic efficiency, we assume n identical households. Each is endowed with a primary factor K, a composite of labor, capital, and land. They buy a composite consumption good, X per household, and they get disutility from total carbon dioxide (CO_2) emissions. Using C to denote emissions per household, their utility function takes the form $U = U(X; nC)$, where U is continuous, quasi-concave, and twice differentiable. It is increasing in X and decreasing in nC, aggregate emissions.[4] This public good or bad is separable in utility, so nC do not affect household choice of X. The household chooses

[4] If n is large enough, an individual household disregards its own contribution to aggregate emissions and takes total emissions as fixed.

X to maximize utility subject to a budget constraint, where the primary factor is fixed at $\bar{K}$ and earns a price P_K. Thus, the budget constraint is: $P_X X \leq I = P_K \bar{K}$, where I is income, total receipts from factor endowments.

We consider a closed economy with perfect market conditions, so competitive firms take all input and output prices as given. They choose inputs to maximize profits subject to their production technology, which is assumed to have constant returns to scale (CRTS). Firms in sector X employ inputs K_X (at price P_K) and electricity E (at price P_E). The intuition is that state RPS policy directly affects the electricity sector, and since electricity is used as an input in almost all productions, the policy can affect all other sectors through various general equilibrium channels. Fossil fuel electricity and renewable electricity are perfect substitutes, so electricity has one price, P_E:

$$X = X(K_X, E) \ , \tag{2}$$

$$E = F + R \ . \tag{3}$$

Intuitively, if fossil fuel electricity and renewable electricity are exactly the same in every respect, a requirement to substitute one for the other would have no effect. Therefore, the differences between them must determine any impact of the policy. Our model focuses on key differences between fossil fuel electricity and renewable electricity, including their environmental impacts and their production costs.

Fossil fuel electricity accounts for almost all greenhouse gas emissions in the electricity sector, while the production of renewable electricity is considered clean, so we model emissions as a by-product of electricity generation from fossil fuels. We define one unit of CO_2 emissions, C, as the amount from producing one unit of fossil fuel electricity:

$$C = F \ . \tag{4}$$

The production of fossil fuel electricity depends on the storable but non-renewable supply of fossil fuels and long-developed technologies, while the production of renewable electricity depends on the non-storable supply of renewable fuels and their not-yet-fully developed technologies. The production of F uses the composite primary factor K_F as the only input with CRTS. Here, we abstract from limits on oil extraction and assume instead that electricity can be generated by a virtually limitless supply of coal.[5] The only costs of production are for labor and

[5] We consider an upward-slopping supply of fossil fuels in one of our extensions later in the paper.

capital to dig it up and burn it in generating plants. We choose units of measurement such that one unit of the primary factor K_F produces one unit of F:

$$F = K_F \quad . \tag{5}$$

Renewable electricity is generated from the composite primary input K. Here, we also distinguish between the production of intermittent renewable electricity R_I and non-intermittent renewable electricity R_N. Intermittent renewable electricity is generated from sources such as wind and solar energy, and non-intermittent renewable electricity is from hydro, biomass, and geothermal power. These two types of renewable electricity are perfect substitutes in their use, but they have different production functions:

$$R = R_I + R_N \quad , \tag{6}$$

$$R_I = A_I(\eta) K_{RI} \quad , \tag{7}$$

$$R_N = A_N(\eta) K_{RN} \quad , \tag{8}$$

where $A_I(\eta)>0$ and $A_N(\eta)>0$ are the total factor productivities (TFP), and where K_{RI} and K_{RN} are primary factors used in production of R_I and R_N. We model each productivity as a function of the pre-existing fraction of total electricity from renewables in order to capture the idea that the marginal cost of integrating more renewable energy into the electric grid must increase with the level of integration. This extra cost might be due to intermittency, remote locations of renewable sources, and transmission constraints. Here, we measure integration as the fraction of electricity derived from renewables, R/E, so a binding RPS means that this integration of renewables is also measured by the exogenous policy scalar η. If costs increase with this integration ratio R/E, then the TFP functions $A_I(\eta)$ and $A_N(\eta)$ are decreasing in η (i.e., $\partial A_I/\partial\eta < 0$ and $\partial A_N/\partial\eta < 0$).

Given the production functions, a value of $A_I > 1$ or $A_N > 1$ would imply that renewable production is cheaper than fossil fuel production (and all of K_F would shift to the cheaper source). If $A_I = A_N = 1$, then all sources of electricity would be equally costly, and any RPS requirement would have no cost and therefore not bind. Since we want to analyze a costly and binding RPS, we assume that $0 < A_I < 1$ and $0 < A_N < 1$.

Our distinction between intermittent and non-intermittent renewable sources is not only to capture the varying degree of intermittency among renewables but also to model the fact that each state can require their own preferred renewable technologies. Those preferences are expressed through each state's definition of eligible renewable energy, their use of credit multipliers, and their targets for different renewable technologies. For example, most states use credit multipliers to award wind or solar technologies more credits toward meeting the renewable requirement. Some states even require a fraction of renewable generation to come from wind or solar (for Illinois, 75%). Our simple model cannot capture the diverse ways that states might encourage or require intermittent renewables like wind and solar power, but we summarize this aspect of RPS rules by assuming each state sets a minimum for intermittent renewable electricity as a fraction of total renewable electricity: $R_I/R \geq b$. This requirement is an integral part of the overall RPS, and it reflects heterogeneous preferences among states. A higher b means that the state requires more intermittent renewable electricity to meet the total renewable requirement.

A plausible reason for those preferences can be related to the state's endowments. For example, Illinois does not count geothermal energy as an eligible renewable source, while most others do, perhaps because Illinois has no geothermal energy. Thus, we specify that b is a function of the state's endowments of intermittent and non-intermittent renewables. We also suppose that a state's required b fraction depends on its initial level of stringency. In addition, for these additional requirement to be relevant, we assume it is costly and therefore binding. Thus,

$$R_I = b(Q_I, Q_N, \eta)R \tag{9}$$

where b varies across states in a way that is strictly increasing in Q_I and strictly decreasing in Q_N (i.e., $\partial b/\partial Q_I$>0 and $\partial b/\partial Q_N$<0). It captures the idea that a state's RPS generally requires more intermittent renewable electricity if the state has more intermittent renewable resources.[6] Similarly, a state's RPS allows a larger fraction of electricity from non-intermittent renewables if the state has more non-intermittent renewable fuels. The function b is non-decreasing in the pre-existing policy scalar η, so $\partial b/\partial \eta \geq 0$. It captures the idea that the policy fraction b can increase with the increase in the required share of electricity from renewables. In fact, some states' RPS policies do ratchet up the fraction of renewable electricity from wind and solar energy as they increase their fraction of electricity from renewables.

Perfect competition and CRTS imply zero-profits, so the value of each sector's output produced and sold must equal the sum of spending on inputs to production:

$$P_X X = P_K K_X + P_E E \quad \text{, and} \tag{10}$$

$$P_E E = P_K K_E \quad , \tag{11}$$

where K_E is the primary factor used in the electricity sector E:

[6] Because R_I must always be a fraction $b(Q_I, Q_N)$ of total R, we do not need another equation that specifies how R_N must also depend on Q_I and Q_N.

$$K_E = K_F + K_{RI} + K_{RN} \quad . \tag{12}$$

And, since all markets must clear in competitive equilibrium, the factor endowment equals the sum of all factor uses:

$$\bar{K} = K_X + K_E \quad . \tag{13}$$

Finally, a comment about the interpretation of E. Taken literally, our basic model above says that electricity is used only by firms in production of $X = X(K_X, E)$, even though 37% of U.S. electricity is used by households.[7] Equivalently, or instead, E can be interpreted as household use of electricity. Substitute the production function for X into utility to get $U = U[X(K_X, E); nC]$, and interpret $X(\cdot)$ as a sub-utility function that depends on two goods in utility: K_X is a consumption good produced using only the primary factor, and E is household electricity. In other words, E can be household use, firm use, or simply aggregate use of electricity.

1.2. Linearization

We study how a small exogenous increase in RPS stringency ($\hat{\eta} > 0$) affects inputs, outputs, and prices. To do so, we totally differentiate and linearize all equations (1) - (13), and we use the "hat" notation to denote a proportional change (e.g., $\hat{X} \equiv dX/X$). First, we totally differentiate and rearrange the policy requirements in equation (1) and (9) to get:

$$\hat{R} - \hat{E} = \hat{\eta} \quad , \tag{14}$$

$$\widehat{R_I} = b_\eta \hat{\eta} + \hat{R} \quad , \tag{15}$$

where the scalar $b_\eta \equiv [\partial b/\partial \eta] \cdot [\eta / b(Q_I, Q_N, \eta)] \geq 0$ is the percentage increase in the fraction $b(Q_I, Q_N, \eta)$ attributable to a one percent increase in required renewable integration.

We also use the initial policy scalar η as the initial renewable share (R/E) in equations below, and we use the policy scalar b as the ratio of intermittent renewable electricity to total renewable electricity (R_I/R). Then, to show how changes to inputs determine changes in each output, we totally differentiate production functions in equations (2) - (8).

$$\hat{X} = \theta_{KX}\widehat{K_X} + \theta_{EX}\hat{E} \quad , \tag{16}$$

$$\hat{E} = \eta\hat{R} + (1-\eta)\hat{F} \quad , \tag{17}$$

$$\hat{C} = \hat{F} \quad , \tag{18}$$

[7] https://www.eia.gov/energyexplained/index.php?page=electricity_use

$$\hat{F} = \widehat{K_F} \quad , \tag{19}$$

$$\hat{R} = b\widehat{R_I} + (1-b)\widehat{R_N} \quad , \tag{20}$$

$$\widehat{R_I} = \alpha_{I\eta}\hat{\eta} + \widehat{K_{RI}} \quad , \tag{21}$$

$$\widehat{R_N} = \alpha_{N\eta}\hat{\eta} + \widehat{K_{RN}} \quad , \tag{22}$$

where θ_{KX} and θ_{EX} denote factor shares in sector X (and $\theta_{KX} + \theta_{EX} = 1$). The scalar $\alpha_{I\eta} \equiv [\partial A_I/\partial\eta] \cdot [\eta/A_I(\eta)] < 0$ is the percentage reduction in $A_I(\eta)$ attributable to a one percent increase in required renewable integration. The scalar $\alpha_{I\eta} \equiv [\partial A_N/\partial\eta] \cdot [\eta/A_N(\eta)] < 0$ is the percentage reduction in $A_N(\eta)$ attributable to a one percent increase in renewable integration.

Similarly, we totally differentiate the zero-profit equation (10) and use the firm's first order conditions to show how the price of output X must change to reflect input cost changes. Then differentiate (11) to ensure that $P_E E$ still equals $P_K K_E$ (with no pure profits):

$$\widehat{P_X} = \theta_{KX}\widehat{P_K} + \theta_{EX}\widehat{P_E} \tag{23}$$

$$\widehat{P_E} + \hat{E} = \widehat{P_K} + \widehat{K_E} \quad . \tag{24}$$

The elasticity of substitution between inputs in production of X is $\sigma_X > 0$, defined as the percentage change in the input quantity ratio in response to a percent change in the input price ratio. For small changes, the definition of σ_X implies:

$$\widehat{K_X} - \hat{E} = \sigma_X\left(\widehat{P_E} - \widehat{P_K}\right) \quad . \tag{25}$$

Next, totally differentiate resource constraint equations (12) – (13) and manipulate:

$$\widehat{K_E} = \delta_F\widehat{K_F} + \delta_{RI}\widehat{K_{RI}} + \delta_{RN}\widehat{K_{RN}} \quad , \tag{26}$$

$$0 = \gamma_X\widehat{K_X} + \gamma_E\widehat{K_E} \quad . \tag{27}$$

where $\delta_F \equiv K_F/K_E$ and $\delta_R \equiv K_R/K_E$ are the initial fractions of the total primary factor used in the production of electricity that are employed in fossil-fuel electricity and in renewable electricity ($\delta_F + \delta_{RI} + \delta_{RN}$=1). We use $\gamma_X \equiv K_X/\bar{K}$ and $\gamma_E \equiv K_E/\bar{K}$ to denote the fraction of the total primary factor used in each sector ($\gamma_X + \gamma_E$=1). Finally, we choose the primary factor K as numeraire, so $\widehat{P_K} = 0$.

1.3. Solutions

We use the fourteen linearized equations (14)-(27) to solve for the fourteen unknown changes ($\hat{X}, \widehat{P_X}, \widehat{K_X}, \widehat{K_{RI}}, \widehat{K_{RN}}, \widehat{K_F}, \widehat{K_E}, \widehat{P_X}, \widehat{P_E}, \widehat{R_I}, \hat{R}, \widehat{R_N}, \hat{F}$ and $\hat{E}$). Thus, we get closed-form solutions for each change as a function of parameters and the exogenous shock, $\hat{\eta} > 0$. Appendix

A shows step-by-step derivations and closed-form solutions for all outcomes. Here, we show how to decompose the effects of the policy shock for ten key outcomes:

$$\widehat{P_E} = \left(\delta_{RI}(1 - A_I) + \delta_{RN}(1 - A_N)\right)\hat{\eta} - \left(\delta_{RI}\alpha_{I\eta} + \delta_{RN}\alpha_{N\eta}\right)\hat{\eta} + \left(1 - \frac{A_I}{A_N}\right)\delta_{RI} b_\eta \hat{\eta} \tag{28}$$

$$\widehat{P_X} = \theta_{EX}\widehat{P_E} \tag{29}$$

$$\hat{X} = -\gamma_E \widehat{P_E} \tag{30}$$

$$\widehat{K_X} = -\gamma_E \widehat{P_E} + \gamma_E \sigma_X \widehat{P_E} \tag{31}$$

$$\hat{E} = -\gamma_E \widehat{P_E} - \gamma_X \sigma_X \widehat{P_E} \tag{32}$$

$$\hat{C} = \hat{F} = -\gamma_E \widehat{P_E} - \gamma_X \sigma_X \widehat{P_E} - \frac{\eta}{1-\eta}\hat{\eta} \tag{33}$$

$$\hat{R} = -\gamma_E \widehat{P_E} - \gamma_X \sigma_X \widehat{P_E} + \hat{\eta} \tag{34}$$

$$\widehat{R_I} = -\gamma_E \widehat{P_E} - \gamma_X \sigma_X \widehat{P_E} + \hat{\eta} + b_\eta \hat{\eta} \tag{35}$$

$$\widehat{R_N} = -\gamma_E \widehat{P_E} - \gamma_X \sigma_X \widehat{P_E} + \hat{\eta} - \frac{b b_\eta}{(1-b)}\hat{\eta} \tag{36}$$

Equation (28) shows the impact of an RPS on the electricity price, one of the most direct and primary effects of a required shift toward renewables. It also shows how we decompose this impact into interpretable components. The first term includes $(1 - A_I)$ times δ_{RI}, the input to intermittent renewables K_{RI} as a fraction of all electricity inputs K_E, plus $(1 - A_N)$ times δ_{RN} (K_{RN} as a fraction of K_E). This first term captures the *differential production cost* between fossil-fuel electricity and intermittent and non-intermittent renewable electricity.[8] Since all are positive, this first term is a positive effect on the price of electricity. The second term also has an unambiguously positive effect on price, since it subtracts δ_{RI}>0 times $\alpha_{I\eta}$<0 (the elasticity of A_I with respect to η) and δ_{RN}>0 times $\alpha_{N\eta}$<0 (the elasticity of A_N with respect to η). This positive "integration cost" term captures how increases in the renewable energy share can raise costs of intermittency, storage limitations, and transmission constraints. With a binding renewable energy requirement, more stringency leads to higher integration costs and a higher electricity price. The

[8] Electricity production functions (5) – (8) imply that $(1 - A_I)$ captures the relative production cost between fossil fuel electricity and intermittent renewable electricity, and $(1 - A_N)$ captures the relative production cost between fossil fuel electricity and non-intermittent electricity.

third non-negative term represents the cost of requiring more intermittent renewable electricity to meet minimum renewable requirement. This term is zero when firms choose non-intermittent and intermittent electricity generations such that their production costs are equalized

Next, the output X is produced using only electricity and primary factors. Since the latter is numeraire, equation (29) shows that the price of X must rise by its electricity input share, θ_{EX}, times the rise in P_E (from equation 28). Then, of course, this increase in P_X means that households reduce consumption. In equation (30), we have $\hat{X} = -\gamma_E \widehat{P_E} < 0$. This effect is not the usual "price effect", however, because the composite good X is the only purchased good in utility. The price P_X therefore serves essentially as a price index over all goods. Its higher price reduces real income, so the reduction in X is really an income effect.

In fact, as we now show, this income effect on X is identical to the overall change in real income. To do so, we solve for the welfare gain or loss (ignoring changes in emissions). The first order condition from consumer optimization yields the change in utility: $dU = \mu P_X dX$, where μ denotes the marginal utility of income. This dollar value of the change in utility is then divided by total income (I) to express it in relative terms. This measure of the change in welfare is:

$$\frac{dU}{\mu I} = \frac{P_X X}{I}\hat{X} = \hat{X} < 0$$

This relative change in welfare is exactly the earlier-derived income effect on X.

Then, in equations (31) and (32), the overall effects of the RPS on the primary input K_X and the electricity input E are decomposed into separate income and substitution effects. The first term in both (31) and (32) is $-\gamma_E \widehat{P_E}$, matching the income effect on X in equation (30). The second terms in (31) is $\gamma_E \sigma_X \widehat{P_E}$, a substitution effect because it depends on the elasticity of substitution in production, σ_X, and the relative change in the electricity price, $\widehat{P_E}$. The price of electricity input rises relative to the numeraire input price P_K, so firms substitute away from use of electricity and toward the primary factor. Thus, the substitution effect on E is $-\gamma_X \sigma_X \widehat{P_E} < 0$, while the substitution effect on K_X is $\gamma_E \sigma_X \widehat{P_E} > 0$. Both substitution and income effects reduce electricity use, so $\hat{E}<0$. The sign of the effect of the policy on the primary factor use K_X is ambiguous, as it depends on whether the substitution effect or income effect dominates.

Finally, equations (33)-(36) show the effect of the policy change on fossil-fuel electricity, CO_2 emissions, and renewable electricity. We decompose the total effect on F and R into three parts and the total effect on R_I and R_N into four parts. The first term in all four equations,

$-\gamma_E\widehat{P_E}$, is an income effect as above. The second term in $\hat{F}$, $\hat{R}$, $\hat{R}_I$, and $\widehat{R_N}$ matches the substitution effect in $\hat{E}$, because the raised price of electricity reduces demand for electricity regardless of sources. The third term in (33) is $-\frac{\eta}{1-\eta}\hat{\eta} < 0$, capturing the *direct policy effect* that reduces fossil fuel electricity as intended. The third term in (34)-(36) is the *direct policy effect* $\hat{\eta} > 0$ that increases renewable electricity (either intermittent or non-intermittent renewable electricity). The last terms in (35) and (36) show the effect on the renewable electricity generation mix if RPS policies ratchet up intermittent renewable electricity requirement as the standards become more stringent (i.e., $b_\eta\hat{\eta} > 0$ and $-\frac{bb_\eta}{(1-b)}\hat{\eta} < 0$).

With the assumption that production of renewable electricity is costlier than production of fossil-fuel electricity (A_I<1, and A_N<1), we find that fossil-fuel electricity is reduced by the income effect, by the substitution effect, and by the direct policy effect. And $\hat{C} = \hat{F}$, so emissions fall unambiguously. However, the overall effect of the RPS on renewable electricity is ambiguous: both the income and substitution effects reduce R, while the direct policy effect increases it. The sign of $\hat{R}$ depends on which effect dominates. Next sections we show the exact conditions when the overall effect of the RPS increases or decreases renewable electricity generation.

2. Model extensions

The advantage of our simple analytical general equilibrium model is that mathematical expressions show exactly which key factors determine the effects of the RPS policy and in which way they do so. As a simplified description of reality, our model surely imposes some key assumptions. In this section, we extend our model to relax our three key assumptions and to see how they affect our main results: (A) upward-sloping supply of fossil fuels, (B) imperfect competition in the electricity generation, and (C) interaction of the RPS with a renewable energy efficiency standard.

A. Upward-sloping supply of fossil fuels

First, we consider an upward sloping supply of fossil fuels. Intuitively, since the RPS policy discourages fossil-fuel electricity generation, a more stringent RPS shifts the demand for fossil fuels to the left. Then reduction in the demand for fossil fuels reduces prices and encourages more use of fossil fuels. The magnitude of the effect of tightening the RPS on reducing the relative price of fossil fuels and thus the relative price of fossil-fuel electricity F depends heavily on the steepness of the supply curve of fossil fuels. In our basic model, we assume a flat supply curve of fossil fuels, so we are unable to capture the effect of increasing renewable requirement on reducing the relative price of F. It turns out that parameters A_I and A_N in our basic model literally are the relative price of renewable electricity to fossil fuel electricity. A reduction in A_I or A_N suggests a reduction in the relative price of fossil-fuel electricity to renewable electricity. So, to account for an upward sloping supply of fossil fuels, we do not need to change our basic model. The only change is the magnitude of the derivatives of A_I and A_N with respect to the policy scalar η.

In the basic model, $\partial A_I/\partial\eta$<0 and $\partial A_N/\partial\eta$<0 capture only the increase in the renewable integration cost. With the upward sloping supply of fossil fuels, $\partial A_I/\partial\eta$ and $\partial A_N/\partial\eta$ must also add a positive term to capture the reduction in the relative cost of fossil-fuel electricity (or equivalently the increase in the relative cost of renewable electricity). The upward sloping of fossil-fuel supply reduces the distortionary effect of the RPS policy on increasing the electricity price and thus the magnitude of the income and substitution effects. Results in our basic model still hold, however, as long as increase in the renewable integration cost is larger than the reduction in the the relative cost of fossil-fuel electricity (i.e., $\partial A_I/\partial\eta$<0 and $\partial A_N/\partial\eta$<0 after accounting for the upward sloping supply of F). Since we expect the supply curve of fossil fuels like coal is pretty flat in our sample years, we expect $\partial A_I/\partial\eta$ and $\partial A_N/\partial\eta$ are still negative and our main findings do not change.

B. Imperfect competition in the electricity market

In some states, electricity generation might be close to perfectly competitive, but in many states, the retail electricity price to consumers is generally regulated. The market is neither perfectly competitive nor monopolistic. So, we extend the model to take into account the imperfect competition in the electricity market and model it as the firm's ability to charge electricity prices higher than their marginal costs. We define $\tau > 0$ as the markup or the difference between electricity price and marginal cost, so τ measures the degree of market power. A higher value of τ implies a higher degree of market power. This assumption does not exactly reflect monopoly behavior, because the monopoly markup would change when costs change, and it does not reflect any particular oligopoly behavior either. It is just a simple way to suppose that firms are not perfectly competitive in some unknown way, and charge a price higher than marginal cost.

Households are owners of the firm, so profits are included in household income. We can think of τ as a consumption tax, where the tax revenue is distributed back to consumers in a lump-sum fashion. In this extension, we express τ as a fraction of the producer price P_E, so the consumer price of electricity is $P_E(1+\tau)$. Appendix B shows step by step our derivations of all results. Here, we focus on several key outcomes to show how imperfect competition might affect the impacts of the RPS:

$$\widehat{P_E} = \left(\delta_{RI}(1-A_I) + \delta_{RN}(1-A_N)\right)\hat{\eta} - \left(\delta_{RI}\alpha_{I\eta} + \delta_{RN}\alpha_{N\eta}\right)\hat{\eta} + \left(1 - \frac{A_I}{A_N}\right)\delta_{RI} b_\eta \hat{\eta} \tag{37}$$

$$\hat{C} = \hat{F} = -\gamma_E \widehat{P_E} - \gamma_X \sigma_X \widehat{P_E} + \frac{\tau}{(1+\tau)}\gamma_X \sigma_X \widehat{P_E} - \frac{\eta}{(1-\eta)}\hat{\eta} \tag{38}$$

$$\hat{R} = -\gamma_E \widehat{P_E} - \gamma_X \sigma_X \widehat{P_E} + \frac{\tau}{(1+\tau)}\gamma_X \sigma_X \widehat{P_E} + \hat{\eta} \tag{39}$$

Changes in the relative price of electricity in (37) are exactly the same as in (28) of our basic model. Thus, incorporating a fixed positive markup τ will not affect the magnitude and direction of the change in the relative producer price (or production cost) of electricity. Compared to equations (33) and (34) of our basic model, equations (38) and (39) have an additional positive term $\frac{\tau}{(1+\tau)}\gamma_X \sigma_X \widehat{P_E} > 0$ that makes the sum of the income and substitution effects less negative. The results come from our assumption that we have a fixed positive markup ($\hat{\tau} = 0$). With a fixed markup, one percentage increase in the production cost of electricity due to the policy shock implies a less than one percentage increase in the consumer price of electricity. The magnitude of income and substitution effects in turn depend on the change in the relative consumer price of electricity. Equations (38) and (39) show that with the consideration of some unknown market power, results in our basic model still hold that $\hat{C}$ is unambiguously negative and that $\hat{R}$ can have opposite signs.[9]

[9] The advantage of using a fixed τ is that sensitivity analysis allows us to study the effect of the policy shock across various levels of the initial market power. We, however, ignore the possibility that the policy shock can affect the market power in the electricity market or $\hat{\tau} \neq 0$. The inclusion of $\hat{\tau} \neq 0$ will add more terms to our solutions in the basic model but will not alter our key results and intuitions.

C. Interaction with an energy efficiency standard

Third, we consider whether interactions between the RPS and an energy efficiency standard enhance or undermine the impacts of the RPS. The RPS requires a minimum renewable electricity per unit of total electricity, so the renewable electricity mandate is satisfied either by increased use of renewables or by reduced use of fossil-fuels (or some of each). A minimum energy efficiency standard (EES), however, requires reduction in electricity used for the same service, regardless of the generating source. Intuitively, the two policies might interact in a way that results in a reduced use of fossil-fuel electricity but no significant change in renewable electricity production. In other words, an energy efficiency standard can work in a way that weakens the impacts of an RPS on renewable deployment.

To model the energy efficiency standard, we introduce the policy scalar or the energy efficiency requirement scalar ϵ. The production of the composite good $X = X(K_X, E)$ is replaced by $X = X(K_X, \epsilon E)$. The increase in energy efficiency also has it cost, and the cost is a function of energy efficiency requirement ϵ. We can express the cost of energy efficiency in terms of the primary input K. We denote the cost of energy efficiency as K_S, so $K_S = K_S(\epsilon)$. The market clearing condition of the basic model is replaced by $\bar{K} = K_X + K_E + K_S$. All derivations are in Appendix C. We show here the change in electricity production in response to an increase in renewable mandate but no change in the pre-existing EES:

$$\widehat{P_E} = \big(\delta_{RI}(1 - A_I) + \delta_{RN}(1 - A_N)\big)\hat{\eta} - \big(\delta_{RI}\alpha_{I\eta} + \delta_{RN}\alpha_{N\eta}\big)\hat{\eta} + \left(1 - \frac{A_I}{A_N}\right)\delta_{RI} b_\eta \hat{\eta} \tag{40}$$

$$\hat{E} = -\frac{1}{1 - \gamma_S}(\gamma_E + \gamma_X \sigma_X)\widehat{P_E} \tag{41}$$

Compared to the basic case with no energy efficiency policy, the impact of RPS on electricity price is the same. The impact of RPS on electricity consumption in the case with a pre-existing energy efficiency standard, however, depend on the new parameter γ_S. The intuition is that energy efficiency programs draw investments from R and F toward energy efficiency technologies. Increase in energy efficiency investment further reduces both renewable and fossil-fuel electricity. So, the magnitude of the interaction effect between RPS and EES depends primarily on the size of γ_S. The inclusion of γ_S does not change main findings of our papers regarding the policy's unambiguous impact on emissions reduction but ambiguous impact on renewable generation.

3. Theorems and their Empirical Predictions

Using our basic analytical model results from section 1, we derive theorems and make empirical predictions about the impacts of tightening an RPS on CO_2 emissions and renewable deployment. First, a rearrangement of equations (33)-(36) and discussion above prove that if the cost of producing renewable electricity is greater than that of fossil-fuel electricity ($A_I < 1$ and $A_N < 1$), then an increase in stringency of the RPS unambiguously reduces emissions ($\hat{C} < 0$) but has ambiguous effect on renewable energy deployment. Our analytical results reconcile the mixed empirical evidence of the effects of RPS on encouraging renewable development in the prior literature, showing the policy shock encourages renewable electricity generation only under certain conditions.

Furthermore, we are able to show the exact conditions when the policy shock reduces both intermittent and non-intermittent renewable electricity as the followings:

$$\widehat{R_I} < 0 \Leftrightarrow (\gamma_E + \gamma_X\sigma_X)\left(\delta_{RI}\left(1 - A_I - \alpha_{I\eta}\right) + \delta_{RN}\left(1 - A_N - \alpha_{N\eta}\right)\right) > 1 + b_\eta\ , \quad (42)$$

$$\widehat{R_N} < 0 \Leftrightarrow (\gamma_E + \gamma_X\sigma_X)\left(\delta_{RI}\left(1 - A_I - \alpha_{I\eta}\right) + \delta_{RN}\left(1 - A_N - \alpha_{N\eta}\right)\right) > 1 - \frac{bb_\eta}{1-b}. \quad (43)$$

These results can be seen by substituting $\widehat{P_E}$ in (28) into (35) for $\widehat{R_I}$ and into (36) for $\widehat{R_N}$ and rearranging. Intuitively, these conditions point to key parameters that resolve the ambiguous effects of the policy on renewables. Because both A_I and A_N are less than one, while $\alpha_{I\eta}$ and $\alpha_{N\eta}$ are less than zero, we know that $(1 - A_I - \alpha_{I\eta}) > 0$ and $(1 - A_N - \alpha_{N\eta}) > 0$. First, a larger σ_X means firms can substitute away from electricity more easily, so they reduce demand for all sources of electricity – which makes $\widehat{R_I}$ and $\widehat{R_N}$ more likely negative. Second, a larger initial share of resources in renewables ($\delta_{RI} \equiv K_{RI}/K_E$ or $\delta_{RN} \equiv K_{RN}/K_E$) means that pre-existing costs of the mandate were already high, and so the added cost of a more stringent RPS has further income effects that reduce renewable generation. Third, a larger absolute value of either integration cost elasticity ($\alpha_{I\eta} < 0$ or $\alpha_{N\eta} < 0$) also means that the policy shock is costly, with negative income effects on renewables. A larger size of any of these parameters makes income and substitution effects larger, discouraging renewables, tending to offset the direct policy effect.

Next, we wish to examine what key local factors *affect* these RPS impacts. Thus, we totally differentiate solutions for $\hat{C}$, $\widehat{R_I}$, and $\widehat{R_N}$ in equations (33), (35), and (36) with respect to key parameters. Proofs of these theorems appear in Appendix D. We also use these theorems to generate empirical hypotheses, which we test statistically using U.S. state-by-year panel data. Many parameters appear in these three equations, however, we focus on the ones for which we have been able to find data, or at least proxies that can represent differences in these key factors across states. Table 1 summarizes our main empirical predictions.

First, we investigate how the pre-existing stringency would be likely to affect the above inequalities (and thus the likelihood that further stringency reduces R_I and R_N). We note that higher stringency means that a state would have a larger initial share of resources in renewables ($\delta_{RI} \equiv K_{RI}/K_E$ or $\delta_{RN} \equiv K_{RN}/K_E$). It also means lower initial A_I and A_N. Thus, (42) and (43) and above discussion, we have the following empirical predictions for C and R:

Theorem T1: The derivative of $\hat{C}$ with respect to η is negative, so states with more stringent pre-existing RPS will have a larger than average negative impact of tightening the RPS on CO_2 emissions. The derivatives of $\widehat{R_I}$ and $\widehat{R_N}$ with respect to η are negative, so states with a more stringent pre-existing RPS will have a smaller than average positive impact (or larger negative impact) of tightening the RPS on renewable energy development.
[Proof: see Appendix D.]

Greater pre-existing stringency requires a higher level of renewable integration, where costs increase with that stringency ($\partial A_I/\partial\eta$<0 and $\partial A_N/\partial\eta$<0). Therefore, the cost of increasing the RPS by one percent rises with the level of the pre-existing standard. The costlier RPS increment causes a larger rise in electricity price and thus more negative income effect and substitution effect, both of which lead to further emission reduction but also discourage renewable electricity generation.

Hypothesis H1: States with a more stringent than average pre-existing RPS will be found to have larger than average impacts of tightening the RPS on reducing CO_2 emissions and smaller than average impacts on encouraging both intermittent and non-intermittent renewable energy deployment.

We also have data on renewable fuel availability, and so we can test empirical predictions about the effect of renewable potential on emissions and use of renewables. As discussed in our analytical model, we distinguish between intermittent renewable potential Q_I and non-intermittent renewable potential Q_N. Theorem 2 shows how intermittent renewable endowment affects the impacts of RPS on carbon emissions and renewable generations.

Theorem T2: The derivative of $\hat{C}$ with respect to Q_I is negative, so states with a larger than average endowment of intermittent renewable resources will have a larger than average negative impact of tightening an RPS on emissions. The derivatives of $\widehat{R_I}$ and $\widehat{R_N}$ with respect to Q_I are negative, so states with a larger than average endowment of intermittent renewable resources will have a smaller than average positive (or larger than average negative) impact of an RPS on intermittent and non-intermittent renewable.[Proof: see Appendix D.]

If states having more intermittent renewable resources, states will likely require more intermittent renewable sources to meet their RPS. If integrating intermittent renewable electricity is more expensive than integrating non-intermittent renewable electricity, more intermittent renewable electricity leads to a higher policy cost. Thus, when a stricter RPS requires more renewable energy, greater intermittent renewable resources mean higher costs and a more negative income effect – which results in a larger reduction in fossil-fuel electricity production and a smaller increase (or larger decrease) in non-intermittent and intermittent renewable electricity production. The periods from 1990 - 2015, given the intermittency, storage limitation, and transmission constraints of intermittent renewable electricity such as wind and solar, the cost of producing intermittent renewable electricity is generally more expensive than the production of non-intermittent renewable electricity. So this theorem yields empirical predictions:

Hypothesis H2: States with greater than average amounts of intermittent renewable energy resources will be found to have larger than average negative impacts of an RPS on CO_2 emissions and smaller than average impacts on encouraging (or larger than average impacts on discouraging) intermittent and non-intermittent renewable energy.

The next theorem looks at how non-intermittent renewable endowment affects the impacts of RPS on carbon emissions and renewable generations.

Theorem T3: The derivative of $\hat{C}$ with respect to Q_N is positive, so states with a larger than average endowment of non-intermittent renewable resources will have a smaller than average negative impact of tightening an RPS on emissions. The derivatives of $\widehat{R_I}$ and $\widehat{R_N}$ with respect to Q_N are positive, so states with a larger than average endowment of non-intermittent renewable resources will have a larger than average positive (or smaller than average negative) impact of an RPS on intermittent and non-intermittent renewable.[Proof: see Appendix D.]

Having more non-intermittent renewable resources means that states will likely use more non-intermittent renewable sources to meet their RPS. If the intermittent renewable electricity is more expensive to produce or integrate than the non-intermittent renewable electricity, the switch to non-intermittent renewable fuels helps to reduce the cost of renewable electricity generation and the policy cost. Thus, when a stricter RPS requires more renewable energy, greater non-intermittent renewable resources mean lower costs and a less negative income effect – which results in a smaller reduction in fossil-fuel electricity production and a larger increase (or smaller decrease) in non-intermittent renewable electricity production.

Hypothesis H3: States with greater than average amounts of non-intermittent renewable energy resources will be found to have smaller than average negative impacts of an RPS on CO_2 emissions and larger than average impacts on encouraging (or smaller than average impacts on discouraging) intermittent and non-intermittent renewable energy.

Next, we find effects of $\alpha_{I\eta} \equiv [\partial A_I/\partial\eta] \cdot [\eta/A_I(\eta)] < 0$ and and $\alpha_{N\eta} \equiv [\partial A_N/\partial\eta] \cdot [\eta/A_N(\eta)] < 0$, the percentage reductions in $A_I(\eta)$ and $A_N(\eta)$ attributable to a one percent increase in required renewable integration.[10]

Theorem T4: The derivatives of $\hat{C}$, $\widehat{R_I}$, and $\widehat{R_N}$ with respect to $\alpha_{I\eta}$ and $\alpha_{N\eta}$ are negative, so states with a larger than average absolute value of the cost parameters $\alpha_{I\eta}$ and $\alpha_{N\eta}$ have a larger than average negative impact of tightening the RPS on CO_2 emissions and smaller than average positive (or larger than average negative) impact on renewable deployment. [Proof: see Appendix D.]

A greater absolute value of $\alpha_{I\eta}$ or $\alpha_{N\eta}$ means costlier integration of renewable energy, so it raises the positive impact of stricter renewable requirements on the price of electricity. The larger $\widehat{P_E}$ has larger negative income and substitution effects on electricity production (from any source). It thus reduces both emissions and renewable electricity generation. The value of $\alpha_{I\eta}$ and $\alpha_{N\eta}$ can depend on the intermittency of renewable sources and the transmission constraints. This theorem gives rise to the following empirical predictions:

Hypothesis H4: In states with greater than average intermittency of renewable resources, tightening the RPS is expected to have a larger than average negative impact on emissions but a smaller than average positive (or larger negative) impact on both non-intermittent and intermittent renewables.

4. Empirical Analysis

4.1 Empirical Strategy and Challenges

Our analytical model shows key parameters that drive the effects of tightening RPS policies on emissions and non-intermittent and intermittent renewable development and in what

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[10] Just to clarify, T1 is about the effect of pre-existing stringency on costs ($\partial A_I/\partial\eta$<0 and $\partial A_N/\partial\eta$<0), while T4 is about the curvature of that cost with further increases in stringency (the elasticity $\alpha_{I\eta}$ and $\alpha_{N\eta}$). T2 and T3 are about the effect of resources on the policy fraction b ($\partial b/\partial Q_I$>0 and $\partial b/\partial Q_N$<0) and thus on costs.

way. We now exploit comprehensive U.S. state-year panel data from 1990 to 2015 to provide empirical evidence for those findings.[11] We use a standard fixed-effect estimating equation as our main specification:

$$Y_{it} = \beta_S SRPS_{it} + \beta_Z Z_{it} + \beta_{SZ}(S_{it} \times Z_{it}) + \beta_V V_{it} + s_i + \lambda_t + \epsilon_{it} \tag{44}$$

where subscripts refer to state i and year t. The dependent variable is an outcome Y (such as per capita CO_2 emissions or renewable electricity). Then $SRPS$ is the key policy variable that measures the stringency of the RPS or the renewable requirements (i.e., our policy parameter η in the analytical model). A set of covariates, Z, includes key factors that jointly determine effects of the RPS (such as pre-existing RPS, renewable endowments, and renewable intermittency). Then the signs and magnitudes of the coefficients β_{SZ} on the interaction terms between the policy variable $SRPS$ and the key factors in Z tell us whether our hypotheses hold. We include a set of control variables V. The time invariant state fixed effect is captured by s_i and can be correlated with other explanatory variables. Finally, λ_t is a vector of year dummies, and the idiosyncratic error term ϵ_{it} captures unobserved characteristics.

A threat to causal inferences here is the non-random adoption of the state RPS policies. Our standard fixed-effect model controls for all observed and unobserved time-invariant and state-specific confounders, but unobserved time-varying confounding factors can result in omitted-variable bias. The sign and magnitude of the bias depend on the correlations between omitted variables and the policy variable. Finding a valid and strong instrument variable for the state RPS policy is in principle our first best option to deal with the endogeneity and omitted variable bias problem, but in practice it is generally a challenging task. Instrumental variable candidates can survive the relevance condition but often fail the exclusion condition. The relevance condition requires the instrument and the policy variable to be correlated. We can find candidates that satisfy this condition such as states' political ideologies or renewable resource potentials. For example, studies show states with a larger republican representation or more renewable potentials are more likely to adopt the RPS.[12] The level of representation of the

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[11] A recent working paper by Greenstone et al. (2019) exploits the similar dataset but addresses different questions from our paper. They answer questions whether the adoption of RPS has effects on outcome variables such as electricity price, renewable shares, and carbon emissions. We are more interested in examining factors that drive those effects and in what way.

[12] Factors determining a state's choice of adopting an RPS are studied in the prior literature (Huang *et al*., 2007; Matisoff, 2008; Chandler, 2009; Lyon and Yin, 2010)

Republican Party or renewable potentials, however, affect states' legislation and various economic activities that we do not observe or control for, and those unobserved activities are likely to affect our outcome variables like emissions and renewable generation. The problem of an invalid or weak instrument variable can be worse than that of the omitted variables bias itself (Angrist and Pischke, 2009).

To address our research questions, the fixed effect model is our second-best option. At the minimum, we are worry-free of all observed and unobserved time-invariant and state-specific confounders. We utilize results from our general equilibrium analytical model and the prior literature to construct control variables that help to mitigate the bias. We use an even-study approach and varying sets of control variables for robustness checks. Even without causality, we want to check whether results are consistent with our theory. Here we are not trying to prove the theory, but we are trying to show the theory is a good representation of what might be driving the results.

4.2 Variables and Data

Dependent Variables

Outcome variables of interest are per capita state CO_2 emissions, per capita non-intermittent and intermittent renewable electricity generation from 1990 to 2015. We obtain annual state CO_2 emissions (in metric tons) and electricity generation (in MWh) from the U.S. Energy Information Administration (EIA). We define non-intermittent renewable electricity as that generated from hydro, biomass, and geothermal power. Intermittent renewable electricity is generated from wind and solar energy. Table 2 provides summary statistics for all variables.

Variables for Renewable Portfolio Standards

First, we construct the RPS adoption dummy *arps* by assigning the value of one to a state that has an enacted RPS and zero otherwise. The data on renewable portfolio standards are from the Database of State Incentives for Renewable and Efficiency (DSIRE).[13] The mean of the RPS adoption dummy in Table 2 is 0.269, which indicates that slightly more than one quarter of the pooled observations have an enacted RPS. This number does not reflect the growing popularity

[13] http://www.dsireusa.org/resources/data-and-tools/

of the RPS, which nearly sixty percent of states have adopted, because some states have only recently adopted RPS policies.

State RPS policies differ in several dimensions. The most important and relevant heterogeneity in RPS policies is their specified targets and timeframes. For example, Missouri sets the RPS renewable target of 15% by 2021 and New York targets 29% by 2015. As shown in our analytical model, we are especially interested in the RPS policy target or the percentage renewable electricity requirement (i.e., the policy scalar η in our analytical model). Here we ignore the future requirements and planning for those future requirements, and use only the actual requirement in each observed year. Thus, we construct the variable *srps* that measures the stringency of RPS or percentage renewable electricity requirement in state i at year t.

Some RPS policies schedule annual "interim" requirements for states before they must meet the final renewable requirement at the expiration of the RPS. Other states set interim standards only once every several years. For those states, we average out the incremental increase in the percentage requirement from one interim goal to the next for the non-interim requirement years. Our *srps* variable represents the annual interim requirement by the RPS in state i at time t. In addition, the types of electric utilities that are subject to the RPS vary by state, or in other words, the coverage of RPS differs from one state to another. To account for that, we first calculate the state's RPS "coverage" (between 0 and 1) based on shares of the electricity sold by the applicable utilities that are covered by the state RPS policies. We use 2015 electricity sales data from Form EIA-861M.[14] Then our *srps* is the product of the calculated coverage and the annual interim RPS requirement.

Factors that determine the impacts of RPS

Our analytical model emphasizes the cost of generating renewable electricity as a key source of differences in the impacts of RPS across states. The cost in turn depends heavily on the state's endowment and intermittency of renewable resources. We construct a non-intermittent renewable potential variable *n-rep* as the log of potential capacity from hydro, biomass, and geothermal energy and an intermittent renewable potential variable *i-rep* as the log of potential capacity from wind and solar energy. We get potential renewable capacity data from a study by the National Renewable Energy Laboratory (Lopez *et al*., 2012). These potential capacity data

[14] https://www.eia.gov/electricity/data/eia861m/

vary across states but not over time. We use *n-rep* and *i-rep* as proxies for the state's non-intermittent and intermittent renewable endowment.

To measure the intermittency of wind energy, we use the relation between power generation and wind speed, as is depicted by a power curve. The power curve specifies: (i) the cut-in speed, which allows wind turbine blades to rotate and generate power, (ii) the rated speed, which enables wind turbines to produce its maximum power level, and (iii) the cut-out speed, above which wind turbines should be shut down to prevent damages. Our measure of wind intermittency, *w-inter*, is defined as the frequency of a typical wind turbine switching between: (1) the power-generation status when wind speed is between the cut-in speed and the cut-out speed, and (2) the shutdown status when wind speed is below the cut-in speed, or above the cut-out speed.[15] In particular, *w-inter* is the log of the average number of "start-stop" switches from one hour to the next hour, over all stations in each state in a year. We use hourly wind speed data provided by the National Oceanic and Atmospheric Administration (NOAA) for various stations located in all states in the year 2005. We get our cut-in speed of 8 (miles/hour), rated speed of 31 (miles/hour), and cut-out speed of 55 (miles/hour) from the Department of Energy.[16]

Other Explanatory Variables

We control for a set of time-varying factors that can affect both a state's emissions and its choice to adopt an RPS.[17] Those variables are per capita gross state product in log form (*lgspc*), logged cooling and heating degree days (*lcdd* and *lhdd*), house and senate League of Conservation Voters scores (*hlcv* and *slcv*), state citizen ideology (*c-ideo*), state government ideology (*g-ideo*), electricity import ratio (*e-imp*), and logged natural gas price (*lngp*). Numbers of cooling and heating days come from the NOAA. Data obtained from the League of Conservation Voters include a rating of each state's Members of Congress on key environmental, public health, and energy issues by their average voting records in a year. States with Members that vote in favor of more environmental bills score higher. State citizen ideology is measured as the mean position of the active electorate in a state on a liberal – conservative continuum scale; state government ideology is the power weighted mean position of the elected public officials in

[15] Gunturu and Schlosser (2011); Ren *et al.* (2017).

[16] https://www.energy.gov/eere/articles/how-do-wind-turbines-survive-severe-storms

[17] Citations are in Footnote 10.

a state on the same continuum. State ideology data from 1990 - 2015 are generously shared by Richard Fording.[18] The electricity import ratio is calculated as the difference between electricity sales and generation in a state as a fraction of the state's electricity sales. Electricity and natural gas data are collected from the U.S. EIA.

State electricity market regulation and other environmental policies can also have significant effects on state CO_2 emissions. We include a dummy explanatory variable *e-res* that equals one if the state has a deregulated or restructured electricity market, and zero otherwise. The decision made by the states to deregulate the electricity market is generally coupled with efforts to bring in more competition in the power sector, lower electricity prices, and promote alternative energy, which can affect state emissions. Data on deregulation statuses are available from the EIA.

We also include a corporate tax incentives dummy variable (cti) that equals one if the state has corporate tax incentives for renewables in a given year, and zero otherwise. We also constructed a binary *spf* variable that equals unity if the state maintains a public benefits fund for renewables in a given year, and zero otherwise. Another policy dummy variable we include is the energy efficiency resource standards (ees) that require electricity utilities to reduce some specified percentage of projected energy sales through energy efficiency measures such as through customers' end-use efficiency programs run by utilities or third-party program operators. Data on renewable policies are from DSIRE.

4.3 Empirical Results

Impacts on Carbon Dioxide Emissions

This sub-section presents empirical evidence for the four hypotheses regarding the effects of state RPS policy on CO_2 emissions (H1.C – H4.C, as summarized in Table 1). Table 3 reports results of estimating equation (44) where the dependent variable is the log of per capita carbon dioxide emissions (i.e., variable C in our analytical model). We use time and state fixed effect models for all columns of the table. The only difference among columns is the set of covariates.

Rows 1-7 show an empirical test of our first hypothesis, which predicts that a more stringent RPS policy has a larger marginal effect on reducing carbon dioxide emissions (H1.C).

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[18] https://rcfording.wordpress.com/state-ideology-data/

Our strategy is to group all state RPS observations into three bins with low, medium, and high stringency. We define three dummies: (1) low stringency bin (*lsb*) that equals one if the state has an enacted RPS and the percentage renewable electricity requirement is less than some threshold τ_l, (2) medium stringency bin (*msb*) that equals one if the percentage renewable electricity requirement is greater than τ_L but smaller than some threshold $\tau_M > \tau_L$, and (3) high stringency bin (*hsb*) if RPS percentage requirement is greater than τ_M. Our choices of thresholds are based on the summary statistic of *srps*. We choose $\tau_L = .021$ and $\tau_M = .045$ which are the 25th percentile and median of all strictly positive values of *srps*. Then, interaction terms between our three bins with the policy stringency (*srps*×*lsb*, *srps*×*msb*, and *srps*×*hsb*) capture the difference in marginal effects of the RPS policy when its stringency is from low to high compared to the omitted bin of no policy.

We find some differences in the marginal effects of the low to high stringency bins. The coefficients on the interaction terms in rows 5-7 of Table 3 are negative and statistically significant at 1% and 5%. Besides the negative sign of those estimated coefficients, their magnitudes are also interesting to interpret. Compared to the no-policy case, increasing RPS requirement from zero to the low stringency bin has the largest marginal effect on emission reduction. The result suggests that it is expensive to meet the first incremental unit of RPS requirement. That can be due to the cost of learning or initial required infrastructures. Our linearization approach model cannot compare the marginal effect of moving from a no-policy scenario to a low stringency scenario, but it does consider the marginal effect of increasing the policy stringency from some positive initial stringency level. The estimated coefficients on the interaction term *srps*×*msb* are less negative than the estimated coefficients on the interaction term *srps*×*hsb*. The result is consistent with H1.C that a more stringent RPS policy has a larger marginal effect on reducing carbon dioxide emissions.

Rows 8 and 9 of Table 3 show estimated coefficients on the interaction terms between state intermittent renewable potential (*i-rep*), non-intermittent renewable potential (*n-rep*), and policy stringency (*srps*). Coefficients on the interaction term s*rps*×*i-rep* are all negative and statistically significant while estimates of the interaction term s*rps*×*n-rep* are all positive and statistically significant. Those signs are all predicted by our second and third hypotheses regarding the effects of RPS on emissions (H2.C and H3.C) with analytical model's proof of T2 and T3. That is, the impact of an incremental increase in the RPS requirement (i.e., $\hat{\eta}$ in our analytical model) on emissions reduction is larger in states with greater intermittent renewable potential but smaller in states with greater non-intermittent renewable potential. For example, the magnitude of the estimates suggests that, on average and all else equal, one percent point increase in the RPS stringency in a state with one percent higher non-intermittent renewable potential (or one percent smaller intermittent renewable potential) increases (or decreases) the state's per capita emissions by about 0.2% times the initial level of the renewable electricity requirement.

Also shown in Table 3, the coefficients on the interaction term between the RPS stringency and state wind intermittency (*srps*×*w-inter*) are negative and statistically significant at 1% and 5% levels. This result is consistent with T4 and our last hypothesis H4.C regarding the effect of RPS on emissions, which says that, *ceteris paribus*, the effect of RPS on emissions reduction is larger in states with greater renewable intermittency.

In Table 3, we control for various factors discussed in the data section. The main purpose of those controls is to mitigate the omitted variable bias. Some of our control variables, however, are potentially endogenous, so we vary our sets of controlled variables for robustness checks. We go from the most parsimonious specification with a minimum number of controlled variables (e.g., column 1 of Table 3) to the specification with the most number of controlled variables (e.g., columns 5 and 8 of Table 3). Our main results are robust regardless of our different sets of controlled variables.

Coefficients on logged heating degree days and logged per capita gross state product are positive and statistically significant across all specifications. One percent increase in per capital GSP increases per capita CO_2 emissions by 0.4% and one percent increase in heating degree days raises per capita emissions by about 0.1%. Coefficients on *e-imp* are negative and statistically significant in all columns, suggesting that importing electricity from elsewhere helps state to reduce their CO_2 emissions. Coefficients on electricity restructured market status (*e-res*) are also negative and statistically significant. Electricity restructured states tend to promote investments in alternative energy and are more likely to adopt and RPS and other renewable energy policies, thus one might expect that deregulated electricity market states emit less.

Changes in the price of natural gas can have opposite effects on emissions. For example, on one hand, a rise in gas prices generally reduces the consumption of natural gas and thus reduces emissions. On the other hand, a rise in gas prices discourages the switch from dirtier fossil fuels to cleaner fossil fuels such as a switch from coal to natural gas, and as a result an increase natural gas price can increase emissions. Results in Table 3 show negative but statistically insignificant coefficients on logged natural gas price. Coefficients on other controlled variables are very small in magnitude and also not statistically significant.

Impacts on Renewable Development

This section show empirical evidence for hypotheses regarding the effects of tightening the state RPS policy on intermittent renewable electricity (H1.RI – H4.RI) and on non-intermittent renewable electricity (H1.RN – H4.RN). Table 4 reports results of estimating equation (44) where the dependent variable is the log of per capita non-intermittent renewable electricity generation.[19] Table 5 shows regression results of equation (44) where the dependent variable is the inverse hyperbolic sine transformation of per capita intermittent renewable electricity generation.[20] Specifications in all columns in Tables 4 and 5 have year and state fixed effects and only differ in the number of control variables. Our interested coefficients are on the interaction terms between our policy stringency *rsps* and a set of key factors that can jointly determine the effect of state RPS policy. We generally expect the signs of coefficients on those interaction terms in Tables 4 and 5 are the same as those in Table 3 as shown in proofs of T1 – T4. Table 6 show the summary of our empirical results.

First, we check if our empirical results are consistent with H1.RI and H1.RN. We divide our samples into low, medium, and high stringency bin as in the previous section. In Table 4, the estimated coefficients on the interaction term $srps \times msb$ are less negative than the estimated coefficients on $srps \times hsb$. Also, estimated coefficients on the interaction between state policy stringency and high stringency bin are statistically significant at 5% level while coefficients on interaction terms between *srps* and lower stringency bins are not statistically significant at usual confidence levels. The results are consistent with H1.RN that a more stringent RPS policy has a smaller marginal effect on encouraging (or larger marginal effect on discouraging) non-intermittent renewable generation. In Table 5, the estimated coefficients on the interaction terms

[19] Delaware is the only state that has zero renewable electricity generation in several years, so logs of the state's renewable electricity generations in those year are not defined and treated as missing observations. For robustness check, we drop the entire Delaware data and run all specifications in Table 4, and we find similar results.

[20] Many observations have zero intermittent renewable electricity, so we use the inverse hyperbolic sine transformation instead of log form for our dependent variable.

srps×*msb* and s*rps*×*hsb* are both negative and statistically significant at 1% and 5%. The signs on the interaction terms are consistent with H1.RI, but estimated coefficients on *srps*× *msb* are more negative than estimated coefficients on *srps*×*hsb*. The result suggests a more stringent RPS policy has a larger marginal effect on encouraging (or smaller marginal effect on discouraging) intermittent renewable generation, which is not consistent with H1.RI. An explanation for this inconsistency is the possibility that states ratchet up intermittent renewable requirement faster as they increase their total renewable requirement.[21]

Other coefficients of our interests are on the interaction terms between state policy stringency *srps* with intermittent and non-intermittent renewable potential and wind intermittency. In Tables 4 and 5, estimated coefficients on the interaction term *srps*×*i-rep* are negative while the estimated coefficients on the interaction term *srps*×*n-rep* are positive. The results are aligned with empirical predictions H2.RI, H2.RN, H3.RI, and H3.RN from T2 and T3 of our analytical model. That is, the impact of tightening RPS on both intermittent and non-intermittent renewable development is smaller in states with greater intermittent renewable potential and greater in states with greater non-intermittent renewable potential. Coefficients on the interaction term s*rps*×*w-inter* are negative in all specifications of Tables 4 and 5, which is expected and in line with H4.RI and H4.RN. The greater intermittency of renewable resources implies higher compliance cost and thus stronger negative income and substitution effect that work to reduce renewable electricity generation.

Robustness check

As shown in Tables 3-5, we show empirical evidence for our H1-H4 by interacting state RPS policy stringency variable with a set of key factors. For robustness checks, first we use the same year and state fixed-effect model but change the number of controlled variables, and we examine if our choice of controls affects our results. We generally find that our results are robust to the choice of controlled variables.

Second, we employ an event-study approach to show some corroborated evidence for main findings of our analytical model. We pool information for states that adopted RPS policies from 1990 to 2015. We group all observations into two bins: the high stringency bin if *srps* is no

[21] The possibility that states ratchet up intermittent renewable requirement faster when state RPS policy gets more stringent is equivalent to the assumptions that $b_\eta > 0$ and b_η increases with η in our analytical model.

less than some threshold τ_H and the low stringency bin otherwise. Then our estimating equation is:

$$Y_{it} = \sum_{k \geq -m, \neq -1} \rho_k H_{it}^k + \beta_V V_{it} + s_i + \lambda_t + \epsilon_{it} \tag{45}$$

where $H_{it}^k = 1$ if, in period t, state i was in the high stringency bin k periods later (or, if k is negative, state i had been in the high stringency bin$-k$ periods earlier. Dependent variable Y_{it} is per capita emissions and renewable electricity generation as in previous sections. A set V is a set of controlled variables. We have fixed time and state effects (s_i and λ_t). Thus, our event here is when state moved to the high stringency bin. Our strategy basically normalize the idea that after controlling for state and time fixed effects and observable time-varying variables, a state that moved to the high stringency bin in 2005 was in much the same position in 2008 as a state that moved to the high stringency bin in 2010 was in 2013.

Our threshold τ_H is the median of all those positive values of state RPS stringency.[22] Our coefficients of interest are ρ_k, and we plot those estimated coefficients in Graphs 1-3. Graph 1 shows estimated coefficients when the dependent variable is logged emission per capita, and Graph 2 and 3 show estimated coefficients when the dependent variables are logged non-intermittent renewable electricity generation per capita and inverse hyperbolic sine transformations of intermittent renewable electricity generation per capita respectively. Event study graphs 1-3 show the estimated coefficients on the vertical axis and time in the horizontal axis. In our event study regression, we normalize the time when states moved to the high stringency bin to zero.

Our estimated coefficients have large standard errors. Also, results shown in our Graphs 1-3 should only be interpreted as suggestive correlations rather than causal effects. Graph 1 shows some evidence that after moving to the high stringency bin, states reduce their emissions. Graphs 2 and 3, however, do not present a strong evidence that having high renewable requirement (i.e., stringency) either reduce or increase their renewable electricity generation. The trends in Graphs 2 and 3 suggest that tightening state RPS policy stringency might help to increase renewable generation at first but the effect fades away and ultimately can go to the opposite direction to reduce renewable generation. The trends in Graphs 2 and 3 corroborate our

[22] We try different threshold values between 50th to 80th percentile, and we get similar results.

analytical findings that income and substitution effects from the tightening of state RPS policy work in the opposite direction with the direct policy effect on encouraging renewable development while all of the effects work in the same direction to reduce emissions.

5. Conclusion

We use an analytical general equilibrium model to study key factors that determine the effects of RPS on carbon emissions and renewable development. The advantage of our analytical model is that we are able to decompose the effects of RPS into different components. Thus we can show (1) the mechanism behind how each state RPS works and (2) what the sources of heterogeneity of the effects of RPS in each state are. Our analytical model explains why empirical papers are more likely to find significant effects of RPS on carbon dioxide emissions but get mixed evidence to find effects of RPS on renewable deployment. Our results prove to be consistent with what have been found in the prior literature.

In addition, our analytical model yields hypotheses regarding which factors determine the sign and magnitude of the impacts of RPS, which we then can test using real U.S. state-level data for 26 years. The results paint a clear picture, for example, of whether and how a key RPS design feature affect the impacts of each state RPS. Our model also shows key determinants of the effect of RPS include the endowment of fossil fuels, non-intermittent and intermittent renewable resources, the intermittency of renewable resources, the pre-existing RPS, the elasticity of substitution between the primary factor (i.e., capital and labor) and energy input, and the electricity market power. Our paper demonstrates that analytically tractable general model models can provide useful and insightful inputs to the empirics.

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TABLES:

Table 1: Summary of Model Predictions for Empirical Results

	$\hat{C}$	$\widehat{R_N}$	$\widehat{R_I}$
Overall (*Level*) of the Effect	$-$	$+/-$	$+/-$
Derivatives			
H1: Pre-existing RPS (η)	$-$	$-$	$-$
H2: Intermittent Renewable Endowment (Q_I)	$-$	$-$	$-$
H3: Non-intermittent Renewable Endowment (Q_N)	$+$	$+$	$+$
H4: Renewable Intermittency (α_η)	$-$	$-$	$-$

Table 2: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
CO_2 emissions (MMT)	103.027	79.4416	5.48992	404.781
Non-intermittent renewable generation (TWh)	7.14389	14.5850	0	105.188
Intermittent renewable generation (TWh)	0.72410	2.05763	0	27.0439
Population (million)	5.68634	6.08003	0.453690	40.5652
Per capita CO_2 emissions (MT)	23.8047	19.0230	8.080129	132.574
Per capita non-intermittent renewable generation (MWh)	1895.05	3162.21	0	18536.2
Per capita intermittent renewable generation (MWh)	232.853	852.298	0	8448.65
RPS adoption (0/1)	0.26923	0.44374	0	1
RPS percentage requirement (0 to 1)	0.01908	0.04967	0	0.36641
Logged non-intermittent renewable potential (GWh)	12.9355	1.13583	9.40662	14.3304
Intermittent renewable potential (GWh)	6.53618	0.73111	4.78224	7.53917
Wind intermittency (0 to 1)	0.20356	0.02436	0.17081	0.27457
Logged heating degree days	3.67833	0.22119	2.63346	4.03382
Logged cooling degree days	2.89124	0.35003	1.62324	3.61773
House LCV scores (0 to 100)	45.8897	26.0857	0	100
Senate LCV scores (0 to 100)	49.2474	33.4004	0	100
Per capita gross state product ($000's)	36947.5	12035.6	15028.5	78824.4
Natural gas price ($/000'cf)	5.09505	2.17939	1.46000	13.4700
Electricity import ratio	0.25022	0.59970	-3.03554	0.82749
High school graduation rate (%)	74.5333	8.41466	48.0000	93.4000
Restructured Electricity Market (0/1)	0.23829	0.42621	0	1
Corporate Tax Incentive (0/1)	0.16137	0.36802	0	1
Public Benefits Fund (0/1)	0.28929	0.45362	0	1
Energy Efficiency Standard (0/1)	0.16471	0.37107	0	1
Citizen ideology (0 to 100)	49.7820	15.0822	8.44989	95.9716
State ideology (0 to 100)	47.4894	14.4126	17.5122	73.6186

Table 3: Effects of RPS on CO_2 Emissions

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
arps	-0.006		-0.005		-0.005			
	(0.008)		(0.007)		(0.007)			
srps	-4.887***	-3.892***	-3.837***	-3.978***	-3.922***			
	(1.648)	(1.259)	(1.267)	(1.267)	(1.276)			
lsb						0.001	0.003	0.003
						(0.008)	(0.008)	(0.008)
msb						-0.035	-0.026	-0.026
						(0.027)	(0.028)	(0.028)
hsb						0.000	-0.004	-0.004
						(0.014)	(0.011)	(0.011)
srps × lsb						-5.565***	-4.385***	-4.470***
						(1.707)	(1.353)	(1.366)
srps × msb						-4.297**	-3.430**	-3.519**
						(1.876)	(1.532)	(1.517)
srps × hsb						-5.118***	-3.909***	-3.998***
						(1.652)	(1.319)	(1.346)
srps × i-rep	-0.229*	-0.202**	-0.199**	-0.199**	-0.196**	-0.238**	-0.201**	-0.198**
	(0.116)	(0.095)	(0.095)	(0.091)	(0.091)	(0.110)	(0.085)	(0.081)
srps × n-rep	0.239**	0.193**	0.192**	0.195**	0.194**	0.251**	0.196***	0.198***
	(0.108)	(0.076)	(0.077)	(0.073)	(0.073)	(0.101)	(0.072)	(0.069)
srps × w-inter	-4.325**	-3.545***	-3.496***	-3.603***	-3.553***	-4.467**	-3.525***	-3.585***
	(1.774)	(1.237)	(1.248)	(1.227)	(1.238)	(1.794)	(1.269)	(1.264)
lhdd	0.131***	0.115***	0.116***	0.114***	0.114***	0.134***	0.116***	0.115***
	(0.033)	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)	(0.032)	(0.032)
lcdd	0.008	0.008	0.008	0.007	0.007	0.008	0.008	0.007
	(0.008)	(0.007)	(0.007)	(0.006)	(0.007)	(0.008)	(0.007)	(0.007)
lgsppc		0.405***	0.404***	0.399***	0.398***		0.402***	0.396***
		(0.088)	(0.088)	(0.089)	(0.089)		(0.089)	(0.090)
hlcv		0.000	0.000	0.000	0.000		0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
slcv		0.000	0.000	0.000	0.000		0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
e-res		-0.016**	-0.015**	-0.015**	-0.015**		-0.015**	-0.015**
		(0.007)	(0.007)	(0.007)	(0.007)		(0.007)	(0.007)
ees		0.002	0.003	0.002	0.002		0.003	0.002
		(0.009)	(0.008)	(0.009)	(0.008)		(0.008)	(0.008)
cti		0.001	0.001	0.001	0.001		0.001	0.000
		(0.009)	(0.010)	(0.009)	(0.009)		(0.009)	(0.009)
spf		-0.007	-0.006	-0.007	-0.007		-0.006	-0.007
		(0.010)	(0.010)	(0.009)	(0.010)		(0.010)	(0.010)
g-ideo		0.000	0.000	0.000	0.000		0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
c-ideo		0.000	0.000	0.000	0.000		0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
e-imp		-0.065***	-0.065***	-0.066***	-0.066***		-0.065***	-0.066***
		(0.023)	(0.023)	(0.023)	(0.023)		(0.023)	(0.023)
lngp				-0.041	-0.041			-0.041
				(0.030)	(0.029)			(0.029)
Year and State Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observation	1196	1196	1196	1196	1196	1196	1196	1196
R-squared	0.627	0.69	0.701	0.691	0.692	0.63	0.692	0.694

Notes: The dependent variable is logged carbon dioxide emissions per capita.
Robust standard errors are clustered at the state level in parentheses.
* Significant at 10%, ** Significant at 5%, *** Significant at 1%

Table 4: Effects of RPS on Non-Intermittent Renewable Electricity Generation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
arps	0.033		0.022		0.022			
	(0.036)		(0.033)		(0.032)			
srps	-9.689*	-9.273**	-9.458**	-8.778**	-8.962**			
	(5.576)	(4.538)	(4.584)	(4.268)	(4.307)			
lsb						-0.014	0.000	0.001
						(0.058)	(0.063)	(0.063)
msb						0.032	0.019	0.019
						(0.165)	(0.158)	(0.159)
hsb						0.118	0.077	0.077
						(0.071)	(0.073)	(0.072)
srps × lsb						-11.000	-10.329	-9.865
						(6.923)	(7.036)	(6.943)
srps × msb						-12.313	-11.416	-10.912
						(8.257)	(8.174)	(7.988)
srps × hsb						-13.186**	-11.692**	-11.185**
						(6.499)	(5.682)	(5.423)
srps × i-rep	-1.617**	-1.495***	-1.502***	-1.484***	-1.491***	-1.811**	-1.623***	-1.611***
	(0.676)	(0.531)	(0.528)	(0.530)	(0.528)	(0.685)	(0.566)	(0.566)
srps × n-rep	1.028*	1.086**	1.087**	1.056**	1.057**	1.227**	1.212**	1.181**
	(0.555)	(0.433)	(0.435)	(0.416)	(0.418)	(0.565)	(0.466)	(0.450)
srps × w-inter	-9.620**	-6.768**	-6.960**	-6.501*	-6.693**	-11.940**	-8.453*	-8.179*
	(3.796)	(3.347)	(3.390)	(3.261)	(3.295)	(4.854)	(4.431)	(4.321)
lhdd	0.547*	0.457	0.455	0.462	0.459	0.566*	0.468	0.472
	(0.293)	(0.275)	(0.275)	(0.276)	(0.276)	(0.302)	(0.285)	(0.285)
lcdd	-0.067	-0.085	-0.085	-0.082	-0.082	-0.074	-0.088	-0.084
	(0.090)	(0.089)	(0.089)	(0.092)	(0.092)	(0.091)	(0.090)	(0.093)
lgsppc		0.410	0.409	0.424	0.423		0.390	0.404
		(0.370)	(0.371)	(0.367)	(0.368)		(0.368)	(0.365)
hlcv		-0.002**	-0.002**	-0.002**	-0.002**		-0.002**	-0.002**
		(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)
slcv		0.000	0.000	0.000	0.000		0.000	0.000
		(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)
e-res		0.099**	0.097**	0.098**	0.096**		0.096**	0.095**
		(0.046)	(0.046)	(0.046)	(0.046)		(0.046)	(0.046)
ees		0.006	0.003	0.006	0.003		0.000	0.001
		(0.033)	(0.035)	(0.033)	(0.035)		(0.034)	(0.034)
cti		-0.116**	-0.116**	-0.115**	-0.116**		-0.114**	-0.114**
		(0.045)	(0.045)	(0.045)	(0.045)		(0.045)	(0.045)
spf		0.020	0.018	0.023	0.021		0.018	0.020
		(0.049)	(0.050)	(0.050)	(0.051)		(0.051)	(0.052)
g-ideo		0.002	0.002	0.002	0.002		0.002	0.002
		(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)
c-ideo		-0.002	-0.002	-0.002	-0.002		-0.002	-0.002
		(0.002)	(0.002)	(0.002)	(0.002)		(0.002)	(0.002)
e-imp		-0.045	-0.045	-0.042	-0.042		-0.045	-0.043
		(0.083)	(0.083)	(0.083)	(0.083)		(0.082)	(0.082)
lngp				0.130	0.131			0.129
				(0.184)	(0.186)			(0.187)
Year and State Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observation	1170	1170	1170	1170	1170	1170	1170	1170
R-squared	0.263	0.304	0.304	0.305	0.305	0.267	0.306	0.306

Notes: The dependent variable is logged non-intermittent renewable electricity generation per capita.
Robust standard errors are clustered at the state level in parentheses.
* Significant at 10%, ** Significant at 5%, *** Significant at 1%

Table 5: Effects of RPS on Intermittent Renewable Electricity Generation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
arps	0.823		0.762		0.769*			
	(0.507)		(0.458)		(0.448)			
srps	-109.264**	-82.875*	-90.915*	-74.360*	-82.416**			
	(48.083)	(48.286)	(47.725)	(41.285)	(40.613)			
lsb						0.175	0.226	0.237
						(0.485)	(0.548)	(0.535)
msb						1.559*	1.403	1.409*
						(0.773)	(0.834)	(0.828)
hsb						1.469*	1.240	1.237
						(0.743)	(0.794)	(0.753)
srps × lsb						-86.991	-65.805	-57.349
						(54.494)	(57.384)	(51.319)
srps × msb						-149.412***	-125.157**	-116.230**
						(47.811)	(50.362)	(44.816)
srps × hsb						-132.168**	-107.946**	-99.089**
						(50.158)	(52.506)	(45.985)
srps × i-rep	-0.923	0.678	0.272	0.380	-0.032	-2.253	-0.713	-0.995
	(5.032)	(5.727)	(5.555)	(4.890)	(4.741)	(4.826)	(5.753)	(4.916)
srps × n-rep	6.894**	4.855	5.084	4.624*	4.853*	8.168***	6.036*	5.785**
	(2.932)	(3.218)	(3.248)	(2.710)	(2.714)	(2.875)	(3.366)	(2.823)
srps × w-inter	-35.788	-25.644	-32.767	-19.846	-26.996	-51.405	-44.423	-38.418
	(54.639)	(62.679)	(63.282)	(57.487)	(57.836)	(57.035)	(67.899)	(62.314)
lhdd	-1.034	-1.585	-1.649	-1.420	-1.484	-0.981	-1.623	-1.460
	(1.351)	(1.351)	(1.366)	(1.329)	(1.337)	(1.376)	(1.418)	(1.386)
lcdd	1.140	0.870	0.865	0.981	0.977	1.084	0.833	0.945
	(0.692)	(0.648)	(0.652)	(0.655)	(0.658)	(0.693)	(0.657)	(0.662)
lgsppc		6.398	6.501	6.959	7.067		6.360	6.928
		(5.159)	(5.100)	(5.037)	(4.978)		(5.148)	(5.021)
hlcv		0.006	0.006	0.005	0.004		0.006	0.004
		(0.006)	(0.006)	(0.006)	(0.006)		(0.006)	(0.006)
slcv		0.009	0.007	0.008	0.007		0.007	0.007
		(0.005)	(0.005)	(0.005)	(0.005)		(0.005)	(0.005)
e-res		-0.213	-0.285	-0.228	-0.301		-0.289	-0.305
		(0.505)	(0.503)	(0.494)	(0.491)		(0.505)	(0.492)
ees		0.123	0.026	0.172	0.074		-0.006	0.043
		(0.544)	(0.531)	(0.533)	(0.521)		(0.537)	(0.526)
cti		-0.412	-0.440	-0.395	-0.422		-0.403	-0.386
		(0.602)	(0.587)	(0.580)	(0.565)		(0.595)	(0.572)
spf		-0.011	-0.084	0.056	-0.018		-0.090	-0.024
		(0.447)	(0.452)	(0.432)	(0.433)		(0.450)	(0.431)
g-ideo		0.022**	0.020**	0.020*	0.018*		0.020**	0.018*
		(0.010)	(0.009)	(0.010)	(0.009)		(0.009)	(0.010)
c-ideo		-0.045**	-0.046**	-0.042**	-0.043**		-0.046**	-0.043**
		(0.019)	(0.019)	(0.019)	(0.018)		(0.019)	(0.019)
e-imp		1.797**	1.789**	1.864**	1.857**		1.785**	1.852**
		(0.716)	(0.723)	(0.694)	(0.702)		(0.730)	(0.708)
lngp				4.068**	4.096**			4.081**
				(1.592)	(1.540)			(1.529)
Year and State Fixed Ef	Y	Y	Y	Y	Y	Y	Y	Y
Observation	1196	1196	1196	1196	1196	1196	1196	1196
R-squared	0.643	0.683	0.588	0.689	0.694	0.646	0.69	0.695

Notes: The dependent variable is the inverse hyperbolic sine of per capita intermittent renewable electricity generation. Robust standard errors are clustered at the state level in parentheses.
* Significant at 10%, ** Significant at 5%, *** Significant at 1%

Table 6: Summary of Empirical Results

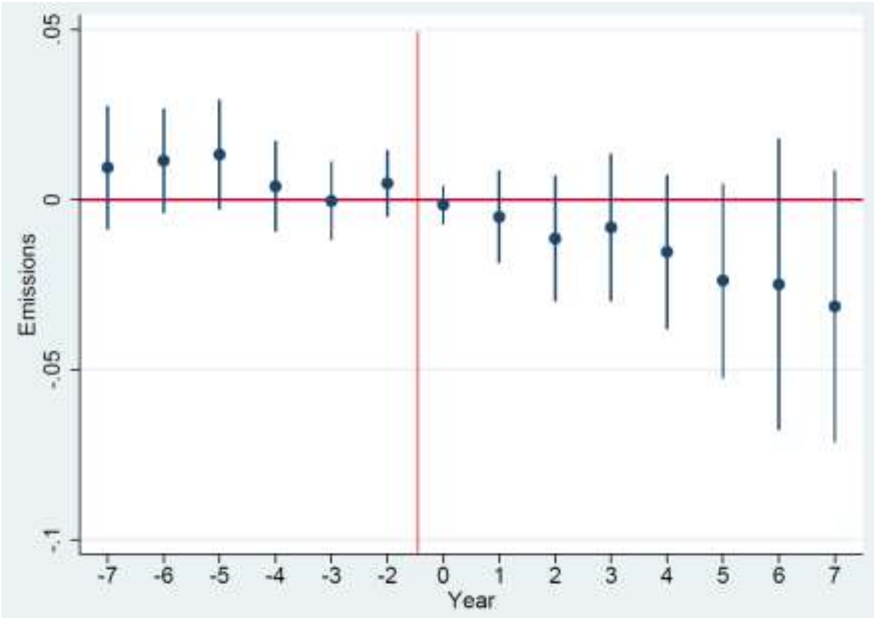
	$\hat{C}$	$\widehat{R_N}$	$\widehat{R_I}$
H1: Pre-existing RPS (η)	√***	√**	⊗
H2: Intermittent Renewable Endowment (Q_I)	√**	√***	√
H3: Non-intermittent Renewable Endowment (Q_N)	√***	√**	√**
H4: Renewable Intermittency (α_η)	√***	√**	√

Notes: * Significant at 10%, ** Significant at 5%, *** Significant at 1%
√: Consistent with Prediction; ⊗: Inconsistent with Prediction

GRAPHS:

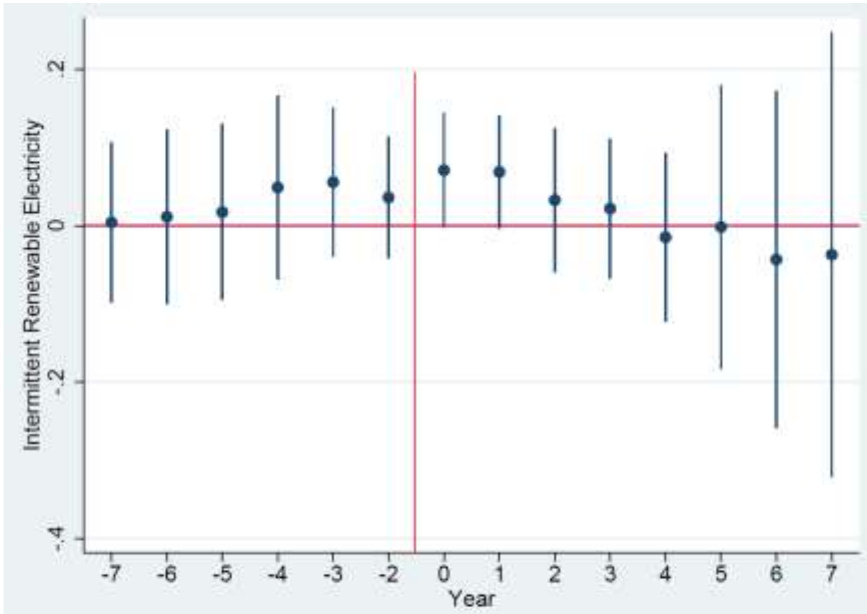
Graph 1:

Effects of Tightening RPS on Emissions – Event Study



Graph 2:

Effects of Tightening RPS on Intermittent Renewable Electricity – Event Study



Graph 3:

Effects of Tightening RPS on Non-intermittent Renewable Electricity – Event Study