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Renewable Portfolio Standards: Effectiveness and Carbon Implications

Alexander S. Albrecht
Claremont McKenna College

Claremont McKenna College

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Alexander Albrecht

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Abstract

A renewable portfolio standard (RPS) policy is a popular regulatory tool implemented within the U.S. and abroad to limit energy sector emissions and incentivize renewable energy. Assessing their effectiveness and efficiency is a key component of achieving further reductions**.** We assess an energy market under an RPS using fixed-effects panel and 2SLS regression models to lend empirical credence to common theory-based concerns about RPS policy, namely (1) that they leave emissions unregulated once the RPS requirement is met and (2) that they do not incentivize full use of renewable energy resources. Our results show these to be valid concerns that should be considered in the selection, design, and implementation of current or future RPS policies.

I. Introduction

Governments across the world are implementing policies intended to decrease carbon emissions and increase renewable energy production in order to lessen the impact of anthropogenic climate change. Other benefits of energy investment include improved national security and economic growth. To realize these environmental and safety benefits, some governments have chosen to implement a renewable portfolio standard (RPS), which requires utilities to source a certain percentage of their electricity from renewable sources (Groba, Indvik, and Jenner, n.d.). In general, choosing policies thoughtfully and tailoring them to their specific situation is integral to maximizing their success in reducing carbon emissions. This paper focuses specifically on renewable portfolio standards (RPS) and their effects on carbon emissions through the lens of an energy market. We examine the relationships between renewable generation, emissions, and utilities' cost-minimizing decisions to provide insights into energy market mechanics when renewable portfolio standards have been chosen as the policy intervention.

Renewable portfolio standards are only one policy option among many. Other potential approaches are carbon tax policies, which assess charges for each emitted ton of carbon dioxide; or cap-and-trade, where a pollution limit is set and emissions allowances are traded on an open market to allow firms to achieve emissions reductions at the lowest possible cost. Another policy option is a feed-in tariff, under which the government purchases renewably-generated energy at a set price above market price to reward renewable energy producers. Each of these approaches, including renewable portfolio standards, have been shown to increase the share of generated renewable energy and reduce emissions (Choi et al. 2018, Benavides et al. 2015, Yin and Powers 2010).

However, questions towards the efficiency and effectiveness of these policy interventions remain.

This paper empirically affirms some of the theoretical concerns with RPS policies, namely that they leave emissions reductions "on the table," so to speak, in a few ways. The first way is that an RPS selectively regulates emissions by mandating a standard, but does not regulate emissions in any way once the standard has been met. To illustrate this, consider that an RPS views a regulated entity that generates 20% of its energy with renewables and 80% of its energy with coal the same way it views one that generates 20% with renewables and 80% with natural gas, even though the emissions outcomes for these two entities would be drastically different. Intuitively, this means that emissions outcomes are not controlled as much as they could be under an RPS. To evaluate this concern empirically, we model whether the marginal cost of coal and natural gas generation, as proxied by input fuel prices, have a significant impact on emissions outcomes. We find that decreases in coal and natural gas fuel prices cause emissions to increase, lending support to the critique. We also find that increasing clean generation reduces carbon emissions, even when demand increases by the same amount. The second way an RPS leaves emissions reductions "on the table" is by allowing entities to stop using renewable generation once the RPS requirement has been met, even if additional renewable capacity exists. The idea is not necessarily to achieve zero carbon emissions, but to achieve the maximum emissions reductions possible given economic, infrastructural, and political constraints. The fact that this maximum is not achieved is an unsurprising but serious drawback of the policy design, and its implications for easily-attainable emissions reductions merits inspection. We find that the amount of renewable generation is likely affected by its cost, and that some renewable generation is brought online only when demand goes up. This supports the critique that an RPS does not facilitate the highest plausible deployment of renewable energy resources. Our results are strengthened by multiple econometric specifications, including fixed-effect panel regression and two-stage least squares regression. We urge future researchers and policymakers to consider the political and economic implications of capturing these unregulated emissions. We hope that this paper strengthens future policy by highlighting some of the current shortcomings with the RPS approach.

We will now provide some pertinent background on the relationship between renewable energy and the grid, including the role of balancing authorities in balancing supply and demand. We will then describe renewable portfolio standards and some of their key features. After establishing this background we summarize some of the relevant literature examining the effectiveness and efficiency of renewable portfolio standards.

1.1 Renewable Energy and the Grid

The electricity grid is built to supply large swaths of the population with instantaneous electricity as demand fluctuates. Aggregating and mobilizing electricity supply over an entire state within moments is no small feat and must be overseen by a balancing authority (BA). The role of the BA is to balance the supply and demand of energy by telling generators when to start and stop generating. Electricity suppliers provide the BA with their unique wholesale prices of energy, from which the BA begins to build its supply from the lowest-cost sources on up. If a BA does not provide adequate supply, customers experience blackouts. Weather-dependent renewable energy can be up to 70% variable for daytime solar due to cloud cover and 100% variable for wind when calm, making planning for anticipated demand more difficult when renewables make up a large portion of total generation (Crabtree et al. 2011). The deployment of increasing amounts of renewable energy to the grid is also limited by existing energy infrastructure, including higher transmission costs from remote renewable generation stations (Greenstone and Nath 2021). This means the optimal share of renewables in the energy mix is well below 100% given current economic, infrastructural, and political constraints. Finding the feasible maximum in renewable deployment and emissions reduction is a central goal in climate policy.

1.2 Renewable Portfolio Standards

One of the most common climate change policy instruments is a Renewable Portfolio Standard (RPS). An RPS is a command-and-control policy that requires a minimum share of a regulated entity's electricity generation to be provided by renewable energy (Groba, Indvik, and Jenner, n.d.). RPS policies usually increase their stringency over time. At the time of writing, thirty-one US states and the District of Columbia have enacted binding RPS policies, with seven more states adding voluntary ones. They are in use internationally in places like the EU, UK, China, Korea, and others.[1] RPS policies are generally intended to increase the "diversity, reliability, public health, and environmental benefits of the energy mix" (Yin and Powers 2010). Though many RPS policies have commonalities, there is significant variation in stringency, requirements, and composition of RPS policies (Yin and Powers 2010). The mechanism of RPS regulation is based on renewable energy credits, or RECs, which represent the "environmental, social, and other non-power attributes of renewable electricity generation" and function as implicit

[1] "Five States Updated or Adopted New Clean Energy Standards in 2021" n.d.

subsidies.[2] They are issued to renewable energy providers as an implicit subsidy for every kilowatt-hour of renewable electricity contributed to the grid. Notably, RECs are still paid out whether carbon-emitting generation goes down or not, establishing a potential disconnect between RECs and emissions reductions. These RECs drive down the marginal cost of renewable energy in the wholesale market, making renewable power more appealing to the BA and therefore increasing its grid share. This price effect – lowering the marginal cost of renewable energy to increase its quantity in the electricity supply – is a key feature of RPS regulation, and this paper examines how this effect materializes in energy markets regulated by an RPS.

RPS policy is popular politically because it operates on subsidy rather than tax grounds and seems to be fairly effective in increasing renewable share and reducing emissions, as previously mentioned, though economists tend to see subsidy regulation as second-best to tax regulation (Fowlie 2015). RPS policy is also advantageous because it sets the required renewable share and lets the market reach compliance for the lowest cost. In this strength lies a potential weakness, however; RPS policies rely on legislators to set the proper standard for renewable generation. If legislators pick a number that is too low, emissions will not be reduced as much as they could be. Despite their popularity, RPS policies and their outcomes should be closely examined to improve our understanding of the policy and its environmental & economic effects. The next section delivers a brief overview of the literature on RPS policy.

[2] US EPA 2022

III. Literature Review

There is a small body of existing literature studying the effectiveness and efficiency of RPS policies, though results are sometimes discordant. Generally, RPS is seen as effective in increasing the share of renewable generation in a region, with only some exceptions (Yin and Powers 2010, Menz and Vachon 2006). However, this is generally accomplished at high cost to the consumer, and it is unclear that RPS policies deliver sufficiently cost-effective emissions reductions.[3] Some relevant papers are described below.

Reguant (2019) compares the carbon tax, FIT, and RPS policy approaches by analyzing effectiveness in reducing greenhouse gas (GHG) emissions and cost distribution on consumers and producers. Reguant finds that large-scale renewable energy policies are most effective if the costs of renewable subsidies are passed directly to consumers. Reguant also finds that marginal emissions abatement costs are lower under a carbon tax and higher under FIT and RPS policies, a finding explained by the fact that carbon taxes achieve GHG reductions by promoting substitution for cleaner natural gas while FIT and RPS policies require more expensive investments in renewable energy technology.

Greenstone and Nath (2021) use differences-in-differences regression design to find that electricity prices are 11% higher and carbon emissions are 10-25% lower seven years after RPS passage. These substantial carbon reductions are noteworthy because they are two to six times larger than they would be if renewables simply replaced coal generation megawatt-for-megawatt. They observe steep declines in coal and petroleum

[3] Further discussion on cost-effectiveness is beyond the scope of this paper.

generation, indicating a broader RPS effect on the "merit order" of the power mix (relative usage of coal and natural gas energy sources), even when renewables are not operating.

Menz and Vachon (2006) find a positive relationship between the establishment of an RPS and wind power development. They also find a positive relationship between requiring electricity suppliers to provide green power options to consumers and wind energy development.

Brown and Bushe (2008) identify correlations between the existence of an RPS and higher wind power generation; they also identify a correlation between an RPS and a higher renewable share of overall electricity generation. They note the importance of these being correlations and not causations.

Carley (2009) finds that RPS implementation is not a significant predictor of renewable energy generation percentage. Carley does not use any explicit measure of policy stringency in the paper, however, she finds that the total amount of renewable energy generation increases with each consecutive year of an implemented RPS. This result may approximate a stringency aspect of RPS policies, an aspect addressed one year later by Yin and Powers.

Yin and Powers (2010) incorporate measures of heterogeneity - differing levels of stringency among RPS policies - to show that RPS policies have a significant positive effect on in-state renewable energy generation. Yin and Powers also note that allowing the "free trade" or leakage of RECs across states significantly weakens the impact of an RPS. In other words, an RPS causes more renewable energy to be added to the grid when accountability for sourcing that renewable energy rests within the regulated state and cannot be outsourced.

Lyon and Yin (2010) find that political ideology and private interests drive the adoption of an RPS instead of local environmental or employment benefits and call for a closer look at whether RPS policies (and environmental federalism) serve the public interest or not.

Shrimali and Kniefel (2011) find, counterintuitively, that implementing an RPS has a negative impact on grid penetration for wind, biomass, and combined renewables while showing a positive impact for geothermal and solar. Their results find economic factors such as electricity prices, natural gas price, per capita GDP, and "share of coal-generated electricity…to be generally insignificant, suggesting the crucial role of policy in increasing the penetration of renewables" (Shrimali and Kniefel 2011).

The general state of the literature is that renewable portfolio standards have a positive impact on renewable energy generation. The next selection of papers highlight some of the problems inherent in increased renewable penetration; namely, their intermittent nature introducing instability. In a high-renewable-share future scenario, high concentrations of solar and wind energy will need to be supplemented by stable low-carbon generation and storage (among other potential responses) to meet demand in the most efficient way (Crabtree et al. 2011). The following are the few papers that illustrate the issues around instability, overbuilding, or over-incentivization of renewables.

Baik et al. (2022) simulate different approaches California could take to reach their goal of a zero-carbon grid by 2045. They emphasize the importance of dispatchable (on-demand) low-carbon energy sources in the transition. In a scenario without dispatchable low-carbon energy, i.e. a grid powered completely by solar, wind, and storage, there is a significant overbuild of solar generation, leading to high amounts of excess energy being curtailed during the day when solar production outstrips demand.

Golden and Paulos (2015) echo the concern about periods of daytime overgeneration by wind and solar generation leading to high levels of curtailment. Curtailment can be minimized with supply- and demand-side measures, but is still wasteful and should be avoided.

Templeman et al. (2013) mention that inefficient design in RPS policies has led to development boom-and-bust cycles where an oversupply of renewable energy drives REC prices down, causing firms to exit. In this overdevelopment case, an investor finds natural gas more appealing than renewables. The effect of too much renewable supply on wholesale power prices and renewable share is an important factor to consider when examining an RPS.

Bose et al. (2019) affirm that subsidies can be important in stages of early innovation but quickly become unsustainable. They use the example of Spain, whose use of a generous subsidy led to a solar capacity ten times what was initially planned. When the subsidy was removed, many solar companies collapsed. They reiterate that government subsidies can over-incentivize the renewable industry and cause overcapacity.

Bento et al. (2018) use a general equilibrium model to simulate the effects of an RPS on emissions reductions and green resource booms. They find that increases in an RPS can generate either large resource booms or large emissions savings depending on the existing standard level and the supply price elasticity of renewable energy. They also find that RPSs with carve-outs for specific renewables cause booms for the targeted renewable(s) while causing busts for non-targeted renewables and lower emissions savings relative to an RPS that treats all renewables equally.

This limited set of literature notes some of the ways that an RPS can introduce inefficiency and fall short of its goals. With this backdrop in mind, my paper will focus on two main research questions gauging the effectiveness of an RPS: first, what is the effect on emissions of increases in clean energy generation; and second, is clean energy generation utilized to its full extent? The answers to these questions are important to the future implementation and refinement of RPS policy to better achieve the emissions-reducing goals of our environmental policies.

IV. Hypothesis Development

This paper's hypotheses follow from the research questions stated above and draw from economic theories about the balancing authority, the entity charged with aggregating and dispatching electricity supply in real time. BAs build up electricity supply to match demand by aggregating the lowest-cost generation sources until supply meets demand (or exceeds it, for protection against fluctuation). Each generation source, be it coal, natural gas, solar, wind, hydroelectric, or anything else has a marginal cost of generation. These vary based on the facility's capital costs, input fuel costs, and operations & maintenance (O&M) costs.[4] The RPS policy effectively lowers the cost of renewable generation by awarding an REC for each kW of clean generation, making it more appealing cost-wise. This makes compliance with the RPS requirement less expensive and more feasible for the regulated entities and increases the renewable share.

Electric utilities are driven by the profit motive and will minimize their total costs to maximize profits, subject to regulations like the RPS. First, utilities need to acquire a certain amount of RECs to comply with the RPS policy. Noncompliance is expensive, so cost-minimizing utilities prioritize compliance. They will do so by generating their own RECs, if that is cheaper than simply buying them, or by buying their RECs, if that is cheaper than generating them for themselves. Once a utility is in compliance with the RPS, they will minimize their costs by generating their lowest-cost electricity when required and sending it to the grid regardless of its carbon intensity. Therefore, it follows that the amount of clean generation brought to the grid depends on the price of clean generation: the lower the price, the higher the amount of clean generation. Because an

[4] "Distributed Energy Resources Initial Draft Report" n.d.

RPS does not expressly incentivize low-carbon fuels past the RPS requirement, the effect of an RPS policy on emissions can vary widely depending on the price and carbon intensity of remaining generation sources (Fowlie 2015). Showing this effect empirically is useful and enables a better prediction of the effect of an RPS on emissions given the variability of nationwide electricity markets. Understanding the level to which additional clean generation reduces emissions under an RPS is also valuable when characterizing the effectiveness and efficiency of the policy.

> *H1: The relative prices of coal and natural gas generation have a significant effect on the magnitude of emissions reductions brought about by an increase in clean generation under a renewable portfolio standard.*

This paper's second question asks whether we generate as much clean energy under the RPS as we could be generating for any given hour. Given the cost structure of electricity markets outlined above, there is an economic reason for utilities to generate the more expensive clean energy up to RPS compliance level, then fill the rest of supply with cheaper carbon-emitting sources. However, it would be detrimental from an emissions point of view if at any hour, more clean energy past the requirement could have been generated, and was not, in favor of cheaper carbon-emitting sources. RPS policies are meant to minimize carbon emissions and showing this policy-specific limit on effectiveness empirically is important for the future responsible adoption of RPS policies, especially when weighing them against other policy intervention options.

> *H2: At any given hour, the amount of renewable generation can vary even when factors that control for supply, demand, and costs are held constant, indicating a sub-maximal amount of renewable generation.*

V. Data

5.1 Data Description

The data used in this paper is balanced panel data from a confidential source and contains hourly-plant data for the 2017 calendar year. The set includes energy generation, energy demand, and emissions data in a state with an RPS policy. Demand is calculated from generation data using the assumption that supply equals demand at any hour, justified by the instantaneous balanced energy market. The dataset also includes hourly weather and monthly price data. These data are non-confidential and come from various governmental and meteorological sources. Heating and cooling degree days are defined as the degrees, in Fahrenheit, above or below 65 degrees for any given day. These are used to proxy for air conditioning and heating energy demand. Degree days are from the Degree Days website.[5] The dataset also includes data on hourly wind speed and cloud cover, the share of each hour with sunlight, and the length of the day. Hourly wind speed and cloud cover data are from NOAA's Local Climatological Data series.[6] Sunrise and sunset data (and therefore day length and daytime hours) are from the Astronomical Applications Department of the U.S. Naval Observatory.[7] All weather and meteorological factors are geographically matched to each plant based on their proximity to one of two main cities in the state. Additional variables in the dataset include the input fuel price of coal and natural gas as a Producer Price Index and the retail price of electricity. Coal and natural gas prices are from 2016 to reflect our assumption of lagged fuel contracts on the part of emitting power plants; they are taken from the Producer Price Index (PPI) given

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[5] www.degreedays.net
[6] https://www.ncei.noaa.gov/cdo-web/datatools/lcd
[7] https://aa.usno.navy.mil/data/RS_OneYear

by the Energy Information Administration (EIA).[8] Note that the units of the PPI are given in percent change in prices relative to base year 1982. Retail electricity prices are from the EIA's Electric Power Monthly release.[9] Each plant (n = 80) has an observation for each hour of the year (n = 8,759) for a total of 700,720 observations. Missing observations in weather data bring the final balanced observation count to 694,092.

5.2 Data Limitations

The data, and thus the study, have a few limitations. First, there is only data for calendar year 2017, so the bias-reducing benefits of a longer time period are lost. More could be learned about the effects of an RPS policy if the data's time frame included observations before and after the policy's implementation (or other large-scale changes to the policy) in the state. Future research using this dataset should be expanded to include additional years. Second, although plant-level generation data is available for most polluting plants, it is not available for renewable power plants. Renewable generation data is only available hourly on aggregate across the subject state. If all plants had plant-level generation data, the individual-level distinction would allow us to take fuller advantage of the fixed-effect panel regression model and could enable more granular hypothesis testing. The third main limitation comes from matching weather data to plants. This paper uses temperature and weather data from two main cities in the state, and while many plants operate in close proximity to those cities, some do not. This makes the weather data less accurate for plants that are far from these cities. Ideally, weather stations would be matched one-to-one to each plant to provide a more accurate

[8] https://fred.stlouisfed.org/series/WPU051 and https://fred.stlouisfed.org/series/WPU0531
[9] https://www.eia.gov/electricity/monthly/

representation of the temperature and weather conditions at each location. This would help clarify the role weather plays in clean generation supply and emissions outcomes. The final limitation is that data on plant-level marginal costs of generation is proprietary. Having access to this data would allow a deeper look at the price mechanism of electricity markets affected by environmental policies. It would also enable policymakers to monitor and tailor their policies to achieve their goals in an effective and efficient way.

5.3 Empirical Models

Empirically, this paper uses fixed-effects panel regression and two-stage least squares regression to test its hypotheses. The fixed effects panel regression model is appropriate because it makes use of the panel nature of the data and considers unobserved factors unique to each plant that could have impacts on variables of interest. Controlling for individual heterogeneity is important because it controls heterogeneity bias and therefore limits the chance of inaccurate regression estimates. The specifics of the models used are described in more detail for each hypothesis. The two-stage least squares regression is appropriate because it removes the simultaneity bias present in the data. Simultaneity bias in our study can be explained as follows. When demand is held constant, an increase in clean generation must mechanically reduce emissions because it is taking carbon-emitting generation offline. Because clean generation and emissions are tied together in this way, our clean generation variable is correlated with its error term. This introduces bias into our estimates. Two-stage least squares regression offers a way to break the simultaneity and isolate the effect of clean generation by using instrumental variables that are not correlated with the error term. The two-stage least squares model will be explained in more detail below.

5.4 Data Summary

The summary statistics for each variable of interest are included in Table 1. Since RPS policies target clean generation, understanding how clean generation changes over time is important to characterize. Appendix 1 shows the average clean generation and total generation over each hour of day, capturing a rise in demand over the evening hours and a bell-shaped distribution of clean generation peaking during the afternoon. The second graph in Appendix 1 shows the average clean generation and total generation for each month of the year, showing a spike through the summer months. The average share of clean generation in the total electricity supply for the entire year is around 8.1%. Appendix 2 is a binned scatterplot showing the quadratic relationship between cooling degree days (degrees over 65° F) and solar generation while controlling for month, hour of day, demand, cloud cover, and light hour. The graph shows that solar generation declines in efficiency as temperatures increase. Appendix 3 is a similar binned scatterplot (with the same set of controls) showing the relationship between hydroelectric generation and cooling degree days. The graph shows a negative relationship between heat and hydroelectric generation, presumably from dryness impacting reservoirs and limiting hydropower availability. Appendices 2 and 3 will be called upon when interpreting regression coefficients.

Table 1
Summary Statistics

VARIABLES	N	Mean	S.D.	Min.	Max.
CO_2 (tons)	700,720	1,223	467.2	379.2	3,130
Demand (MWh)	700,720	3,202	1,074	1,375	6,649
Clean Generation (MWh)	700,720	252.3	199.7	-1.182	868.3
Coal Price (PPI)	700,720	189.6	3.304	184.3	195.2
Natural Gas Price (PPI)	700,720	96.37	20.30	64.40	132.5
Retail Price (¢ per MWh)	700,720	8.651	0.622	7.920	9.680
Day Length (minutes)	700,720	731.6	108.2	562	898
CDD65 (°F)	700,720	7.944	10.14	0	38
HDD65 (°F)	700,720	8.981	10.28	0	47.60
Cloud (binary)	696,574	0.417	0.493	0	1
Wind Speed (mph)	694,092	7.206	6.360	0	50.33
Light Hour (binary)	700,720	0.550	0.483	0	1

VI. Methodology

We use two different fixed-effects panel regressions to examine each of our hypotheses before combining the two in a two-stage least squares regression. Our first hypothesis, regarding the effect of coal and natural gas input fuel costs on the magnitude of emissions reductions under an RPS, is tested using the regression below. We use coal and natural gas fuel input prices as a proxy for the marginal cost of coal and natural gas generation.[10] Our first model is specified in the following way:

$$\boldsymbol{CO2_t = \beta 1\ cleangen_t + \beta 2\ demand_t + \beta 3\ coalprice_t + \beta 4\ natgasprice_t + \beta 5\ hdd65_{it}}$$
$$\boldsymbol{+ \beta 6\ cdd65_{it} + T_t + P_i} + \varepsilon_{it}$$

Weather data was geographically matched to plants based on proximity to two large cities, leaving our "i" dimension to denote each power plant region. The "t" dimension denotes each hour of the year. The variable $\boldsymbol{CO2_t}$ is hourly total carbon dioxide emissions from monitored power plants, in tons; $\boldsymbol{cleangen_t}$ is the hourly total emissions-free generation, in MWh; $\boldsymbol{coalprice_t}$ is the monthly change in the price of coal as an input fuel, as a Producer Price Index; and $\boldsymbol{natgasprice_t}$ is the monthly change in the price of natural gas as an input fuel, as a Producer Price Index. In some versions of the model, we replace coal and natural gas fuel prices with the final consumer price $\boldsymbol{retailprice_t}$ as a measure of robustness. We also chose to include our temperature variables $\boldsymbol{hdd65_{it}}$ and $\boldsymbol{cdd65_{it}}$ to account for any variation in carbon emissions due to changes in temperature. The matrix $\boldsymbol{T_t}$ contains two sets of time fixed effect dummy variables: a vector of

[10] On the recommendation of Professor Laura Grant at Claremont McKenna College.

interacted hour of day and day of week control dummies and a vector of control dummies indicating the month. The matrix $\boldsymbol{P_i}$ contains plant region fixed effects. Finally, ε_{it} is the error term. We ran the first model in four iterations to see whether including different price controls or temperature data would alter our parameter estimates.

Our second model engages our second hypothesis, which predicts that an RPS leads a state to produce less renewable energy than it could be producing at any hour. We have assumed that the three broad-scale factors determining the amount of clean generation are supply, demand, and cost. We use variables that approximate supply and demand to predict the amount of clean generation on the grid at any given hour. If we find that a significant amount of the variation in clean generation is left unexplained by supply and demand, we will know that cost plays a significant role in limiting clean generation below what it could be. This would not be surprising, as it seems intuitive that cost would play an important role in any case, and the price effect explained above means that cost should theoretically play a role. This specification aims to empirically show that renewable energy is not produced to its feasible maximum at any hour. This model allows us to measure the relative size of that cost effect in addition to confirming its existence, enabling economists and policymakers to better understand the relative strengths of the determinants of renewable energy production. This model used to test our second hypothesis is a fixed-effects panel regression, specified below:

$$\boldsymbol{cleangen_t = \beta 1\ demand_t + \beta 2\ cdd65_{it} + \beta 3\ hdd65_{it} + \beta 4\ daylength_{it} + \beta 5\ lighthour_{it} + \beta 6\ cloud_{it} + \beta 7\ windspd_{it} + T_t + P_i + \varepsilon_{it}}$$

In this model, $\boldsymbol{cleangen_t}$, $\boldsymbol{demand_t}$, and the vectors of time and plant dummies are the same as in Model 1. The new variables are specifically weather-related: $\boldsymbol{cdd65_{it}}$ is cooling degree days, in degrees F; $\boldsymbol{hdd65_{it}}$ is heating degree days, in degrees F; $\boldsymbol{daylength_{it}}$ is the length of the day, in minutes; $\boldsymbol{lighthour_{it}}$ is a variable that indicates the share of any hour that experienced daylight; $\boldsymbol{cloud_{it}}$ is a binary indicator equaling 1 when there were clouds in the sky, and $\boldsymbol{windspd_{it}}$ is wind speed, in mph. These weather factors are matched to each plant by their proximity to two main cities in the state. We ran the second model in four iterations as well to see if including different price measures and squares of some variables would alter our parameter estimates.

Our final model is a two-stage least squares (2SLS) regression that uses the fitted values for $\boldsymbol{cleangen_t}$ from Model 2 to better predict the impact of clean generation on carbon emissions as in Model 1. Implementing 2SLS is appropriate because it breaks the problem of simultaneity, where an explanatory variable is correlated with its error term. In this paper, clean generation is mechanically related to carbon emissions: holding demand constant, an increase in clean generation will reduce carbon emissions. 2SLS avoids this issue by replacing the actual clean generation values, which are affected by this mechanical simultaneity, with the fitted values from Model 2, which are not. In this way, 2SLS allows us to reduce bias in our estimated parameters and obtain more accurate results. The 2SLS model is as follows, where $\boldsymbol{cleangen^*_t}$ are the fitted values obtained from Model 2:

$$CO2_t = \beta 1\ cleangen^*_t + \beta 2\ demand_t + \beta 3\ coalprice_t + \beta 4\ natgasprice_t + \beta 5\ hdd65_{it} + \beta 6\ cdd65_{it} + T_t + P_i + \varepsilon_{it}$$

Our 2SLS model is run in two specifications, one with coal and natural gas input fuel prices and one with the retail price of electricity.

VII. Results and Discussion

7.1 Model 1

All regression coefficients in Model 1 are statistically significant at the 1% level. As clean generation increases by one MWh, carbon emissions go down by 0.380 tons, slipping to 0.350 tons when temperature controls are added. Similarly, a one-MWh increase in demand is associated with a 0.441-ton increase in carbon emissions, shrinking to a 0.420-ton increase with temperature controls. Together, these indicate that bringing clean generation online does reduce emissions when demand is held constant (i.e. when clean generation replaces dirty generation). However, the relative magnitude of these coefficients suggests that when demand and clean generation both increase by one MWh, there will be a net increase in emissions. Fortunately, this counterintuitive result is addressed later by the 2SLS model.

This study finds that the price of coal and natural gas as input fuels are significantly negatively correlated with carbon dioxide emissions at the 1% level. Specifically, as seen in Table 2, the price of coal has a coefficient of -22.78 and the price of natural gas has a coefficient of -2.090. Holding all else constant, these mean that when the coal PPI goes up by one point, CO_2 emissions go down by 22.78 tons; and when the natural gas PPI goes up by one point, CO_2 emissions go down by 2.090 tons. These results support our hypothesis, which predicted that emissions would go down as the marginal cost of carbon-emitting generation, as proxied by coal and natural gas fuel prices, goes up. The observed effect of coal and gas prices implies that an increase in fuel input prices reduces the incidence of coal-burning electricity generation by passing the load to cheaper natural gas or renewable generation. Natural gas emits less CO_2 than coal, and renewables emit none, so this price shift reduces overall carbon emissions for any given hour by 22.78 tons. This is in line with economic theory and our hypothesis. The effect of natural gas prices on emissions is also significant but smaller in magnitude, indicating that the proposed mechanism affects coal and natural gas heterogeneously. We believe this effect could be caused by an asymmetrical substitution effect between coal and natural gas generation such that the market is more likely to substitute natural gas for coal than coal for natural gas. There are a few factors that could contribute to this asymmetry. First, natural gas plants are more flexible than coal plants, meaning they can ramp up and down (start and stop generating electricity) faster and at lower cost than coal, making them more appealing to developers and balancing authorities (Trabish 2014). Second, coal generation has been slowly falling out of favor with the public as we look towards lower-carbon generation sources as a solution to anthropogenic climate change. This has led to an international push to phase out heavily-polluting coal.[11] Each of these effects could reduce or reverse the hypothesized negative effect of natural gas prices on CO_2 emissions, resulting in the positive coefficient we observe in the results. It

[11] (“Phasing out Coal – World Energy Outlook 2021 – Analysis” n.d.)

appears that natural gas generation is too integral to electricity supply to respond much to changes in its input prices, indicating that its supply is relatively inelastic.

When we substitute the retail price of electricity for coal and natural gas prices, we see that a one-cent increase in the retail price reduces carbon emissions by 427.6 tons, dropping to 345.6 tons when temperature covariates are included. One reason for this could be that a higher retail price indicates a higher share of expensive clean generation. This would increase the retail price of electricity and reduce emissions, which is the observed result.

The coefficients on heating degree days showed that emissions decrease by 0.481 tons for each additional degree below 65° F. Conversely, the cooling degree day coefficient showed an emissions increase of 5.025 tons per degree above 65° F. We believe these effects are likely caused by seasonal variation not picked up by the month dummy variables. Our state uses far more energy in the warm months than the cold ones, and this demand pattern would create this type of temperature-based emissions fluctuation. A full table of regression coefficients is below.

Table 2
FE Panel Regression
Effect of Carbon-Emitting Generation Costs on CO2 Emissions

	(1)	(2)	(3)	(4)
VARIABLES	Coal & Gas Prices	Retail Prices	(1) with HDD and CDD	(2) with HDD and CDD
Clean Generation	-0.380***	-0.380***	-0.350***	-0.350***
	(0.00200)	(0.00200)	(0.00200)	(0.00200)
Demand	0.441***	0.441***	0.420***	0.420***
	(0.000383)	(0.000383)	(0.000425)	(0.000425)
Coal Price	-28.25***		-22.78***	
	(0.224)		(0.244)	
Natural Gas Price	-2.584***		-2.090***	
	(0.0351)		(0.0385)	
Retail Price		-427.6***		-345.6***
		(5.081)		(5.657)
HDD65			-0.481***	-0.481***
			(0.0395)	(0.0395)
CDD65			5.025***	5.025***
			(0.0438)	(0.0438)
Observations	700,720	700,720	700,720	700,720
R-squared	0.889	0.889	0.891	0.891
Number of plants	80	80	80	80

Notes: Data are from confidential sources, Degree Days, NOAA, U.S. Naval Observatory, and EIA (sources linked in data section). Fixed effects for each plant are included in the model. Standard errors are displayed in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Time and plant-level dummy variables were included in the regression but suppressed from this output table.

7.2 Model 2

This study finds that factors of supply and demand explain 79.4% of the variation in clean generation (R-squared = 79.4), leaving 21.6% of the variation unaccounted for by the model. We believe that the rest of this variation is due partially to the effect of cost and partially due to the omission of other relevant variables affecting the supply of clean generation. As outlined in the hypothesis development section, economic theory suggests that the cost of renewable energy generation is a partial determinant of the amount of clean generation supplied. Given that marginal cost data for renewable generation sources is unavailable and difficult to proxy, we believe that this R-squared value shows that cost plays a role in determining the quantity of renewable energy supplied. The magnitude of that role is anywhere from zero to twenty percent of the variation in clean generation, though theory and the regression results imply that it is higher than zero. Table 3 shows the coefficients for the variables included in the regression.

Demand has a significant positive correlation with clean generation, with a coefficient of 0.0666 to 0.0667 at the 1% level across specifications. This means that when demand goes up by one MWh, clean generation goes up by 0.0666 - 0.0667 MWh. These results show that clean generation increases as demand increases, lending further support to our assertion that cost plays a role in clean energy supply. Furthermore, this result shows that the market does not produce as much renewable energy as it could in any given hour. If the market produced as much renewable energy as it could, we would expect demand to have a statistically insignificant effect on clean generation. In this scenario, the supply of renewable energy would rely completely on factors of availability like sunlight, wind, and infrastructure capacity (under the assumption that renewable generation never exceeds demand, as shown in Appendix 1). The existence of the demand effect reinforces the fact that some renewable capacity is switched on or off due to changes in demand. If in any hour the market procured as much renewable energy as possible regardless of cost, the observed result would not occur.

The coefficient for heating degree days (HDD65) is -0.217 and shrinks to -0.210 when squares are included even though the square of HDD65 itself is statistically insignificant. This means that for each degree below 65° F, clean generation decreases by 0.210 - 0.217 MWh. This effect could be due to the reduced availability of solar and hydropower in the cooler months of late fall and winter caused by reduced sunlight and lack of snowmelt. The coefficient for cooling degree days (CDD65) is -2.739, indicating that as the temperature increases by one degree above 65° F, clean generation decreases by 2.739 MWh. When we include the square of cooling degree days, the coefficient changes to -3.012, increasing the effect of an additional degree on clean generation to 3.012 MWh. This could be attributed to the energy draw of air conditioning systems, which consume more energy as temperature rises. This result indicates that clean generation decreases during hotter hours, which could be due to a decrease in solar panel efficiency at higher temperatures, a phenomenon that is documented in the literature and supported within our data in Appendix 2 (Prudhvi and Chaitanya Sai 2012). Another factor could be the reduction in hydroelectric generation during hotter periods, especially during the late summer when dry conditions contribute to lower reservoir levels. This effect in the data is shown in Appendix 3. These effects are all associated with the late summer and slipped through despite the month dummy variables used in the regression.

Day length's coefficient of -0.425 is likely also affected by the summertime: for each minute of increasing day length, clean generation decreases by 0.425 MWh for the same reasons mentioned above. If it is a daylight hour, clean generation increases by 59.474 MWh, likely because of increased solar generation; if it is a cloudy hour, clean generation decreases by 5.898 MWh, also likely from the effect of reduced light on solar panels. Lastly, as wind speed increases by one mile per hour, clean generation increases by 2.216 MWh, which aligns with our intuition about wind generation.

This section would be remiss to avoid mentioning the other source of unaccounted-for variation in the model. This model accounted for demand and proxied for clean supply by using day length, daylight hour indicators, cloud cover indicators, and wind speed. There are certainly other meteorological and infrastructural factors that contribute to the supply side of renewable energy generation that this model does not incorporate, and these would most likely shrink the role that cost plays in the determination of the amount of clean generation. We believe our model provides a reasonably accurate insight into the supply-side determinants of clean supply given the data, but we acknowledge that the model is not exhaustive. More research into this question with more extensive data on supply-side determinants would be welcomed. The full table of regression coefficients is below.

Table 3
FE Panel Regression
Effects of Determinants of Clean Generation

	(1)	(2)	(3)	(4)
VARIABLES	Base	Retail Price	(1) and Squares	(2) and Squares
Demand	0.0667***	0.0667***	0.0666***	0.0666***
	(0.000243)	(0.000243)	(0.000243)	(0.000243)
HDD65	-0.217***	-0.217***	-0.210***	-0.210***
	(0.0240)	(0.0240)	(0.0637)	(0.0637)
Square of HDD65			-0.00230	-0.00230
			(0.00148)	(0.00148)
CDD65	-2.739***	-2.739***	-3.012***	-3.012***
	(0.0259)	(0.0259)	(0.0736)	(0.0736)
Square of CDD65			0.00882***	0.00882***
			(0.00186)	(0.00186)
Day Length	-0.425***	-0.425***	-0.427***	-0.427***
	(0.00649)	(0.00649)	(0.00651)	(0.00651)
Light Hour	59.47***	59.47***	59.38***	59.38***
	(0.669)	(0.669)	(0.669)	(0.669)
Cloud	-5.898***	-5.898***	-6.177***	-6.177***
	(0.339)	(0.339)	(0.341)	(0.341)
Wind Speed	2.216***	2.216***	2.577***	2.577***
	(0.0188)	(0.0188)	(0.0458)	(0.0458)
Square of Wind Speed			-0.0163***	-0.0163***
			(0.00185)	(0.00185)
Retail Price				-297.8***
				(3.476)

Observations	694,092	694,092	694,092	694,092
R-squared	0.794	0.794	0.794	0.794
Number of plants	80	80	80	80

Notes: Data are from confidential sources, Degree Days, NOAA, U.S. Naval Observatory, and EIA (sources linked in data section). Fixed effects for each plant are included in the model. Standard errors are displayed in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Time and plant-level dummy variables were included in the regression but suppressed from this output table.

7.3 Two-Stage Least Squares

Implementing a 2SLS model reduces bias and refines the parameter estimates obtained by Model 1. Every coefficient except for the retail price coefficient (statistically insignificant) is significant at the 1% level. In this model, a one-MWh increase in clean generation brings a decrease in carbon emissions of 0.727 tons across specifications, almost double the original estimate. A one-MWh increase in demand brings a 0.443-ton increase in carbon emissions, which is similar to the original estimate. These results show that breaking the simultaneous mechanical connection between clean generation, demand, and emissions is important to understanding the impact of additional clean generation on emissions. In Model 1, clean generation had a smaller magnitude impact on emissions than demand. This earlier result implied that emissions would marginally increase if demand and clean generation both increased by one MWh, which is counterintuitive. The 2SLS model indicates that in the same scenario, emissions would fall; clean generation's 2SLS regression coefficient is larger than that of demand. This result is more in line with economic theory and our hypotheses, and thus supports the choice to implement 2SLS in the first place to reduce bias in our estimates. Coal and natural gas fuel input prices have similar magnitude coefficients in this 2SLS model as compared to Model 1. This indicates that the effects discussed previously – asymmetrical substitution to natural gas or renewable generation when fuel input prices rise – remain compelling in the 2SLS model.[12]

Heating degree days have a coefficient of -0.645, meaning that carbon emissions go down by 0.645 tons for each degree below 65° F. Cooling degree days have a coefficient of 3.887, meaning that carbon emissions go up by 3.887 tons for each degree above 65° F. Similar to Model 1, we believe that these are seasonal effects (as highlighted in Appendix 1) whose effects leaked into these coefficients despite our month dummy variables.

Finally, the 2SLS model renders the retail price coefficient statistically insignificant. This is surprising, especially considering the high significance of retail price in Models 1 and 2. Its insignificance in the 2SLS model may indicate that the retail price of electricity does not affect the consumer's level of energy consumption and therefore carbon emissions. It would be promising for future integration of renewable energy if consumer demand were actually this inelastic – consumers would pay the increased cost of a higher renewable energy mix without having their preferences disrupted. This would stand in contrast to the balancing authority's decision making process, where the generation source with the lowest marginal cost of generation is selected for energy production. Overall, the 2SLS model refines our estimates in Model 1 and shows that increasing the costs of carbon-emitting generation reduces carbon emissions. We also see that increasing clean generation will reduce emissions even when demand increases by the same amount, showing that raising the clean share of generation

[12] Previous discussion of these effects on pages 23-24.

is a valid mechanism to reduce carbon emissions. Finally, it is clear that the marginal costs of coal and natural gas generation affect the composition of the energy mix and carbon emissions. This lends support to the RPS critique that emissions are not regulated past the RPS criteria.

Table 4
2-Stage Least Squares Panel Regression
Determinants of Energy-Sector CO2 Emissions

	(1)	(2)
VARIABLES	Coal and Gas Price	Retail Price
Clean Generation*	-0.727***	-0.727***
	(0.0109)	(0.0109)
Demand	0.443***	0.443***
	(0.000824)	(0.000824)
Coal Price	-26.95***	
	(0.281)	
Natural Gas Price	-2.667***	
	(0.0427)	
HDD65	-0.645***	-0.645***
	(0.0407)	(0.0407)
CDD65	3.887***	3.887***
	(0.0544)	(0.0544)
Retail Price		0.211
		(1.538)
Observations	694,092	694,092
R-squared	0.885	0.885
Number of plants	80	80

* = fitted values

Notes: Data are from confidential sources, Degree Days, NOAA, U.S. Naval Observatory, and EIA (sources linked in data section). Fixed effects for each plant are included in the model. Standard errors are displayed in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Time and plant-level dummy variables were included in the regression but suppressed from this output table.

VIII. Conclusion

Renewable portfolio standards are a popular policy instrument with a proven track record of emissions reductions, but they are still imperfect (Greenstone and Nath 2021, Reguant 2019). This paper aims to highlight some of these problems in an empirical way to enable policymakers and economists to improve their policy design and attain critical carbon emissions reductions. We focused our analysis on two shortcomings of RPS policy: first, that the emissions from energy generation left uncovered by the RPS requirement are unregulated by the policy, and second, that the market under an RPS does not generate as much clean energy as it could over any time period.

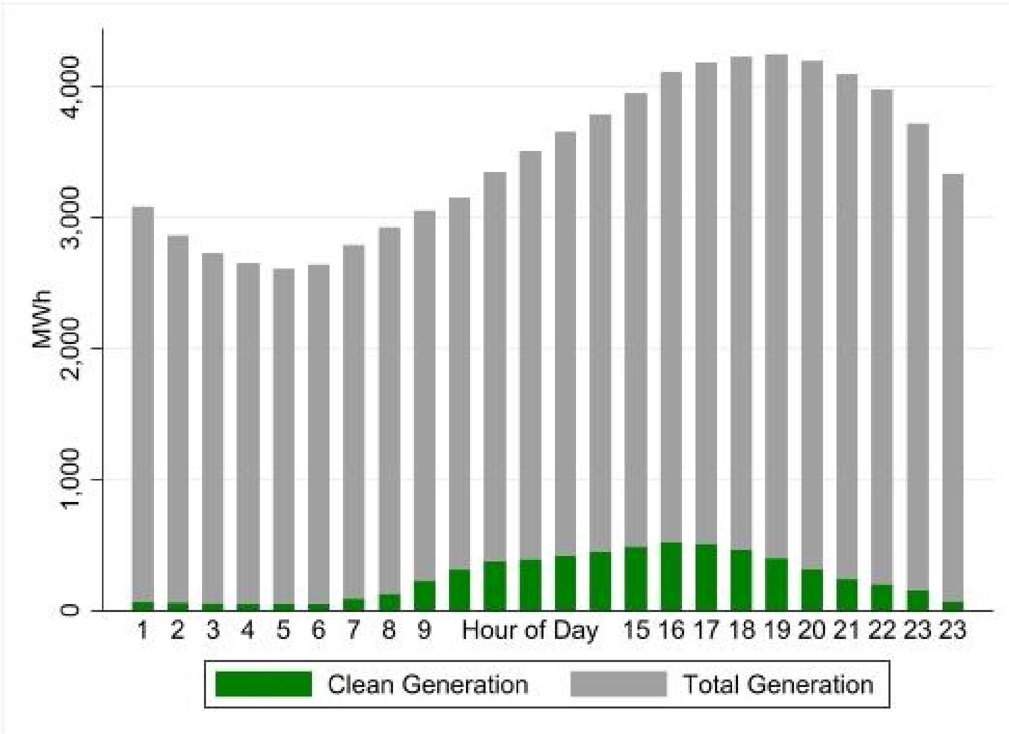
Our first hypothesis was meant to perceive to what degree carbon emissions – left unregulated once the minimum RPS level is achieved – are affected by the fuel input prices of carbon-intensive generation. We tested this hypothesis with Model 1 and a two-stage least squares regression model. Across all specifications, we found that carbon emissions fall when coal and natural gas prices rise, indicating that generation switched over to cheaper and cleaner natural gas or renewables and that fuel prices determine the level of emissions reductions under an RPS. This result was augmented by the smaller relative effect of natural gas prices on emissions, which revealed an asymmetry of substitution between coal and natural gas for reasons of generating flexibility and social preferability. The data show that emissions reductions under an RPS have the potential to vary significantly depending on the prices of carbon-intensive input fuels, supporting our hypothesis that emissions are not regulated as fully as they could be under an RPS. Policymakers should tailor current and future policies with this critique in mind when considering whether an RPS is the best policy choice to reduce carbon emissions and increase renewable energy penetration.

Our second hypothesis sought to characterize the issue of suboptimal utilization of renewable energy resources. We tested this hypothesis with Model 2. We found that factors of supply and demand do not directly account for all variation in clean generation at any hour, indicating that the price effect by which the RPS operates – the allocation of credits to reduce the wholesale cost of clean energy and increase its quantity on the grid – appears to be valid. Our interpretation is supported by the positive relationship between demand and clean generation, showing that renewables are not utilized to a reasonably full capacity at all times. If our interpretation is correct, this means that some achievable emissions reductions are left "on the table" under an RPS. Policymakers should consider whether these emissions can be captured by future iterations of an RPS or if another policy might be better suited to the task. With that being said, we acknowledge that this model suffers from some indeterminacy, and though economic theory and the evidence provided in the paper indicate that this price effect and emissions consequences probably exist, our model does not explicitly prove that it is so.

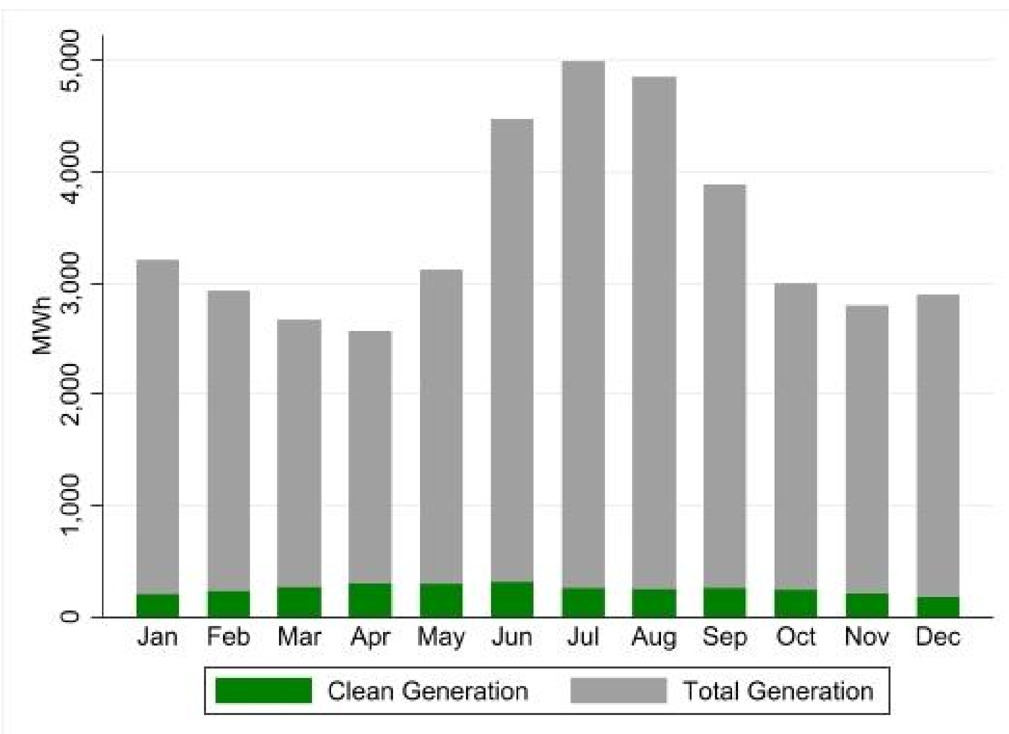
Renewable portfolio standards should continue to be challenged to best achieve our goal of reducing carbon emissions in the electricity sector. RPS policies have had success in reducing carbon emissions, but they do not live up to their full potential.

Further care should be taken to consider whether further emissions reductions can be squeezed from an RPS in a politically and economically feasible way. This paper hopes to add to a body of research assessing the effectiveness and efficiency of RPS policies with an eye towards future emissions reductions and further development of renewable energy. More research on the effectiveness of RPS and environmental policies in general is needed if we are to succeed in reducing carbon emissions and preserving the life-sustaining qualities of our planet.

Appendix 1

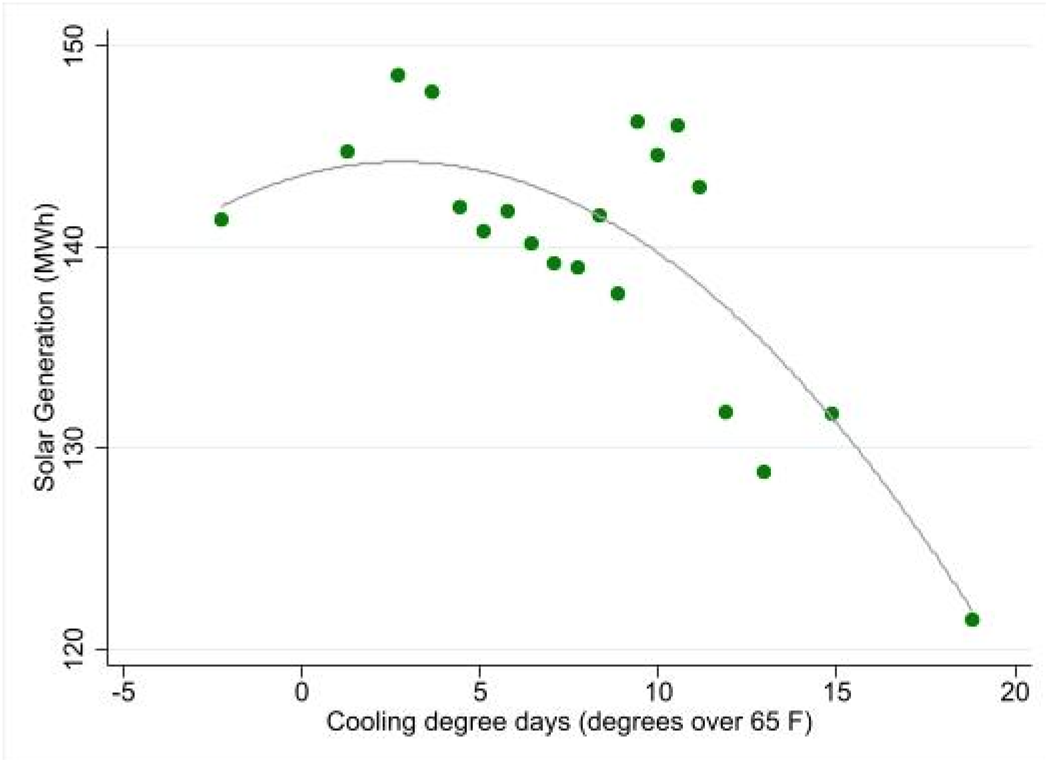


MWh
0
1,000
2,000
3,000
4,000
1 2 3 4 5 6 7 8 9 Hour of Day 15 16 17 18 19 20 21 22 23 23
Clean Generation
Total Generation



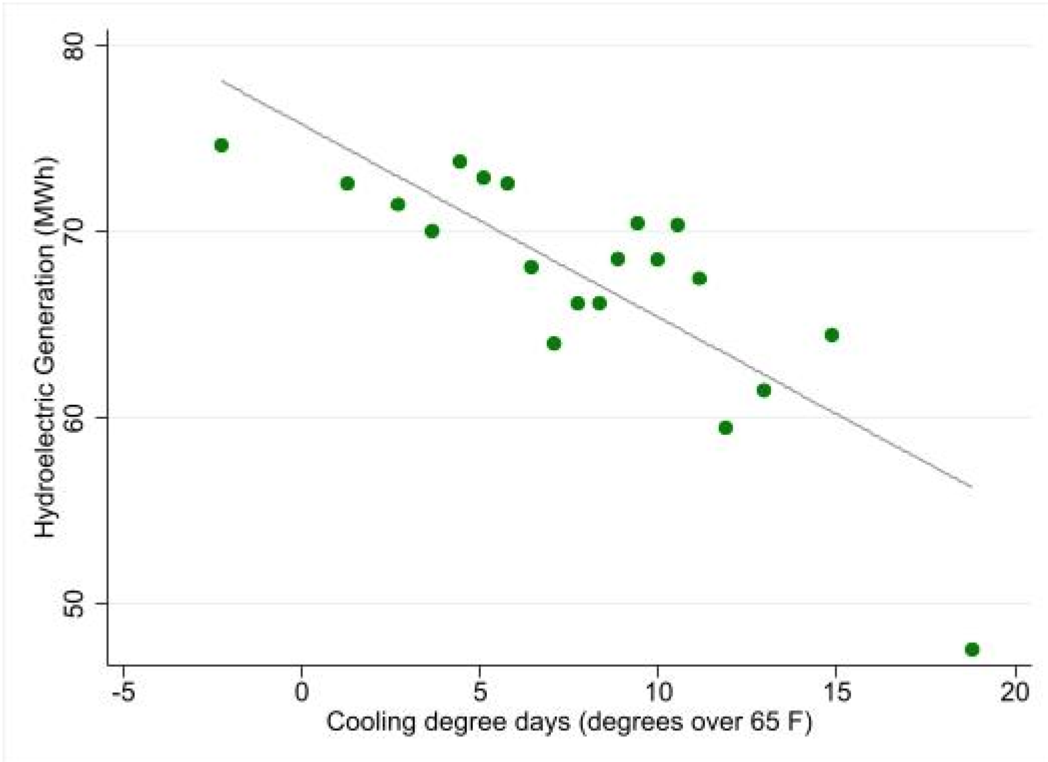
MWh
0
1,000
2,000
3,000
4,000
5,000
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Clean Generation
Total Generation

Appendix 2



Solar Generation (MWh)
120
130
140
150
-5
0
5
10
15
20
Cooling degree days (degrees over 65 F)

Appendix 3


Hydroelectric Generation (MWh)
80
70
60
50
-5
0
5
10
15
20
Cooling degree days (degrees over 65 F)

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