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SOLAR GENERATED ELECTRICITY: AN ANALYSIS OF WHAT SECTORS ARE MOST AFFECTED BY RENEWABLE PORTFOLIO STANDARDS AND RELATED POLICIES

By

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The members of the Committee appointed to examine
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Abstract

The aim of this thesis is to analyze state-specific Renewable Portfolio Standards (RPS) to understand their design and spillover effect onto non-utility (commercial, residential, industrial) sectors. Past research has overlooked non-utility sectors, often focusing on overall renewable energy growth and electricity generation from a combined end-result perspective. Solar capacity and solar generated electricity data from 5 states are used to establish which non-utility sectors experienced the highest level of solar growth from RPSs and related policies between 2010 and 2019. An explanatory sequential design is utilized, where interrupted time series analyses and exploratory case studies are performed to analyze each policy's effectiveness at increasing solar growth (measured in capacity or electricity generation). It was concluded that the commercial sector experienced the highest level of solar growth of the sectors analyzed. In addition, policies regarding net metering, aggregate net metering, and Solar Renewable Energy Credits were found to significantly increase solar growth in the commercial sector. The residential sector was found to only exhibit significant solar growth from financial incentives, while the industrial sector displayed no significant solar growth from the RPS policies analyzed. The findings of this research can help influence future renewable energy policy designs and act as a vehicle for research on other renewable energy sources.

Thesis Advisor ____________________________________

Dr. Joseph Kantenbacher

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Introduction

Greenhouse gases are the largest contributor to global warming (Ahima 2020). The combustion of fossil fuels forms carbon dioxide (CO_2), which is the leading anthropogenic greenhouse gas contributor and further adds to the greenhouse gases present in our atmosphere (EIA 2020). In 2018, the United States emitted 6,677 million metric tons of CO_2 equivalent, with transportation (28%), electricity (27%), and industry (22%) being the major sources (EPA 2019). The residential and commercial sectors (grouped into one), and agricultural sector contributed modest amounts, with each responsible for 10% of emissions (EPA 2019). In total, 78% of the United States emissions come from fossil fuels (EPA 2019). Eliminating our dependence on fossil fuels is one of the most effective ways of decreasing greenhouse gas emissions and lessening the effects of climate change (Corfee-Morlot et al. 2019).

Deploying renewable energy technologies for the production of clean energy is an effective way to meet our ever-increasing energy demands while reducing climate change (Long et al. 2016). In 2020, renewable energy accounted for 21% of electricity production in the United States and is projected to double by 2050 (EIA 2021). Solar and wind technologies are responsible for the majority of this projected growth (EIA 2021). From 2013 to 2018 the United States saw a 50% decrease in the cost of solar and 27% decrease in the cost of wind, leading to more affordable installation (EIA 2020). These decreases in costs caused an increase in solar and wind installations, meaning more electricity can be generated from these renewables (EIA 2020).

In addition to rapidly declining installation costs, policies can help accelerate the deployment of renewables, thereby pushing along efforts to decrease climate change. Renewable energy policies can be separated into two categories: (1) financial incentives and (2) rules and regulations (Delmas et al. 2011). The first category, financial incentives, consists of policies that include tax incentives, grants, loans, and rebates that encourage renewable energy production and implementation (Menz et al. 2006). The second category, rules and regulations, includes policies such as the Renewable Portfolio Standard (RPS), Mandatory Green Power Options (MGPO), and fuel disclosure rules that work on mandating action and requiring specific percentages of energy and electricity production on an annual basis (Menz et al. 2006). As of 2007, all but three states (Alabama, Alaska, and Mississippi) have implemented at least one rules and regulations renewable energy policy (Delmas et al. 2011). To date, Alabama, Alaska, and Mississippi have not implemented an RPS, MGPO, or fuel disclosure rules (rules and regulation policies) but do offer a plethora of financial incentives (DSIRE 2021).

In the United States, a key public policy method for expanding renewables use is the RPS, which requires electric utilities operating in a given state to provide a specified percentage of electricity from renewables to its customers, leading to an increase in renewable energy production (EPA 2021). Beyond the RPS required percentage, an array of supplementary policies compose an RPS, working to assist in reaching the specific percentage requirement. Net metering is a policy that allows residential and commercial customers who produce their own electricity to receive compensation for the electricity they supply (EPA 2021). A solar carve-out is a policy mechanism established by a state's RPS and requires solar electricity to account for a specific portion of a state's RPS percentage requirement (EPA 2021). Additionally, Solar Renewable Energy Credits (SRECs) are performance-based and are earned through solar electricity generation (1 SREC per MWh generated) (EPA 2021). SRECs are traded in markets and assist utilities in meeting solar carve-out targets. Future, specific programs, acts, and policies outside the RPS umbrella can contribute to solar electricity generation and RPS targets (see Appendix B). For example, Property Assessed Clean Energy (PACE) policies allow home or business owners to receive financing from a local government to cover up-front renewable energy costs, in exchange, financing is repaid through a special assessment on their property tax over a period of years or decades (SEIA n.d.). PACE allows the burden of initial costs to be distributed over a period of time, making renewable energy installation more affordable (SEIA n.d.).

This research focuses on RPS policies and their role in solar electricity growth. RPS policies are the main focus of this paper due to wide adoption efforts and their integral role in promoting renewable energy growth (Shields 2021). While RPS policies directly affect utility sector electricity producers (SEIA n.d.), they may potentially have second-order effects on renewables deployment in non-utility sectors. This research takes a sectoral approach to denote which non-utility sectors are impacted the most by differing state-level RPSs. Each policy included in an RPS can have different effects on each sector; analyzing by sector captures variability in policy effectiveness. This approach was taken because in previous policy effectiveness research little attention has been given to the commercial, residential, and industrial sectors who also generate solar electricity. Policy spillover effects in past research demonstrate RPSs' ability to have an impact outside their intended domain, including significant spillover across state borders (Dincer et al. 2014). The intention of this research is to evaluate and analyze the spillover affect that RPS policies have on sectoral solar electricity growth. Therefore, the indirect impacts of RPS policies are interpreted for how they differentially impact each sector in terms of solar electricity growth. Figure 1 illustrates how policies under the RPS umbrella, in addition to state acts and programs, affect both utility and non-utility sectors.

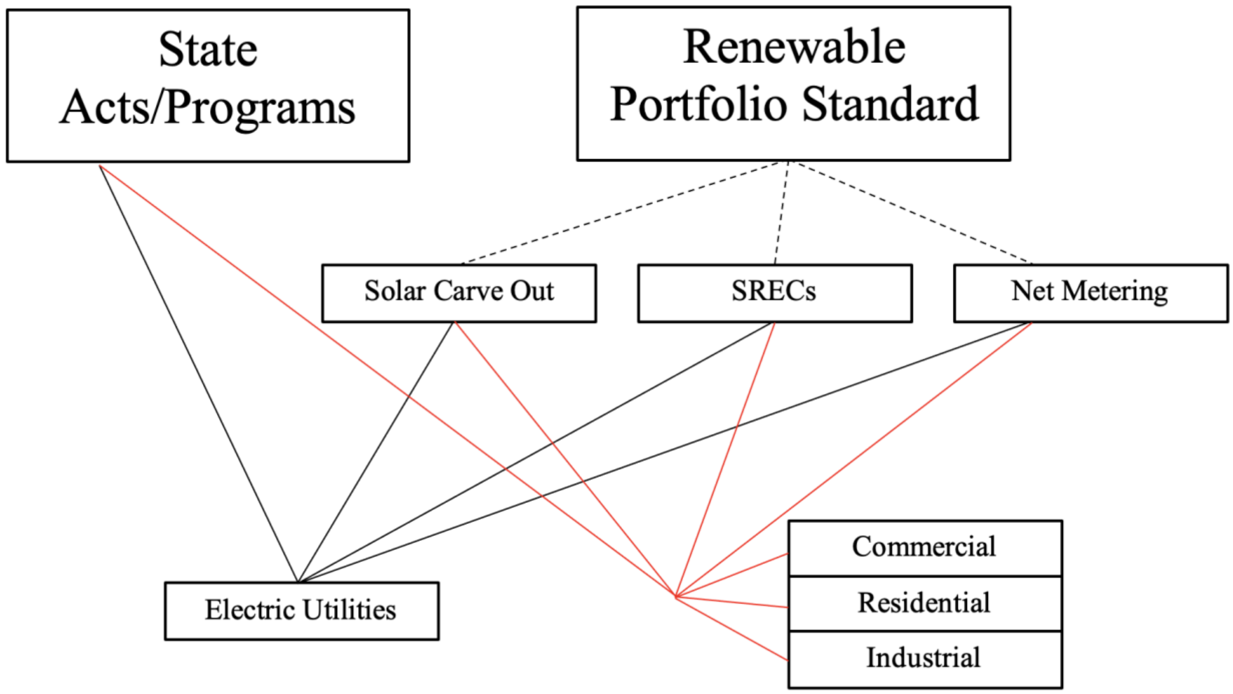

Figure 1 - Illustrates how policies underlying an RPS affect electric utilities as well as the three major renewable energy producing sectors. State Acts/Programs was included to show how other legislation outside of the RPS can also have an effect on each sector. The black lines represent policies that affect electric utilities while the red lines represent policies that affect the three sectors. Policies categorized under an RPS are denoted with a dashed black line.

Three sectors were evaluated to quantify solar electricity growth at the state level. Each sector has varying levels of responsibility regarding electricity consumption that leads to greenhouse gas emissions (EPA 2018). The Environmental Protection Agency (EPA) defines each sector in terms of their electricity consumption as a percent of total national electricity consumption. In addition to the electricity consumption percentage, the customers that comprise each sector and contribute to electricity consumption are detailed. While this research was specific to solar electricity growth, defining these sectors in terms of consumption allowed for a deeper understanding of each sector's composition. The commercial sector (35% of electricity consumption) was defined to include government facilities, service-providing facilities and equipment, and other public and private organizations (EPA 2018). The industrial sector includes facilities and equipment use electricity for processing, producing, and assembling goods, including the industries of manufacturing, mining, agriculture, and construction. This sector comprised the smallest share of the three discussed at 27% of electricity consumption (ibid.). Lastly, the residential sector is the largest (37% of electricity consumption) and was defined by the EPA to include single-family homes and multi-family housing (ibid.). Major contributors to the residential sector include residential heating, cooling, lighting, and ventilation (ibid.). The transportation sector was not included due to its relatively small share of electricity consumption at only 0.2% (ibid.).

Utilizing these three sectors allows for assessments to be made regarding which sectors demonstrate the most growth under RPS policies. Unlike other sources of electricity from renewables, solar power can be readily incorporated into non-utility sectors (i.e., commercial, industrial, residential). Within solar, only solar PV is examined in this research due to substantial data being available (compared to other solar technologies) and because it is the most common renewable energy technology used to generate electricity in each sector (NREL n.d.).

Objectives

The first goal of this research is to understand RPS policy design and its spillover effect on non-utility sectors. RPS policies are a relatively young form of policy that differs dramatically among each state (DSIRE 2021). A second goal is to formulate recommendations for policy makers and future researchers studying RPSs and renewable energy policies to establish better suited policy decisions.

Particularly, this research includes the following sub-objectives:

1. To determine which specific RPS policies provided the most assistance and solar growth among each sector.
2. To develop an understanding of which sectors (commercial, industrial, residential) are affected the most in terms of solar electricity growth from RPS policies.
3. To draw conclusions regarding why RPS policies benefitted certain sectors more than others.

Literature Review

The first RPS policy was adopted by the state of Iowa in 1983 with intent of increasing their production of electricity from renewable energy sources (Zhou et al. 2020). To date, 29 states and the District of Columbia have adopted an RPS with 8 additional states implementing voluntary goals related to increase renewable energy production (EIA 2019).

An RPS is a policy that requires or encourages electricity producers to meet specific targets for electricity production from renewable-based sources (EIA 2019). This policy is structured to include increasing electricity production targets with the end goal of increasing the quantity of electricity produced from renewable-based sources. While the main focus of RPS policies is to increase electricity production from renewables, multiple states have allowed additional forms of technology that are deemed eligible under their RPS (DSIRE 2021). For instance, Illinois groups organic waste for energy production, biodiesel, landfill gas, and anerobic digestion under their RPS (DSIRE 2021).

The effectiveness of RPSs vary due to differences in the supplementary policies included and the stringency of their requirements (Yin et al. 2011, Ogundrinde et al. 2018). The strength of RPS policies can be determined through multiple factors including the renewable electricity target, compliance speed, jurisdictional reach, and resource eligibility in addition to specific design choices that vary by state (Davies 2014). RPSs continue to be the most widely adopted form of renewable energy policy regarding electricity production and continuously demonstrate their strength in promoting electricity generation from renewable-based sources (Zhou et al. 2020). Past research provides information on RPS effectiveness, policy implications, and RPSs' role in electricity production, although it fails to differentiate by non-utility sector when looking at solar electricity generation and capacity.

Research on RPS policy effectiveness has identified a decrease in renewable energy generation when analyzing the effect of RPSs (Upton et al. 2017). These effects range from RPSs being ineffective at increasing renewable energy generation, to RPSs having a weak effect on renewable energy generation relative to states without an RPS (Delmas et al. 2011, Upton et al. 2017). To elaborate further, Upton et al. (2017) found that RPSs impact on electricity generation was insignificant when comparing states who have adopted an RPS to states who have not. These findings are in contrast with other studies where RPSs were found to have a significant and positive impact on renewable energy development (Yin et al. 2010) and renewable energy generation (Carley 2009). Some of the variation in results can be attributed to differences in methodology, including treating RPSs as a dichotomous variable (Zhou et al. 2020), employing a cross-sectional approach, and ignoring heterogeneity among RPS policies (Yin et al. 2010).

Another branch of literature within the RPS realm focuses on which components of RPS policies are hindering (working against) rather than helpful to renewable energy development. Ogundrinde et al. (2018) reported several factors that appeared to make RPS policy mandates less effective. These include weak enforcement of policies, the introduction of renewable energy credits, policies that are too ambitious, and variances in scope, depth, and structure (2018). Other research has identified design parameters that are critical to RPS policy effectiveness. Davies (2014) singled out four design parameters that determine policy efficacy: the renewable electricity target, compliance speed, jurisdictional reach, and resource eligibility. Research tends to concentrate on policy effectiveness and its links to energy infrastructure and electricity production rather than the actual components that comprise RPS policies.

The geographic levels for assessing RPS policies are variable within the body of previous research. Ogundrinde (2018) utilized Regional Transmission Organizations (RTOs) to categorize and differentiate the effectiveness of RPS policies in the United States. As the electrical grid in the United States does not obey state lines, RTOs are tasked with managing and coordinating the multi-state electric grid system (Ogundrinde et al. 2018). Seven RTOs were identified that account for roughly two-thirds of the country's annual electricity production demand (ibid.). Of these seven RTOs, conclusions were reached regarding which RTOs contribute to different renewable energy technologies (wind and solar) and their growth among each RTO (ibid.). Other research has approached the spatial component by limiting the categorization of RPS policies to state borders, which is consistent with the policy's scope of coverage (Yin et al. 2010, Zhou et al. 2020, Delmas et al. 2011, Upton et al. 2017). More specifically, research on how an RPS policy impacts an individual state has been published. Roundtree (2019) discussed the impacts of Nevada's RPS on the state of Nevada rather than comparing their RPS to other states. Holistic and specific research on state RPSs has allowed for RPS policies to be analyzed from a multitude of perspectives.

Statistical analysis has been the most common form used to determine RPS effectiveness and its contribution to renewable energy growth and development. The majority of research has taken this approach, through varying in the specifics of the analyses. Regression analysis has been the most common form of statistical methodology with Yin et al. (2010), Zhou et al. (2020), Delmas et al. (2011), Upton et al. (2017), and Carley (2009) utilizing this approach in their research. Other forms of statistical analysis include calculating the correlation between energy capacity and strength of RPS using a time series evaluation (Ogundrinde et al. 2018). Time series analyses were performed by both Yin et al. (2010) and Carley (2009) in addition to Ogundrinde et al. (2018). On the other hand, non-statistical approaches were also used by researchers when studying RPS effectiveness and contribution to renewable energy growth. Roundtree (2019) used a case study approach, utilizing expert interviews, policy documents, recent news pieces, peer-reviewed journal articles, and agency reports to formulate conclusions and examine RPS policies.

Research on RPS effectiveness, its contribution to increasing electricity production from renewable-based sources, and its policy designs tend to saturate the RPS research domain while looking past RPS benefits to non-utility sectors. Few publications mention this research question, often focusing on overall renewable energy growth and electricity generation from a combined end-result perspective. This gap in research highlights a lack of understanding on which sectors benefit the most from RPS policies and their design implications.

Methods

Research Methods

This research took a mixed-method approach that utilized an explanatory sequential design. The mixed method approach has been categorized as the third methodological movement and is critical in achieving the goals set in this research (Doyle et al. 2009).

Quantitative Approach

For the residential and commercial sectors, numerous interrupted time series (ITS) analyses were performed with the goal of determining variations in solar electricity generation and capacity from RPS policy modifications. (The industrial sector was unable to be analyzed this way; see Data below.) Specific policies and policy changes were classified as intervention points to observe changes in solar electricity growth in pre-policy versus post-policy data. ITS is a form of statistical analysis that can be performed by multiple methods. Most of the past research has achieved the ITS design through segmented regression or forecast models (Turner et al. 2021). This research utilized both segmented regression and Autoregressive Integrated Moving Average (ARIMA) forecasting to structure the ITS design. Both segmented regression and ARIMA forecasting are explained in detail in the subsequent pages.

ARIMA forecasting uses a combination of an Autoregressive (AR) and Moving Average (MA) model to forecast future values based on past values (Schaffer 2021). Observed data can then be compared with forecasted data to analyze policy effectiveness.

Segmented Regression

Segmented regression is a method of breaking data into sections that correspond with breakpoints and fitting a regression to the data between breakpoints. This allowed the data to be analyzed for changes in slope (which represents the rate of solar PV deployment) before and after the breakpoint (policy intervention). A comparative p-value was calculated to determine whether two slopes were statistically different from one another (see Appendix A). Because this work has a constrained amount of data available (see below), a significance level of 0.1 was selected as the threshold for rejecting the null hypothesis that the difference between the pre-slope and post-slope is zero (see Appendix A). A policy was considered to cause significant growth if the comparative p-value was under 0.1.

Segmented Linear Regression Model:

$$\mathrm{y} = \beta_0 + \beta_1 x_1 \; ; \; ((x < P)\,(x > P)) + \ldots + \varepsilon$$

Segmented Multiple Regression Model:

$$\mathrm{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \; ; \; ((x < P)\,(x > P)) + \ldots + \varepsilon$$

y = Dependent Variable Predicted Value

$ß_0$ = Intercept Coefficient

$ß_i + x_i \ldots$ = Regression Coefficient ($ß_i$) of the Independent Variable (x_i)

P = Policy Intervention Date

x = Time

ε = Error Term

Segmented Component:

$$\big((x < P)\ (x > P)\big) + \dots$$

Parameters were added to the linear and multiple regressions to create data subsets. For example, a policy modification that took place on August 2015 (Month 68) would substitute 68 for *P* with *x* representing time (months in this case). These parameters subset the data into pre-policy (only data before month 68) and post-policy (only data after month 68). Multiple segmented components may be included to establish several subsets to signify multiple interventions (policy modifications).

Autoregressive Integrated Moving Average (ARIMA)

An ARIMA model is a statistical method used to satisfy the ITS design. It uses a combination of an Autoregressive (AR) model and a Moving Average (MA) model to forecast future values based on past values (Schaffer 2021). The AR model predicts Y_t (dependent variable) by one or multiple lagged values of Y_t. The equation below depicts the first component of the ARIMA model, the AR model (Schaffer 2021). Variables are defined as: *c* is a constant, ϕ is the magnitude of the autocorrelation, p is the number of lags, and ε_t is the error.

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots \phi_p Y_{t-p} + \varepsilon_t$$

The second component of ARIMA is the MA model. In this model, Y_t is predicted by one or multiple lagged values of the error (ε_t) (Schaffer 2021). The equation below depicts the MA model, where *c* is a constant, θ is the value of the autocorrelation of the errors, ε_t is the error, and *q* is the number of lags.

$$Y_t = c + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots \theta_q \varepsilon_{t-q}$$

Together, the AR and MA models compose the ARIMA model. The ARIMA model allows for values to be forecasted using past data. ARIMA models follow the format ARIMA(p, d, q), where p is equal to the quantity of auto regressive terms, d is how many times the data was differenced, and q is the quantity of lags present in the data. This format can be observed in the title of each ARIMA forecast graph.

Segmented linear regression, segmented multiple regression, and ARIMA forecasting all fall under the ITS umbrella. Selecting only one statistical method was popular in past research, with much of the research published on ITS having taken this route (Turner et al. 2021). An alternative route was utilized in this research. All three, segmented linear regression, segmented multiple regression, and ARIMA forecasting were used in this research. This approach was taken to establish a "checklist" that ensured each policy/modification showed consistent results across all three statistical methods before the results were accepted (checked all three boxes).

To satisfy the ITS design, both segmented linear regressions and segmented multiple regressions were performed. Each segmented linear regression estimated the linear relationship between time and solar capacity (if residential) or solar electricity generation (if commercial). Segmented multiple regressions included the same linear model, but with additional independent variables that control for economic factors that may have also influenced the rate of solar PV deployment.

Data

Data required for this research came in two main forms: information about electricity production and information about policies.

Solar Electricity Production

Solar generated electricity data from the EIA’s 860 survey was utilized. The EIA categorizes data on a monthly and annual basis and reports industrial and commercial sector data by state (EIA 2021). This dataset was used because it presented data that was collected through a universal approach that remained consistent across each state and promoted transparency. The EIA collects this data monthly through the EIA-860 survey, which compiles existing electricity data from state-level generators that operate electrical power plants with 1-megawatt or greater capacity (EIA 2020). This project used observations from January 2010 to December 2019. (New Jersey is an exception, with the EIA reporting data from January 2010 to June 2021 for the commercial and industrial sectors).

Total solar PV output from the industrial sector is quite small relative to the EIA’s unit for reporting data (thousand MWh). Consequently, after being rounded to the nearest whole number, available data was reported by the EIA as 0 or 1 thousand MWh of production in a given month. On this account, data from the industrial sector could not be analyzed using segmented regression because the data presented as binary rather than continuous and normally distributed. Because of the lack of precision in the data, the nominally continuous data was treated as categorical (binary) data such that a value of 1 represents a month in which solar electricity production was high enough to round to 1 thousand MWh (Production). Conversely, a value of 0 indicates that electricity production was insufficient to be reported at the 1000-MWh level (No Production, even though actual production may have been greater than 0 thousand MWh). Given the categorical and nature of the electricity data, chi-square tests were utilized to analyze the pre-and-post-policy patterns of solar electricity production by the industrial sector.

For this research, Independent Power Producer (IPP) solar production data was included in the commercial sector due to a large quantity of solar electricity being outsourced from IPPs by corporations (Mostow 2015). An IPP is a non-utility power producer that operates facilities for the generation of electricity (EIA n.d.). A 2019 report by the Solar Industries Association (SEIA) found the top ten commercial solar producers accounted for nearly 30% of installed solar capacity in the commercial sector (SEIA 2019). Each of the 10 had signed into multiple power purchase agreements with IPPs throughout the past 10 years, with companies like Apple reporting that IPPs account for the largest portion of their solar portfolio (Sylvia 2019). IPP data was collected through the same EIA-860 survey used for commercial and industrial solar generated electricity data (EIA 2020).

Residential solar generation data was not reflected in the EIA database due to most individual residential solar electricity generators not meeting the 1-megawatt threshold for reporting. This constraint was addressed through the inclusion of residential data from the SEIA that reflects solar electricity capacity in this sector (SEIA 2020). Each state's residential sector data was collected annually and observed from 2010 to 2019.

Because data from the EIA were reported in megawatt-hours (MWh) while data from the SEIA were measured in megawatts (MW), the industrial and commercial sectors were analyzed in terms of generation while the residential sector was analyzed in terms of capacity. *Generation* is a measure of electricity output over time, while *capacity* is the maximum potential level of electricity production. Data was unable to be converted from MW to MWh due to solar units not consistently operating at full capacity. Residential solar data could not be to be measured in MWh due to insufficient data on actual residential power generation. However, the industrial and commercial sectors are measured in MWh due to data being reported through the EIA-860 survey that generators complete to report electricity generation in MWh. For this reason, each sector was compared with itself (pre-policy modification versus post-policy modification), remaining within sectoral boundaries to avoid a conflict in units.

RPS Policy Data

Data regarding RPS policy design was derived from the Database of State Incentives for Renewables and Efficiency (DSIRE) hosted by North Carolina State University. This database documents each state's RPS policy and the policies that fall under each state's RPS in detail. It also provides information on existing RPSs and changes in policy that occurred throughout the duration of its implementation. In addition to the material provided by DSIRE, each individual state's RPS qualification requirements (requirements on whether a solar installation qualifies for certain policies under an RPS) were analyzed in order to further understand the breadth, scope, and requirements of each state's RPS policy. The design and required qualifications of these policies differ substantially by state, making RPS qualification requirement information pivotal to the accuracy of this research.

Control Variables

Control data were selected based on their relation to solar generated electricity and installed solar capacity. Control variables were needed to accurately estimate changes in the outcome variable. In addition, controls help ensure internal validity in the models by limiting the influence of confounding variables (Bhandari 2021). The following control variables were included in the analysis:

- Elect.Price [$/kWh] → Electricity rate per month by state (EIA 2021)
- PV.Price.Com [$/Watt] → Commercial solar PV price per watt (NREL 2021)
- Energy.CPI [Index YEAR = 100]→ Energy CPI (FRED 2021)

The control data come from a range of sources including The National Renewable Energy Laboratory (NREL), Federal Reserve Economic Data (FRED), and the EIA. The electricity rate variable (Elect.Price), energy CPI variable (Energy.CPI), and solar module price variable (PV.Price.Com) were included across all commercial sector multiple regression models in order to stay consistent.

States Included

State selection was based on multiple factors. The states included in this research were Massachusetts, New Jersey, Pennsylvania, Nevada, and Florida. First, these states were chosen because each had sufficient data on solar electricity generation and capacity by sector that was accessible through the EIA and SEIA databases utilized in this research. In addition, each of these states have an established RPS policy, except for Florida, which acted as a comparison state. States with established RPS policies were selected to avoid RPS policies that were recently implemented and potentially hindering to the conclusions of this research due to their untested nature.

Statistical Software

The programming language R was used with the statistical software RStudio (version 4.0.3) to run the ITS analyses and provide graphics for visualization. The following table portrays which statistical packages were used when running each statistical method. All packages were imported from the Comprehensive R Archive Network.

Table 1 – Statistical packages used for each statistical method.

Segmented Linear Regression	Segmented Multiple Regression	ARIMA Forecasting
multikink dplyr ggplot2	multikink dplyr	forecast tseries ggplot2 dplyr

Qualitative Approach

The second component of the explanatory sequential design was qualitative. A case study approach was taken to further examine RPS policy implications and supplement quantitative data. Brief case studies were performed on the state demonstrating the least benefit and the state demonstrating the greatest benefit to the residential sector regarding solar growth. In both, an exploratory case study approach was utilized to explain the casual links associated between RPS policy design and solar electricity capacity in the residential sector. In addition, a simplified comparative study addressed the similarities and differences in each case study.

An explanatory sequential design approach was taken due to quantitative data analysis not fully addressing the research question. Including a qualitative section involving case studies allowed for the two ends of the spectrum (least and most beneficial to residential sector) of solar electricity capacity to be evaluated for why their policy designs yielded those results. The benefit to the residential sector was utilized as the determining factor for which states received a case study due to its relevance to more individuals, rather than using the commercial or industrial sector where fewer entities would be directly impacted. In addition, these case studies were supplementary to the quantitative data in the residential sector due to this data being annual and limited in scale. Supplementing residential data with qualitative data was necessary to fully analyze the residential sector. RPS policy information from DSIRE, reports from the EIA, newspaper articles, and RPS policy compliance information were utilized in the case studies.

Results

This section was structured to include graphs, summary statistics, and analyses. Analysis began with Massachusetts, addressing each applicable sector. The industrial sector was only included in New Jersey and Pennsylvania due to industrial sector data limitations in the other states. The time series data used in this research exhibited trends between the dependent variable (solar electricity generation or capacity) and the independent variable (time), causing adjusted R^2 values to be inflated and portray a high fit. Therefore, adjusted R^2 values are an over-estimate of goodness-of-fit.

Massachusetts

Commercial Sector

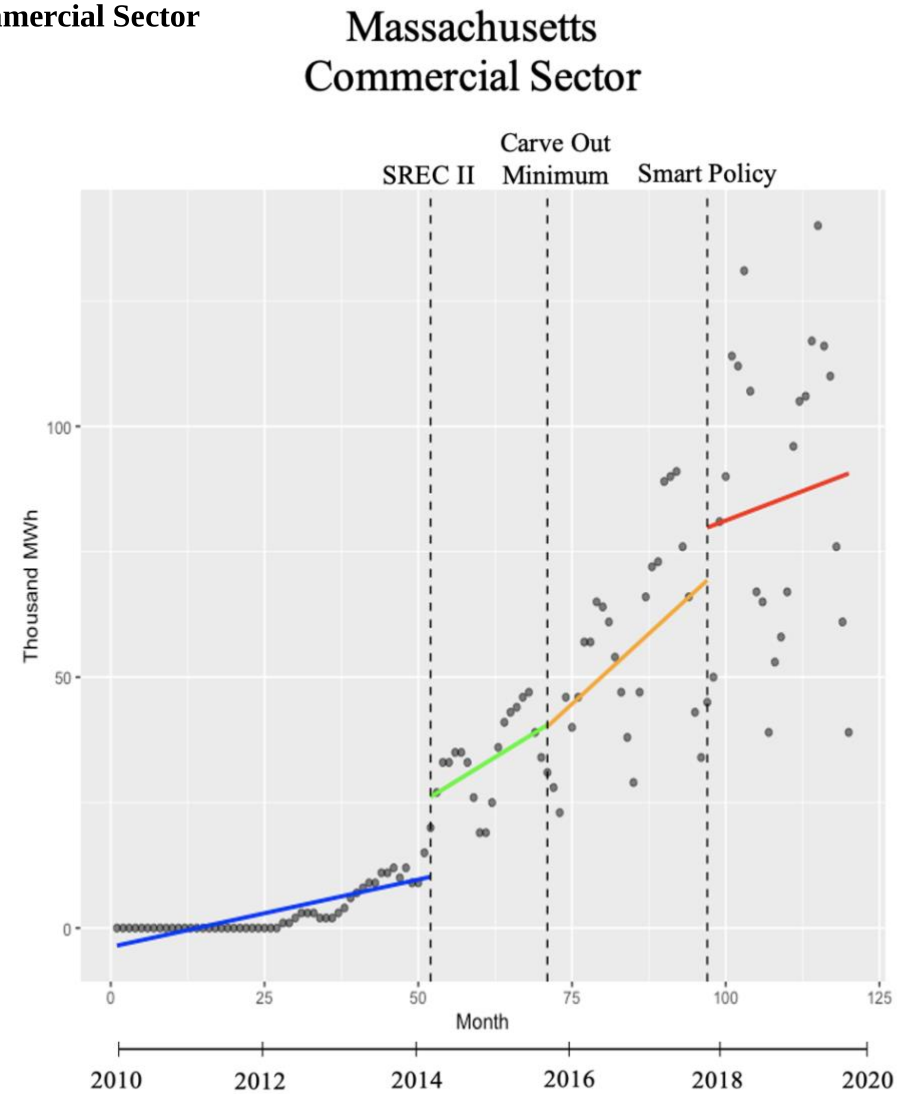

Figure 2 - Segmented linear regression of solar electricity generation in Massachusetts' commercial sector.

Table 2 - Segmented linear regression slopes and comparative p-value of pre-slope versus post-slope (Massachusetts' commercial sector). (p < .10)* (p < .05)** (p < .01)***

	SREC II		**Carve Out Minimum**		**Smart Policy**	
Period	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**
Intercept	-3.77 *** (0.76)	-13.13 (11.21)	-13.13 (11.21)	-39.42 (33.45)	-39.42 (33.45)	34.27 (48.94)
Time (Months)	0.27 *** (0.02)	0.76** (0.29)	0.76** (0.29)	1.12** (0.42)	1.12** (0.42)	0.47 (0.21)
Adjusted R^2	0.69	0.23	0.23	0.18	0.18	0.17
Degrees of Freedom	50	19	19	25	25	20
N	51	20	20	26	26	21
Comparative P-value	0.097*		0.484		0.522	

Table 3 - Segmented multiple regression slopes, summary statistics, and comparative P-value (Massachusetts' commercial sector - SREC II). (p < .10)* (p < .05)** (p < .01)***

	Pre-policy	**Post-policy**
Intercept	-6.34 (9.35)	-87.71 (46.62)
Time (Months)	0.77*** (0.12)	1.39** (0.59)
Elect.Price	0.85 (0.45)	10.31*** (2.32)
Energy.CPI	-0.09 (0.04)	-0.11 (0.12)
PV.Price.Com	4.92** (2.32)	-2.59 (8.12)
Adjusted R^2	0.87	0.69
Degrees of Freedom	23	37
N	27	41
Comparative P-value	0.172	

A holistic view illustrating how RPS policy modifications affected solar generated electricity is achieved by analyzing Figure 2. Table 2 reports results after running segmented linear regressions on each RPS policy modification. The SREC II modification significantly increased the rate of solar production compared to the pre-policy period ($\beta = 0.27$ vs. 0.76, $p = 0.097$). In addition to increasing the rate of production, a notable level change occurred, suggesting the SREC II modification had an immediate effect on solar electricity generation. A segmented multiple regression was performed to analyze the effect of the SREC II modification (see Table 3). The increase of commercial solar electricity production after the SREC II modification approached significance ($p = 0.172$). The p-value for each coefficient tested the null hypothesis that the coefficient was equal to zero. P-values were denoted by asterisks with values below 0.1 causing the null hypothesis to be rejected.

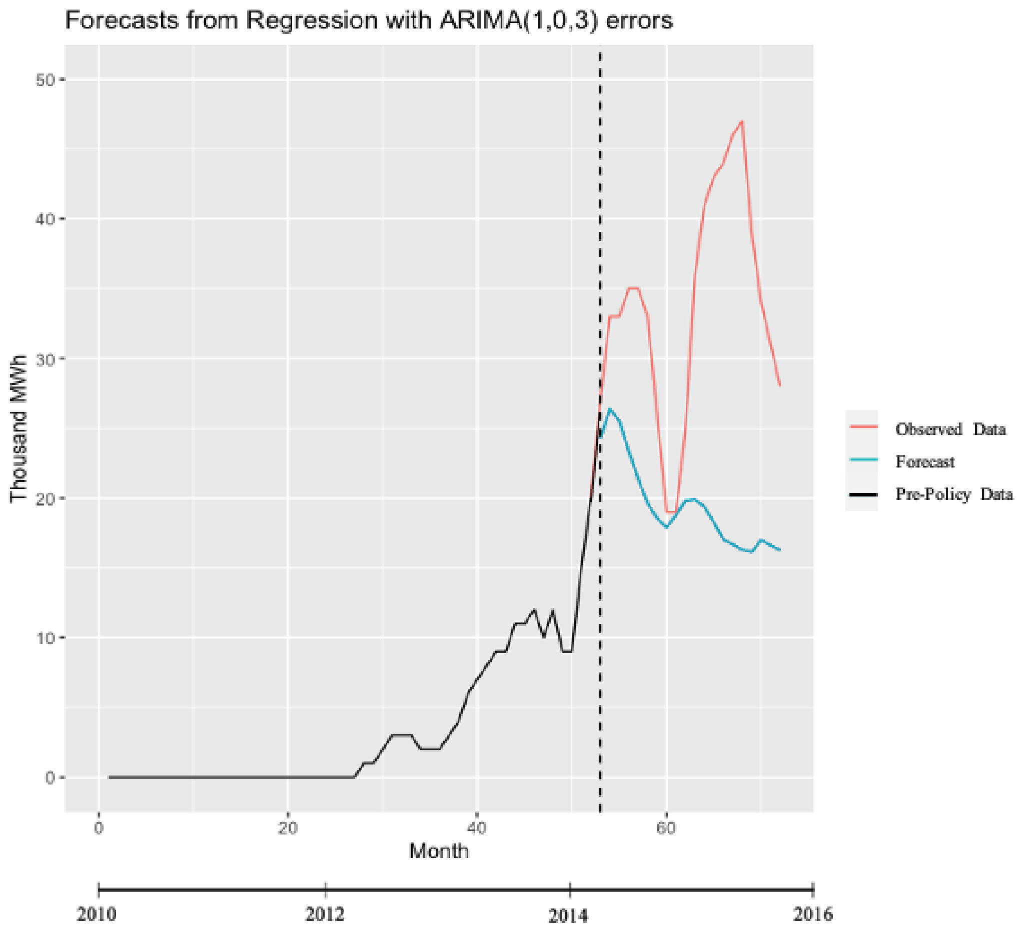

Figure 3 - ARIMA forecast predicting solar electricity generation had the SREC II modification not occurred (Massachusetts' commercial sector).

Table 4 - Components and summary statistics for the SREC II modification ARIMA forecast model (Massachusetts' commercial sector).

Best Fit Model	ARIMA(1, 0, 3)
Control Variables	Elect.Price, Energy.CPI
MAE	0.79
MASE	1.25

An ARIMA model (see Figure 3) was tasked to predict how solar generated electricity would have changed if the SREC II modification had not occurred. The ARIMA forecast predicted lower solar electricity generation would have likely occurred if the SREC II modification had not been implemented. Table 4 details summary statistics, including the Mean Average Error (MAE) (0.79), and the Mean Average Scaled Error (MASE) (1.25). Summary statistics imply the ARIMA forecast was not entirely accurate, due to a relatively high MASE value (1.25). The ARIMA forecast affirms conclusions cast by the segmented linear and multiple regression analyses suggesting the SREC II modification had a significant and positive effect on solar generated electricity in Massachusetts' commercial sector. The PV.Price.Com control variable was not included in this ARIMA model (or subsequent models) due to unacceptable MAE and MASE values once the variable was added.

Massachusetts

Residential Sector

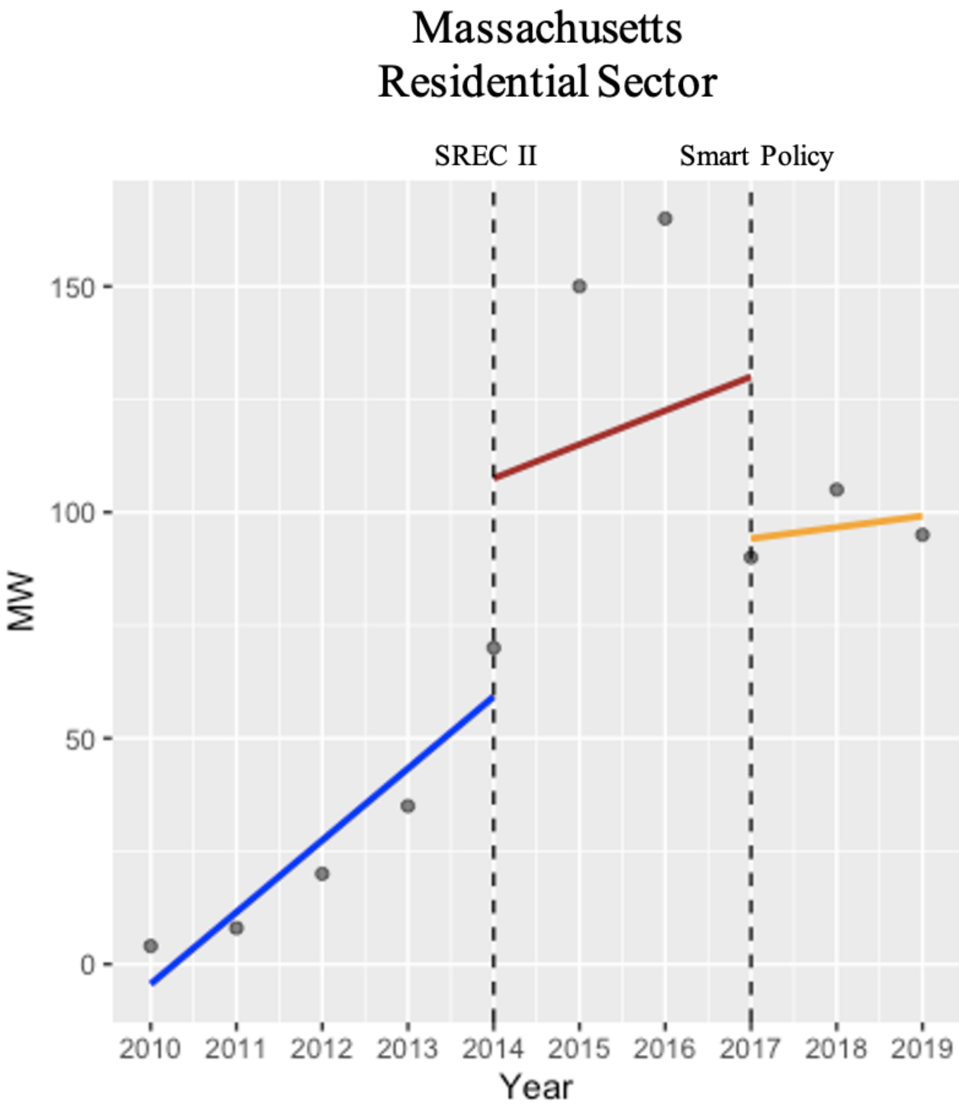

Figure 4 - Segmented linear regression of solar capacity in Massachusetts' residential sector.

Table 5 - Segmented linear regression slopes and comparative p-value of pre-slope versus post-slope (Massachusetts' residential sector).($p < .10$)* ($p < .05$)** ($p < .01$)***

	SREC II		**Smart Policy**	
Period	**Pre**	**Post**	**Pre**	**Post**
Intercept	-4.67 (-5.33)	76.49 (85.12)	76.49 (85.12)	77.83 (16.65)
Time (Years)	15.9* (3.28)	7.51 (21.8)	7.51 (21.8)	2.5 (5.21)
Adjusted R^2	0.85	0.12	0.12	0.48
Degrees of Freedom	3	2	3	1
N	5	4	4	3
Comparative P-value	0.735		0.845	

Figure 4 illustrates how the SREC II policy modification and Smart Policy affected solar capacity in Massachusetts' residential sector. The Solar Carve-out modification was not included in this analysis due to proximity concerns with the SREC II modification. Table 5 reports results after running segmented linear regressions on each RPS policy modification. Neither the SREC II (β = 15.9 vs. 7.51, p = 0.735) nor the Smart Policy (β = 7.51 vs. 2.5, p = 0.845) modification significantly increased the rate of solar capacity growth when compared to the pre-policy period. In addition, both policies demonstrated notable level changes, suggesting the SREC II modification had an immediate positive effect on solar capacity while the Smart Policy had an immediate negative effect. Degrees of freedom were low due to a data constraint from residential sector data being reported annually.

New Jersey

Commercial Sector

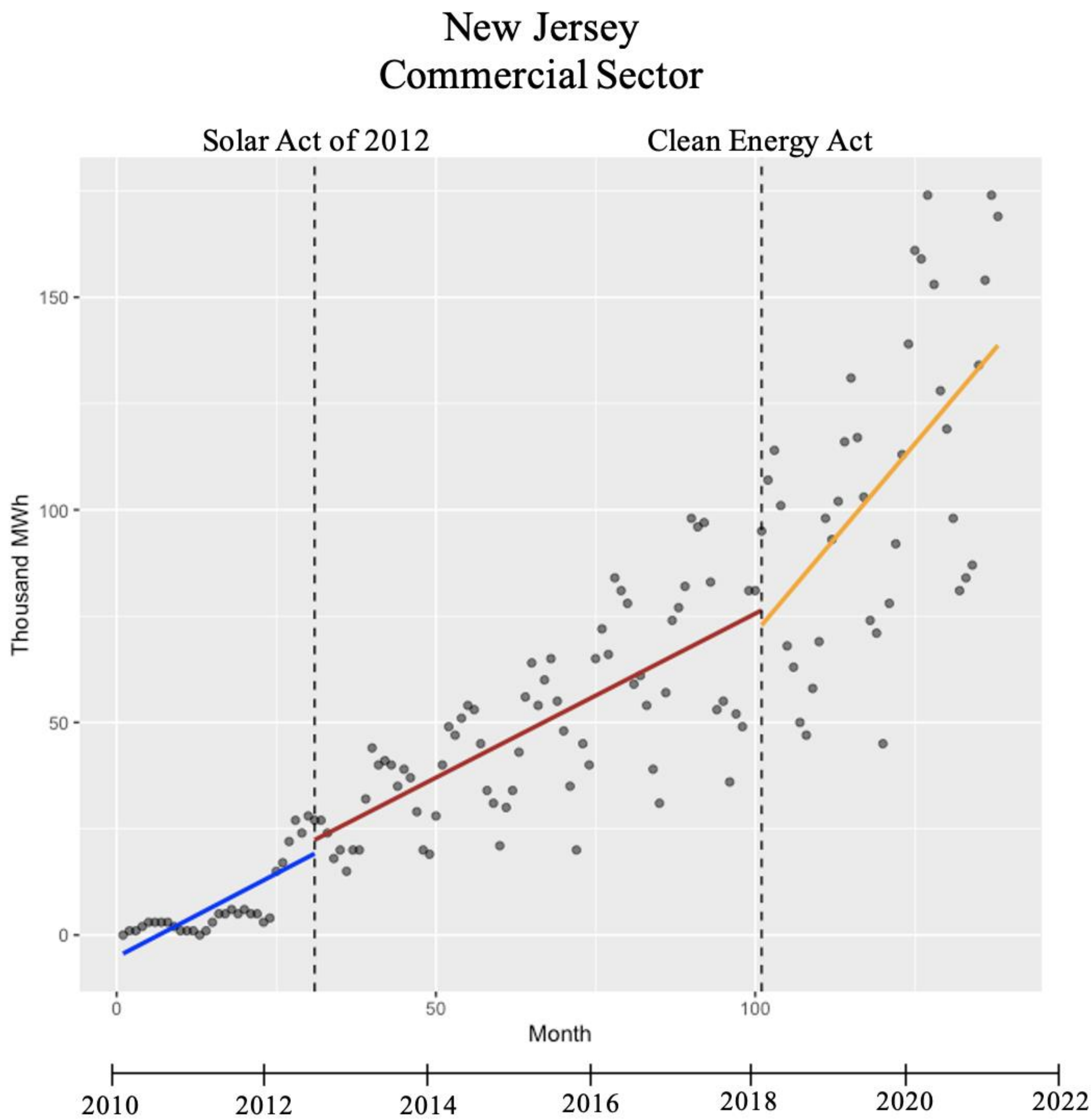

Figure 5 – Segmented linear regression of solar electricity generation in New Jersey's commercial sector.

Table 6 - Segmented linear regression slopes and comparative p-value of pre-slope versus post-slope (New Jersey's commercial sector). ($p < .10$)* ($p < .05$)** ($p < .01$)***

	Solar Act		Clean Energy Act	
Period	**Pre**	**Post**	**Pre**	**Post**
Intercept	-5.16* (2.03)	-1.55 (6.07)	-1.55 (6.07)	-106.78* (55.41)
Time (Months)	0.78*** (0.11)	0.77*** (0.08)	0.77*** (0.08)	1.74*** (0.46)
Adjusted R^2	0.62	0.52	0.52	0.27
Degrees of Freedom	28	68	68	33
N	30	70	70	35
Comparative P-value	0.927		0.032**	

Table 7 - Segmented multiple regression slopes, summary statistics, and comparative P-value (New Jersey's commercial sector - Clean Energy Act). ($p < .10$)* ($p < .05$)** ($p < .01$)***

	Pre-policy	Post-policy
Intercept	-183.91* (89.21)	-368.40 (232.51)
Time (Months)	0.97* (0.49)	1.45** (1.22)
Elect.Price	12.47*** (2.81)	29.36*** (7.46)
Energy.CPI	-0.08 (0.11)	-0.18 (0.29)
PV.Price.Com	7.05 (15.41)	-36.39 (45.80)
Adjusted R^2	0.61	0.57
Degrees of Freedom	64	31
N	69	36
Comparative P-value	0.292	

A broad view illustrating how RPS policy modifications affected solar generated electricity is achieved by analyzing Figure 5. Table 6 reports results after running segmented linear regressions on each RPS policy modification. The Clean Energy Act significantly increased the rate of solar production compared to the pre-policy period ($\beta = 0.77$ vs. 1.74, $p = 0.032$). A segmented multiple regression was performed to analyze the effect of the Clean Energy Act (see Table 7). The increase of commercial solar electricity production after the Clean Energy Act remained well above the established significance level ($p = 0.292$).

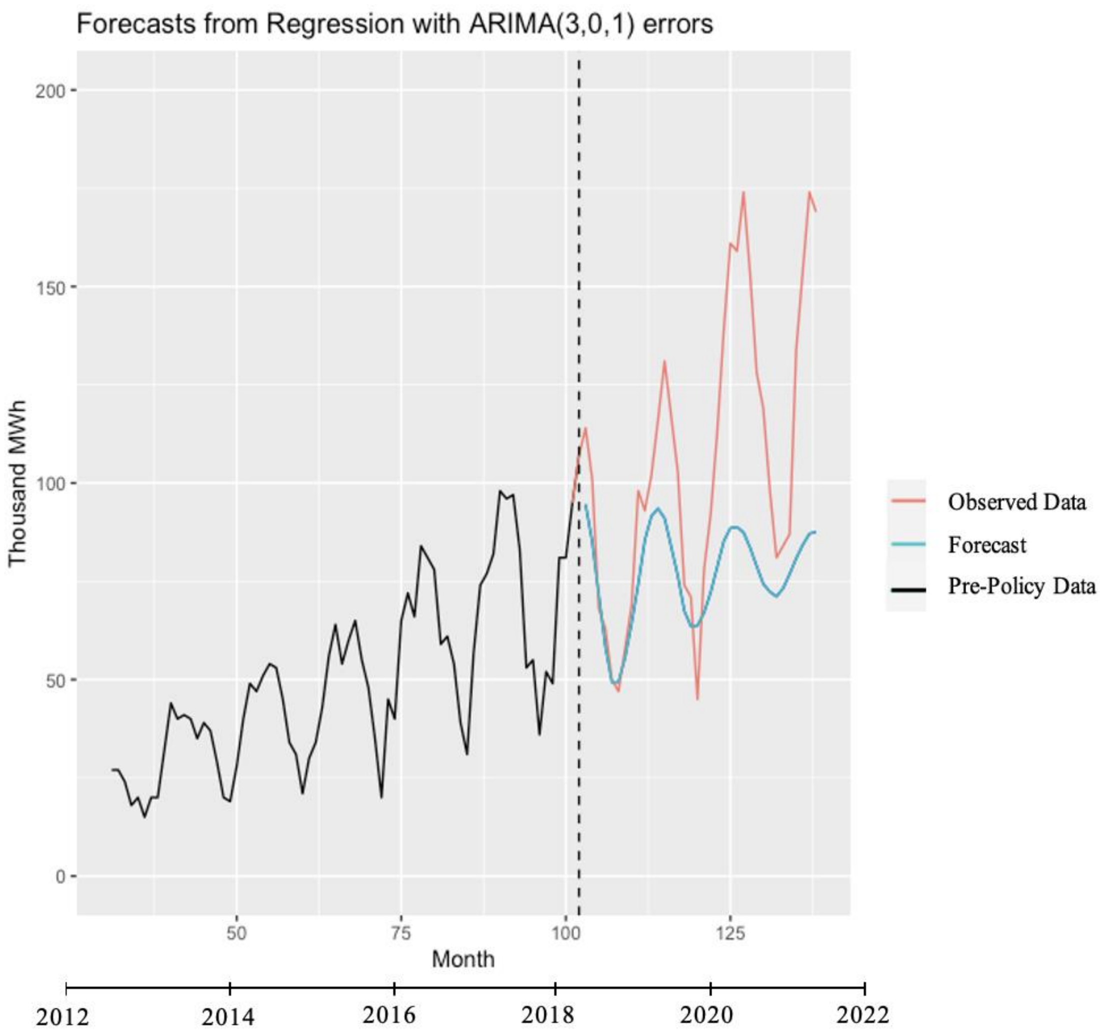

Figure 6 – ARIMA forecast predicting solar electricity generation had the Clean Energy Act not occurred (New Jersey's commercial sector).

Table 8 - Components and summary statistics for the Clean Energy Act ARIMA forecast model (New Jersey's commercial sector).

Best Fit Model	ARIMA(3, 0, 1)
Control Variables	Elect.Price & Energy.CPI
MAE	6.67
MASE	0.77

An ARIMA model (see Figure 6) was tasked to predict how solar generated electricity would have changed if the Clean Energy Act had not occurred. The forecast predicted very little variance in solar electricity generation for the first year, although, observed data outpaced the ARIMA forecast in the years following. Summary statistics (see Table 8) MAE (6.67) and MASE (0.77) both reflect an accurate ARIMA forecast. Analysis of the ARIMA forecast suggest the Clean Energy Act had an initial delayed response with an overall weak effect on solar electricity production. The ARIMA forecast analysis was consistent with the segmented multiple regression results, although it failed to illustrate the same effect demonstrated by the segmented linear regression.

New Jersey

Residential Sector

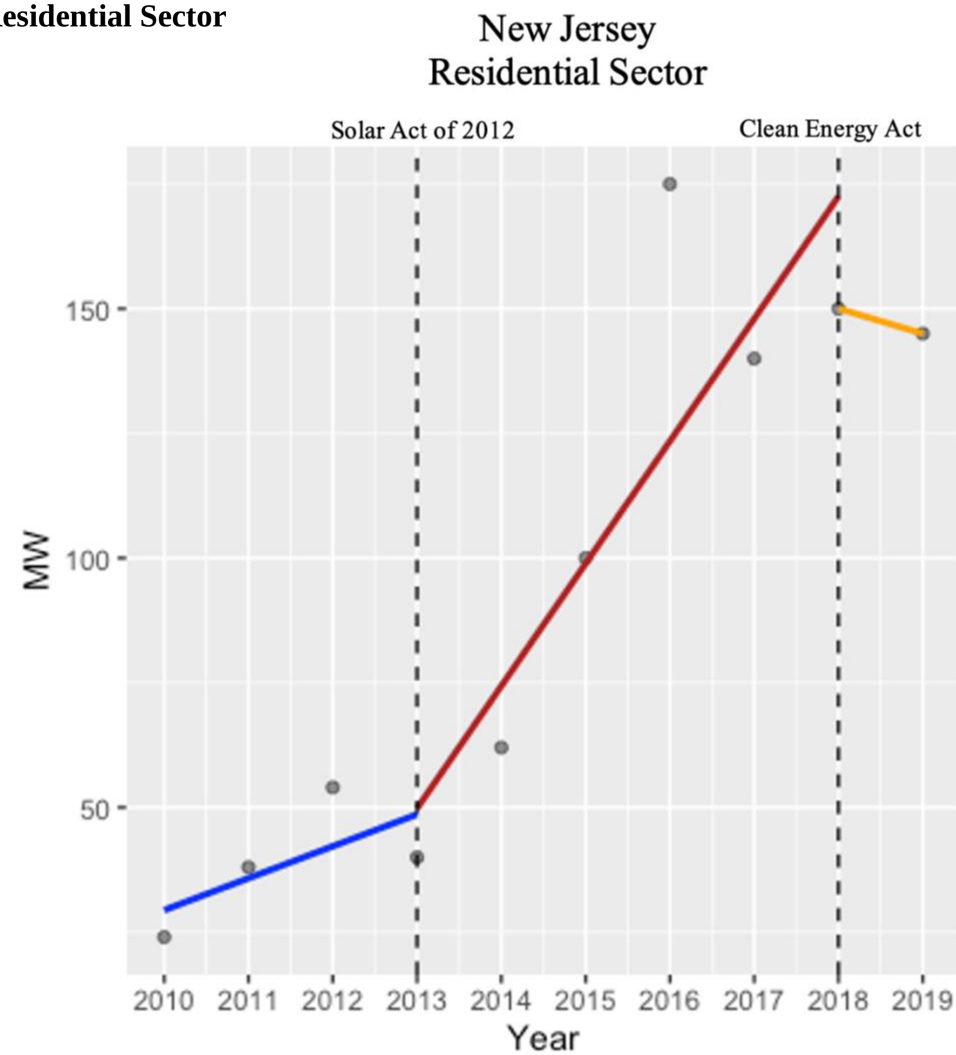

Figure 7 – Segmented linear regression of solar capacity in New Jersey's residential sector.

Table 9 - Segmented linear regression slopes and comparative p-value of pre-slope versus post-slope (New Jersey's residential sector). Clean Energy Act post-policy data is insufficient in measuring policy effectiveness (N/A). ($p < .10$)* ($p < .05$)** ($p < .01$)***

	Solar Act		**Clean Energy Act**	
Period	**Pre**	**Post**	**Pre**	**Post**
Intercept	25.88* (11.35)	-26.74 (34.60)	-26.74 (34.60)	N/A
Time (Years)	6.43 (4.95)	31.3* (8.97)	31.3* (8.97)	N/A
Adjusted R^2	0.18	0.74	0.74	N/A
Degrees of Freedom	2	3	3	N/A
N	4	5	5	N/A
Comparative P-value	0.015**		N/A	

Figure 7 illustrates how the Solar Act of 2012 and Clean Energy Act affected solar capacity in New Jersey's residential sector. Table 9 reports results after a segmented linear regression was performed on each Act. The Solar Act of 2012 significantly increased the rate of solar capacity growth compared to the pre-policy period (β = 6.4 vs. 31.3, $p = 0.015$). The Clean Energy Act was unable to be analyzed due to insufficient post-policy data. Degrees of freedom were low due to a data constraint from residential sector data being reported annually.

New Jersey

Industrial Sector

A chi-square test of independence was performed to examine the relation between industrial solar PV production and timeframe (pre- versus post-policy; see Table 10). The relation between these variables was significant, X^2 (1, N = 121) = 22.14, $p < 0.001$. The industrial sector was more likely to produce solar electricity rounding to 1 thousand MWh in a month after the Clean Energy Act was in effect compared to a month before the policy existed.

Table 10 - Contingency table for Clean Energy Act (New Jersey's industrial sector)

	Production	No Production
Pre-policy	16	85
Post-policy	13	7
Chi-square		22.14
Degrees of freedom		1
P-value		< 0.001

Pennsylvania's

Commercial Sector

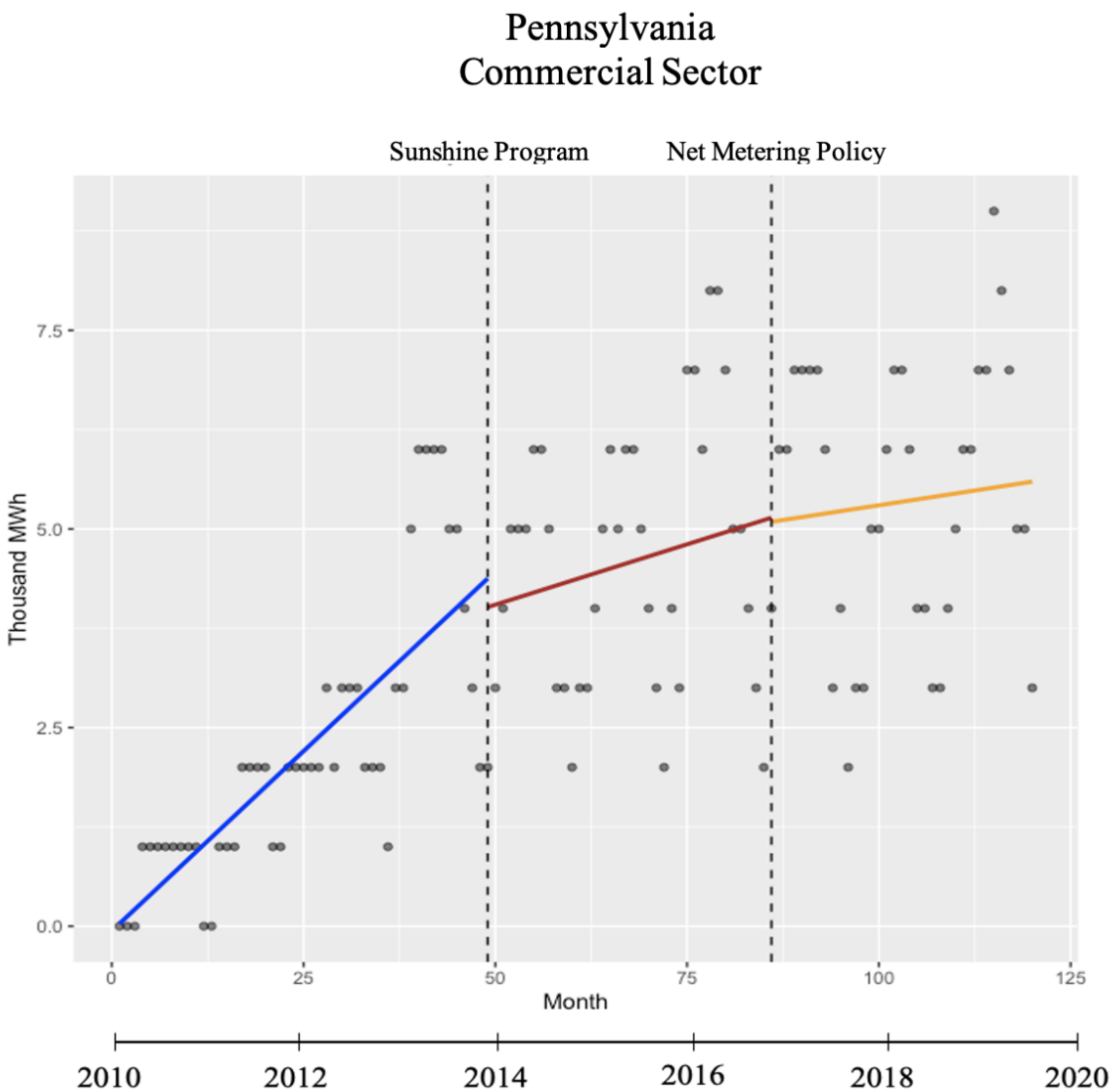

Figure 8 – Segmented linear regression of solar electricity generation in Pennsylvania's commercial sector.

Table 11 - Segmented linear regression slopes and comparative p-value of pre-slope versus post-slope (Pennsylvania's commercial sector). ($p < .10$)* ($p < .05$)** ($p < .01$)***

	Sunshine Program		**Net Metering Policy**	
Period	**Pre**	**Post**	**Pre**	**Post**
Intercept	-0.16 (0.29)	2.52 (1.68)	2.52 (1.68)	3.82 (3.03)
Time (Months)	0.09*** (0.01)	0.03 (0.02)	0.03 (0.02)	0.02 (0.01)
Adjusted R^2	0.64	0.12	0.12	0.09
Degrees of Freedom	46	36	36	32
N	48	38	38	34
Comparative P-value	0.013**		0.684	

Table 12 - Segmented multiple regression slopes, summary statistics, and comparative p-value (Pennsylvania commercial sector – Sunshine Program). ($p < .10$)* ($p < .05$)** ($p < .01$)***

	Pre-policy	**Post-policy**
Intercept	3.32 (4.89)	-5.33 (7.46)
Time (Months)	0.16*** (0.05)	0.10** (0.03)
Elect.Price	0.23 (0.19)	0.87** (0.29)
Energy.CPI	-0.02 (0.02)	-0.03* (0.02)
PV.Price.Com	-0.26 (0.32)	0.66* (0.80)
Adjusted R^2	0.49	0.29
Degrees of Freedom	43	38
N	48	43
Comparative P-value	0.382	

A holistic view illustrating how policy affected solar generated electricity is achieved by analyzing Figure 8. Table 11 reports the results of a segmented linear regression performed on both the elimination of the Sunshine Program and Net Metering Policy. The Sunshine Program coming to an end significantly decreased the rate of solar production compared to the pre-policy period (β = 0.097 vs. 0.031, p = 0.013). A segmented multiple regression was performed to further analyze the effect of the Sunshine Program ending (see Table 12). The decrease in commercial solar electricity production after the Sunshine Program ended was not significant (p = 0.382).

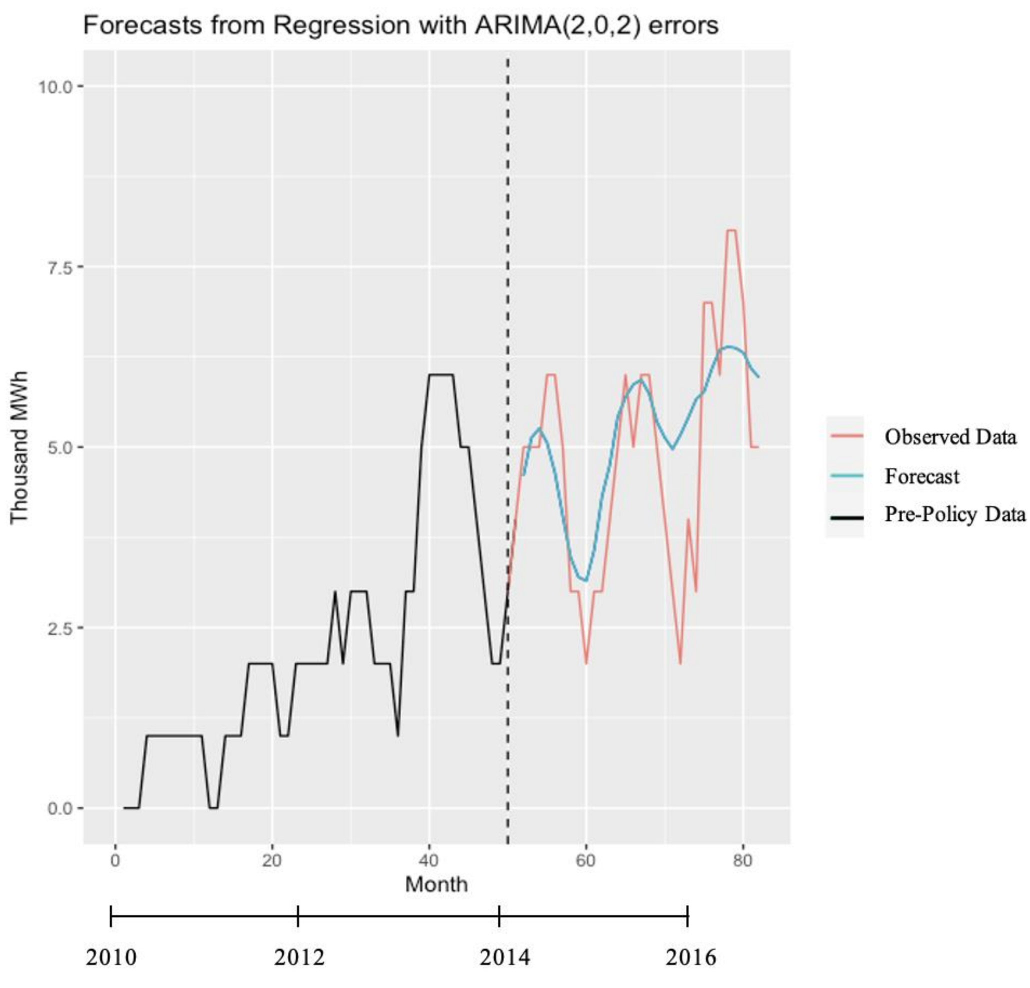

Figure 9 – ARIMA forecast predicting solar electricity generation had the Sunshine Program continued (Pennsylvania's commercial sector).

Table 13 - Components and summary statistics for the Sunshine Program ARIMA forecast model (Pennsylvania’s commercial sector).

Best Fit Model	ARIMA(2, 0, 2)
Control Variables	Elect.Price & Energy.CPI
MAE	0.443
MASE	1.006

An ARIMA model (see Figure 9) was tasked to predict how solar generated electricity would have changed if the Sunshine Program had continued. The forecast suggests there would have been no immediate effect on solar electricity production in the commercial sector, although, over time electricity production would have likely been higher than the observed data. Summary statistics (see Table 13) MAE (0.443) and MASE (1.006) both reflect a moderately accurate ARIMA model. Analysis of the ARIMA forecast was consistent with the segmented linear and multiple regression results (see Table 11 & 12).

Pennsylvania's

Residential Sector

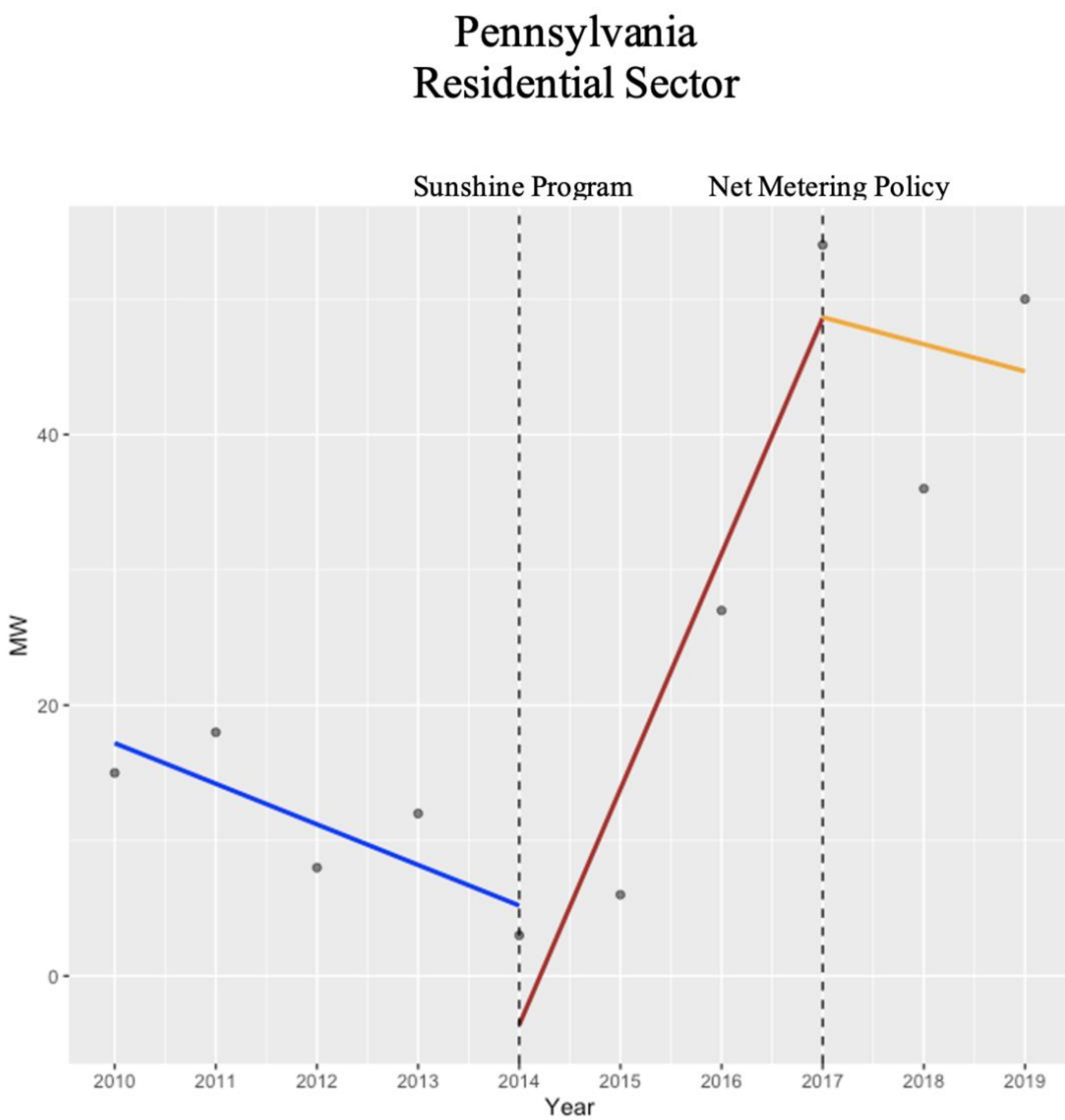

Figure 10 – Segmented linear regression of solar capacity in Pennsylvania's residential sector.

Table 14 - Segmented linear regression slopes and comparative p-value of pre-slope versus post-slope (Pennsylvania's residential sector). ($p < .10$)* ($p < .05$)** ($p < .01$)***

	Sunshine Program		**Net Metering Policy**	
Period	**Pre**	**Post**	**Pre**	**Post**
Intercept	19.44* (3.73)	-96.38 (21.13)	-96.38 (21.13)	68.04 (18.29)
Time (Years)	-3 (1.28)	17.4 (3.89)	17.4 (3.89)	-2.1 (4.24)
Adjusted R^2	0.53	0.86	0.86	0.11
Degrees of Freedom	3	2	2	1
N	5	4	4	3
Comparative P-value	< 0.001***		0.053*	

Figure 10 illustrates how the Net Metering Policy and Sunshine Program ending affected solar capacity in Pennsylvania's residential sector. Table 14 reports results of the segmented linear regressions performed on both policies. The Sunshine Program ending significantly increased the rate of solar capacity growth compared to the pre-policy period ($\beta = -3$ vs. 17.4, $p = <0.001$). The Net Metering Policy significantly decreased the rate of solar capacity growth compared to the pre-policy period ($\beta = 17.4$ vs. -2.1, $p = 0.053$). Degrees of freedom were low due to a data constraint from residential sector data being reported annually.

Pennsylvania

Industrial Sector

A chi-square test of independence was performed to examine the relation between industrial PV production and timeframe (pre- versus post-Sunshine Program; see Table 15). The relation between these variables was significant, X^2 (1, N = 83) = 12.17, $p < 0.001$. The industrial sector was more likely to produce solar electricity rounding to 1 thousand MWh in a month after the Sunshine Program was in effect compared to a month before the program existed.

Table 15 - Contingency table for the Sunshine Program (Pennsylvania's industrial sector).

	Production	No Production
Pre-policy	20	29
Post-policy	27	7
Chi-square		12.17
Degrees of freedom		1
P-value		< 0.001

A chi-square test of independence was performed to examine the relation between industrial PV production and timeframe (pre- versus post-Net Metering Policy; see Table 16). The relation between these variables was not significant, X^2 (1, N = 74) = 0.85, p = 0.36. The industrial sector was no more likely to produce solar electricity rounding to 1 thousand MWh in a month after the Net Metering Policy was in effect compared to a month before the program existed.

Table 16 - Contingency table for the Net Metering Policy (Pennsylvania's industrial sector).

	Production	No Production
Pre-policy	27	7
Post-policy	28	12
Chi-square		0.85
Degrees of freedom		1
P-value		0.36

Nevada

Commercial Sector

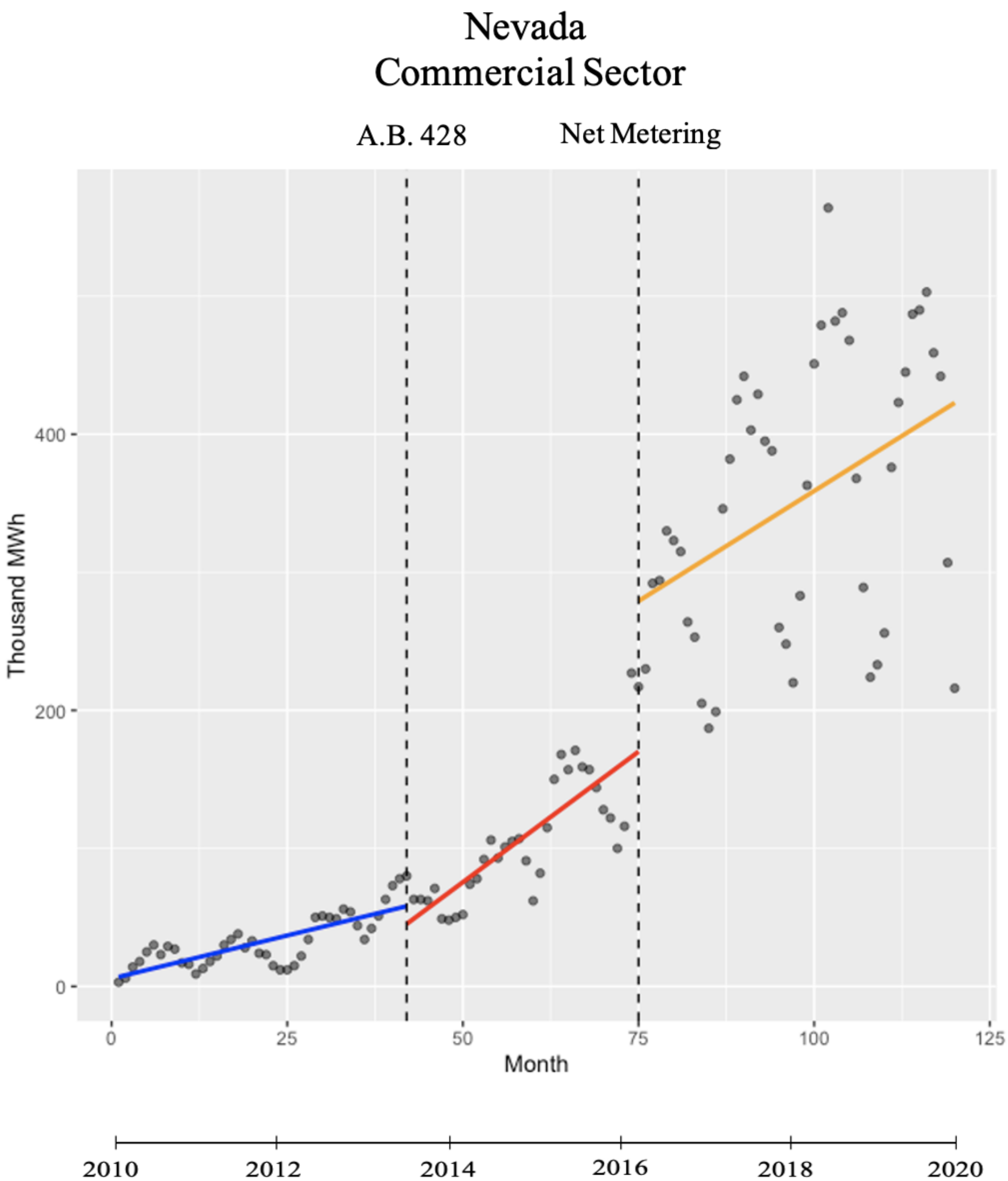

Figure 11 – Segmented linear regression of solar electricity generation in Nevada's commercial sector.

Table 17 - Segmented linear regression slopes and comparative p-value of pre-slope versus post-slope (Nevada's commercial sector). ($p < .10$)* ($p < .05$)** ($p < .01$)***

	A.B. 428		Net Metering Policy	
Period	**Pre**	**Post**	**Pre**	**Post**
Intercept	5.62 (3.83)	-113.63*** (29.33)	-113.63*** (29.33)	39.83 (88.63)
Time (Months)	1.25*** (0.16)	3.78*** (0.49)	3.78*** (0.49)	3.19*** (1.05)
Adjusted R^2	0.61	0.64	0.64	0.15
Degrees of Freedom	40	32	32	42
N	42	34	34	44
Comparative P-value	< 0.001***		0.61	

Table 18 - Segmented multiple regression slopes, summary statistics, and Comparative P-value (Nevada's commercial sector – A.B. 428). Only data from month 1 -73 was used to avoid effects from the Net Metering Policy ($p < .10$)* ($p < .05$)** ($p < .01$)***

	Pre-policy	Post-policy
Intercept	-54.35 (41.64)	-155.21 (171.94)
Time (Months)	1.15 (0.60)	2.72*** (1.37)
Elect.Price	8.09** (2.18)	13.58* (5.29)
Energy.CPI	-0.44*** (0.16)	-0.19 (0.41)
PV.Price.Com	-2.86 (3.35)	-8.68 (13.11)
Adjusted R^2	0.72	0.70
Degrees of Freedom	37	26
N	42	31
Comparative P-value	0.17	

A holistic view illustrating how RPS policy modifications affected solar generated electricity is achieved by analyzing Figure 11. Table 17 reports results of segmented linear regressions ran on A.B. 428 and the Net Metering Policy modification. A.B. 428 significantly increased the rate of solar electricity production compared to the pre-policy period ($\beta = 1.25$ vs. 3.78, $p = < 0.001$). The Net Metering Policy modification reported a non-significant change in solar electricity production compared to the pre-policy period ($\beta = 3.78$ vs. 3.19, $p = 0.61$), although, a substantial level change occurred once the policy began. A segmented multiple regression was performed to further analyze the effect of A.B. 428 on solar electricity production (see Table 18). The increase of commercial solar electricity production after A.B. 428 approached moderate significance ($p = 0.17$)

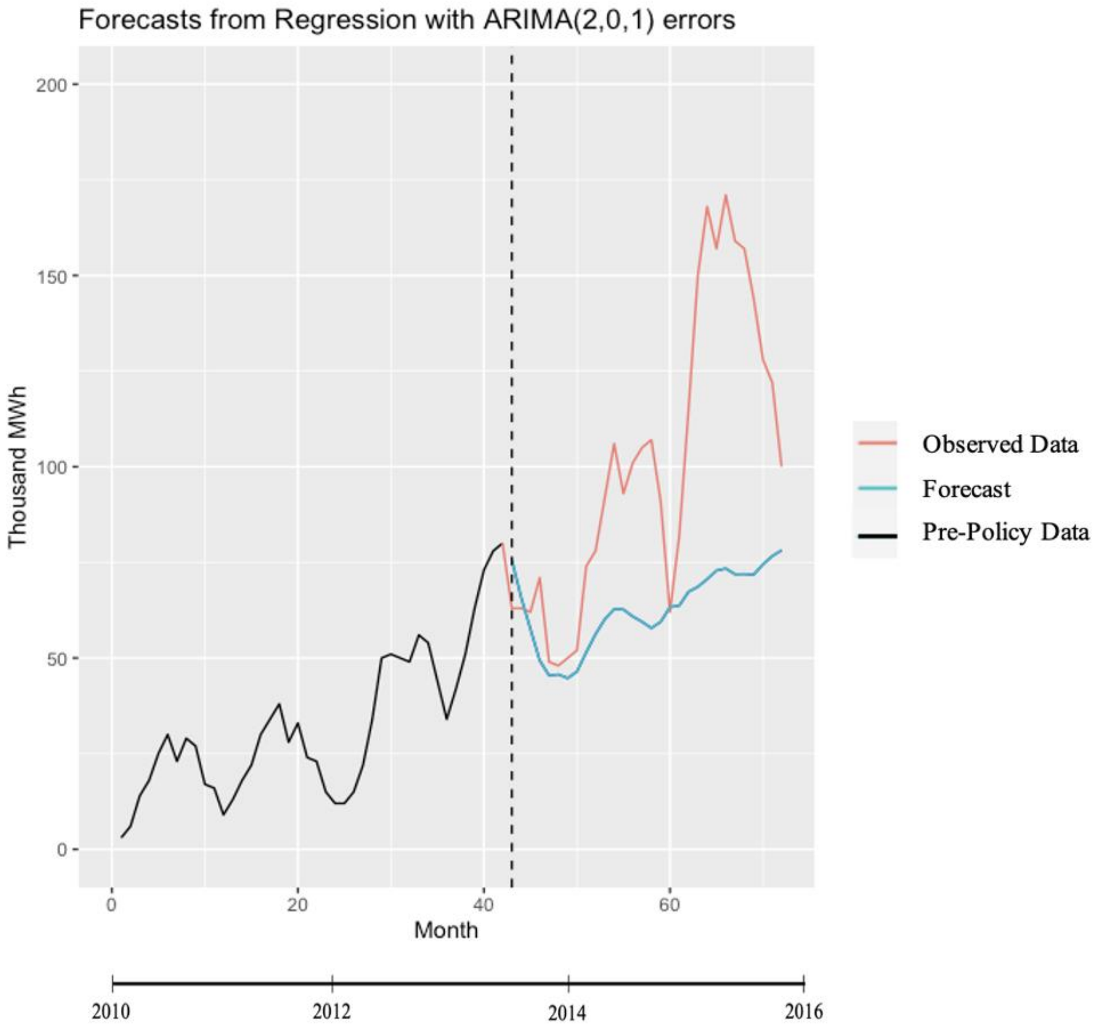

Figure 12 – ARIMA forecast predicting solar electricity generation had A.B. 428 not occurred (Nevada's commercial sector).

Table 19 - Components and summary statistics for A.B. 428 ARIMA forecast model (Nevada's commercial sector).

Best Fit Model	ARIMA(2, 0, 1)
Control Variables	Elect.Price & Energy.CPI
MAE	4.42
MASE	0.75

An ARIMA model (see Figure 12) was tasked to predict how solar generated electricity would have changed if A.B. 428 had not been implemented. The forecast indicated no immediate effect on solar electricity production, while displaying a decrease in production after the first year (compared to the observed data). Summary statistics (see Table 19) MAE (4.42) and MASE (0.75) both reflect an accurate ARIMA model. Analysis of the ARIMA forecast was consistent with the segmented linear regression results (see Table 17) and moderately consistent with the segmented multiple regression results (see Table 18). Suggesting A.B. 428 had a significant and positive effect on solar electricity production in Nevada's commercial sector.

Nevada

Residential Sector

Figure 13 – Segmented linear regression of solar capacity in Nevada's residential sector.

Table 20 - Segmented linear regression slopes and comparative p-value of pre-slope versus post-slope (Nevada's residential sector). ($p < .10$)* ($p < .05$)** ($p < .01$)***

	A.B. 428		Net Metering Policy	
Period	**Pre**	**Post**	**Pre**	**Post**
Intercept	5*** (0)	-65.61 (22.72)	-65.61 (22.72)	13.56 (32.4)
Time (Years)	0 (0)	22.3 (13.89)	22.3 (13.89)	18.6 (14.16)
Adjusted R^2	N/A	0.34	0.34	0.49
Degrees of Freedom	2	2	2	2
N	4	4	4	4
Comparative P-value	0.09*		0.76	

Figure 13 illustrates how A.B. 428 and the Net Metering Policy modification affected solar capacity in Nevada's residential sector. Table 20 reports the results of segmented linear regressions ran on both policies. A.B. 428 significantly increased the rate of solar capacity growth compared to the pre-policy period (β = 0 vs. 22.3, p = 0.09). The Net Metering Policy modification non-significantly decreased the rate of solar capacity growth compared to the pre-policy period (β = 22.3 vs. 18.6, p = 0.76). Degrees of freedom were low due to a data constraint from residential sector data being reported annually.

Florida

Commercial Sector

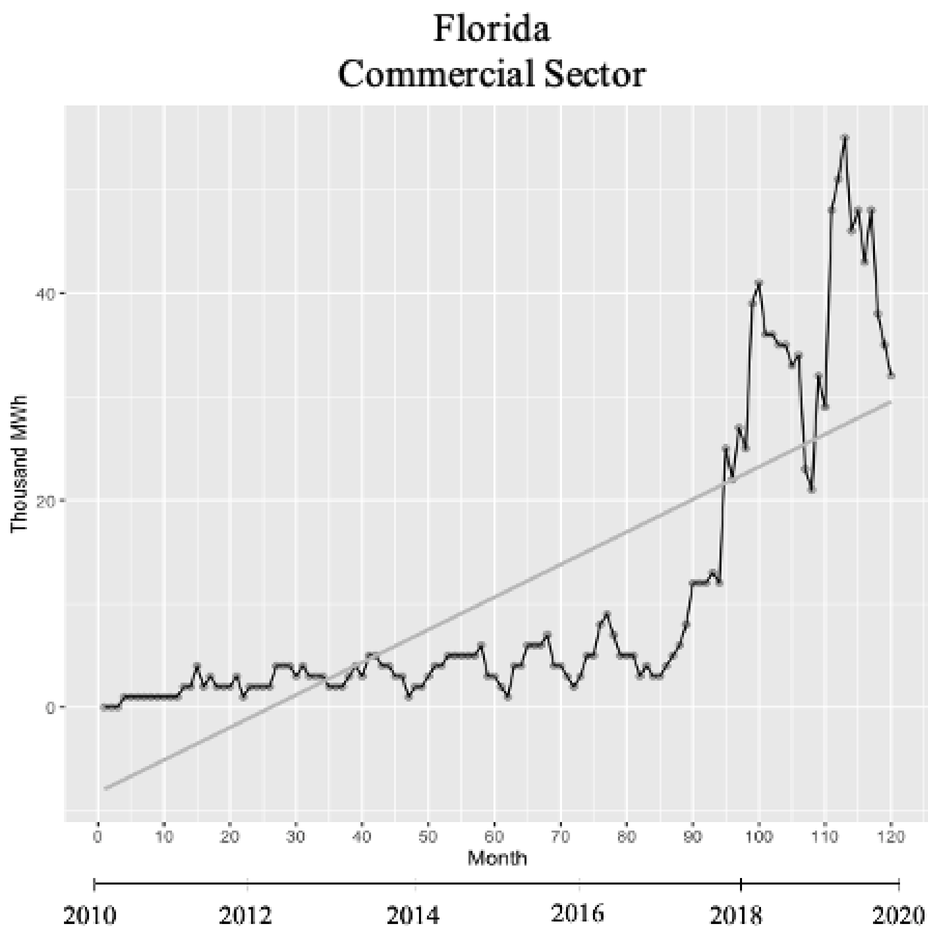

Figure 14 – Data and linear regression of solar electricity production in Florida's commercial sector.

Figure 14 illustrates an overview of solar electricity production in Florida's commercial sector. The black line represents the data points while the gray line represents a linear regression line. Graphical analysis (see Figure 14) indicated minimal growth took place from 2010 to 2017, with a significant increase at the end of 2017. Further discussion of Florida is outlined in the discussion section.

Florida

Residential Sector

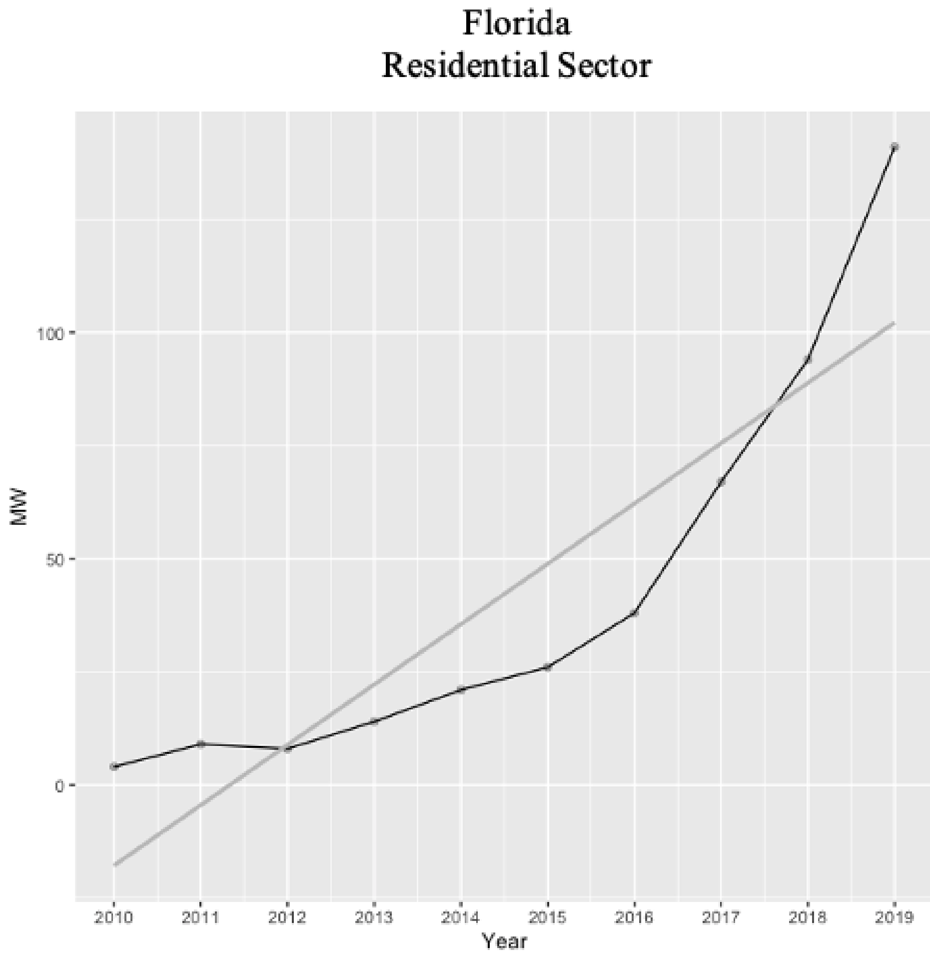

Figure 15 – Data and linear regression of solar capacity in Florida's residential sector.

Figure 15 illustrates an overview of solar electricity production in Florida's residential sector. The black line represents the data points while the gray line represents a linear regression line. Graphical analysis (see Figure 15) indicated marginal growth took place from 2010 to 2016, with a significant increase in 2016 that continued through 2019.

Summary of Results

Table 21 - Summary of results denoted by solar growth level.

	MA		NJ			PA			NV	
	Com	**Res**	**Com**	**Res**	**Ind**	**Com**	**Res**	**Ind**	**Com**	**Res**
SREC II										
Carve-out Min										
Smart Policy										
Solar Act										
Clean Energy Act										
Sunshine Program										
Net Metering Policy (PA)										
A.B. 428										
Net Metering Policy (NV)										

Policy not tested

No Growth

Modest Growth

Significant Growth

Case Studies

As stated earlier, case studies were performed on the state that demonstrated the least benefit and the state that demonstrated the greatest benefit to the residential sector regarding solar growth. These exploratory case studies explain the causal links associated between RPS policy design and solar electricity capacity in the residential sector. Of the states analyzed, Pennsylvania's residential sector displayed the least growth in solar capacity while New Jersey displayed the most growth. Case studies, framed around supposition, were conducted to develop a better understanding of the structure of these states' RPSs and supplement the lack of quantitative data available for the residential sector

Case Study 1 - Pennsylvania

Solar capacity growth in the residential sector was the lowest when comparing Pennsylvania to the other states analyzed in this research. While the lowest growth occurred in Pennsylvania, moderate growth still took place. Establishing reasoning for why growth was sub-par was accomplished through the analysis of Pennsylvania's RPS structure, components, and compliance requirements.

Background

Pennsylvania adopted its RPS in November of 2004 to increase electricity production from renewables (DSIRE 2018). The RPS included a net metering policy and the Alternative Energy Portfolio Standard (AEPS). The AEPS required 18.5% of electricity generation come from alternative sources by 2020 (ibid.). In addition to the AEPS, a carve-out was established that categorized sources as tiers. Tier 1 included sources such as solar PV, wind, geothermal, and low-impact hydro, while Tier 2 included waste coal, large-scale hydro, biomass, and wood pulping (ibid.). A PV Tier was also established, exclusively applying to solar PV electricity generation (ibid.). By 2021, Tier 1 was to account for 8% electricity production, Tier 2 was to account for 10%, and the PV Tier was to account for 0.5% (ibid.).

Pennsylvania's RPS and its components have remained relatively unchanged since their adoption in 2004. That said, a substantial net metering policy modification was added to their RPS in late 2016 (DSIRE 2018). This policy modification introduced net metering aggregation, expanded the systems eligible for net metering, and required utilities to offer net metering to more customers through raising the eligibility cap (DSIRE 2021). The Sunshine Program contributed to solar capacity growth in Pennsylvania but is considered separate from their RPS. The Sunshine Program began in 2008 and ended in December of 2013, using rebates and SRECs to help reduce the cost burden of solar (Althoff et al. 2018). This program coming to an end substantially decreased the price of SRECs from over $300 to less than $20 per credit (Althoff et al. 2018).

Evaluation

Supplementing solar capacity data with RPS policy information allowed for more confident conclusions to be cast on why solar growth in Pennsylvania's residential sector was sub-par. Quantitative data illustrated an initial decrease in residential solar capacity once the Sunshine Program came to an end. This finding was congruent with the qualitative analysis above, stating the end of the Sunshine Program caused rebates to halt and SREC prices to fall. A substantial decrease in SREC prices and the elimination of solar rebates (corresponding to the Sunshine Program ending) may have contributed to lower solar capacity growth. The association between a decrease in financial assistance and relatively low growth is portrayed as a determining factor for solar capacity in the residential sector.

When analyzing the effect of the net metering policy modification on solar capacity the conclusions were more implicit. The recency of this policy modification made it difficult to fully analyze its effect. The quantitative data available was limited after the modification was put into effect, only allowing for two years of capacity data after the modification began. This was not enough data to formulate conclusions regarding the effectiveness of the policy. While lack of quantitative data impeded the ability to evaluate the modification, qualitative data acted in filling the gaps in the analysis.

Examining the net metering policy modification compliance information unearthed factors that suggest it had a modest effect on solar capacity in the residential sector. First, the aggregate net metering component of the modification favored businesses and those with multiple buildings and electric meters under one account (DSIRE 2021). These characteristics are unrepresentative of the residential sector and likely had a minimal effect. Second, the policy modification did not require all electricity providers to offer net metering to their residential customers (DSIRE 2021). Limiting the reach and installing a cap on net metering may have restrained the policy modifications potential and restricted the quantity of individuals who could participate. Due to these factors, it can be inferred that the net metering policy modification had a modest effect on solar capacity in the residential sector. The policy modification appeared to be suited toward the commercial sector and did not directly address the residential sector.

Case Study 2 - New Jersey

Solar capacity growth in the residential sector was the highest in New Jersey when compared to the other states analyzed in this research. Establishing reasoning for why growth was highest was accomplished through the analysis of New Jersey's RPS structure, components, and compliance requirements.

Background

New Jersey's RPS was adopted in 1999 and has undergone multiple updates since its start (DSIRE 2019). The RPS percentage requirement in New Jersey was found to be very dynamic, with changes occurring in 2004, 2006, 2010, and 2018 (ibid.). As of 2018, New Jersey's RPS percentage requirement was set to 35% by 2025 (ibid.). This recent percentage requirement update was supported by a series of policies that fall under the RPS umbrella. New Jersey's carve-out was one of these policies and categorized renewable energy sources into classes (ibid.). Class I included any electricity derived from solar PV, wind, tidal action, geothermal, landfill gas, or anaerobic digestion (ibid.). Class II was large scale and only included electricity generated from hydroelectric facilities of 3MW or less (ibid.). The carve-out percentage requirement for Class I has remained very dynamic and steadily increased from 0.74% in 2005 to 21% in 2021 (ibid.). Conversely, the Class II percentage requirement has remained unchanged since 2005, staying fixed at 2.5% (ibid.). In addition to the carve-out, a solar carve-out was established in 2005 and required a specific annual percentage of solar generated electricity (ibid.). The percentage requirement in the solar carve-out followed the same dynamic structure as the Class I carve-out. Solar carve-out percentage requirements have increased from 0.01% in 2005 to 5.1% in 2021 (ibid.).

In addition to the solar carve-out, net metering and SRECs were included in New Jersey's RPS to contribute to the percentage requirement (ibid.). Like the dynamic percentage requirements observed in the solar carve-out, net metering and SRECs have also undergone an array of changes over the past ten years. State policies such as the Solar Act of 2012 and Clean Energy Act have worked in amending RPS policy components (ibid.).

Evaluation

The Solar Act was not included under the RPS umbrella but significantly impacted the existing solar carve-out and net metering policy (Solar Act 2012). This Act increased the solar carve-out requirement to 4.1% by 2028 (although later increased), modified net metering to include aggregation, and amended components of the RPS to improve interconnection standards and increase renewable energy financing (Solar Act 2012). The changes caused by the Solar Act were pivotal in generating solar capacity growth in the residential sector. It can be inferred that the Solar Act positively impacted solar capacity in the residential sector due to it directly affecting policies that drive solar installation. This inference agrees with quantitative data analysis from New Jersey's residential sector which portrayed a statistically significant increase in solar capacity after the Solar Act began.

New Jersey passed the Clean Energy Act in 2018 (Clean Energy Act 2018). The Clean Energy Act accelerated the total carve-out requirement to 5.1% and created a trigger to shutdown New Jersey's SREC program once the requirement was met (Clean Energy Act 2018). The requirement was met in April 2020, setting off the trigger and closing the SREC program (DEP 2021). In addition, the Clean Energy Act increased New Jersey's RPS percentage requirement to 35% by 2025 and established a Community Solar Energy Pilot Program that allowed utility customers to engage in solar projects remotely located from their property (Clean Energy Act 2018).

It can be inferred that the Clean Energy Act had an initial positive impact on solar capacity due to the 5.1% carve-out requirement being met early. Quantitative data for New Jersey's residential sector was insufficient in that it only provided data for one year after the policy was implemented, making analysis trivial. Therefore, qualitative analysis was utilized to understand the Clean Energy Act's effect on solar capacity in New Jersey's residential sector. The creation of the Community Solar Energy Pilot Program may have increased solar capacity in the residential sector through increased eligibility and participation in community solar. Assumptions on how solar capacity was affected by the elimination of the SREC program were formulated by referencing other states. For instance, Pennsylvania eliminated its SREC program and observed modest solar capacity growth in the subsequent years (Althoff et al. 2018). If this same effect is seen in New Jersey, it may counteract the benefits from the Community Solar Energy Pilot Program and generate minimal solar capacity growth in the future.

Comparative Study

There were a host of differences in RPS design when comparing Pennsylvania and New Jersey. Variation in structure, components, and compliance requirements encompass the variability present in RPSs. Comparing Pennsylvania's RPS to New Jersey's revealed stark differences in the quantity of percentage requirement modifications. Pennsylvania's RPS utilized a fixed percentage requirement for its carve-out and AEPS, while New Jersey's took a variable approach with dynamic solar carve-out requirements and an RPS percentage requirement that has been increased four times since its start. In addition, both states' RPS included a policy modification that eliminated its SREC program. Pennsylvania eliminated its SREC program in 2013, after only five years, while New Jersey shut down its program in 2020, after 21 years (DSIRE 2021). Differences regarding financial assistance (rebates, financing, tax credits) were also apparent, with New Jersey offering much more financial assistance than Pennsylvania. Lastly, net metering eligibility was more universal and inclusive in New Jersey, while Pennsylvania's net metering policies were rather ineffective and appeared to be designed around the commercial sector.

Discussion

Past research provides information on RPS effectiveness, policy implications, and RPSs' role in electricity production, although they fail to consider non-utility sectors when looking at solar electricity generation and capacity (Upton et al. 2017, Davies 2014, Zhou et al. 2020). This paper addressed which non-utility sectors benefitted most, measured in solar growth, from differing state-level RPS policies. Analyzing policy effectiveness was achieved using segmented linear regression, segmented multiple regression, ARIMA forecast models, chi-square tests, and a pair of exploratory case studies.

Key Findings

Data analysis of RPS policies indicated the commercial sector had the greatest response to RPS policies when compared to the residential and industrial sectors. Specifically, policies regarding net metering, aggregate net metering, and SRECs saw positive responses in the commercial sector. In addition, the commercial sector experienced the highest-level of solar electricity growth since 2010 when compared to the other sectors. Conclusions regarding the residential sector come from quantitative and qualitative analyses. Quantitative analysis found the residential sector had the greatest response (in terms of solar capacity) to financial assistance and rebates granted through state programs targeted to amend their RPS. The industrial sector potentially exhibited some response to RPS policies, with the Clean Energy Act in New Jersey and the Sunshine Program in Pennsylvania co-occurring with solar electricity growth. However, the association between policy inception and industrial electricity production is tenuous due to limitations surrounding industrial sector data and analysis.

Interpretation of Results

The first objective of this research was to understand RPS policy design and its spillover effect on non-utility sectors. Pennsylvania and New Jersey's RPSs were quantitative and qualitatively analyzed to fully understand each RPS in detail. The design of each RPS was found to differ considerably from the other, consistent with findings of past research (Yin et al. 2011, Ogundrinde et al. 2018). Qualitative analysis revealed variation in structure, components, eligibility, and compliance requirements when the two states' RPSs were compared.

RPS policies were found to have a considerable spillover effect on non-utility sectors, especially the commercial sector. However, the relative size of non-utility sector electricity generation was small compared to total electricity consumption per state. This implies that the policies analyzed had a positive effect on non-utility sectors but that this spillover had little effect on the total solar PV electricity production per state. Therefore, the magnitude of these spillover effects was thought to be limited.

Policies regarding net metering and SRECs were found to increase solar electricity production in the commercial sector. Solar electricity production significantly increased in New

Jersey and Nevada after a net metering policy, or policy with a notable net metering component (see Appendix B) occurred. The residential sector displayed significant increases in solar capacity growth after financial assistance and rebates were established. State Acts and Programs (see Appendix B) were responsible for granting the financial assistance and rebates and were found to be most effective at increasing solar capacity in the residential sector. These Acts and Programs remain separate from RPSs, indicating the RPS specific policies and modifications analyzed in this research only caused non-significant increases in solar capacity in the residential sector and had a minimal spillover effect. Analysis indicated that the industrial sector's solar electricity production did increase concurrently with the institution of certain RPS policies and modifications, specifically the Clean Energy Act (New Jersey) and Sunshine Program (Pennsylvania). However, limitation in both the precision of the electricity production data and of the capacity of chi-square analysis to control for confounding factors (e.g., the price of solar panels or of natural gas) mean that changes in the industrial sector cannot be attributed to acts of policy alone.

The second objective of this research was to develop recommendations to increase solar production to help future researchers studying RPSs and renewable energy policies establish better suited policy decisions. Recommendations were based on qualitative and quantitative analyses that examined individual policy effectiveness and ability to increase solar capacity and electricity production. Below is list of recommendations formulated by the findings of this research.

1. Develop a net metering policy
2. Allow aggregate net metering
3. Maintain a healthy SREC market
4. Structure a solar carve-out with dynamic percentage requirements
5. Supplement an RPS with state acts and programs
6. Offer multiple sources of financial assistance

The majority of recommendations given above apply to each sector. Certain recommendations, such as offering multiple sources of financial assistance and supplementing an RPS with state Acts and Programs were found to significantly increase solar capacity in the residential sector but only showed a moderate effect in the other sectors. Although these recommendations only displayed significant results in one sector, they were still included as they had a positive yet non-significant effect on solar electricity production in one or more of the other sectors.

The first sub-objective in this research was to determine which specific RPS policies provided the most solar growth among each sector. Identifying which RPS policies provided solar growth was achieved through quantitative analysis. Net metering and policies closely related (see Appendix B) were found to have significantly increased solar electricity production in the commercial sector. Compared to other policies analyzed in the commercial sector, net metering policies outpaced other RPS policies regarding solar growth.

Surprisingly, the specific RPS policies analyzed in the residential sector were associated with non-significant solar growth. No policy (or policy modification) under an RPS was found to provide any significant solar growth. State Acts and Programs (see Appendix B) were identified as the only interventions to increase solar growth in the residential sector. Specifically, the Solar Act of 2012 in New Jersey, the Sunshine Program in Pennsylvania, and A.B. 428 in Nevada provided significant solar growth in the residential sector.

Like the residential sector, quantitative analysis indicated the industrial sector experienced non-significant growth when analyzing specific RPS policies and modifications. The Clean Energy Act (New Jersey) and Sunshine Program (Pennsylvania) were the only interventions to significantly increase solar growth in the industrial sector. Policies under the RPS umbrella displayed non-significant solar growth, highlighting a weak spillover effect and a lack of policies that stimulate the industrial sector.

The second sub-objective was to develop an understanding of which sectors (commercial, industrial, residential) were affected the most in terms of solar growth from RPS policies. Quantitative data analysis identified the commercial sector experienced the most growth of the sectors analyzed. The residential and industrial sectors both displayed very minor growth when compared to the commercial sector. That said, the residential sector experienced higher solar growth than the industrial sector. One explanation for why the commercial sector experienced the highest level of solar growth stems back to the design and policy components of an RPS. Multiple variations in RPS policy design were identified earlier when discussing the first objective. Past research found variations in policy design and stringency can influence the effectiveness of an RPS (Yin et al. 2011, Ogundrinde et al. 2018). Findings in past research and conclusions cast in this research both point to variations in RPS policy design influencing RPS effectiveness, indicating that variation in RPS policy design contributed to stark differences in sectoral solar growth.

Additional explanations unrelated to RPSs and other renewable energy policies may have contributed to differences in solar growth among each sector. Although, these explanations are not discussed due to them being outside the scope of this research. Future research should identify additional explanations to better understand variations in sectoral solar growth.

The last sub-objective was to draw conclusions regarding why RPS policies benefitted certain sectors more than others. Potential reasoning for why particular policies impacted certain sectors more than others include differences in eligibility, the status of other policies, and specific design choices. Differences in eligibility can influence the number of individuals who qualify for a given policy, limiting the policy's potential. Qualitative analysis determined net metering eligibility was a notable factor when policies in New Jersey and Pennsylvania's were compared. Other policies and their intention, reach, and stringency may have been a factor in sectoral solar growth, leading to different levels of solar growth in each sector. Lastly, specific policy design choices may have influenced a given policy's effectiveness and impacted which sectors exhibited differing levels of solar growth.

Comparison State – Florida

Florida was selected to compare to the states analyzed in this research. A significant increase in solar growth in Florida's commercial and residential sectors was observed in 2017. However, there were no major renewable energy regulatory policies that occurred at that time. Although, multiple state incentives and tax exemptions coupled with the third lowest solar PV module cost in the nation was inferred to have significantly influenced solar growth (DSIRE 2021, Marsh 2021). In addition, Florida has some of the highest solar irradiance in the nation along with a higher population than every state included in this research, yet it only generated nearly half of the solar generated electricity of Nevada and New Jersey (NREL 2018, Census 2020). High solar potential coupled with a large population would likely be associated with high levels of solar growth. However, solar growth in Florida was modest compared to the other states analyzed, suggesting that Florida would have likely experienced higher solar growth if an RPS policy had been implemented.

Comparison with Previous Research

The interpretation displayed similar and contrasting findings to conclusions published in past research. RPS stringency and subsidies were found to have a significant and positive impact on renewable energy development (Yin et al. 2010). Quantitative and qualitative analysis performed on the residential sector found a similar result. An association between financial assistance and increases in solar capacity was inferred from these analyses. However, past research found that RPSs impact on electricity generation was insignificant when comparing states who have adopted an RPS to states who have not (Upton et al. 2017). While some specific RPS policies were ineffective at increasing solar generated electricity, others were effective. In addition, growth in three of the four commercial sectors analyzed (Massachusetts, New Jersey, and Nevada) displayed nearly double the solar generated electricity of Florida (no RPS). Lastly, a conclusion formulated by Ogundrinde et al. (2018) that the introduction of SRECs make RPSs less effective was observed in this research. While this finding was parallel with analysis of the residential sector, the opposite effect was seen in the commercial sector.

Limitations and Future Research Opportunities

There were multiple limitations in this research that constrained the ability to analyze certain sectors and policies. Limitations regarding solar capacity data made for weak linear regressions and multiple regressions that were impossible to effectively perform. This was due to issues regarding degrees of freedom resulting from residential data being reported annually rather than monthly. These data limitations should be addressed by future research through looking at the data through a panel (rather than each state individually) and including dichotomous variables (rather than segmenting the data). Together, these changes would increase the number of observations and potentially address some of the limitations.

Data limitations also impacted policy analysis in the industrial sector because post-intervention data was insufficient to analyze the effect of the policy. In addition, industrial sector data, as reported by the EIA , was insufficiently variable to permit analysis by regression. Because industrial output is relatively small, the quality of the industrial data did not fully capture changes in the sector and made it difficult to analyze using the methods that were used in the other sectors.

The relationship of time was inconsistent across all data, meaning some of the data did not have a linear relationship with time. This inconsistency was a limitation that could be overcome in future research through additional statistical models and processes. A population control was not included, limiting each model's ability to account for population changes over time. Future analysis should include a population control in each model as well as monthly fixed effects in order to incorporate seasonality into the regression models. In addition, running full regressions when time itself was not significant should be avoided in order for accurate models to be formulated. Limitations regarding proximity of policies made it difficult to confidently differentiate one policy's effectiveness from another. An increase in data observations would likely work in addressing this limitation. Federal policies were not included in this research due to state-level policies being the focus, therefore, the effects of federal policies were not analyzed. This limitation could be addressed in the future through the inclusion of policies like the Clean Power Plan, with state policy interaction terms to measure a policy's effect on solar electricity generation. Subtle but substantial changes to the models and data would create stronger models that offer increased accuracy in results and clarify conclusions.

Future research should work in filling gaps where certain policies could not be fully analyzed due to data limitations. In addition, developing a statistical model that incorporates the same sector from multiple states would allow for conclusions to be cast on what factors or events impacted states differently. Research should focus on creating stronger models that utilize quality data to formulate the most accurate conclusions. Lastly, future research should further analyze the industrial sector to formulate more confident conclusions, explore why solar electricity generation was so limited, and investigate how states can tailor their RPS policies to increase generation in this sector.

Conclusion

This research was developed to formulate conclusions regarding which non-utility sectors were most impacted by differing state-level RPS policies, as measured by solar electricity generation and capacity growth. Analysis indicated the commercial sector demonstrated the highest solar growth when compared to the residential and industrial sectors. The commercial sector was also found to have benefitted the most from differing RPS policy modifications, with more modifications showing statistically significant effects on growth than either of the other sectors. When looking at the effectiveness of certain RPS policy modifications, net metering, aggregate net metering, and SRECs demonstrated statistically significant effects on solar electricity growth in the commercial sector. The industrial sector displayed no growth in response to RPS policy modifications, commonly displaying a slight negative effect on solar electricity growth. However, the industrial sector did experience growth after the inception of the Clean Energy Act in New Jersey and Sunshine Program in Pennsylvania (not grouped under the RPS). Recommendations to increase residential solar capacity growth were drawn from case studies. These include establishing a dynamic RPS percentage requirement; maintaining a healthy SREC market; structuring a solar carve-out with dynamic percentage requirements; offering multiple sources of financial assistance to burden installation costs; and requiring all electricity providers to offer net metering.

The implications of these findings can influence future policy decisions regarding RPSs and renewable energy. Policy makers looking to maximize the benefit of RPSs by way of spillover might want to look at including net metering, aggregate net metering, dynamic percentage requirements, and SRECs in their future policy designs. Conclusions and recommendations, backed by evidence, can help in guiding policy design and gearing policies toward sectors where solar growth is limited. The structure of this research can be applied to other renewable energy sources to further analyze the effect of policy.

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Appendix A

Comparative P-value

A two-part statistical test was used to determine if two slopes were statistically different from one another. The slopes were considered statistically different if the comparative p-value was less than 0.1. The first component was an equation developed and tested by Clogg et al. (1995) and confirmed by Paternoster et al. (1998). Coefficients ($ß_1$ & $ß_2$) and standard errors ($SEß_1{}^2$ & $SEß_2{}^2$) are used to output a value classified as Z.

$$Z = \frac{\beta_1 - \beta_2}{\sqrt{SE\beta_1^2 + SE\beta_2^2}}$$

Comparative P-value using a Cumulative Distribution Function

The cumulative distribution function comprised the second component of the two-part test. Where P is the probability that Z will have a value less than or equal to x and Z represents the value given by the equation above (Note: P in this equation is different from P in the segmented regression equation.)

$$F(x) = P(Z \leq x)$$

This equation was used to test the null hypothesis that the difference between the pre-slope and post-slope is zero. The null hypothesis can be rejected if the resulting p-value is less than 0.1. A significance level of 0.1 was selected to indicate marginal significance. The p-value was increased from 0.05 to better reflect what is considered statistically significant when analyzing policy effectiveness in this research.

Appendix B

Smart Policy – The Smart Policy (Massachusetts) officially began in 2018, although speculation began in 2017 when the policy was announced (DOER 2017). Its intention was to provide incentives for qualifying solar PV projects and to re-structure the state's SREC program by converting credits from variable to fixed. (DSIRE 2021).

Solar Act – The Solar Act of 2012 (New Jersey) mandated 4.1% of electricity sales come from solar by 2028 (DSIRE 2021). Subsections of the Act include modifications to net metering (including aggregation) and SRECs in addition to RPS amendments to improve interconnection standards and increase renewable energy financing (Solar Act 2012).

Clean Energy Act – The Clean Energy Act (New Jersey) was passed in 2018 (Clean Energy Act 2018). It increased the 4.1% mandate from the Solar Act to 5.1% and created a trigger to shut down New Jersey's SREC program once 5.1% was met (Clean Energy Act 2018). Additionally, the Act increased New Jersey's RPS percentage requirement to 35% by 2025 and developed a Community Solar Energy Pilot Program (Clean Energy Act 2018)

Sunshine Program – The Sunshine Program (Pennsylvania) began in 2008 and ended in December of 2013, using rebates and SRECs to help reduce the cost burden of solar (Althoff et al. 2018). The program's closure caused SREC prices to plummet from over $300 to less than $20 per credit (Althoff et al. 2018).

A.B. 428 – Assembly Bill 428 (Nevada) was passed in 2013 and directed the Public Utilities Commission to evaluate "the comprehensive costs of and benefits from net metering" (Davies et al. 2017). Changes in net metering were coupled with financial incentives ($185 million by 2014) to promote solar power in the state (Davies et al. 2017).