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State level trends in renewable energy procurement via solar installation versus green electricity

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STATE LEVEL TRENDS IN RENEWABLE ENERGY PROCUREMENT VIA SOLAR INSTALLATION VERSUS GREEN ELECTRICITY

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ABSTRACT

In the past 5 years, consumer options for procuring renewable energy have increased, ranging from rooftop solar installation to utility green pricing to Community Choice Aggregation. These options vary in terms of costs and benefits to the consumer as well as grid integration implications. However, little is known regarding how the presence of a wide range of options for utility-scale renewable procurement affects demand for distributed residential solar installations. In theory, there are three possible relationships, (1) positive correlation, where utility-scale and distributed resources complement each other to increase overall production, (2) negative correlation, where utility-scale and distributed resources are substitutes, and (3) no correlation, suggesting that these different procurement choices are unrelated. To examine the relationship, aggregated at the state level, we use a mixed effects regression model with panel data from 2016 to 2019 for all fifty US states plus the District of Columbia, controlling for policy, resource availability, and demographics. Although there was no evidence of a relationship between demand for utility-scale and distributed options across states, the estimated random effects suggest variation between states. An investigation of Vermont (positive), North Dakota (negative), and Oregon (zero) suggest that the policy environment, available resources, and average energy cost may explain this heterogeneity. As more data becomes available over time, there will be additional opportunities to explore this relationship.

Keywords: Voluntary Procurement, Renewable Energy, Consumer Demand, Utility-Scale, Distributed, Photovoltaic Solar

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1. INTRODUCTION

As costs for renewable energy have decreased and consumer demand has increased, options for procuring renewable energy have proliferated. In fact, total voluntary procurement (i.e., renewable energy procured above state mandates) has more than quintupled between 2010 and 2020 (Heeter, 2022). For example, residential consumers who want to purchase renewable energy can install solar panels on their roof, subscribe to a green pricing program via their utility or contract with a third-party developer.

However, the characteristics and implications of these options vary widely. At a high level, these options can be divided into (a) distributed or (b) utility-scale renewable procurement options, which vary in terms of costs and benefits to consumers, as well as the grid (see summary in Table 1-1). As a result, it may be valuable to incentivize some procurement options over others or encourage combined procurement options in different regions.

Distributed renewable generation involves installing generation technology (e.g., solar) on the consumer’s property. This can require a large up-front investment from the consumer for installation and maintenance, but they also benefit from opportunities to sell excess generation to the grid (via net-metering). In addition, this option reduces reliance on the electrical grid and ensures that consumers are directly benefiting from renewable generation (rather than increasing renewable content elsewhere on the grid). However, this option can increase grid integration challenges since the generation is behind-the-meter (BTM) and difficult for utilities to control (McAllister et al., 2019).

Distributed solar also requires higher engagement from consumers, since they must coordinate with installers and may be inconvenienced by construction.

In contrast, there are many options for utility-scale procurement for residential consumers, including (1) power purchase agreements (PPAs), (2) competitive suppliers, (3) unbundled renewable energy credits (RECs), (4) utility green pricing, and (5) community choice aggregation (CCA). These options vary in terms of the price premium, monetary benefits, grid implications and effort required. In general, utilities have more control over utility-scale renewable generation since it is directly connected to the grid for transmission and distribution (O'Shaughnessy et al., 2017).

In Power Purchase Agreements (PPAs), a consumer enters a long-term contract to buy electricity directly from a generator, typically between 5 and 20 years (NREL, 2016). In the most common form, customers purchase electricity that is credited towards their electricity demand (O'Shaughnessy et al., 2017). Although the utility still charges fees for transmission and distribution services, these agreements tend to have lower generation costs and provide a hedge against economic volatility due to their length. Depending on the interconnection terms, these generators may provide grid services, such as curtailment and ancillary services (O'Neill & Chernyakhovskiy, 2016).

In restructured electricity markets, consumers can purchase renewable energy from competitive suppliers. In this arrangement, the consumer receives electricity as well as Renewable Energy Certificates (RECs) (O'Shaughnessy et al., 2017). Typically, the consumer pays a price premium, but competition may lower prices overall.

When producing renewable electricity, generators may choose to sell the electricity itself wholesale into the market as well as the REC, which represents the environmental value, in a separate market. When the REC is separated from the generated electricity, it is “unbundled” (O’Shaughnessy et al., 2017). Unbundled RECs are highly flexible as no actual electricity is exchanged. Typically, they are directly purchased to offset the environmental impact of fossil fuel generation.

Utility green pricing programs offer renewable energy to consumers at a price premium. In some cases, these funds are invested in additional renewable generation that is owned by the utility. In other cases, the utility retires RECs in proportion to the quantity of green power sold (O’Shaughnessy et al., 2017). Often, green pricing programs are tax deductible, providing some benefits to consumers who wish to purchase them (Swezey & Bird, 2001).

Lastly, Community Choice Aggregation (CCA) programs enroll consumers by default to achieve economies of scale for lowering electricity prices (O’Shaughnessy et al., 2017). Many CCAs explicitly aim to increase renewable energy generation and provide higher renewable content by default. In addition, similar to utility green pricing program, CCAs will offer packages at a price premium with even higher renewable energy content (e.g., 100% renewable). CCAs pull customers from existing investor-owned utility companies and increase demand for renewable energy in their local grids (O’Shaughnessy et al., 2019).

To investigate the relationship between distributed and utility-scale procurement options, this study aims to answer the following research questions:

(1) What is the relationship between the share of utility-scale renewable procurement and distributed solar installation at the state level in the US?

(2) How does this relationship vary between states?

Table 1-1. Distributed and Utility-Scale Renewable Procurement Options

Procurement Options	**Cost to Consumer**	**Benefit to Consumer**	**Grid Integration**	**Consumer Engagement**
Distributed Options				
Solar Generation	High up-front installation cost, Maintenance costs	Tax credits, Rebates, Excess solar compensation (e.g., net metering)	Reduced reliance on grid, Limited utility control for BTM	Coordination with installer, Disruptions from installation
Utility-Scale Options				
Power Purchase Agreement (PPA)	No up-front cost	Long term contract provides a hedge against volatility	Generator may provide grid services	Enrollment in long-term contract
Competitive Suppliers	Price premium	Consumer receives RECs	Generator may provide grid services	Purchase directly from generator
Unbundled RECs	Additional cost for renewable energy offset	Environmental value	None, financial instrument	Purchase from third party REC merchant
Utility Green Pricing	Price premium per kWh of electricity	Consumer receives RECs	May involve utility-owned renewable investment or RECs	Enrollment in program
Community Choice Aggregation (CCA)	Price premium per kWh of electricity	Oftentimes lower electric prices than investor-owned utilities due to economies of scale & collective buying power	Contract with renewable energy generators	Enrollment by default with opt-out option

This relationship can inform policy-makers' efforts to increase renewable generation by incentivizing distributed generation, utility-scale procurement, or a combination of the two. Demand for distributed versus utility-scale renewable generation has long-term implications for grid planning and integration challenges.

Overall, there was no evidence of a relationship between utility-scale procurement and distributed solar generation when aggregated at the state level. However, analysis of state-level random effects suggests there is significant variation between states. In particular, the type of generation incentivized by existing policy as well as available energy resources may play a role in determining this relationship.

2. LITERATURE REVIEW

In this section, we summarize literature on (1) distributed generation adoption, (2) utility-scale procurement, and (3) choosing between renewable options.

2.1. DISTRIBUTED GENERATION ADOPTION

Residential distributed solar generation increases as individual households decide to install solar panels on their property. These decisions are influenced by policy, economic, contextual, and socio-economic factors. Distributed generation increases as policies favoring renewable energy adoption increase. Policy factors include Renewable Portfolio Standards (RPS), CCAs, and access to markets. RPS are associated with higher levels of distributed solar generation, likely due to increased pressure for utilities to provide incentives (Carley, 2009a; Li & Yi, 2014; Sarzynski et al., 2012; Wiser et al., 2011). There is mixed evidence regarding whether states that have had an RPS for a longer amount of time have more distributed solar installations (Crago & Koegler, 2018; Crago and Chernyakhovskiy, 2017). Given the recent emergence of CCAs, little research has been able to evaluate the effect on distributed solar. Deregulated electricity markets tend to have more distributed solar installations (Carley, 2009a).

Similarly, economic incentives for renewable energy adoption tend to increase distributed generation. For instance, net metering laws, and other legislation favoring compensation for distributed solar generation, increase residential photovoltaic installations (Carley, 2009a; Michaud & Pitt, 2018; Crago & Koegler, 2018; Matisoff & Johnson, 2017). However, these effects tend to be much more pronounced when following best practices (Michaud & Pitt, 2018) and combined with interconnection legislation (Michaud & Pitt, 2018; Borchers et al., 2014). The existence of state-wide rebates have increased distributed solar installations (Borchers et al., 2014; Crago & Chernyakhovskiy, 2017; Hughes & Podolefsky, 2015; Crago & Koegler, 2018; Matisoff & Johnson, 2017; Sun & Sankar, 2022; Sarzynski et al., 2012), sped up adoption (Bauner & Crago, 2015), and increased capacity (Carley, 2009a). Evidence suggests that front-loaded rebates may be the most effective in incentivizing distributed solar (Sun & Sankar, 2022). In one case, rebates have not influenced distributed generation, despite decreasing costs associated with installing distributed generation, likely because the financial incentives in this study assisted the residential sector less than the commercial sector, where a significant increase in distributed installations was seen. (Shrimali & Jenner, 2013). Additionally, tax credits can increase solar capacity additions (Borchers et al., 2014; Durham et al., 1988; Michaud & Pitt, 2018) and speed up adoption (Bauner & Crago, 2015). For example, tax credits increased the average rate of return for installing solar by 16-25% in Hawaii (Coffman et al., 2016). However, in general, state-level tax incentives tend to not be significantly effective (Li & Yi, 2014; Sarzynski et al., 2012; Carley, 2009a; Matisoff & Johnson, 2017; Shrimali & Jenner, 2013), likely since tax credits may be less visible to consumers than other forms of incentives. Some evidence suggests that city-level tax credits are more effective than state-level tax credits (Li & Yi, 2014), likely because city-level tax credits are more specialized and targeted towards a smaller population. Studies also suggest that rebates are more effective than tax credits in increasing distributed solar installations (Crago & Chernyakhovskiy, 2017; Carley, 2009a; Sarzynski et al., 2012). However, Schelley (2014) found that almost all early solar adopters had at least one form of tax or cash incentive.

Contextual factors, such as availability of energy resources and the average cost of electricity, also influence distributed generation adoption. Places with more sunlight, or solar insolation, tend to have more distributed solar installations because they can generate more electricity (Crago and Chernyakhovskiy, 2017; Michaud & Pitt, 2018; Borchers et al., 2014; Hsu, 2018; Crago & Koegler, 2018; Li & Yi, 2014; Kwan, 2012; Bennett et al., 2020). In addition, adoption of solar tends to increase as the average cost of energy increases (Durham et al., 1988; Crago & Chernyakhovskiy, 2017; Michaud & Pitt, 2018; Hsu, 2018; Crago & Koegler, 2018; Carley, 2009a; Matisoff & Johnson, 2017; Kwan, 2012), though a few studies failed to find a significant effect (Borchers et al., 2014; Shrimali & Jenner, 2013).

Lastly, socio-economic factors include demographics and political lean. Many studies have found more solar installations in places with higher incomes (Borchers et al., 2014; Crago & Koegler, 2018; Carley, 2009a; Kwan, 2012; Bennett et al., 2020) and that those with lower incomes tend to have decreased access to solar installations (Schunder et al., 2020). However, some studies found that income was not a significant predictor of adoption (Durham et al., 1988; Michaud & Pitt, 2018; Hsu, 2018; Matisoff & Johnson, 2017; Mundaca & Samahita, 2020). In general, gender is not a significant predictor of distributed solar capacity (Mundaca & Samahita, 2020; Kwan, 2012; Jirakiattikul et al., 2021). However, younger individuals are more likely to adopt distributed solar than older individuals (Reames, 2020; Mundaca & Samahita, 2020). Kwan (2012) found that solar adoption occurred most often for individuals aged 34 to 55, with older and younger populations installing at lower rates, and Bennet et al. (2020) found that older people were more likely to adopt distributed solar. Studies suggest that White populations tend to install distributed solar at higher rates than minority groups (Kwan, 2012; Reames, 2020; Sunter et al., 2019; Bennett et al., 2020) and that minority groups tend to have less access to distributed solar (Schunder et al., 2020). Democratic-leaning areas tend to install distributed solar at higher rates than more Republican-leaning areas (Crago & Chernyakhovskiy, 2017; Borchers et al., 2014; Crago & Koegler, 2018; Kwan, 2012), though Bennet et al. (2020) found higher distributed generation in more Republican-leaning areas. Finally, most studies have found that increased educational attainment is associated with an increase in distributed solar installations (Durham et al., 1988; Hsu, 2018; Kwan, 2012; Jirakiattikul et al., 2021; Bennett et al., 2020).

2.2. UTILITY-SCALE RENEWABLE PROCUREMENT

Similar to distributed generation, utility-scale renewable procurement is also a household-level decision that is sensitive to policy, economic, contextual, and socio-economic factors.

For the most part, different policy factors influence distributed generation versus utility-scale procurement, with only a few policies having a significant impact on both. States with an RPS tend to have higher utility-scale procurement (Carley, 2009b; Carley, 2017; Sahu, 2015), although this finding is not replicated by Yin & Powers (2017). CCAs make up the majority of voluntary utility-scale renewable procurement customers (O'Shaughnessy et al., 2018; O'Shaughnessy et al., 2019). For the eight states that allow CCAs, this is a significant driver of utility-scale procurement. Lastly, states with a deregulated energy market tend to have less utility-scale procurement (Carley, 2009b); Carley (2009b) speculates this may be because deregulated utilities tend toward the cheapest sources of fuel, which tend to be fossil fuels.

Incentive policies affect utility-level adoption similarly to distributed generation, although some policies are specific to one form or the other. Net metering is less influential in predicting utility-scale renewable procurement, since it is only related to distributed generation Sahu (2015) found a positive relationship between utility-scale procurement and net metering, but Yin & Powers (2017) found that no relationship. Utility-scale renewable subsidies, such as rebates, consistently increase utility-scale procurement (Carley, 2009b; Carley, 2017; Sardianou & Genoudi, 2013; Ntanos et al., 2018; Zhai & Williams, 2012). The role of utility-scale renewable tax credits is mixed, with studies finding that tax credits increase (Sardianou & Genoudi, 2013; Sahu, 2015), decrease (Carley, 2009b), or are unrelated (Kahn, 1996) to utility-scale procurement. It is possible that consumer decision-making is focused on the overall installation cost, rather than the opportunity for utility-scale renewable tax credits (Zhai & Williams, 2012).

When it comes to contextual factors, there is again little evidence that both distributed generation and utility-scale procurement are affected by the same factors. Although increased solar resources are associated with increased utility-scale procurement, there is no relationship for wind resources and states with more biomass resources tend to have less utility-scale procurement (Carley, 2009b). Additionally, demand for utility-scale renewable energy tends to be price inelastic, suggesting that price may not be an important measure for adoption of utility-scale renewable energy programs (Dagher et al., 2017). Yin & Powers (2017) did not find energy cost to be a significant factor in predicting utility-scale adoption of renewable energy, but Carley (2009b) found that an increased cost of energy predicted lower adoption of utility-scale renewable energy.

Finally, demographic factors tend to affect both distributed generation and utility-scale procurement in similar ways. Higher incomes are associated with greater utility-scale renewable energy adoption (Kowalska-Pyzalska, 2018; Lin & Kaewkhunok, 2021; Menegaki, 2004; Sardianou & Genoudi, 2013; Zarnikau, 2003). Similarly, states with a higher gross state product tend to have increased utility-scale renewable adoption (Carley, 2009b; Carley, 2017). There is little evidence that gender influences an individual's willingness to pay for utility-scale renewable energy (Sardianou & Genoudi, 2013; Lin & Kaewkhunok, 2021; Zarnikau, 2003), though Menegaki (2004) found that women are more willing to pay for utility-scale renewable energy than men. Generally, studies have found that willingness to pay for utility-scale renewables is lower in those over 55 (Zarnikau, 2003) and increases as age decreases (Kowalska-Pyzalska, 2018; Menegaki, 2004). However, one study found that older heads of households were actually more likely to invest in utility-scale renewable energy adoption (Lin & Kaewkhunok, 2021). Sardianou & Genoudi (2013) found that middle aged consumers were most likely to adopt utility-scale renewable energy over older consumers and younger consumers. Predominantly White areas tend to have higher rates of utility-scale renewable adoption (Tidwell & Tidwell, 2021) and White people tend to have a higher willingness to pay for utility-scale renewable energy (Zarnikau, 2003). Higher education attainment consistently predicts a higher likelihood of adopting voluntary utility-scale renewable energy (Menegaki, 2004; Kowalska-Pyzalska, 2018; Sardianou & Genoudi, 2013; Lin &

Kaewkhunok, 2021; Zarnikau, 2003; Ntanos et al., 2018). Finally, individuals with more liberal attitudes predicted higher levels of utility-scale renewable energy adoption than those with conservative attitudes (Menegaki, 2004) and areas with more right-leaning attitudes had lower rates of utility-scale renewable energy adoption than those with more left-leaning attitudes (Carley, 2017).

2.3. CHOOSING BETWEEN PROCUREMENT OPTIONS

Little research has examined the relationship between a consumer's likelihood to procure renewable energy from one source of energy versus another. Frederiks et al. (2015) contend that more research is needed to determine the primary determinants – including predictive variables, moderating variables, and mediating variables – of renewable energy consumption, as well as the impact of public policy on assisting consumers to make optimal energy decisions, especially for consumers who have multiple options for procuring renewable energy.

We propose three possible models for how individuals choose between renewable options, a complements, substitutes, or no relationship (summarized in Table 2-1). In a complements relationship, individuals who adopt one type of renewable energy are more likely to adopt another, so there is a positive relationship between distributed and utility-scale procurement. For example, households with solar may be motivated to also subscribe to a 100% renewable utility green pricing program to ensure that all of their energy needs are met by renewable energy. In a substitutes relationship, individuals who adopt one type of renewable energy are less likely to adopt another, so there is a negative relationship. For example, households may be less likely to adopt distributed solar if it is easier to satisfy their environmental goals with utility-scale options. Consumers may engage in satisficing, in which, rather than seeking out the optimal options, they simply search for the first satisfactory option and then stop (Frederiks et al., 2015). If there is no relationship, this suggests that one of these options is dominating, but not replacing the other option.

Table 2-1. Summary of Possible Models for Relationship Between Distributed and Utility-Scale Procurement Options

Possible Relationship	**Direction**	**Driver**
Complements	Positive	Motivated by environmental goals
Substitutes	Negative	Motivated by economics to satisfice
Unrelated	Zero	One option dominates, but does not replace

As discussed in the previous section, some factors influence both distributed solar generation and utility-scale procurement in the same way, which may lead to a positive correlation between the two categories of renewable procurement. For example, factors such as the presence of RPS tend to predict both higher levels of distributed generation and increased amounts of voluntary utility-scale procurement. Ndebele (2020) found that consumers who already subscribed to one form of voluntary renewable energy showed a willingness to pay for additional renewable energy (aligning with the complements model).

Some factors, such as average energy costs, may have opposite effects on adoption decisions. Higher energy costs are associated with decreased utility-scale procurement and higher distributed solar generation. This is likely because of desires to offset the cost of utility-provided energy. Some research suggests that physical options (i.e., distributed generation) tend to be substitutes of virtual options (i.e., utility-scale renewable energy) as the cost of solar installation increases (Fikru et al., 2022). Consumers may be less likely to enroll in utility-scale renewable programs if they are already engaging in energy-efficient behavior, which includes rooftop solar (Hobman & Frederiks, 2014).

In some cases, there are factors that only influence one of the procurement options. For instance, we would expect CCAs to be associated with an increase in utility-scale renewable adoption, but not directly affect residential solar adoption since CCA procurement is a type of utility-scale procurement. Similarly, net metering is expected to increase distributed generation but not directly affect utility-scale procurement because it only incentivizes distributed generation. Additionally, many other policy variables are specific to one form or the other (e.g., solar tax credits for distributed, voluntary procurement subsidies for utility-scale) and have been shown to influence one form but may not influence the other. If these factors tend to be the primary predictors, then distributed generation and utility-scale procurement may vary independently.

3. METHODOLOGY

3.1. DATA

In this state-level analysis, data are available for all 50 states as well as Washington DC with one observation per year for four years from 2016-2019 (*N* = 204). The data, R code, and appendices are publicly available in an Open Science Framework repository (https://osf.io/kf7wd/).

To estimate distributed procurement (P_{DIS}) per state per year, EIA data on small-scale PV generation was used to estimate residential solar adoption (EIA, 2020). To make comparisons across states, percent of total energy generation (GEN_{TOT}) that is residential solar (GEN_{DIS}) per state per year was calculated. The data are highly skewed, so a log transformation was used with an added constant normalize the data. The formula for this measure is:

$$P_{DIS}=\log(GEN_{DIS}/GEN_{TOT}+1/1000000)$$

To estimate utility-scale procurement (P_{UTL}) per state per year, National Renewable Energy Laboratory (NREL) data on utility-scale voluntary renewable energy procurement in the residential sector was included in the model (O’Shaughnessy et al., 2018; Heeter & O’Shaughnessy, 2019; Heeter & O’Shaughnessy, 2020). Utility-scale procurement is the sum in MWhs per state per year of Utility Green Pricing, Competitive Suppliers, Unbundled Renewable Energy Credits (REC), Community Choice Aggregation (CCA), and Power Purchase Agreements (PPA). Similarly, the percent of residential utility-scale renewable procurement per state per year as a fraction of total procurement was calculated and a log transformation with a log-linear correction was used.

To account for policy effects, the model included binary variables for each state in each year to indicate whether there was deregulation of the electricity market, Community Choice Aggregation (CCA), solar compensation, renewable portfolio standards (RPS), tax credits for residential solar installations, or rebates for residential solar installations (Database of State Incentives for Renewables & Efficiency, 2021). Solar compensation was used in place of the term “net metering” in order to ensure that states which use a form of mandatory distributed solar generation compensation other than net metering were included in the analysis. In addition, to account for economic and environmental effects, the model used the average cost of energy from EIA data (EIA, 2020) and personal income from US Bureau of Economic Analysis data (Bureau of Economic Analysis, 2020). Solar insolation was calculated for each state by averaging NREL data for all cities in the state (Marion & Wilcox, 1994). Demographic data, including gender (%), race (%), and average age are aggregated values at the state level based on US Census data (US Census Bureau, 2019). In addition, political lean was estimated based on the electoral college vote in 2016 (US National Archives, 2016). Electoral college data from 2016 was used instead of data from 2020 because it was the most recent election in all four years studied (2016-2019). A logarithmic transformation was applied to data which exhibited a log-normal scale (insolation, personal income, and energy cost).

3.2. MODELING APPROACH

This model estimates how the availability of utility-scale procurement options influence distributed procurement (i.e., residential solar installation). To control for differences between states, two different approaches were used. The primary model uses random effects to control for differences between states by estimating separate intercepts and slopes for each state. In addition, we control for policy, economic, contextual, and time fixed effects. The equation for the regression model is given below.

$$
\begin{aligned}
\log(\mathit{distributed\ generation}) \\
&= \alpha_i + \beta_i(\log(\mathit{utilty\ scale\ procurement})) + \gamma(\mathit{Year}) \\
&+ \delta(\mathit{Insolation}) + \zeta(\mathit{Personal\ Income}) + \eta(\mathit{Energy\ Cost}) \\
&+ \theta(\mathit{CCA}) + \iota(\mathit{RPS}) + \kappa(\mathit{Solar\ Compensation\ Legislation}) \\
&+ \lambda(\mathit{Rebates}) + \mu(\mathit{Tax\ Credits}) + \nu(\mathit{Deregulated\ Electric})
\end{aligned}
$$

In addition, we estimate a fixed effects model, which also includes demographic controls. Additional regression models are included in Appendix C as robustness checks.

4. RESULTS AND DISCUSSION

4.1. DESCRIPTIVE STATISTICS

In the last 4 years, utility-scale procurement has grown faster than distributed procurement. As shown in Figure 4-1, distributed generation (red bars on left) increased each year, nearly doubling from 2016 to 2019. In addition, utility-scale procurement nearly tripled, increasing by 173%. The vast majority of utility-scale procurement is from PPAs, followed by Competitive Suppliers. The prevalence of PPAs is likely because they provide consumers with green electricity at a stable, predefined rate which can act as a hedge against uncertainty (NREL, 2018).

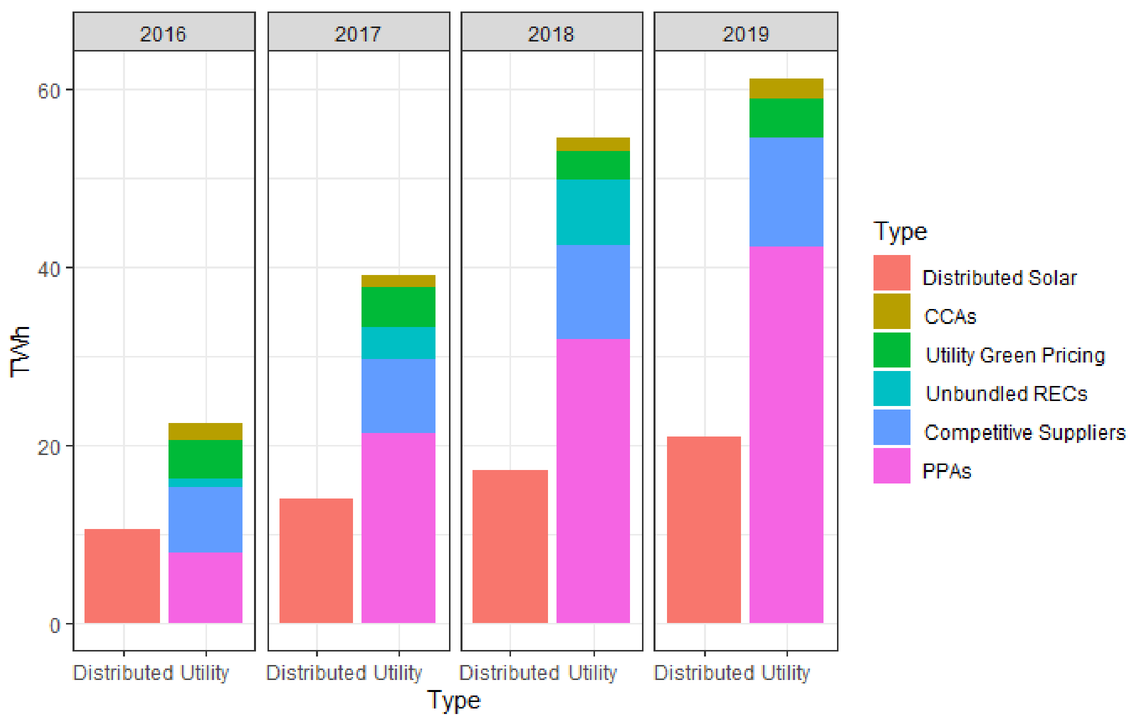

Figure 4-1. Both Distributed Solar Generation and Utility-Scale Procurement Increase Over Time

Pearson correlations in Table 4-1 suggest there are distinct patterns for distributed and utility-scale renewable procurement. Higher insolation was associated with higher utility-scale procurement, $r(244) = 0.18$, $p = .003$, more so than distributed generation, $r(244) = -0.05$, $p = .047$. For distributed generation, the strongest correlations were with rebates $r(244) = 0.54$, $p < .001$ followed by personal income per capita $r(244) = 0.47$, $p < .001$. For utility-scale procurement, the strongest correlation was with the RPS laws, suggesting that RPS laws tend to incentivize utility-scale options $r(244) = 0.23$, $p < .001$. A correlation table with the additional demographic variables included in the fixed effects model (Model 2) only, as well as descriptive statistics and histograms for each variable are provided in the Appendix.

Table 4-1. Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11
1. Distributed PV Generation	1										
2. Utility-Scale Procurement	0.02	1									
3. Tax Credits	0.34*	0.12	1								
4. Rebates	0.54*	0	0.11	1							
5. Solar Compensation	0.22*	-0.05	-0.02	0.18*	1						
6. RPS	0.18*	0.27*	0.07	0.18*	0.34*	1					
7. CCA	0.07	0.06	-0.04	0.05	0.13	0.24*	1				
8. Deregulated Electric	0.3*	0.04	-0.13	0.36*	0.11	0.31*	0.54*	1			
9. Daily Insolation	-0.05	0.18*	0.11	-0.11	-0.12	0.01	-0.2*	-0.42*	1		
10. Energy Cost	0.39*	0	0.08	0.37*	0.15*	0.29*	0.33*	0.37*	-0.35*	1	
11. Income	0.45*	0.03	-0.05	0.51*	0.01	0.28*	-0.04	0.29*	-0.02	0.28*	1

Note: *p < .05

4.2. MODELING RESULTS

The relationship between utility-scale and distributed generation was estimated at the state-level using mixed effects (Model 1) as well as fixed effects (Model 2) for comparison. A Hausman test was employed to detect model misspecification, where the null hypothesis would suggest that the mixed effects model performs better, and the alternative hypothesis suggests the fixed effects model performs better (Hausman, 1978). The Hausman test rejected the null hypothesis, suggesting that the fixed effects model is superior due to model misspecification, $\chi^2(14) = 34.13$, p = .002.

An Augmented Dickey-Fuller test can be used to test for stationarity or the existence of a unit root. In a Dickey-Fuller test, the null hypothesis states that there is a unit root whereas the alternative hypothesis verifies that the data is stationary (Dickey & Fuller, 1979). The test found that every predictor variable was stationary at the .01 significance level, as shown in Table 4-2. This provides evidence that a first differences model or a difference in differences model may not be superior to a standard regression model.

A Durbin-Watson test was used to determine the serial independence, or autocorrelation, of variables in the regression which were not consistent across each year. In this test, the null hypothesis states that the variables are serially independent, and the alternative hypothesis states that the variables are serially correlated (Durbin & Watson, 1971; Hatekar, 2010, p. 379). The mixed effects model DW = 1.60, p=.0009 rejected the null hypothesis, determining that there is serial correlation in idiosyncratic errors, whereas the fixed effects model DW=2.22, p=.95 accepted the null hypothesis, determining that there is little risk of serial correlation.

The mixed effects model was still included as the primary model (Model 1) because this research aimed to study the heterogenous differences in procurement trends between states and the mixed effects model allows for varying slopes and intercepts for each state. In addition, the high conditional R^2 value of the mixed effects model suggests that the random effects in the mixed effects model explain significantly more variation than the fixed effects alone.

Table 4-2 Augmented Dickey-Fuller Test

Variable	**Dickey-Fuller Statistic**
Distributed Generation	-11.858**
Utility-Scale Procurement	-12.906**
Personal Income	-11.581**
Energy Cost	-15.217**
Male	-14.543**
White	-14.776**
Age	-15.833**

Across states, both the mixed effects and fixed effects models suggest there is no statistically significant relationship between distributed and utility-scale procurement decisions when controlling for policy, environmental, and socio-economic variables (Table 4-3). Consistent with the literature, the models suggest that the implementation of residential solar tax credits (Durham et al., 1988; Michaud & Pitt, 2018), solar compensation legislation (Carley, 2009a; Crago & Koegler, 2018; Matisoff & Johnson, 2017; Michaud & Pitt, 2018), and rebates (Model 2 only) (Crago & Chernyakhovskiy, 2017; Crago & Koegler, 2018; Hughes & Podolefsky, 2015; Sarzynski et al., 2012; Sun & Sankar, 2022) are associated with higher rates of distributed solar generation in the residential sector. These results are expected as they all provide a financial incentive to install distributed solar. In addition, states with higher distributed solar generation tend to have higher average energy costs and incomes. However, both models suggest that the ratio of distributed solar generation decreases when an RPS is present. This contrasts with the literature, which estimates that RPS laws have increased residential solar distribution; however, studies in the literature tended to use distributed solar installations as a response variable when measuring distributed solar, whereas this study uses distributed solar generation, indicating that RPS may play a role in increasing installations but not necessarily impact the total amount of distributed generation (Carley, 2009a ; Crago & Koegler, 2018; Li & Yi, 2014; Sarzynski et al., 2012; Wiser et al., 2011). In addition, we do not find an effect for solar insolation, which has been a significant predictor of solar generation in other models (Bennett et al., 2020; Borchers et al., 2014; Crago and Chernyakhovskiy, 2017; Crago & Koegler, 2018; Hsu, 2018; Kwan, 2012; Li & Yi, 2014; Michaud & Pitt, 2018). Additional models serving as robustness checks are included in the Appendix.

Table 4-3. Mixed and Fixed Effects Model Estimation of Log (Distributed Solar Generation Ratio)

Variables	Model 1 (Mixed Effects) Estimate (SE)	Model 2 (Fixed Effects) Estimate (SE)
Constant	-56.72 (19.62)**	13.79 (13.39)
log(Utility-Scale Procurement Ratio)	0.03 (0.05)	-0.01 (0.05)
RPS	-1.24 (0.49)*	-0.8 (0.28)**
CCA Legislation	-0.42 (0.83)	-0.64 (0.39)
Deregulated Electric	1.17 (0.71)	0.26 (0.35)
Solar Compensation	2 (0.81)*	1.54 (0.39)***
Tax Credit	2.14 (0.61)**	2.12 (0.28)***
Rebate	1.05 (0.67)	1.22 (0.33)***
Solar Insolation	1.2 (0.98)	0.34 (0.51)
Energy Cost	2.18 (0.48)***	2.93 (0.6)***
Personal Income	4.09 (1.66)*	3.74 (0.84)***
Female		0.97 (0.18)***
White		0.03 (0.01)*
Age		-0.34 (0.06)***
Democratic Lean		0.75 (0.29)*
N	204	204
Number of States + Washington, DC	51	51
Year Fixed Effects	Yes	Yes
Marginal R^2	0.5028	0.6195
Conditional R^2	0.9338	

***p < .001, **p < .01, *p < .05

4.3. STATE ANALYSES

Based on the mixed effects model, state-level estimates of the coefficient for the utility-scale procurement ratio were also examined. As shown in Figure 4-2, the state-level random effect coefficients range from -0.1 to 0.3, suggesting that this relationship between distributed and utility-scale procurement varies between states. To investigate this relationship, we highlight 3 states for discussion (1) Vermont, positive relationship, (2) North Dakota, negative relationship, and (3) Oregon, no relationship. Table 4-4 shows data for each of these three states.

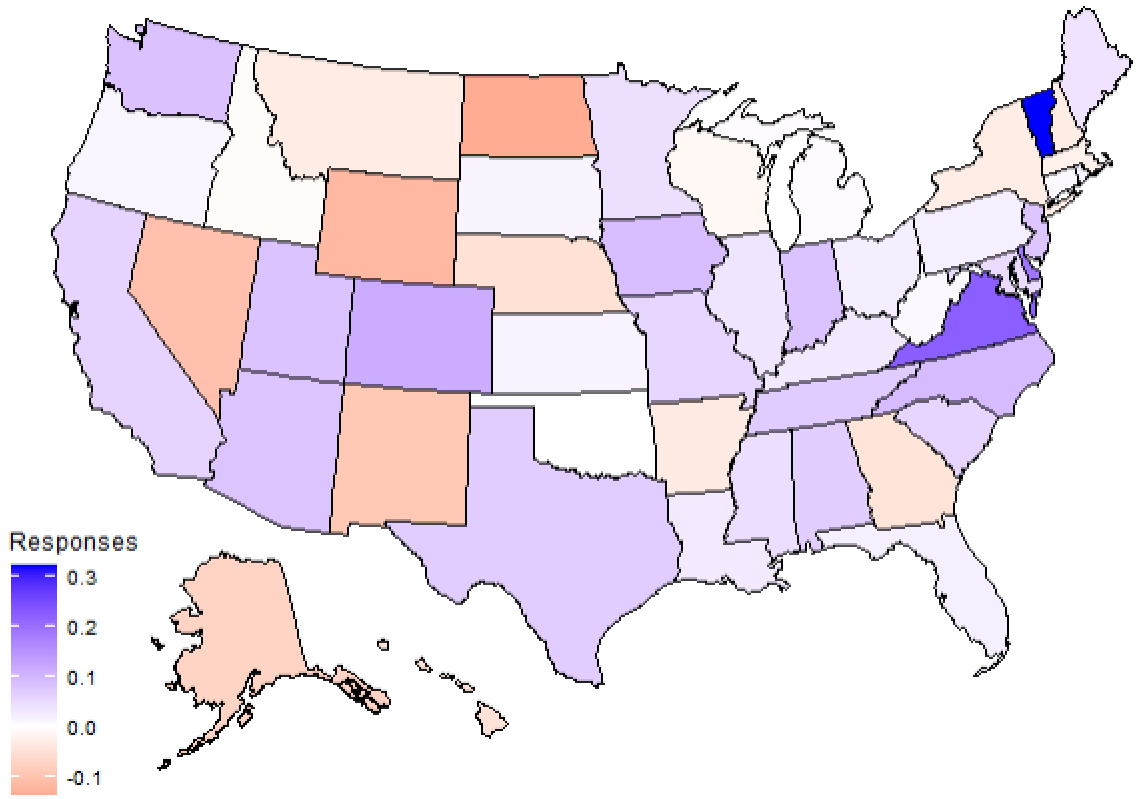

Figure 4-2. State Random Effects Relationship Between Utility-Scale Procurement and Distributed Generation

In Vermont, the model suggests that as utility-scale procurement increases by 1%, distributed solar generation also increases by 0.32%. This is largely attributed to a policy environment that encourages both distributed and utility-scale renewable procurement. While Vermont does not have solar PV tax credits, there is net metering at the retail rate which allows for extra generated electricity to be credited to the customer's next electricity bill (DSIRE, 2021; Vermont, 2022). Vermont's Clean Energy Development Fund (CEDF) specifically incentivizes distributed generation by providing funding for solar, wind, geothermal, and other types of renewable generation (DSIRE, 2021; Vermont, 2016). Roughly 26% of the fund's budget goes to funding biogas, with 23%

going towards incentive programs for consumers to adopt renewables and another 22% going to tax credits for solar energy (with tax credits being counted separately from other forms of incentives); the remaining budget is divided up among efficiency technologies, wind, hydro, and other costs associated with promoting clean energy (Symington et al., 2013). In 2016, Vermont established a goal as part of their Comprehensive Energy Plan to procure 90% of energy used in the state from renewable sources by 2050. To achieve this goal, the Vermont Renewable Energy Standard requires utilities to meet 75% of energy sales with utility-scale renewable energy and 10% with distributed generation by 2032 (Vermont, 2016). As of 2020, electricity generation in Vermont is almost entirely from renewable sources, primarily utility-scale hydro-electric (58%) and wind (15%). Vermont’s utilities are regulated monopolies and there is no CCA-enabling legislation (DSIRE, 2021). Overall, Vermont is a net importer of energy, as demand for electricity is approximately three times the available in-state production (EIA, 2021).

Vermont has less-than-average solar insolation, approximately a third of a standard deviation below the national average (Marion & Wilcox, 1994). However, Vermont’s average energy cost was, on average, 14.72 cents per kWh, which was a standard deviation higher than the average (10.97 cents per kWh), suggesting that high energy costs are contributing to Vermont consumers’ willingness to engage in distributed generation, but not high enough to discourage utility-scale renewable adoption (EIA, 2020). Lastly, the demographics of Vermont are consistent with populations that tend to adopt distributed solar at higher rates. Vermont’s population is more female, White, and older (US Census Bureau, 2019). Average personal income in Vermont was at $52,100, averaged across all years, only slightly higher than the average across all states, or less than a tenth of a standard deviation (US Census Bureau, 2019). The state also voted for the Democratic nominee in 2016 (US National Archives, 2016).

In contrast, for North Dakota, the model suggests that as utility-scale procurement increases by 1%, distributed solar generation decreases by 0.20%. This is largely attributed to weak incentives for renewables in the context of high fossil fuel reserves within the state. North Dakota has a modest RPS, targeting 10% renewable generation by 2015, but there are no future goals or penalties (DSIRE, 2021). North Dakota compensates excess solar production at the avoided-cost rate, which is usually significantly lower than the retail rate (DSIRE, 2021; Lawson, 2019; Schelly et al., 2017). North Dakota does not have any incentives for distributed renewable generation and the utilities are regulated monopolies (DSIRE, 2021).

North Dakota is a net-exporter of electricity and produces seven times more electricity than is consumed within the state due to the small population and large amounts of available energy resources. Overall, electricity is cheap at 8.77 cents per kWh, over half a standard deviation lower than the average of 10.97 cents per kWh (EIA, 2020). North Dakota is the second largest producer of crude oil and has the largest deposit of lignite coal in the U.S. Most of the electricity production is from coal (57%), followed by wind (31%) and hydroelectric (8%). North Dakota has abundant solar resources, receiving 2.6 standard deviations more solar insolation than the average state (Marion & Wilcox, 1994). Despite favorable environmental conditions, there are no utility-scale geothermal or solar generation facilities (EIA, 2021). Given the economic reliance on coal, fossil fuels are likely perceived as more favorable than renewable energy (Crowe & Li, 2020). Additionally, production of ethanol – a major source of renewable energy in North Dakota – has plateaued in recent years, indicating new renewable generation may be stagnating (Coon et al., 2012). This stagnation may lead to a reduction in utility-scale procurement because ethanol is included in some utility-scale renewable options (O'Shaughnessy et al., 2017). North Dakota's population is more male, less White, and younger (US Census Bureau, 2019). North Dakota averaged $57,600 in personal income, putting it above the national average for the period studied (US Census Bureau, 2019). The state voted for the Republican nominee in 2016 (US National Archives, 2016).

Lastly, in Oregon, the model suggests that there is no relationship between utility-scale procurement and distributed solar generation, $\beta = -0.03$. While Oregon has policy incentives for distributed solar, there is less solar insolation, minimizing uptake. Oregon incentivizes distributed solar via rebates, net metering, and an RPS. Oregon has four solar rebate programs, one of which is funded by the state budget rather than a public benefits fund (DSIRE, 2021). The state-funded rebate reimburses consumers between $0.20 and $1.80 per kW depending on a consumer's income and eligibility for utility incentives (DSIRE, 2021). The Energy Trust of Oregon administers the remaining three rebate programs, two of which reimburse consumers for new installations of solar photovoltaics, focusing on those specifically with low income, and one of which is awarded based on an "energy performance score" in new housing units (DSIRE, 2021). Oregon net metering allows utilities to compensate consumers for excess solar generation with either energy credits which can be credited to future months and rolled-over for up to a year or purchased at the avoided-cost rate (DSIRE, 2021). Oregon also has an RPS which requires large utility companies to sell at least 15% green power by 2015, increasing every 5 years to a total of 50% green energy sold by 2040 (DSIRE, 2021; State of Oregon, 2021). The state does not have CCA-enabling legislation or residential solar tax credits, however, it does have a deregulated electricity market (DSIRE, 2021).

Table 4-4. Select States' Averages and Standard Deviations

State	**Vermont**	**North Dakota**	**Oregon**
Observed Relationship	Positive Correlation	Negative Correlation	No Correlation
Relationship Level (β)	0.32	-0.20	-0.03
Tax Credits	No	No	No
Rebates	Yes	No	Yes
Solar Compensation	Yes – at Residential Retail Rate	Yes – at Avoided Cost Rate	Yes – Either as Energy Credit or at Avoided Cost Rate
RPS	Yes - 75% by 2032	Yes – 10% by 2015	Yes – 50% by 2040
CCA	No	No	No
Deregulated Electric	No	No	Yes
Daily Insolation (KJ/m^2/day)	13,375	26,011	12,614
Energy Cost (2017 cents/KWh)	14.72 (0.08)	8.70 (0.33)	8.73 (0.24)
Personal Income (2017 Dollars/year)	$52,127 ($694)	$53,764 ($1,088)	$49,415 ($1,545)
Female %	49.4 (0.13)	50.5 (0.25)	49.6 (0.06)
White %	94.1 (0.25)	86.8 (0.56)	84.1 (0.44)
Age	42.9 (0.24)	36.3 (0.84)	39.5 (0.24)
Democratic Lean	Democrat	Republican	Democrat

Oregon is below-average state for solar insolation, at about half a standard deviation below the mean (Marion & Wilcox, 1994). Energy costs are also lower, just over half of a standard deviation below the average, largely due to hydroelectric resources (EIA, 2020; EIA, 2021a). Only 2% of Oregon’s energy came from solar energy (EIA, 2021a). Oregon’s population is more female, more White, and older (US Census Bureau, 2019). The state averaged $49,400 in personal income, putting it slightly below the national average (US Census Bureau, 2019). Oregon also voted for the Democratic presidential candidate in 2016 (US National Archives, 2016). The state is a net importer of electricity (Oregon Department of Energy, 2020).

5. CONCLUSION

This study estimated the relationship between distributed and utility-scale renewable procurement across the US. In theory, there are three possible relationships, (1) positive correlation, where utility-scale and distributed resources complement each other to increase overall production, (2) negative correlation, where utility-scale and distributed resources are substitutes, and (3) no correlation, suggesting that these different procurement choices are unrelated. When aggregated across states, there is no evidence of a relationship between utility-scale and distributed procurement ratios. However, when disaggregated, there are heterogeneous effects across the different states, with a few clear outliers.

At the state level, the relationship between distributed and utility-scale procurement is influenced in part by the interactions between policy incentives, available energy resources, and energy costs. An examination of Vermont (positive relationship), North Dakota (negative relationship), and Oregon (no relationship) demonstrates the variability between states. Vermont has aggressive renewable energy goals and imports most of their electricity from nearby states (primarily hydro). The primary difference between Vermont and Oregon, which have comparable solar insolation, is the cost of electricity. Electricity is much more expensive in Vermont. In contrast, North Dakota does not incentivize renewable energy, largely due to a large amount of fossil fuel resources in the state. As a result, there is weak uptake of distributed solar, despite a higher level of solar insolation than Vermont and Oregon.

Ultimately, this suggests that consumers are sensitive to the choice framing or how the choice between distributed and utility-scale options are presented. Research suggests that households are more likely to adopt solar if they see their neighbors adopting solar (Rai & Robinson, 2015). In addition, a meta-regression analysis of willingness-to-pay for renewable energy studies suggested that the willingness to pay depended more on a given study's methodology (such as survey design and administration), rather than the factors measured by that study (such as income or the share of renewable energy generated by an option) (Ma et al., 2015). This suggests that consumer decisions may be highly sensitive to how they are presented, so decision-makers need to decide whether or not to actively incentivize both options.

Because these results suggest that the relationship between distributed generation and utility-scale procurement for renewable procurement varies considerably between states, policymakers should keep this in mind when designing policy to promote renewable procurement. For instance, policymakers may allow those who opt-in to green pricing programs with their utility to gain additional rebates on solar panels they purchase in the near future, thus incentivizing the adoption of multiple renewable options at once. For states in which renewable options tend to be positively related, a policymaker may be able to increase multiple forms of renewable procurement simultaneously even if only one form of renewable procurement is specifically incentivized.

Additionally, in terms of policies, this work suggests that providing rebates and tax credits for installing residential solar panels correlates with an increase in generation from residential solar panels, consistent with literature (Bauner & Crago, 2015; Crago & Chernyakhovskiy, 2017; Crago & Koegler, 2018; Durham et al., 1988; Hughes &

Podolefsky, 2015; Michaud & Pitt, 2018; Sarzynski et al., 2012; Sun & Sankar, 2022). Solar compensation tended to be associated with a significant increase in distributed generation as well, again consistent with the literature (Carley, 2009a; Crago & Koegler, 2018; Matisoff & Johnson, 2017; Michaud & Pitt, 2018). Finally, even after controlling for policies, states which voted for the democratic candidate in 2016 tended to see higher levels of distributed solar procurement (Carley, 2017; Menegaki, 2004).

There are 2 primary limitations for this study, (1) high level of aggregation and (2) limited data availability. First, aggregating data at the state level masks decision-making dynamics at the household, municipal, and utility levels. However, there is very limited data availability at a lower resolution than the state-level. For example, there are differences in how NREL and EIA collect data, which makes it difficult to join. In addition, utility territories can cover multiple states, so the policy environment is not consistent for utility-level analysis. More detail is provided in Appendix C.

Second, data was only available for 4 years (2016-2019). Over time, more data will become available and increase opportunities for more appropriate modeling approaches. For example, it may be worthwhile to consider the presence of moderating and mediating variables or use two-stage models. Energy is a complex system and many factors influence these decisions. Future studies will be able to perform much more robust analyses, being able to detect smaller effects and see a more holistic view of how consumers view utility-scale renewable options.

Overall, our findings suggest that future research should explicitly consider how options for renewable procurement influence each other. Consumers are not making decisions in a vacuum and perceive advantages and disadvantages for these different options. To speed up renewable deployment, it may be advantageous to specifically incentivize complementary adoption, where consumers leverage both distributed and utility-scale resources.

APPENDIX A.

DESCRIPTIVE STATISTICS PLOTS

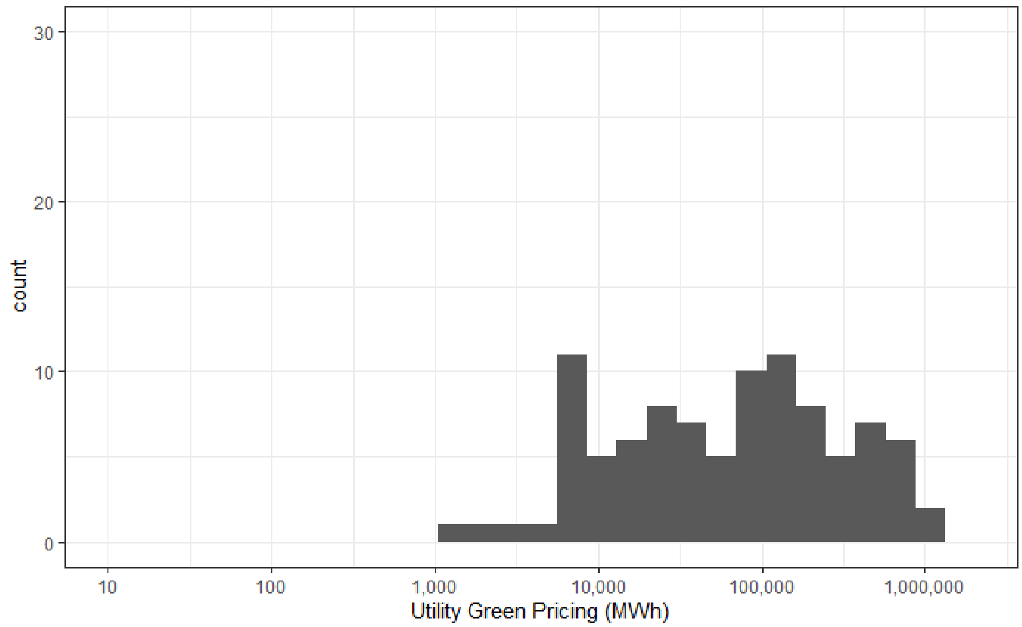

Figure A-1. Utility Green Pricing Histogram

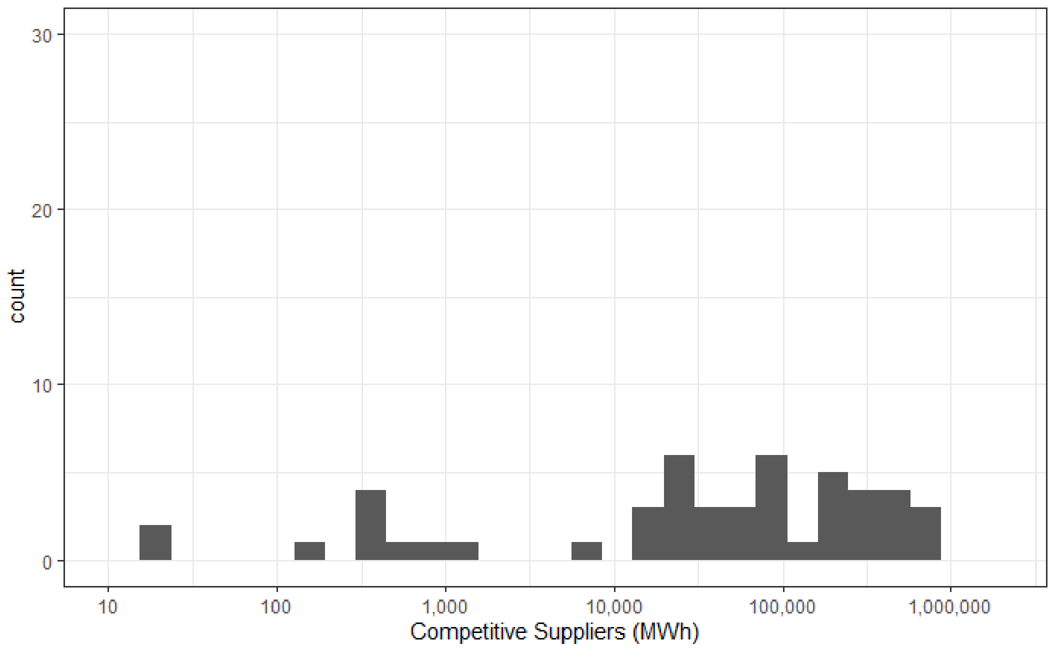

Figure A-2. Competitive Suppliers Histogram

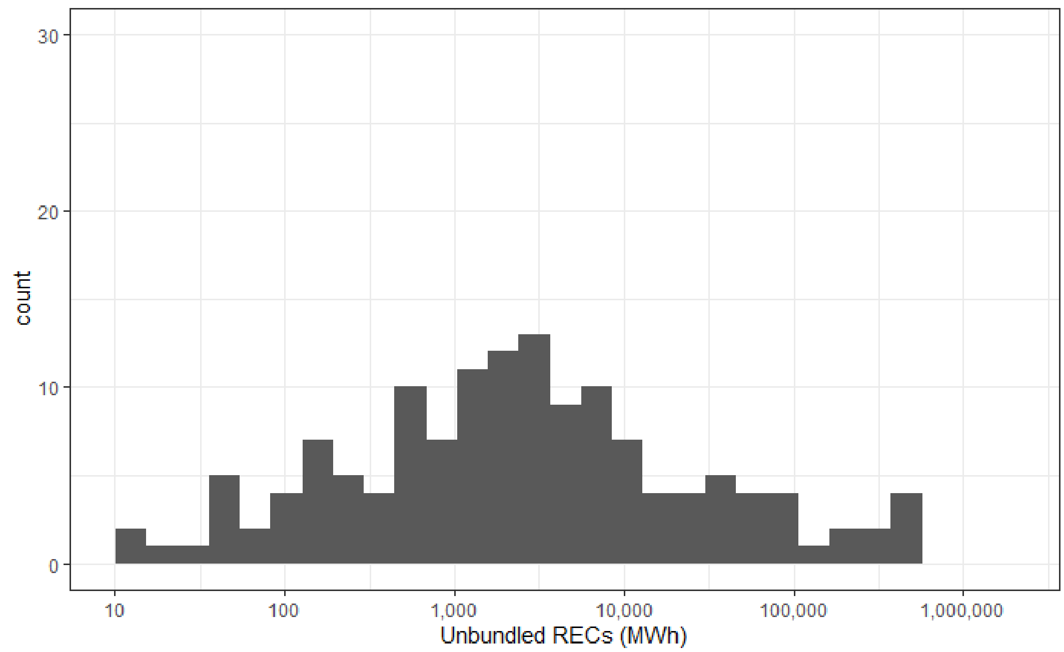

Figure A-3. Unbundled RECs Histogram

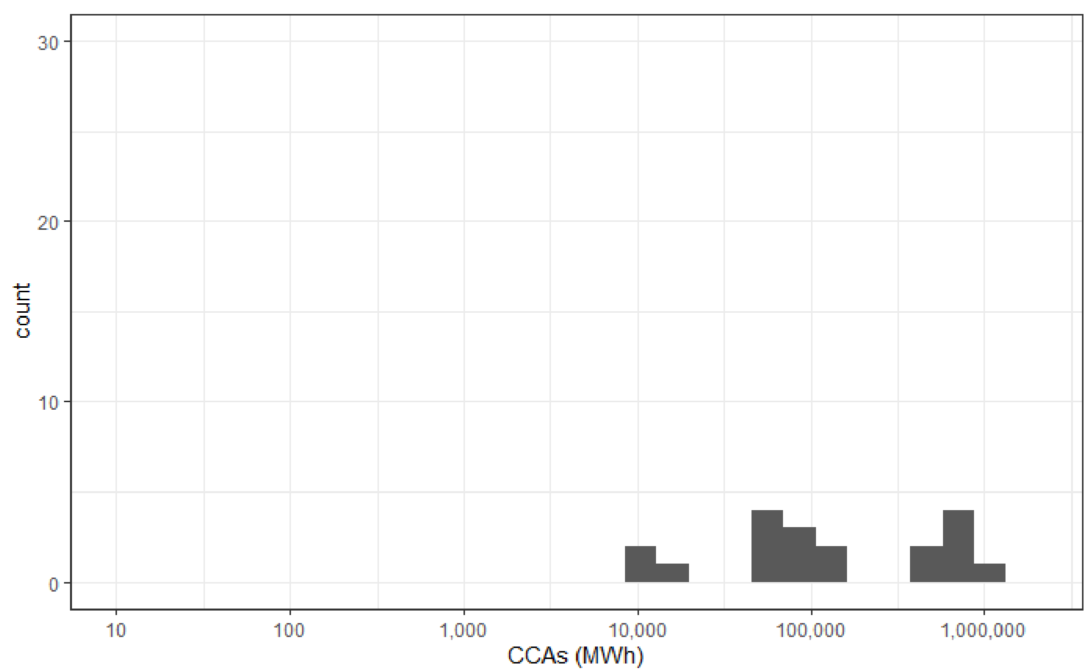

Figure A-4. Community Choice Aggregation Procurement Histogram

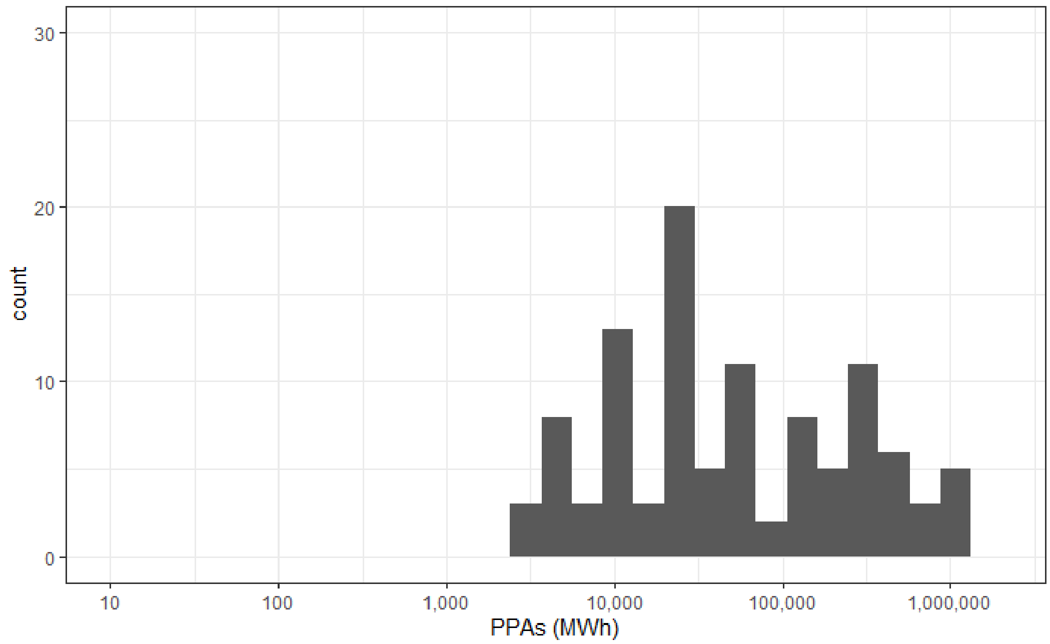

Figure A-5. Power Purchase Agreements Histogram

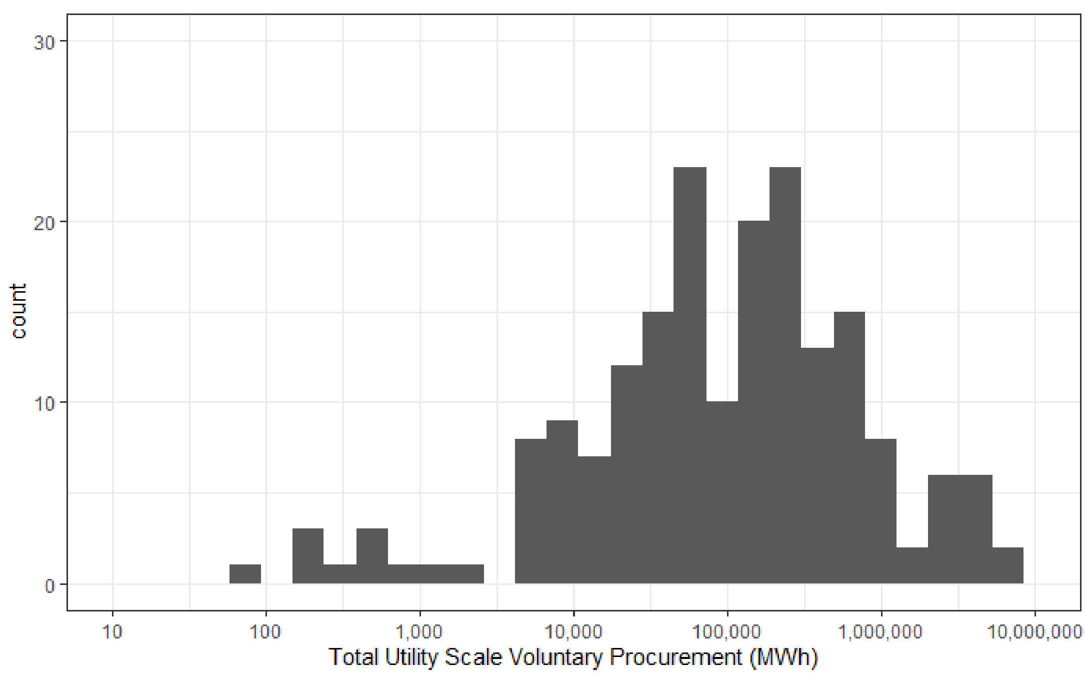

Figure A-6. Total Utility-Scale Voluntary Procurement Histogram

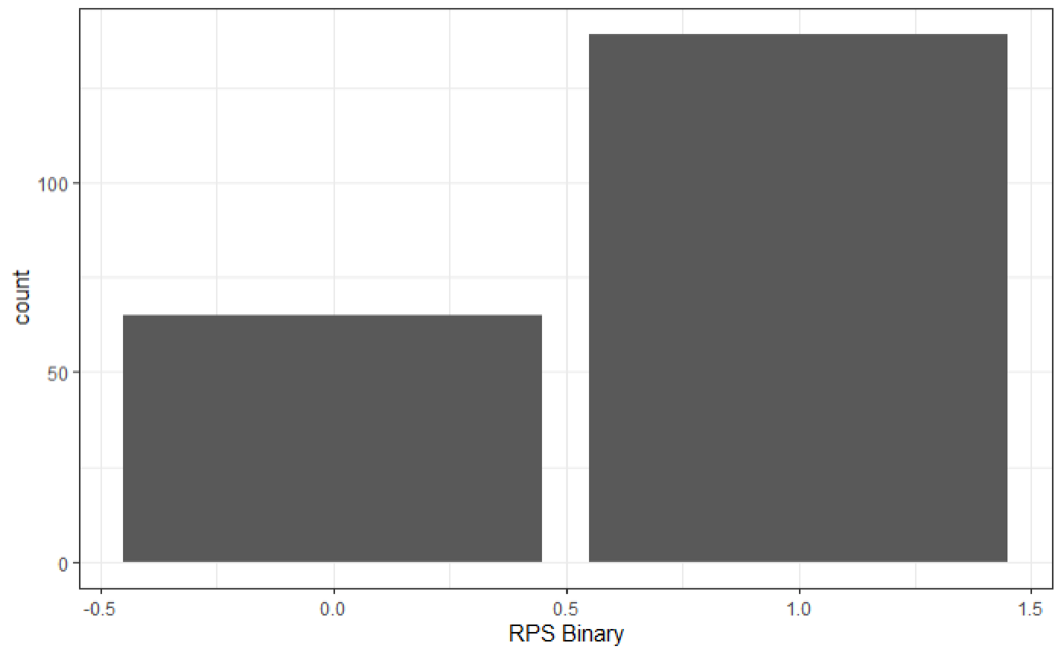

Figure A-7. Renewable Portfolio Standards Binary Bar Graph

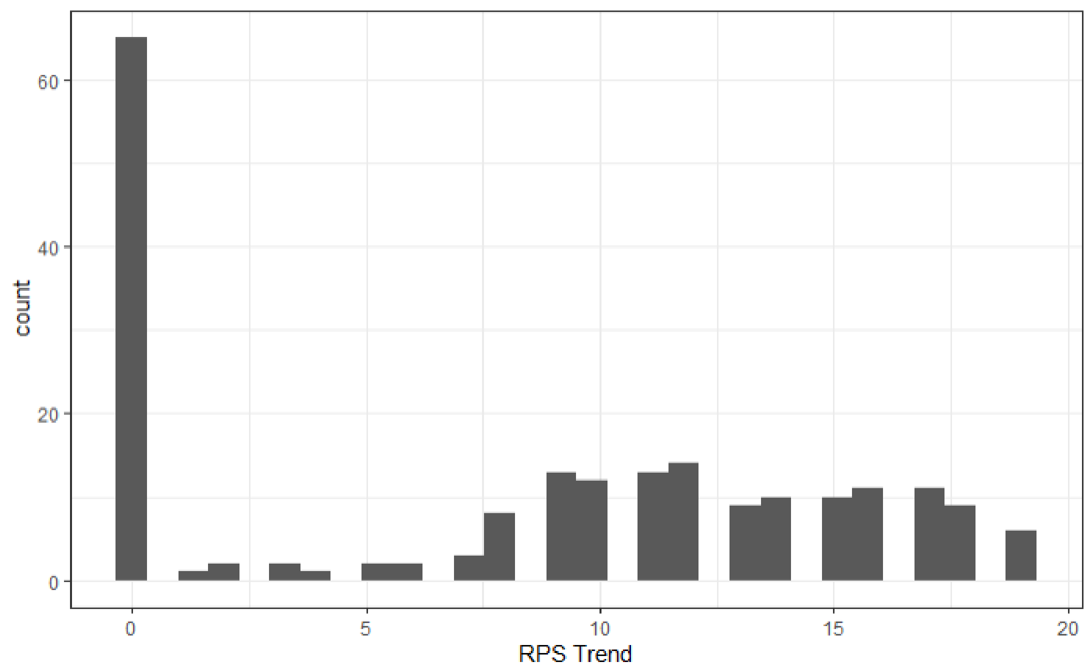

Figure A-8. Renewable Portfolio Standards Trend Histogram

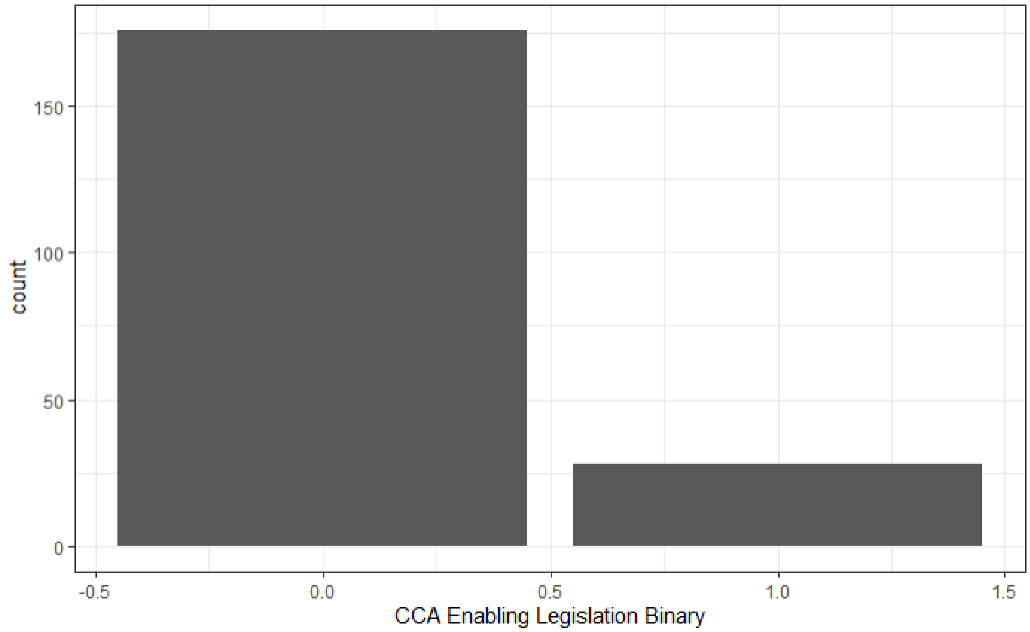

Figure A-9. CCA Enabling Legislation Histogram

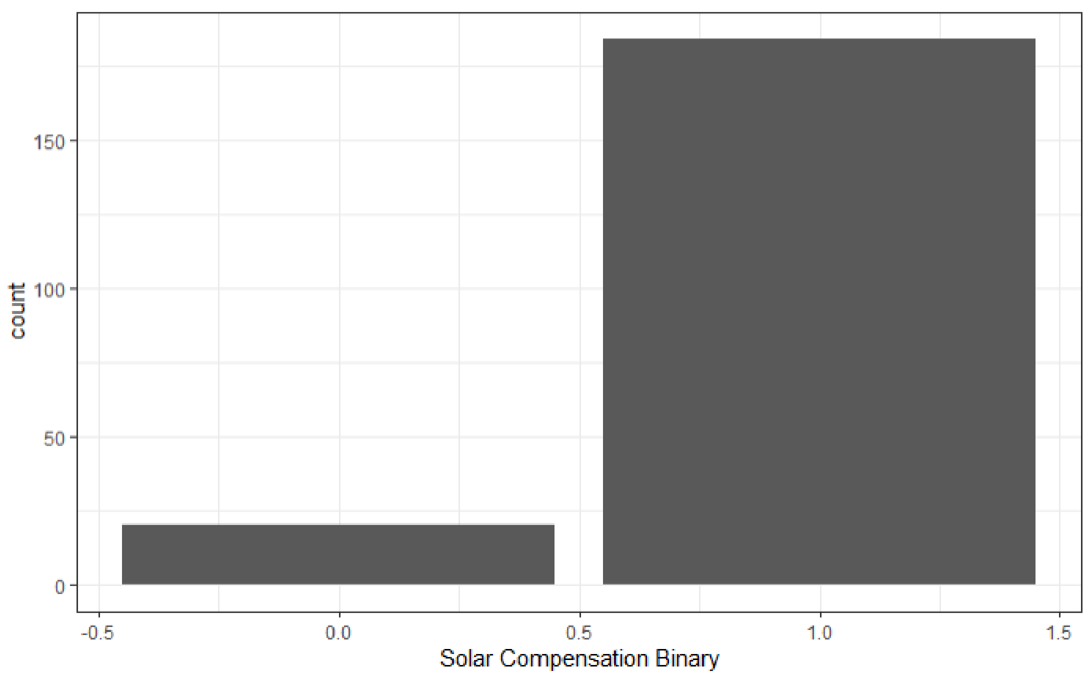

Figure A-10. Solar Compensation Legislation Histogram

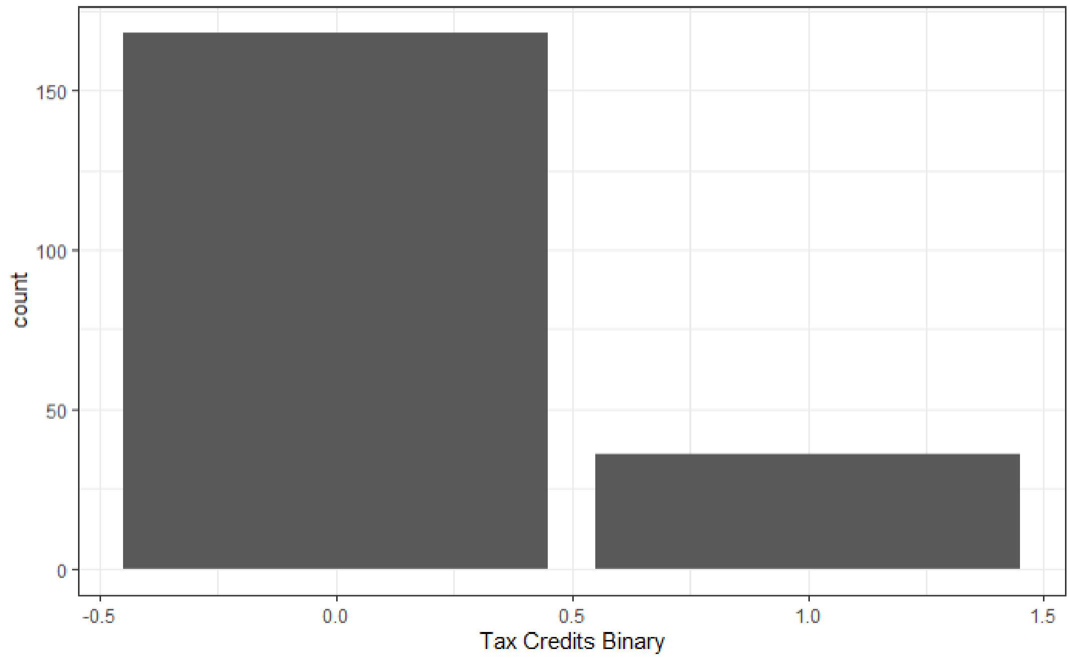

Figure A-11. Distributed Solar Tax Credits Histogram

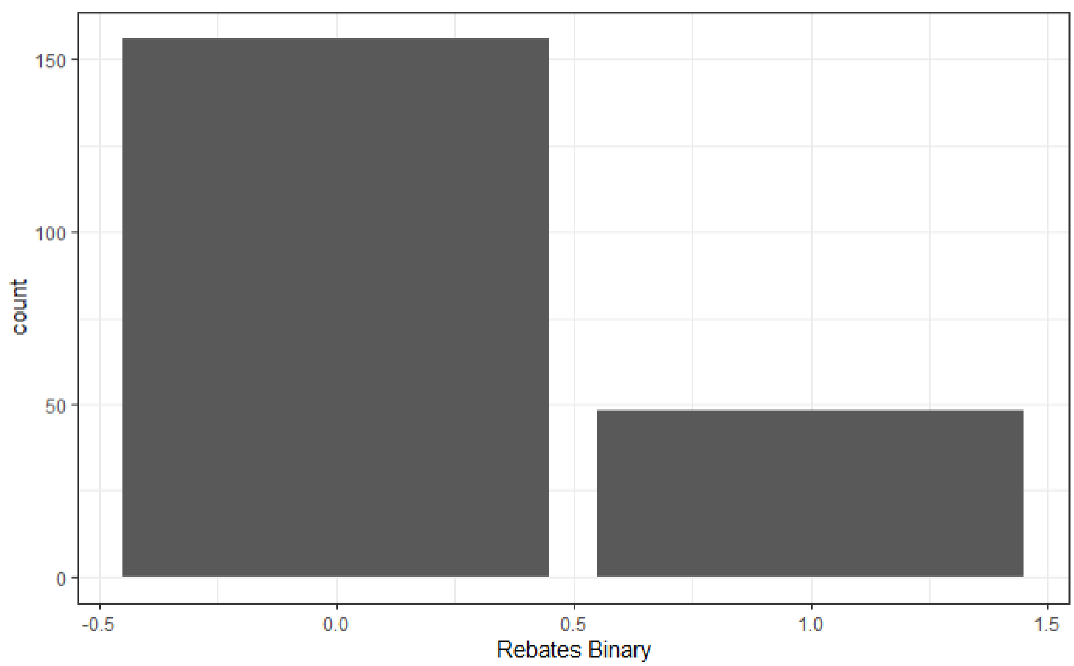

Figure A-12. Distributed Solar Tax Credits Histogram

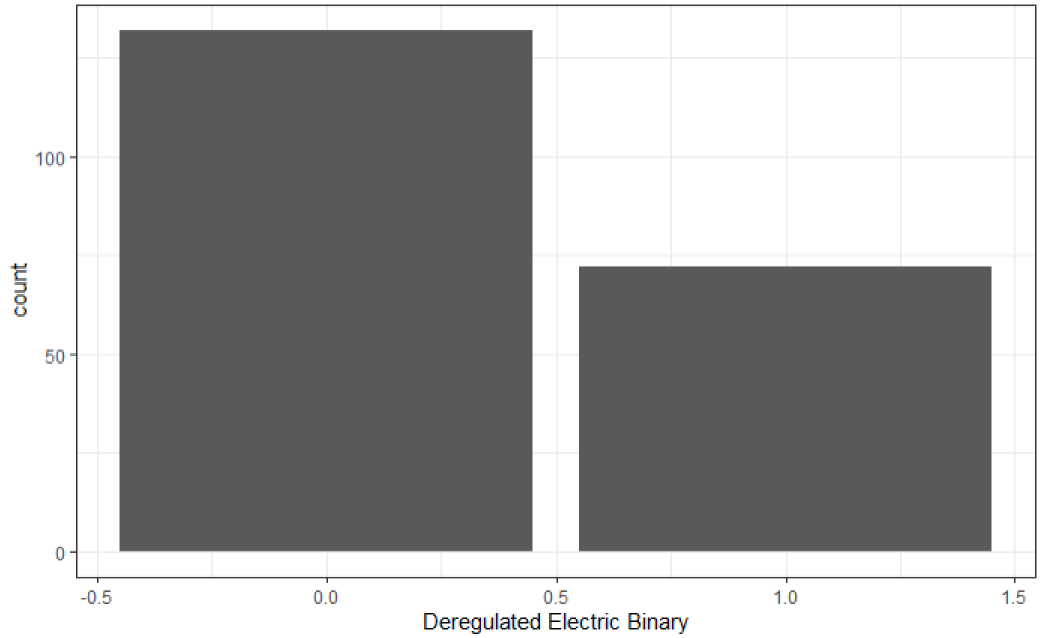

Figure A-13. Deregulated Electric Market Histogram

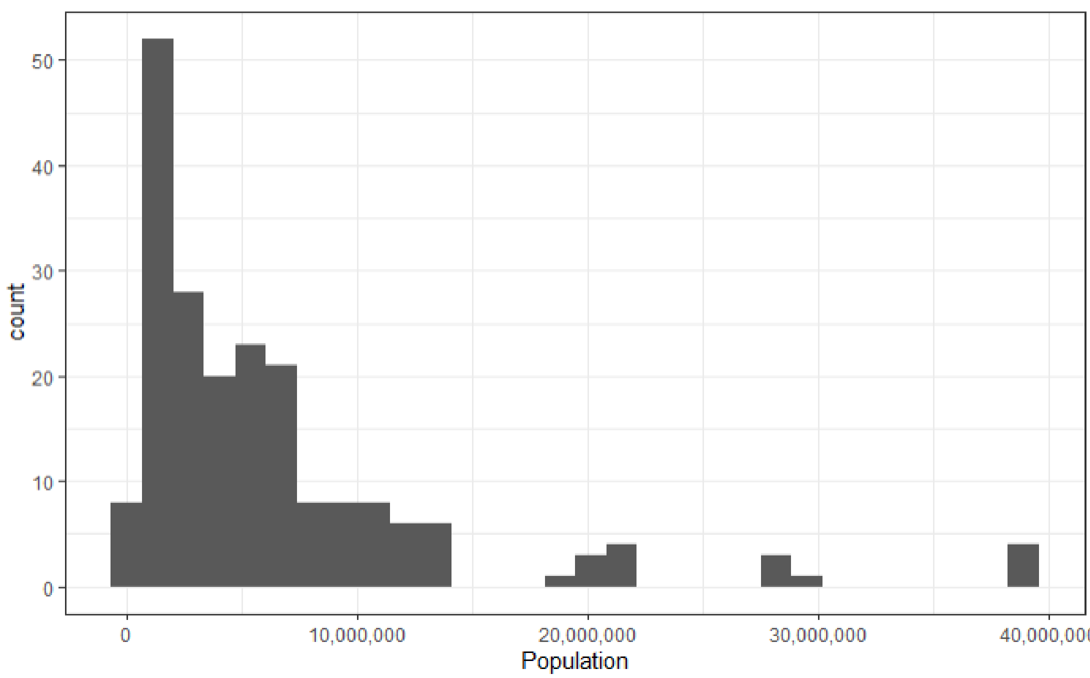

Figure A-14. Population Histogram

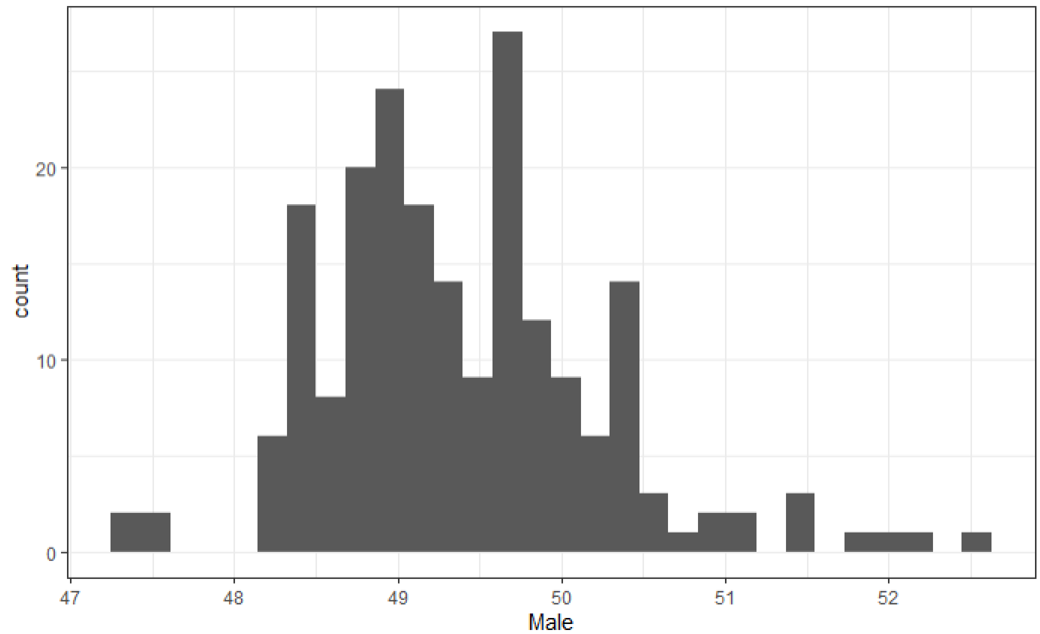

Figure A-15. Percentage of Male Population Histogram

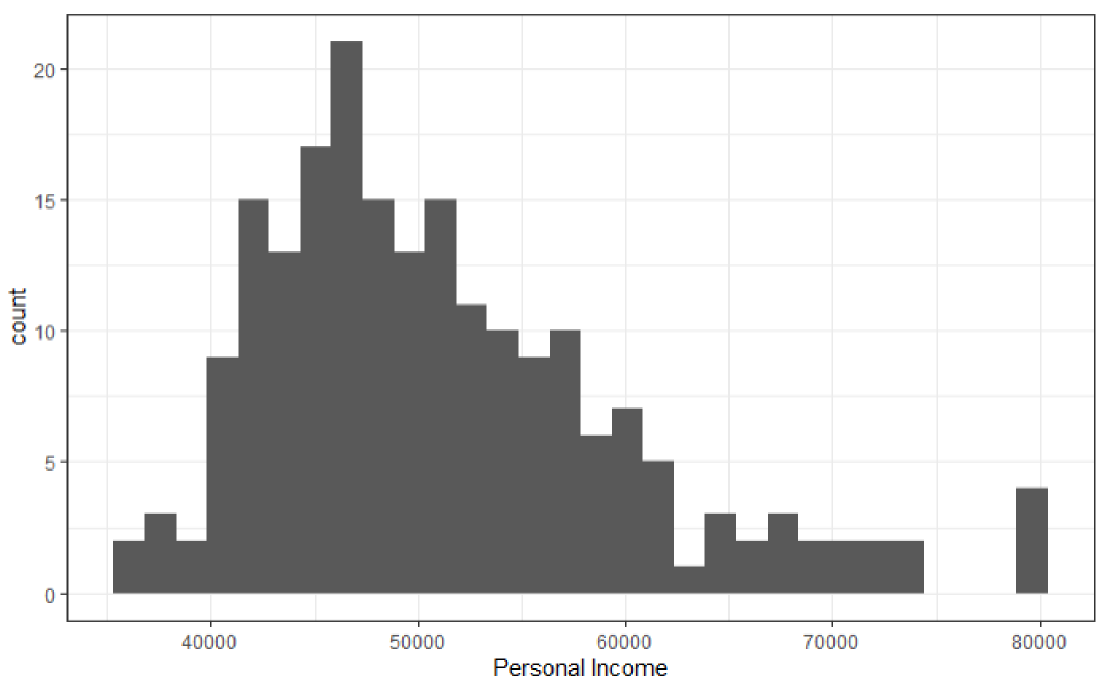

Figure A-16. Personal Income Histogram

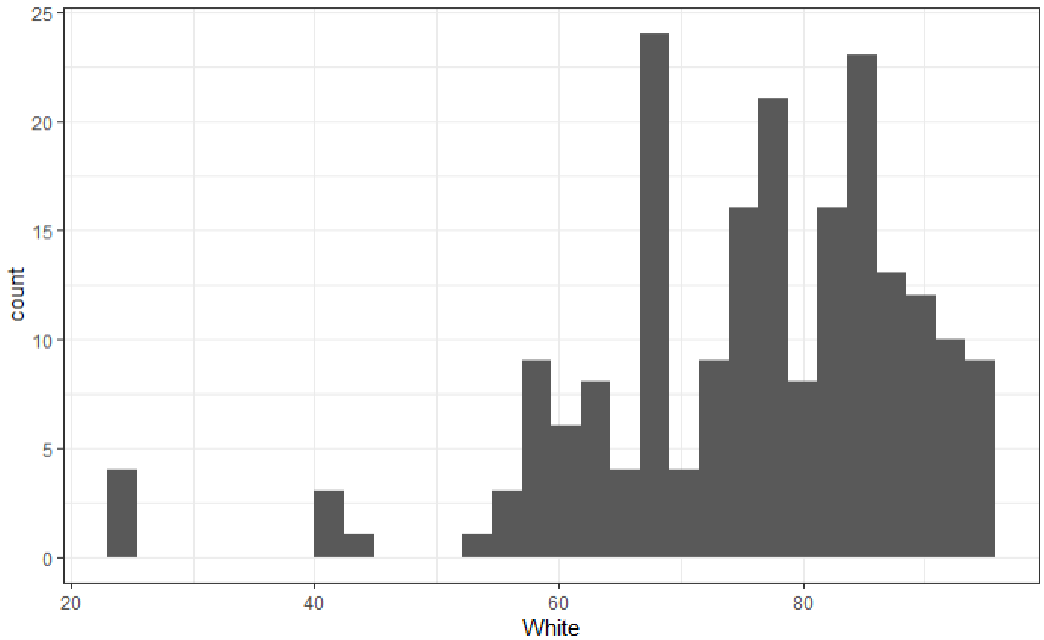

Figure A-17. Percentage of White Population Histogram

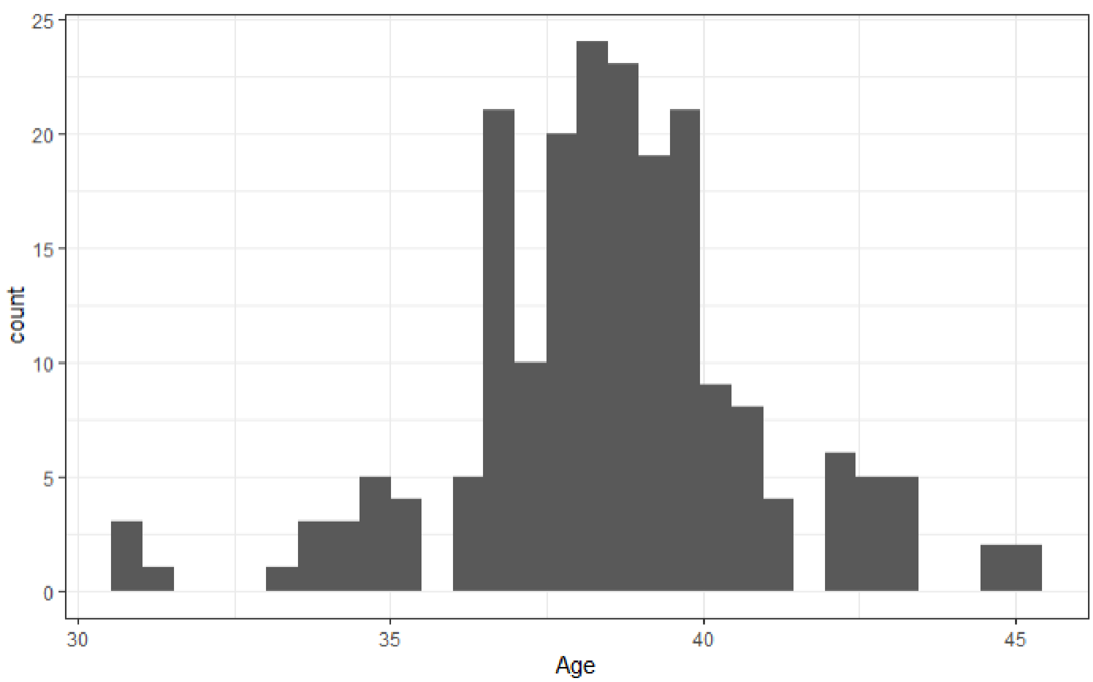

Figure A-18. Age Histogram

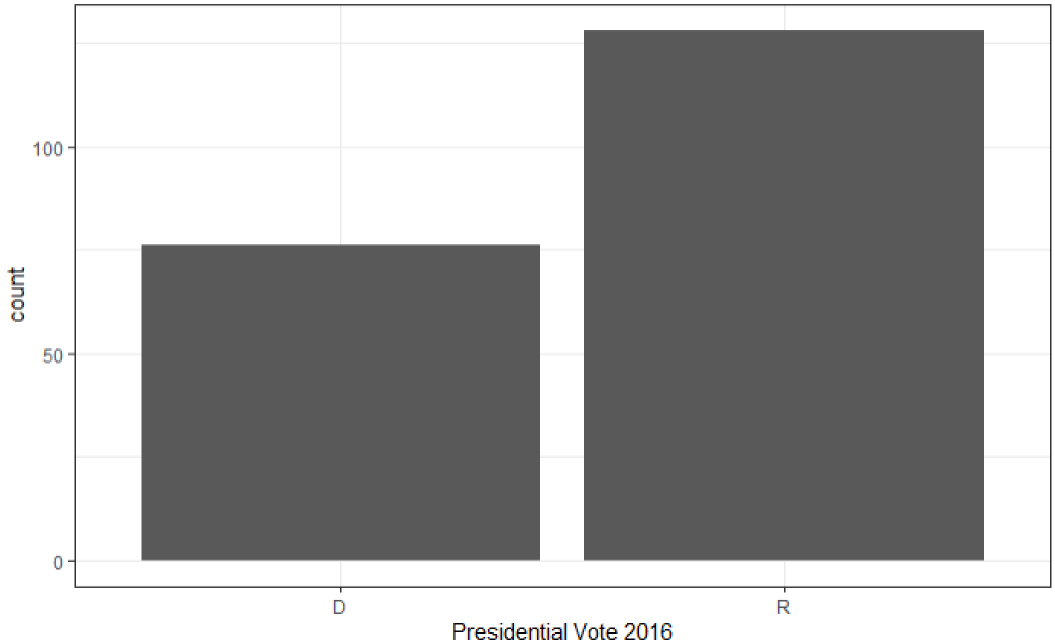

Figure A-19. 2016 Presidential Vote Histogram

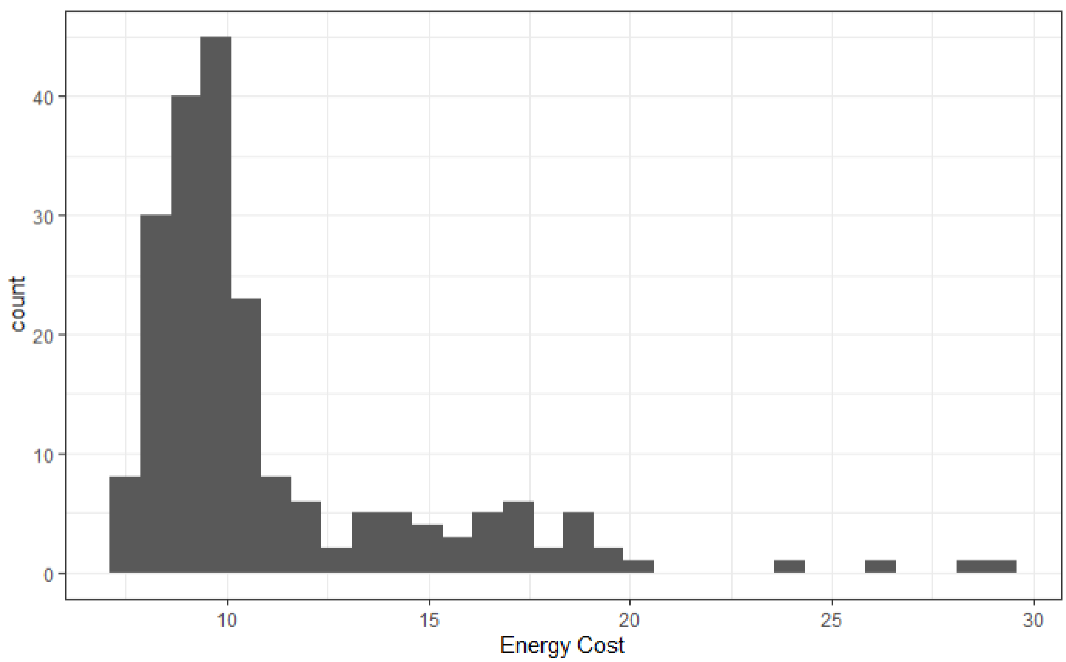

Figure A-20. Energy Cost Histogram

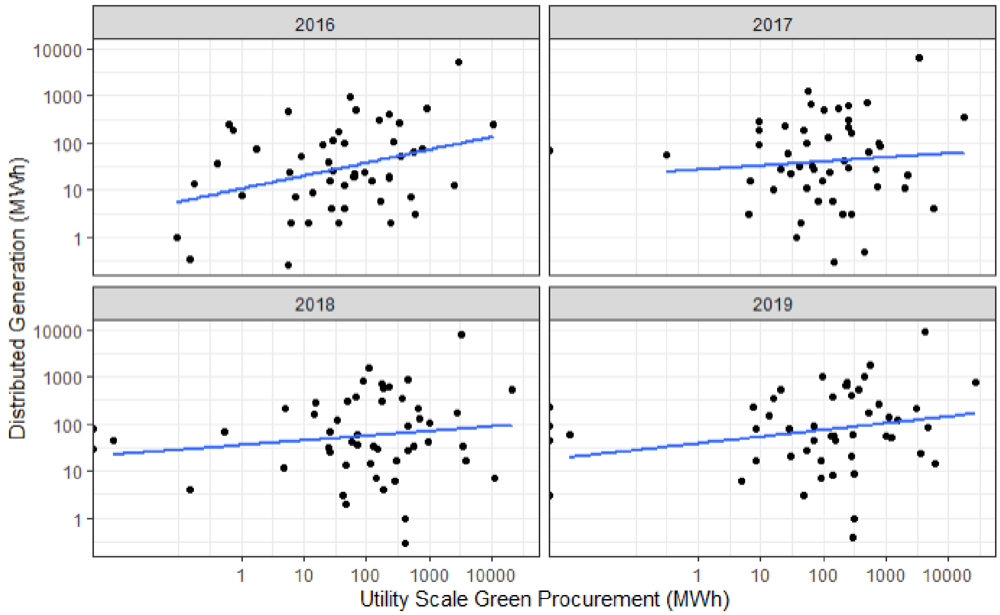

Figure A-21. Utility-Scale vs Distributed Broken Down By Year

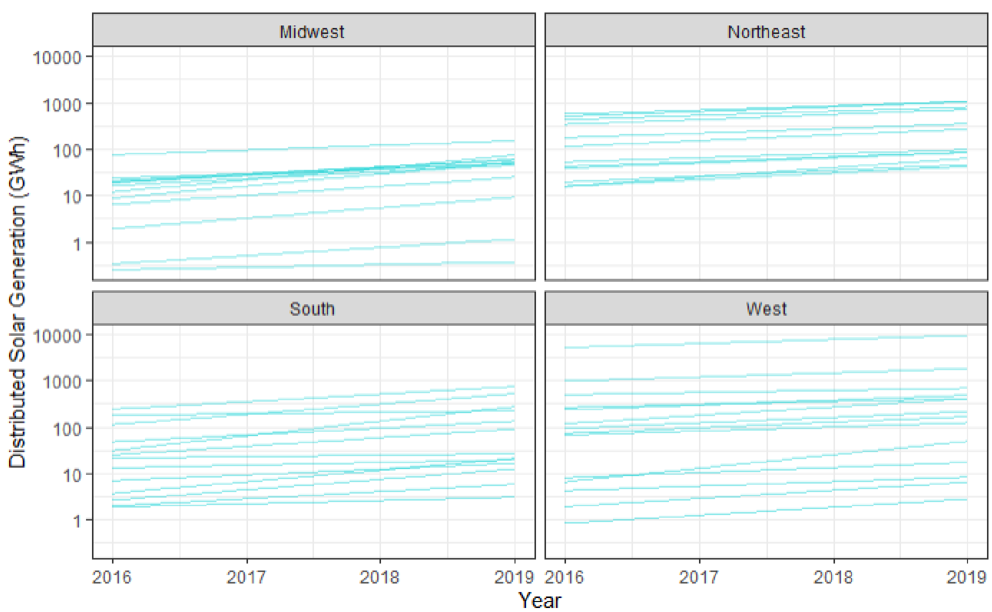

Figure A-22. Distributed Solar Generation Trend by Region

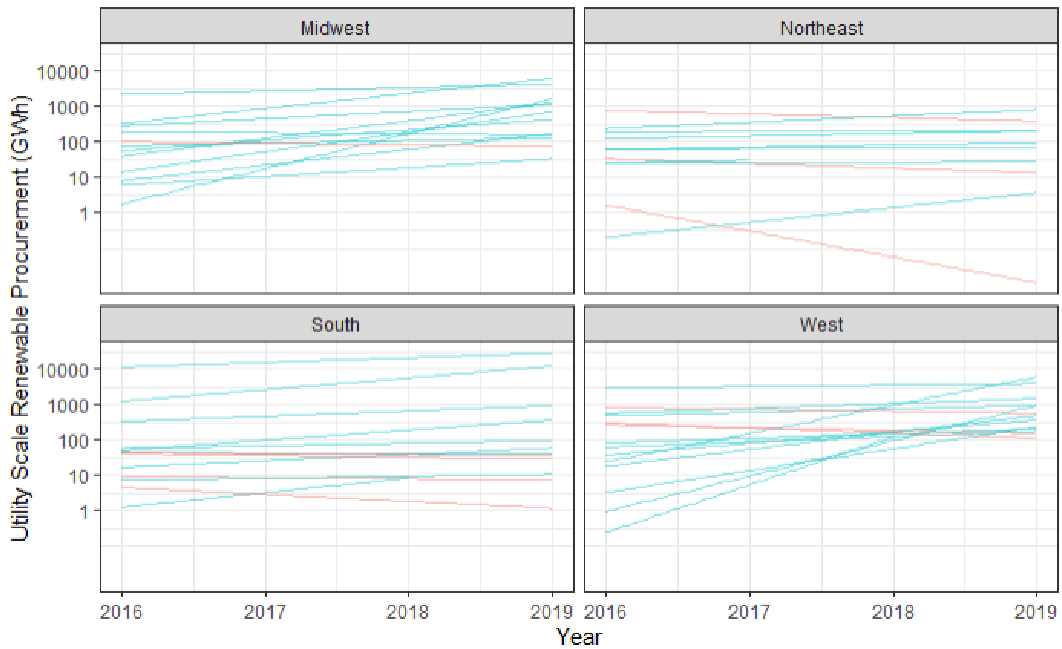

Figure A-23. Utility-Scale Procurement Trend by Region

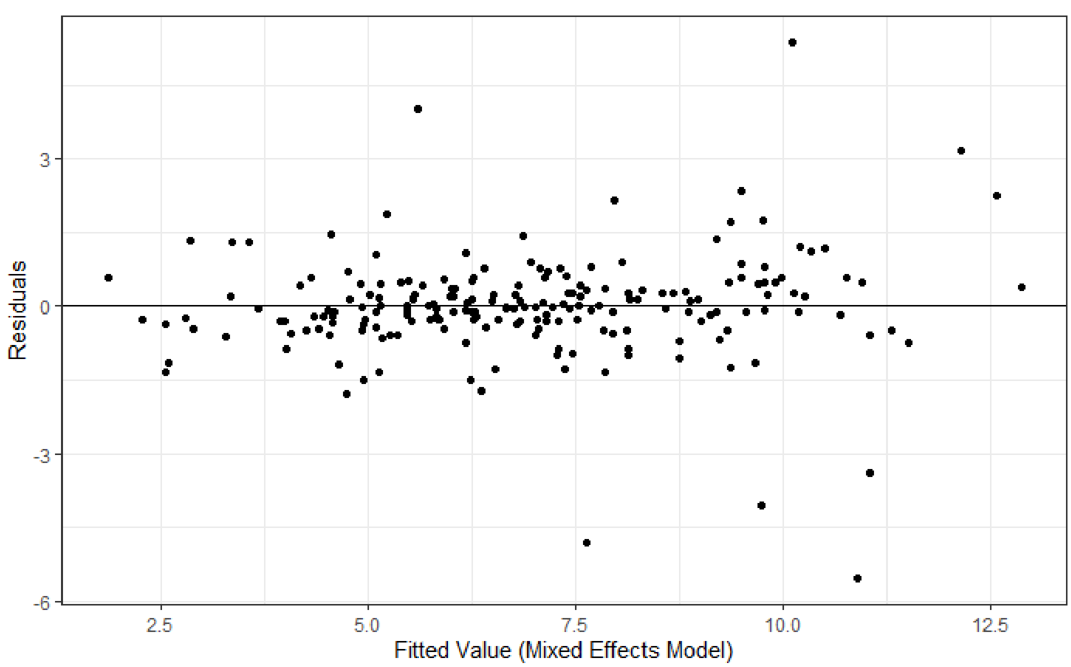

Figure A-24. Mixed Effects Residual Plot

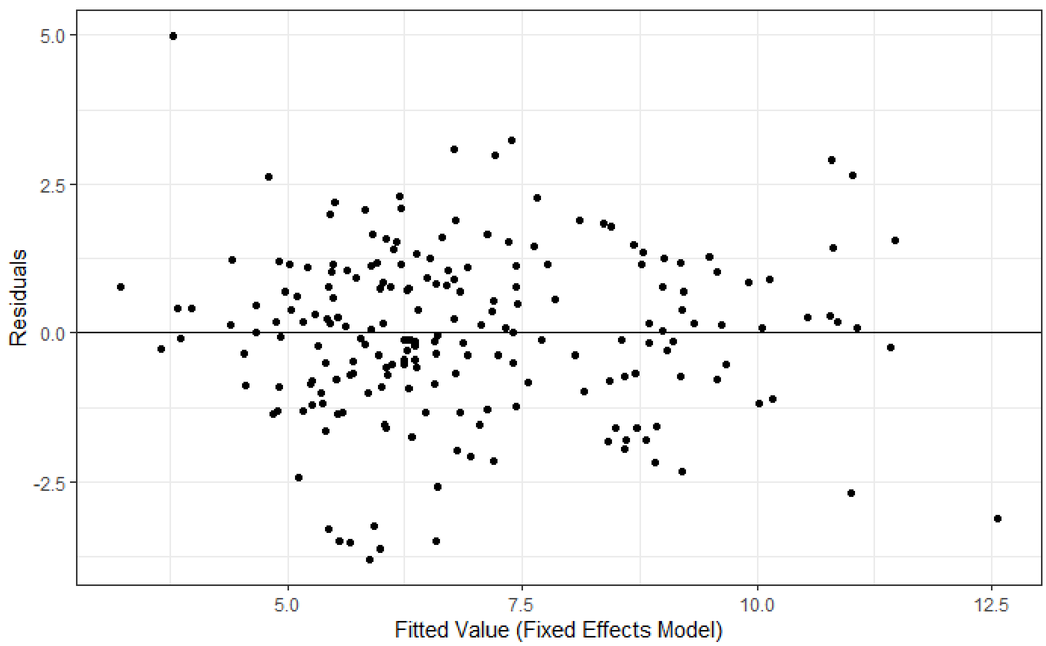

Figure A-25. Fixed Effects Model Residual Plot

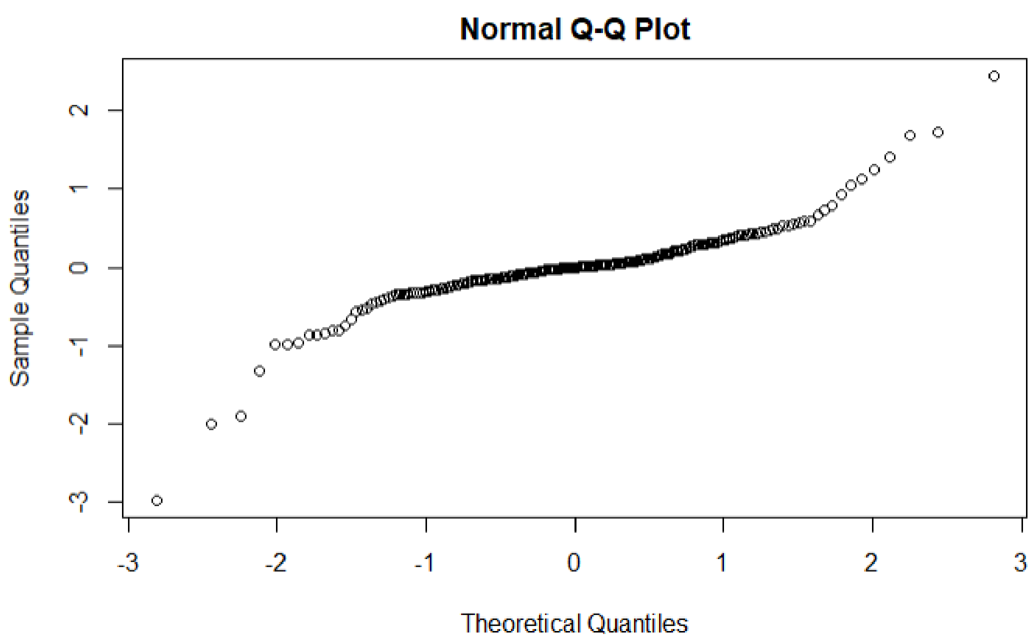

Figure A-26. Mixed Effects Model Q-Q Plot

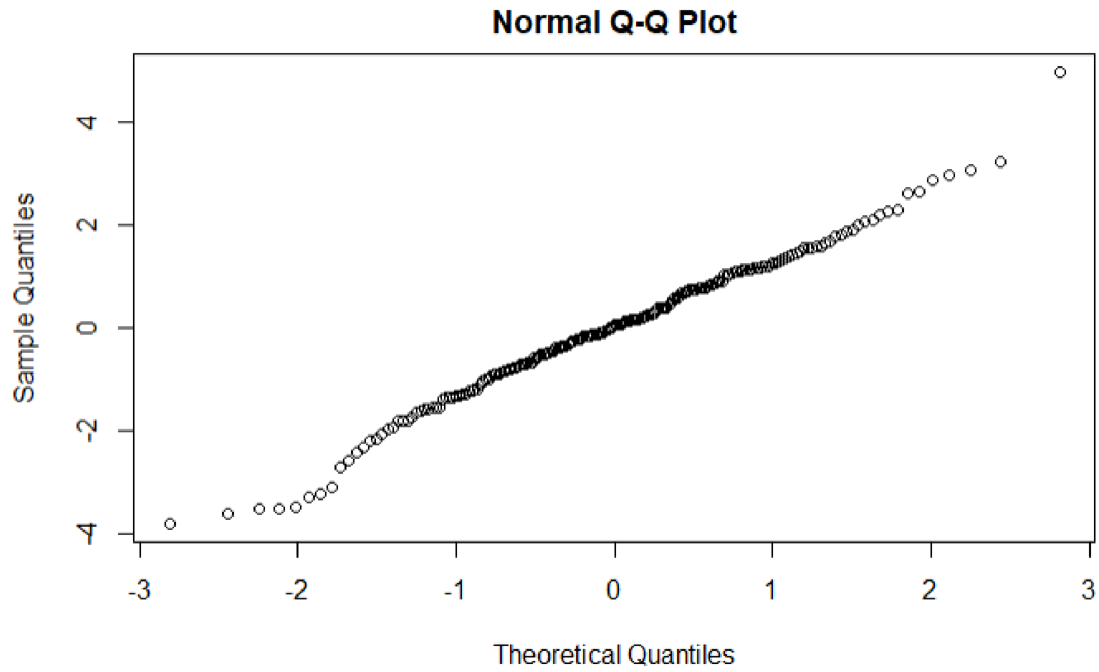

Figure A-27. Fixed Effects Model Q-Q Plot

APPENDIX B.

FIXED EFFECTS CORRELATIONS

Table B-1. Fixed Effects Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Distributed PV Generation		0.02	0.34 ***	0.54 ***	0.22 **	0.18 *	0.07	0.3 ***	-0.05	0.39 ***	0.45 ***	0.2 **	-0.3 ***	0.01	-0.39 ***
2. Utility-Scale Procurement	0.02		0.12 .	0	-0.05	0.27 ***	0.06	0.04	0.18 *	0	0.03	-0.21 **	0.07	-0.16 *	-0.13 .
3. Tax Credits	0.34 ***	0.12 .		0.11	-0.02	0.07	-0.04	-0.13 .	0.11	0.08	-0.05	-0.14 *	-0.04	-0.07	0.04
4. Rebates	0.54 ***	0	0.11		0.18 **	0.18 **	0.05	0.36 ***	-0.11	0.37 ***	0.51 ***	0.1	-0.26 ***	0.18 *	-0.43 ***
5. Solar Compensation Laws	0.22 **	-0.05	-0.02	0.18 **		0.34 ***	0.13 .	0.11	-0.12 .	0.15 *	0.01	0.12 .	-0.07	0.19 **	-0.25 ***
6. RPS Laws	0.18 *	0.27 ***	0.07	0.18 **	0.34 ***		0.24 ***	0.31 ***	0.01	0.29 ***	0.28 ***	0.06	-0.04	0.11	-0.42 ***
7. CCA Laws	0.07	0.06	-0.04	0.05	0.13 .	0.24 ***		0.54 ***	-0.2 **	0.33 ***	-0.04	0.18 *	-0.05	0.1	-0.28 ***
8. Deregulated Electric	0.3 ***	0.04	-0.13 .	0.36 ***	0.11	0.31 ***	0.54 ***		-0.42 ***	0.37 ***	0.29 ***	0.38 ***	-0.09	0.25 ***	-0.45 ***
9. Daily Insolation	-0.05	0.18 *	0.11	-0.11	-0.12 .	0.01	-0.2 **	-0.42 ***		-0.35 ***	-0.02	-0.34 ***	0.06	-0.45 ***	0.04
10. Energy Cost	0.39 ***	0	0.08	0.37 ***	0.15 *	0.29 ***	0.33 ***	0.37 ***	-0.35 ***		0.28 ***	0.05	-0.35 ***	0.28 ***	-0.34 ***
11. Personal Income	0.45 ***	0.03	-0.05	0.51 ***	0.01	0.28 ***	-0.04	0.29 ***	-0.02	0.28 ***		0.02	-0.08	0.18 **	-0.43 ***
12. Female	0.2 **	-0.21 **	-0.14 *	0.1	0.12 .	0.06	0.18 *	0.38 ***	-0.34 ***	0.05	0.02		-0.31 ***	0.35 ***	-0.1
13. White	-0.3 ***	0.07	-0.04	-0.26 ***	-0.07	-0.04	-0.05	-0.09	0.06	-0.35 ***	-0.08	-0.31 ***		0.25 ***	0.23 ***
14. Age	0.01	-0.16 *	-0.07	0.18 *	0.19 **	0.11	0.1	0.25 ***	-0.45 ***	0.28 ***	0.18 **	0.35 ***	0.25 ***		-0.17 *
15. Presidential Vote	-0.39 ***	-0.13 .	0.04	-0.43 ***	-0.25 ***	-0.42 ***	-0.28 ***	-0.45 ***	0.04	-0.34 ***	-0.43 ***	-0.1	0.23 ***	-0.17 *	

APPENDIX C.

ALTERNATIVE REGRESSION MODELS

Table C-1. Regression Model With First Differences Model Included for Comparison

Variables	Model 1 (Mixed Effects) Estimate (SE)	Model 2 (Fixed Effects) Estimate (SE)	Model 3 (First Differences) Estimate (SE)
Intercept	-56.72(19.62)**	13.79(13.39)	0.2(0.15)
Utility-Scale Procurement	0.03(0.05)	-0.01(0.05)	0.03(0.03)
RPS	-1.24(0.49)*	-0.8(0.28)**	
CCA Legislation	-0.42(0.83)	-0.64(0.39)	
Deregulated Electric	1.17(0.71)	0.26(0.35)	
Solar Compensation	2(0.81)*	1.54(0.39)***	
Rebate	1.05(0.67)	1.22(0.33)***	
Tax Credit	2.14(0.61)**	2.12(0.28)***	
Insolation	1.2(0.98)	0.34(0.51)	
Energy Cost	2.18(0.48)***	2.93(0.6)***	2.8(0.59)***
Personal Income	4.09(1.66)*	3.74(0.84)***	8.22(7.79)
Female		0.97(0.18)***	-0.05(0.17)
White		0.03(0.01)*	0.03(0.01)*
Age		-0.34(0.06)***	-0.22(0.07)**
Political Lean		-0.75(0.29)*	
2017	0.35(0.14)*	0.34(0.29)	0.03(0.09)
2018	0.57(0.15)***	0.58(0.29).	-0.03(0.09)
2019	0.78(0.16)***	0.87(0.3)**	
Number of Observations	204		
R^2 (Marginal)	0.5028	0.6195	0.3046
R^2 (Conditional)	0.9338		

Table C-2. Regression Table with RPS Trend Instead of RPS Binary

Variables	Model 1 (Mixed Effects) Estimate (SE)	Model 2 (Fixed Effects) Estimate (SE)
Constant	-53.54 (19.76)**	9.26 (15.60)
Utility-Scale Procurement Ratio	0.02 (0.05)	-0.02 (0.05)
RPS Trend	-0.06 (0.04)*	-0.05 (0.02)*
CCA Legislation	-0.34 (0.82)	-0.64 (0.39)
Deregulated Electric	1.10 (0.70)	0.30 (0.34)
Solar Compensation	1.8 (0.79)*	1.46 (0.41)***
Rebate	1.25 (0.65)	1.34 (0.30)***
Tax Credit	2.09 (0.70)**	1.99 (0.26)***
Solar Insolation	1.23 (0.99)	0.34 (0.51)
Energy Cost	2.10 (0.49)***	3.00 (0.66)***
Personal Income	3.77 (1.63)*	3.63 (0.72)***
Female		0.93 (0.22)***
White		0.03 (0.01)*
Age		-0.32 (0.07)***
Democratic Lean		0.72 (0.31)*
N	204	204
Number of States + Washington, DC	51	51
Year Fixed Effects	Yes	Yes
Marginal R^2	0.5028	0.6195
Conditional R^2	0.9338	

***p < .001, **p < .01, *p < .05

Table C-3. Mixed and Fixed Effects Model Estimation of Log (Distributed Solar Generation Ratio) with Demographic Variables Included in Mixed Effects Model

Variables	Model 1 (Mixed Effects) Estimate (SE)	Model 2 (Fixed Effects) Estimate (SE)
Constant	-27.25(23.04)	13.79 (13.39)
Utility-Scale Procurement Ratio	0.05(0.05)	-0.01 (0.05)
RPS	0.93(0.16)***	-0.8 (0.28)**
CCA Legislation	3.31(1.77).	-0.64 (0.39)
Deregulated Electric	2.43(0.49)***	0.26 (0.35)
Solar Compensation	0.64(0.14)***	1.54 (0.39)***
Rebate	0.36(0.13)**	1.22 (0.33)***
Tax Credit	0.1(1.03)	2.12 (0.28)***
Solar Insolation	-0.95(0.86)	0.34 (0.51)
Energy Cost	-1.48(0.5)**	2.93 (0.6)***
Personal Income	2.01(0.87)*	3.74 (0.84)***
Female	1.38(0.72).	0.97 (0.18)***
White	2.02(0.64)**	0.03 (0.01)*
Age	1.1(0.75)	-0.34 (0.06)***
Democratic Lean	-0.08(0.15)	0.75 (0.29)*
N	204	204
Number of States + Washington, DC	51	51
Year Fixed Effects	Yes	Yes
Marginal R^2	0.5170	0.6195
Conditional R^2	0.9483	

***p < .001, **p < .01, *p < .05

APPENDIX D.

CHALLENGES FOR UTILITY-LEVEL ANALYSIS

First, there appear to be substantial differences in the way that data is collected by NREL and the EIA. Many times, companies will report to NREL higher rates of renewable procurement in MWh than the EIA reports total energy procurement. Thus, it was impossible to calculate the percentage of voluntary renewable procurement at the utility level. Additionally, when it comes to residential solar, the EIA only reports the amount of energy sold back to the utility rather than the total amount produced, making it difficult to calculate the share of residential solar energy generation.

Another problem lies in how utilities are separated. Many privately owned utilities have a number of different sub-divisions. Thankfully, the EIA reports data using utility ID numbers as the unit of analysis, making data collection easy. However, NREL tends to collect data for the entire corporation, it is difficult to join the multiple data sets. Additionally, some utilities cross state lines, making it difficult to control for state policy factors.

There are also a number of variables which cannot easily be collected for individual utilities. For instance, solar insolation tends to be an important control. However, in order to calculate the insolation for a utility area, one must first collect a GIS file containing the exact borders and area of the utility. From there, one would need to use that file to calculate the average insolation throughout the utility’s area of service using insolation data from the National Solar Radiation Database (NSRDB) provided by NREL. The other major variables which cannot easily be gathered for individual utilities are demographic data, such as average age, race, and sex data.

BIBLIOGRAPHY

Bauner, C., & Crago, C. L. (2015). Adoption of residential solar power under uncertainty: Implications for renewable energy incentives. Energy Policy, 86, 27–35. https://doi.org/10.1016/j.enpol.2015.06.009

Bennett, J., Baker, A., Johncox, E., & Nateghi, R. (2020). Characterizing the Key Predictors of Renewable Energy Penetration for Sustainable and Resilient Communities. Journal of Management in Engineering, 36(4), 04020016. https://doi.org/10.1061/(asce)me.1943-5479.0000767

Bird, L., Bolinger, M., Gagliano, T., Wiser, R., Brown, M., & Parsons, B. (2005). Policies and market factors driving wind power development in the United States. Energy Policy, 33(11), 1397–1407. https://doi.org/10.1016/j.enpol.2003.12.018

Borchers, A. M., Xiarchos, I., & Beckman, J. (2014). Determinants of wind and solar energy system adoption by U.S. farms: A multilevel modeling approach. Energy Policy, 69, 106–115. https://doi.org/10.1016/j.enpol.2014.02.014

Bureau of Economic Analysis. (2020). BEA : Regional Economic Accounts - Previously Published Estimates. Apps.bea.gov. https://apps.bea.gov/regional/histdata/

Carley, S. (2009a). Distributed generation: An empirical analysis of primary motivators. Energy Policy, 37(5), 1648–1659. https://doi.org/10.1016/j.enpol.2009.01.003

Carley, S. (2009b). State renewable energy electricity policies: An empirical evaluation of effectiveness. Energy Policy, 37(8), 3071–3081. https://doi.org/10.1016/j.enpol.2009.03.062

Carley, S., Baldwin, E., MacLean, L. M., & Brass, J. N. (2017). Global Expansion of Renewable Energy Generation: An Analysis of Policy Instruments. Environmental and Resource Economics, 68(2), 397–440. https://doi.org/10.1007/s10640-016-0025-3

Coffman, M., Wee, S., Bonham, C., & Salim, G. (2016). A policy analysis of Hawaii's solar tax credit. Renewable Energy, 85, 1036–1043. https://doi.org/10.1016/j.renene.2015.07.061

Coon, R., Hodur, N., & Bangsund, D. (2012). Renewable Energy Industries' Contribution to the North Dakota Economy. In Agribusiness and Applied Economics: Vol. Report 702. North Dakota State University.

Crago, C. L., & Chernyakhovskiy, I. (2017). Are policy incentives for solar power effective? Evidence from residential installations in the Northeast. Journal of Environmental Economics and Management, 81, 132–151. https://doi.org/10.1016/j.jeem.2016.09.008

Crago, C. L., & Koegler, E. (2018). Drivers of growth in commercial-scale solar PV capacity. Energy Policy, 120, 481–491. https://doi.org/10.1016/j.enpol.2018.05.047

Crowe, J. A., & Li, R. (2020). Is the just transition socially accepted? Energy history, place, and support for coal and solar in Illinois, Texas, and Vermont. Energy Research & Social Science, 59, 101309. https://doi.org/10.1016/j.erss.2019.101309

Dagher, L., Bird, L., & Heeter, J. (2017). Residential green power demand in the United States. Renewable Energy, 114, 1062–1068. https://doi.org/10.1016/j.renene.2017.07.111

Database of State Incentives for Renewables & Efficiency. (2021). DSIRE. Programs.dsireusa.org. https://programs.dsireusa.org/system/program

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series With a Unit Root. Journal of the American Statistical Association, 74(366), 427. https://doi.org/10.2307/2286348

Durbin, J., & Watson, G. S. (1971). Testing for Serial Correlation in Least Squares Regression. III. Biometrika, 58(1), 1. https://doi.org/10.2307/2334313

Durham, C. A., Colby, B. G., & Longstreth, M. (1988). The Impact of State Tax Credits and Energy Prices on Adoption of Solar Energy Systems. Land Economics, 64(4), 347. https://doi.org/10.2307/3146307

EIA. (2020, March 26). Detailed State Data - U.S. Energy Information Administration. Www.eia.gov. https://www.eia.gov/electricity/data/state/

EIA. (2021a). Oregon - State Energy Profile Analysis - U.S. Energy Information Administration (EIA). Www.eia.gov. https://www.eia.gov/state/analysis.php?sid=OR

EIA. (2021b, May 20). North Dakota - State Energy Profile Analysis - U.S. Energy Information Administration (EIA). Www.eia.gov. https://www.eia.gov/state/analysis.php?sid=ND

EIA. (2021c, September 19). Vermont - State Energy Profile Analysis - U.S. Energy Information Administration (EIA). Www.eia.gov. https://www.eia.gov/state/analysis.php?sid=VT#:~:text=44-

Energy Trust of Oregon Board of Directors. (2020). Energy Trust of Oregon 2021 Annual Budget. State of Oregon. https://www.energytrust.org/wp-content/uploads/2020/12/2021-Approved-Binder_WEB.pdf

EPA. (2015, August 19). What Is CHP? US EPA. https://www.epa.gov/chp/what-chp#:~:text=CHP%20is%20an%20energy%20efficient

Fikru, M. G., & Canfield, C. (2022). Demand for renewable energy via green electricity versus solar installation in Community Choice Aggregation. Renewable Energy, 186, 769–779. https://doi.org/10.1016/j.renene.2022.01.008

Frederiks, E. R., Stenner, K., & Hobman, E. V. (2015). Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour. Renewable and Sustainable Energy Reviews, 41, 1385–1394. https://doi.org/10.1016/j.rser.2014.09.026

Hatekar, N. R. (2010). Principles of Econometrics: An Introduction (Using R) (p. 379). B-42, Panchsheel Enclave, New Delhi, 110 017, India Sage Publications India Pvt Ltd.

Hausman, J. A. (1978). Specification Tests in Econometrics. Econometrica, 46(6), 1251–1271. https://doi.org/10.2307/1913827

Heeter, J. (2022). Voluntary Green Power Procurement. Www.nrel.gov. https://www.nrel.gov/analysis/green-power.html

Heeter, J., & O’Shaughnessy, E. (2019). U.S. Voluntary Green Power Market Data 2018 | NREL Data Catalog. Data.nrel.gov; National Renewable Energy Laboratory. https://data.nrel.gov/submissions/120

Heeter, J., & O’Shaughnessy, E. (2020). U.S. Voluntary Green Power Market Data 2019 | NREL Data Catalog. Data.nrel.gov; National Renewable Energy Laboratory. https://data.nrel.gov/submissions/151

Hobman, E. V., & Frederiks, E. R. (2014). Barriers to green electricity subscription in Australia: “Love the environment, love renewable energy … but why should I pay more?” Energy Research & Social Science, 3, 78–88. https://doi.org/10.1016/j.erss.2014.07.009

Hsu, J. H.-Y. (2018). Predictors for adoption of local solar approval processes and impact on residential solar installations in California cities. Energy Policy, 117, 463–472. https://doi.org/10.1016/j.enpol.2018.03.008

Hughes, J. E., & Podolefsky, M. (2015). Getting Green with Solar Subsidies: Evidence from the California Solar Initiative. Journal of the Association of Environmental and Resource Economists, 2(2), 235–275. https://doi.org/10.1086/681131

Jirakiattikul, S., Lan, T. T., & Techato, K. (2021). Advancing Households' Sustainable Energy through Gender Attitudes towards Rooftop PV Installations: A Case of the Central Highlands, Vietnam. Sustainability, 13(2), 942. https://doi.org/10.3390/su13020942

Kahn, E. (1996). The production tax credit for wind turbine powerplants is an ineffective incentive. Energy Policy, 24(5), 427–435. https://doi.org/10.1016/0301-4215(96)00014-6

Kowalska-Pyzalska, A. (2018). An Empirical Analysis of Green Electricity Adoption Among Residential Consumers in Poland. Sustainability, 10(7), 2281. https://doi.org/10.3390/su10072281

Kwan, C. L. (2012). Influence of local environmental, social, economic and political variables on the spatial distribution of residential solar PV arrays across the United States. Energy Policy, 47, 332–344. https://doi.org/10.1016/j.enpol.2012.04.074

Lawson, A. (2019). Net Metering: In Brief. Congressional Research Service. https://www.everycrsreport.com/files/20191114_R46010_058b35011000a3009a1ff07a76ca504f00258c98.pdf

Li, H., & Yi, H. (2014). Multilevel governance and deployment of solar PV panels in U.S. cities. Energy Policy, 69, 19–27. https://doi.org/10.1016/j.enpol.2014.03.006

Lin, B., & Kaewkhunok, S. (2021). The role of socio-Culture in the solar power adoption: The inability to reach government policies of marginalized groups. Renewable and Sustainable Energy Reviews, 144, 111035. https://doi.org/10.1016/j.rser.2021.111035

Ma, C., Rogers, A. A., Kragt, M. E., Zhang, F., Polyakov, M., Gibson, F., Chalak, M., Pandit, R., & Tapsuwan, S. (2015). Consumers' willingness to pay for renewable energy: A meta-regression analysis. Resource and Energy Economics, 42, 93–109. https://doi.org/10.1016/j.reseneeco.2015.07.003

Marion, W., & Wilcox, S. (1994). Solar Radiation Data Manual for Flat-Plate and Concentrating Collectors. https://www.nrel.gov/docs/legosti/old/5607.pdf

Matisoff, D. C., & Johnson, E. P. (2017). The comparative effectiveness of residential solar incentives. Energy Policy, 108, 44–54. https://doi.org/10.1016/j.enpol.2017.05.032

Mcallister, R., Manning, D., Bird, L., Coddington, M., & Volpi, C. (2019). New Approaches to Distributed PV Interconnection: Implementation Considerations for Addressing Emerging Issues. https://www.nrel.gov/docs/fy19osti/72038.pdf

Menegaki, A. (2008). Valuation for renewable energy: A comparative review. Renewable and Sustainable Energy Reviews, 12(9), 2422–2437. https://doi.org/10.1016/j.rser.2007.06.003

Menz, F. C., & Vachon, S. (2006). The effectiveness of different policy regimes for promoting wind power: Experiences from the states. Energy Policy, 34(14), 1786–1796. https://doi.org/10.1016/j.enpol.2004.12.018

Michaud, G., & Pitt, D. (2018). Non-utility Photovoltaic Deployment: Evaluation of U.S. State-level Policy Drivers. Strategic Planning for Energy and the Environment, 38(3), 52–80. https://doi.org/10.1080/10485236.2019.12043348

Mundaca, L., & Samahita, M. (2020). What drives home solar PV uptake? Subsidies, peer effects and visibility in Sweden. Energy Research & Social Science, 60, 101319. https://doi.org/10.1016/j.erss.2019.101319

National Renewable Energy Laboratory. (2021). NSRDB Data Viewer. Maps.nrel.gov. https://maps.nrel.gov/nsrdb-viewer/

Ndebele, T. (2020). Assessing the potential for consumer-driven renewable energy development in deregulated electricity markets dominated by renewables. Energy Policy, 136, 111057. https://doi.org/10.1016/j.enpol.2019.111057

NREL. (2016). Using Power Purchase Agreements for Solar Deployment at Universities. https://www.nrel.gov/docs/gen/fy16/65567.pdf

Ntanos, S., Kyriakopoulos, G., Chalikias, M., Arabatzis, G., & Skordoulis, M. (2018). Public Perceptions and Willingness to Pay for Renewable Energy: A Case Study from Greece. Sustainability, 10(3), 687. https://doi.org/10.3390/su10030687

O’Neill, B., & Chernyakhovskiy, I. (2016). DESIGNING WIND AND SOLAR POWER PURCHASE AGREEMENTS TO SUPPORT GRID INTEGRATION. NREL; National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy16osti/66543.pdf

O’Shaughnessy, E., Heeter, J., & Sauer, J. (2018). U.S. Voluntary Green Power Market Data 2017 | NREL Data Catalog. Data.nrel.gov. https://data.nrel.gov/submissions/98

O'Shaughnessy, E., Heeter, J., Gattaciecca, J., Sauer, J., Trumbull, K., & Chen, E. (2019). Community Choice Aggregation: Challenges, Opportunities, and Impacts on Renewable Energy Markets. https://www.nrel.gov/docs/fy19osti/72195.pdf

O'Shaughnessy, E., Heeter, J., & Sauer, J. (2018). Status and Trends in the U.S. Voluntary Green Power Market (2017 Data). https://www.nrel.gov/docs/fy19osti/72204.pdf

Oregon Department of Energy. (2020). ENERGY BY THE NUMBERS. https://www.oregon.gov/energy/Data-and-Reports/Documents/2020-BER-Energy-by-the-Numbers.pdf

Rai, V., & Robinson, S. A. (2015). Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors. Environmental Modelling & Software, 70, 163–177. https://doi.org/10.1016/j.envsoft.2015.04.014

Reames, T. G. (2020). Distributional disparities in residential rooftop solar potential and penetration in four cities in the United States. Energy Research & Social Science, 69, 101612. https://doi.org/10.1016/j.erss.2020.101612

Sahu, B. K. (2015). A study on global solar PV energy developments and policies with special focus on the top ten solar PV power producing countries. Renewable and Sustainable Energy Reviews, 43, 621–634. https://doi.org/10.1016/j.rser.2014.11.058

Sardianou, E., & Genoudi, P. (2013). Which factors affect the willingness of consumers to adopt renewable energies? Renewable Energy, 57, 1–4. https://doi.org/10.1016/j.renene.2013.01.031

Sarzynski, A., Larrieu, J., & Shrimali, G. (2012). The impact of state financial incentives on market deployment of solar technology. Energy Policy, 46, 550–557. https://doi.org/10.1016/j.enpol.2012.04.032

Schelly, C. (2014). Residential solar electricity adoption: What motivates, and what matters? A case study of early adopters. Energy Research & Social Science, 2, 183–191. https://doi.org/10.1016/j.erss.2014.01.001

Schelly, C., Louie, E. P., & Pearce, J. M. (2017). Examining interconnection and net metering policy for distributed generation in the United States. Renewable Energy Focus, 22-23, 10–19. https://doi.org/10.1016/j.ref.2017.09.002

Schunder, T., Yin, D., Bagchi-Sen, S., & Rajan, K. (2020). A spatial analysis of the development potential of rooftop and community solar energy. Remote Sensing Applications: Society and Environment, 19, 100355. https://doi.org/10.1016/j.rsase.2020.100355

Shrimali, G., & Jenner, S. (2013). The impact of state policy on deployment and cost of solar photovoltaic technology in the U.S.: A sector-specific empirical analysis. Renewable Energy, 60, 679–690. https://doi.org/10.1016/j.renene.2013.06.023

State of Oregon. (2021). State of Oregon: Energy in Oregon - Renewable Portfolio Standard. Www.oregon.gov. https://www.oregon.gov/energy/energy-oregon/Pages/Renewable-Portfolio-Standard.aspx

Sun, B., & Sankar, A. (2022). The changing effectiveness of financial incentives: Theory and evidence from residential solar rebate programs in California. Energy Policy, 162, 112804. https://doi.org/10.1016/j.enpol.2022.112804

Sunter, D. A., Castellanos, S., & Kammen, D. M. (2019). Disparities in rooftop photovoltaics deployment in the United States by race and ethnicity. Nature Sustainability, 2(1), 71–76. https://doi.org/10.1038/s41893-018-0204-z

Swezey, B., & Bird, L. (2001). Utility Green-Pricing Programs: What Defines Success? https://www.nrel.gov/docs/fy01osti/29831.pdf

Symington, G., Richards, P., Bradley, J., Catlin, E., Ibey, A., Swanson, S., & Wiquist, W. (2013). Vermont Clean Energy Development Fund Five Year Strategic Plan. Vermont Clean Energy Development Fund. https://publicservice.vermont.gov/sites/dps/files/documents/Renewable_Energy/CEDF/Reports/CEDF%205%20Year%20Strategic%20Plan%20-%20January%202013.pdf

Tidwell, J. H., & Tidwell, A. (2021). Decarbonizing via disparities: Problematizing the relationship between social identity and solar energy transitions in the United States. Energy Research & Social Science, 77, 102099. https://doi.org/10.1016/j.erss.2021.102099

US Census Bureau. (2019). Explore Census Data. Data.census.gov. https://data.census.gov/cedsci/table?q=ACSDP1Y2019.DP05&g=0100000US%2404000%24001&tid=ACSDP1Y2019.DP05&moe=false&tp=false&hidePreview=true

US National Archives. (2016, December 14). 2016 Electoral College Results. National Archives. https://www.archives.gov/electoral-college/2016

Vermont. (2016). Renewables | Department of Public Service. Vermont.gov. https://publicservice.vermont.gov/renewable_energy

Vermont. (2022). Net-Metering | Public Utility Commission. Puc.vermont.gov. https://puc.vermont.gov/electric/net-metering

Wiser, R., Barbose, G., & Holt, E. (2011). Supporting solar power in renewables portfolio standards: Experience from the United States. Energy Policy, 39(7), 3894–3905. https://doi.org/10.1016/j.enpol.2010.11.025

Yin, H., & Powers, N. (2010). Do state renewable portfolio standards promote in-state renewable generation?. Energy Policy, 38(2), 1140–1149. https://doi.org/10.1016/j.enpol.2009.10.067

Zarnikau, J. (2003). Consumer demand for “green power” and energy efficiency. Energy Policy, 31(15), 1661–1672. https://doi.org/10.1016/s0301-4215(02)00232-x

Zhai, P., & Williams, E. D. (2012). Analyzing consumer acceptance of photovoltaics (PV) using fuzzy logic model. Renewable Energy, 41, 350–357. https://doi.org/10.1016/j.renene.2011.11.041

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