RENEWABLE ENERGY AND ELECTRIC VEHICLE CONVERSION: A NATIONAL EVALUATION OF THE CLEAN ENERGY TRANSITION

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RENEWABLE ENERGY AND ELECTRIC VEHICLE CONVERSION: A NATIONAL EVALUATION OF THE CLEAN ENERGY TRANSITION

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Economics

Abstract

This study applies economic modeling to assess the importance of variables thought to benefit or hinder the clean energy transition in all 50 states and one district in the United States. The study will discuss existing theories and literature behind the drivers of renewable energy generation. Linear and logit regression techniques are used to evaluate four different models. The results find that an increase in state population, renewable energy incentives, and average peak sun hours increases renewable energy generation, while an increase in the amount of protected land and people registered as Democrats decrease renewable energy generation. They also find that an increase in state population, the amount of protected land, and people registered as Democrats increase per capita electric vehicle registrations. The study shows that any state can excel in the energy transition given beneficial geographical attributes, increased clean energy incentives, and political accord.

KEYWORDS: (Renewable Energy, Electric Vehicles, Clean Energy, Incentives, Politics, Geography, Demographics)

ON MY HONOR, I HAVE NEITHER GIVEN NOR RECEIVED UNAUTHORIZED AID ON THIS THESIS

Larson Baker

Signature

Dedication

This thesis is dedicated to my parents, Barrett and Kristin Baker, and my siblings, Martha and Charlie Baker, for providing me with unparalleled support throughout my four and a half years at Colorado College. I would also like to thank my thesis advisor, Mark Eiswerth, for guiding me through this process and helping me navigate the incredible fields of renewable energy and environmental economics. Additionally, thank you to all my economics, business, and environmental studies professors who made this work possible and continuously educated me.

TABLE OF CONTENTS

Introduction

The past two years have been filled with pivotal events, both beneficial and harmful, that have been caused by global warming and concern for climate change. In 2021, 20 weather-related disasters totaled more than $1 billion in damages in the U.S. (Rivelli, 2022), global surface temperature reached 1.5 degrees Fahrenheit warmer than the twentieth-century average (Lindsey & Dahlman, 2022), and global sea level set a record high at 3.8 inches above 1993 levels (Lindsey, 2022). Evidence supporting global climate change is becoming irrefutable, placing the question of how to slow it and eventually stop it at the forefront of developed nations. Renewable energy offers a potential way out. If renewables can account for 80% of global power generation, CO_2 emissions can decrease by 70% by 2050 (ClimateAction.org, 2017). Additionally, switching from fossil fuels to renewable energy could save the world as much as $12 trillion dollars (Fisher, 2022) . These incentives have caused renewable electricity generation to increase 7%, or 522 terawatts, in 2021 and account for nearly 27% of all global electricity generation. As it currently stands, the United States is significantly trailing Europe and China, suggesting that more needs to be done (Bojek, 2022).

As a member of the Paris Climate Agreement, the United States has pledged to reduce carbon emissions to net zero by 2050, although current projections indicate this is not likely the case. Despite being a contested topic for the greater part of the last decade, recent data suggests that two-thirds of Americans believe the government should do more to support greenhouse gas reduction and climate change mitigation policies (Tyson & Kennedy, 2020). This past year, the Biden Administration passed the Inflation Reduction Act, which sets aside roughly $360 million for incentives, tax credits, and investment into

America's energy transition. While the funds will directly support climate reduction start-ups, electric vehicle producers, and consumers of electric vehicles, states and their residents bear a large responsibility in promoting renewable energy development and implementing clean energy into the macro grid or smaller micro-grids. Despite having the available technology and necessary labor force, RE projects across the country have been delayed, canceled, or postponed (Ryder, 2022). Additionally, some states, like California, have heightened climate mitigation policies while others, like Alabama, have very limited policies. These discrepancies and many others have led the United States to its current position, where renewable energy generation and EV adoption is prominent in certain locations and nearly non-existent in others; why is this the case?

By reviewing each state, this paper will determine how political structures, geographic locations, and resident demographics influence the conversion to renewable energy and electric vehicles. The paper will use regression and logit analyses to measure two dependent variables, total production of renewable energy, and per capita electric vehicle registrations by state, as functions of states political, geographic, and demographic variables. Under each category of variables (political, geographic, and demographic) a handful of independent variables will be employed to provide an all-inclusive analysis of any given state. The effect of all political, geographical, and demographic variables on each dependent variable will be observable, allowing for specific results and suggestions for each outcome. The results of this model can be used to inform policymakers at the state level about inherent existing barriers to converting to sources of clean energy. Additionally, the results will suggest existing factors that drive policy creation and the following success of implementing said policy.

The models hypothesize the following:

1. Democratic states have greater amounts of renewable energy generation and EV adoption because of existing political structures.
2. Renewable energy pledges and incentives aimed at climate change mitigation increase states' conversion ability.
3. Wealthier states and states with higher levels of educational attainment will have an increased amount of renewable energy production and electric vehicle registrations.
4. States with greater amounts of sunshine and less amounts of protected land will have an increased amount of renewable energy production and electric vehicle registrations.

The following chapter will contain relevant literature and past studies that help identify explanatory variables for state-level renewable energy generation and electric vehicle conversion. This chapter also discusses areas of improvement through identifying shortcomings and controversies in existing literature. The third section will analyze and discuss the data that will be used in the model. The methodology section will be provided to demonstrate why and how data was selected. This section will also give reasons for regression and logit models and propose the models themselves. A results section will follow detailing results that support and refute the hypotheses listed above. This paper will conclude with a discussion of the implications of these results. Limitations of the study will also be discussed.

Literature Review

There has been an increasing number of studies done on renewable energy in the past decade. Prior literature has a heavy focus on looking at the adoption of solar, wind (offshore and onshore), and other renewable energies; however, they tend to focus strictly on one aspect of renewable energy and represent cities or individual cases. This section will review the literature on renewable energy conversion and adoption to contextualize research at the state level and identify regression variables.

Many explanatory variables have been discussed in the literature as influencing the conversion and general adoption of renewable energy, but perhaps none are more critical than political variables. Hess and Gentry (2019) used a survey to measure the challenges and implications of renewable energy policies. They found that 64% of respondents in cities that had goals to produce 100% renewable energy described their community as liberal or very liberal, with 29% saying their community is moderate/divided and 7% saying it is Republican. Numerous additional studies support these findings and suggest that renewable generation is a partisan issue. In 2014, Borchers et al. used a tobit regression to analyze explanatory variables that influence farms' willingness to adopt solar. They found that farms in democratic-leaning states have a higher probability of solar adoption (Borchers et al., 2014). While this is a small-scale example, additional studies support his findings. A study done by Bedsworth and Hanak (2013) used national and California surveys to analyze explanatory variables pertaining to climate policy adoption. In both surveys, they "found larger partisan gaps in support for general climate policy than for some of the specific action areas that could reduce GHG emissions, such as clean energy and energy efficiency". Support for climate policy adoption among Republicans was lower than Democrats and Independents in the 2008 and 2012 election. These results suggest that Republican voter shares and states should have a strong negative effect on the adoption of general local policies. Krause (2011) found similar results when analyzing explanatory variables for climate protection motivation. Through using a multilevel model approach that incorporated local and state-level variables, the model found that “citizens with higher levels of education and democratic political leanings appear to be significant motivations for local climate protection innovation”. Additionally, Mayer (2019) found that Republicans are about 40–80% less likely to support the Clean Power Plan, a climate change policy, than non-republicans. While the majority of the literature does support the assertion that renewable energy generation and climate change policy adoption are more favorable in Democratic-leaning states, other studies have failed to find political significance or found contrary results. A study by Adesanya et al. in 2020 focused on 5 municipalities that have achieved commitments to 100% renewable energy: Burlington, Vermont; Aspen, Colorado; Greensburg, Kansas; Georgetown, Texas; and Rock Port, Missouri. While the previous studies have suggested that Republican presence hinders the energy transition, this study shows 100% RE involvement from a mix of other political parties, including Republicans. This contradicts the literature and suggests that 100% renewable energy transition in the U.S. is also evident in places with politically conservative mayors and city council managers (Adesanya et al., 2020). By including political variables as explanatory variables for renewable energy generation, this study will be able to assess the current landscape of state-level political opposition to climate change mitigation policies and practices.

Among the literature, demographics (age, education, sex, race, income) are often cited as being an explanatory variable for measuring renewable energy adoption and conversion. A study done by Kunkel et al. in 2022 attempts to find reasons for and against the adoption of 100% renewable electricity in cities across the United States. Using a standard linear probability approach, the model assesses how 100% RE adoption policies are correlated with demographics, institutional arrangements, and prior sustainability actions. The model found that population size and college education had significant positive relationships with 100RE commitments (Kunkel et al., 2022). Firestone and Kempton (2007) found similar results when addressing reasons for public opposition to offshore wind projects. Through running a logistic regression on the likelihood of supporting a proposed project, they "found that the odds that someone whose highest level of educational attainment is a high school degree will support the project are 91.3% less than someone with a graduate or professional degree and 78.2% less for those individuals who have some college-level instruction short of a bachelor's degree". The model also produced a negative statistically significant coefficient for age of -0.27, indicating that the likelihood of support decreases by 3% as a person ages one year. Zarnikau (2003) further supports these findings when assessing willingness to pay a premium for utility investments in renewable energy and energy efficiency. He found that younger residents and residents with higher levels of educational attainment are more willing to pay a premium for renewable energy and energy efficiency investments. Breetz et al. (2022) cited similar findings when studying municipal adoption of 100% renewable electricity policies. Through using a matched pair analysis with municipalities that had adopted policies and demographically similar municipalities that had not, they found that

100RE locations of adopters have a lower median age, were 36% more likely to have a four-year college degree, and 17 times more likely to have a research university in their location. While these results are representative of support for offshore wind projects, renewable energy and energy efficiency investments, and municipal 100RE commitments, they can be extrapolated to the broader renewable energy landscape. This literature suggests that higher state education levels correlate with increased renewable energy conversion, and states containing older populations will face increased opposition throughout most aspects of the energy transition.

Contrary to this paper's hypothesis, existing literature has identified primarily negative relationships with variables representing wealth. Kunkel et al. (2022) found that 100RE commitments were more likely in cities with lower median income and higher poverty rates. Additionally, Breetz et al. (2022) found that the poverty rate is 27% higher among municipal adopters of renewable energy than non-adopters. While these studies found that less amounts of wealth are correlated with increased renewable energy, Krause (2011) found that larger populations and higher levels of per capita general revenue are significant enabling resources for climate protection initiatives. Controversy exists among studies examining monetary variables suggesting that both things like poverty rate and state GDP should be included in future analyses. These studies do not directly address the reasons for increased poverty rates associated with higher adoption rates and were not done on the state level, leaving room for improvement.

Apart from political and demographic variables, the literature also suggests that geographic variables influence states' willingness to adopt and convert to renewable energy. Studies that directly look at geographic metrics on the state level are severely limited; however, studies have been conducted on national or country levels. A study done by Fadley and Fontes in 2019 used a fixed effects panel approach to test for the role of geographic proximity on the intensity of renewable energy adoption. They found that geographical spillovers in the diffusion of renewable energy technologies are likely to occur, suggesting that states within close proximity to states that have high adoption proxies will see increased renewable energy generations themselves (Fadly & Fontes, 2019). It should be noted, however, that the effects of geographical spillovers are inconclusive over time. Aguirre and Ibikunle (2014) investigated factors affecting renewable energy growth at the country level. One of the variables they used was *renewables potential* which was obtained through estimations for wind, solar, and biomass energy by country. The results of their fixed effects model demonstrated that solar and biomass potential show statistically significant positive relationships with renewable energy growth/conversion, while wind potential had a statistically significant negative relationship. Borcher et al. (2014) similarly found that higher levels of solar resources result in a higher probability of adoption. Although the wind potential results of Aguirre and Ibikunle (2014) seem counterintuitive, Carley (2009) found similar results when applying a bivariate regression on state renewable energy electricity policies. Using total MWh of renewable energy electricity as the dependent variable, she found that the amount of windy land area in a state is negatively associated with RE share and RE total. "The least windy states had an average RE generation of 1.72 million MWh, the mid-level windy states had 2.29 million MWh, and the windiest states had 0.70 million MWh". These results suggest that potential renewable energy capacity is hindered by a geographic or other attribute that inherently supports renewable energy generation.

Furthermore, these studies were conducted nearly a decade ago, making it increasingly important to re-assess the effect potential renewable generation has on renewable energy adoption.

While the primary purpose of this study is to focus on renewable energy generation, existing literature does suggest that electric vehicle conversion is more prominent in cities where renewable energy is being produced. A cross-country panel study on electric vehicle demand found that a one-percent increase in renewables would lead to a 2-6% increase in electric vehicle demand per 1,000 people (Li et al., 2017). Additionally, the study found that new energy policies encourage the parallel development of renewables and electric vehicles. These results suggest that electric vehicle registrations could be used as an additional proxy to measure states' success in the clean energy transition and that renewable energy and electric vehicles are positively correlated. It also suggests that the independent variables associated with increased renewable energy generation will similarly be associated with increased electric vehicle demand and registrations.

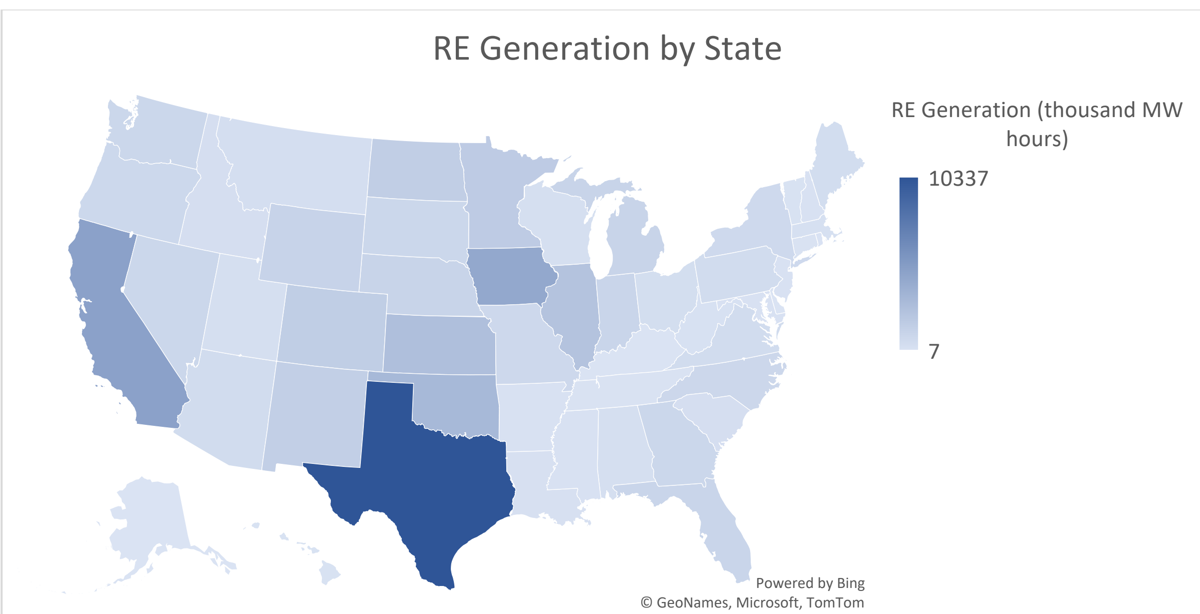
This study will look to improve upon the weakness and questions outlined in the literature above by implementing a model that contains all relevant political, demographic, and geographic variables cited that are hypothesized to influence renewable energy adoption and generation. The results will provide updated information and knowledge on variables that measure states' success in converting to renewable energy and transitioning to electric vehicles.

Methodology and Data

Dependent Variables

The first dependent variable used in the study is total generation from renewable energy sources. Data for this variable comes from the Energy Information Administration (EIA, 2022) and measures all aspects of renewable energy, solar, wind, and biomass but excludes renewable energy produced from hydroelectric sources. The data excludes hydroelectricity because certain states, states that are near oceans or have an increased amount of water features, will be able to produce more RE than states with limited water features. Excluding hydroelectric sources of renewable energy levels controls for hydropower and enables the measure to be representative of states' efforts given similar geographic features. Net renewable energy generation is measured in thousand megawatt hours across each state. Figure 3.1 represents a heat map of renewable energy generation by state and demonstrates that Texas is a significant outlier.

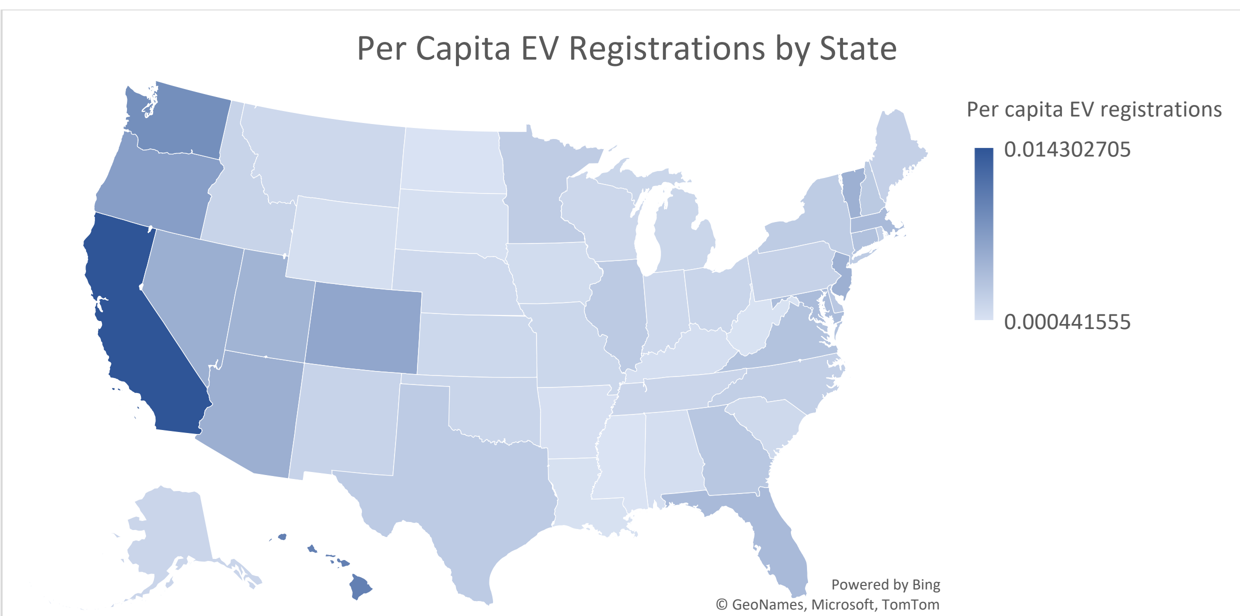
Figure 3.1: Renewable Energy Generation by State



Source: eia.gov

The second dependent variable used in the regressions is per capita electric vehicle registrations per state. For the purposes of this study, the number of registered electric vehicles will act as an additional proxy for measuring states' willingness to adopt and convert to clean sources of energy. The data for electric vehicle registrations comes from the United States Department of Energy, and is representative of all registrations through June, 2022 (U.S. Department of Energy, 2022). Stata tests for multicollinearity demonstrate that the number of EV registrations and net generation of RE are not correlated, suggesting that regressions on each dependent variable should provide different statistically significant independent variables. Per capita electric vehicle registrations is used instead of the number of electric vehicle registrations to control for state size and population. Obviously states with larger populations will have greater amounts of electric vehicle registrations than states with smaller populations. Figure 3.2 demonstrates that California has many more electric vehicle registrations than any other state.

Figure 3.2: Per Capita Electric Vehicle Registrations



Source: afdc.energy.gov

In addition to these dependent variables, two additional logit models will be employed and use versions of the same dependent variables. Each dependent variable in the logit models uses the mean amount of RE generation and per capita electric vehicle registrations to code each state either zero or one. If a state is coded 1, then that state has greater than the mean amount of renewable energy generation or per capita electric vehicle registration. If a state is coded 0, then that state has less than the mean amount of RE generation or per capita electric vehicle registrations. These mean variables allow for states generation and registration coefficients to be viewed as a likelihood through marginal effects and percentage changes.

Independent Variables

The independent variables used to estimate states' renewable energy generation will be discussed in three separate categories: demographic, political, and geographic. Each category consists of numerous explanatory variables, however not all these variables will be used in the final models. These variables will be discussed in depth below.

Demographic and Socioeconomic. The independent variables pertaining to demographics that will be considered for use in this study are median age, state population size, population density, % not completed high school, % not completed college, state GDP (millions of dollars), and state poverty rate.

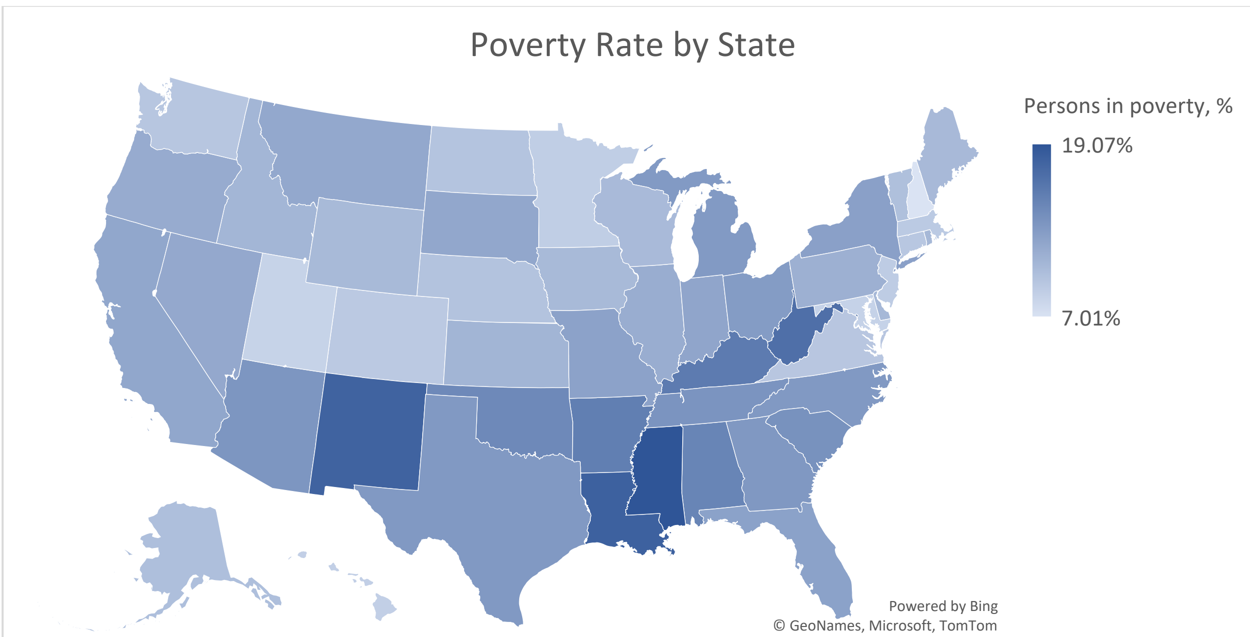
Median age is included because previous literature suggested that older populations have a harder time adopting renewable energy than younger populations. Values for median age were attained from the United States Census Bureau via the American Community Surveys (U.S. Census Bureau, 2021). State population and population density are also significant variables to consider when assessing renewable energy generation.

States with larger, more dense populations would likely have less available land to build renewable energy plants on. Additionally, bigger states could be more likely to receive federal funding, and likely have higher tax revenues which could translate to increased renewable energy generation. It is also likely that states with larger populations could have higher amounts of renewable energy generation simply because they need more energy to serve a larger population. Population size and population density were both attained from the United States Census Bureau (U.S. Census Bureau, 2021).

Existing literature suggests that educational attainment supports renewable energy adoption. This study includes two explanatory variables for education, % not completed high school and % not completed college. Tests for correlation demonstrated a strong linear negative relationship between the two variables so % not completed high school is dropped in the final models to avoid multicollinearity. States that possess higher levels of educational attainment, and lower percentages for these two variables, will likely possess populations that are more educated on global climate change, and the need for carbon emission reduction. This increased knowledge should translate to greater awareness and support for renewable energy generation. Data on educational attainment was collected from the United States Census Bureau (U.S. Census Bureau, 2022).

The last variables within the demographic and socioeconomic category are financial variables in the form of state GDP and state poverty rate. These variables are included in the study because the literature has demonstrated adverse or unexpected relationships with renewable energy generation. States with increased amounts of GDP have more money to dedicate toward renewable energy generation and production, so the expected relationship is positive. However, states have agency in deciding where money goes. Poverty rate is included to see if states with increased poverty rates produce greater amounts of renewable energy as the literature suggests. The census bureau calculates poverty rate by taking mean family income divided by the poverty threshold. Figure 3.3 shows that southern states generally have greater impoverished populations than northern states. Data for state GDP was obtained from World Population Review (World Population Review, 2022), while poverty rate was obtained from the United States Census Bureau (U.S. Census Bureau, 2021).

Figure 3.3: Poverty Rate by State



Source: census.gov

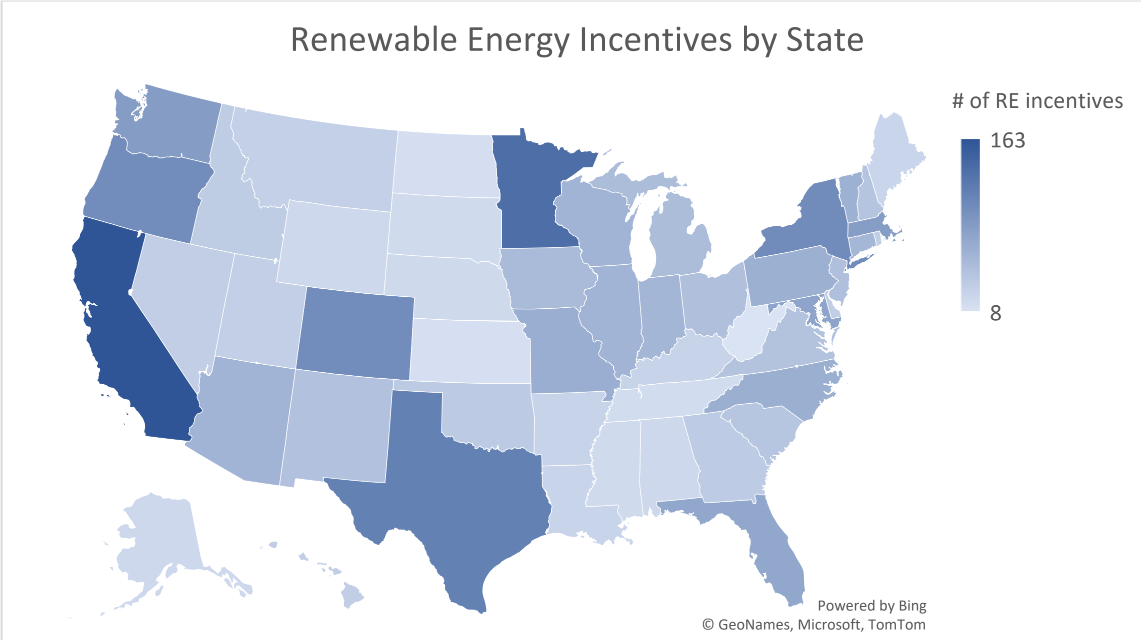
Political. In order to measure the effect states' political landscapes have on renewable energy development and electric vehicle adoption the models will consider using % registered Republican, % registered Democrat, Renewable Portfolio Standards (RPS), and renewable energy incentives as explanatory variables for measuring states' annual renewable energy generation. Although % registered Republican and % registered

Democrat rarely sum to 1, % registered Republican will be dropped from the final model to avoid multicollinearity. Additionally, the literature suggests that Democratic states increase the likelihood of clean energy adoption, making it the more prominent variable of the two. Data on state party affiliation was acquired through Gallup (Gallup, 2018).

RPS is a categorical variable within the model and can take the form of 0, 1, or 2. States coded 0 have no renewable portfolio standards or goals. States coded 1 have renewable portfolio goals but have not yet generated Renewable Portfolio Standards. States coded 2 have Renewable Portfolio Standards. The difference between goals and standards is that renewable portfolio standards require states to produce a certain amount of their total electricity generation from renewable sources while goals do not require a certain percentage to be met. Data for the RPS variable was acquired through the Energy Information Administration (EIA, 2022).

In addition to Renewable Portfolio Standards, renewable energy and energy efficiency incentives will be included in the model. Data on existing state level incentives was hardcoded from the Database of State Incentives for Renewables and Efficiency (DSIRE) (NC Clean Energy Technology Center, 2022). Existing literature suggests that states with increased amounts of incentives for both consumers and producers will likely have more electric vehicle registrations and renewable energy generation than states that provide little incentives. Figure 3.4 demonstrates how many incentives states have, with California having the most.

Figure 3.4: Renewable Energy Incentives by State

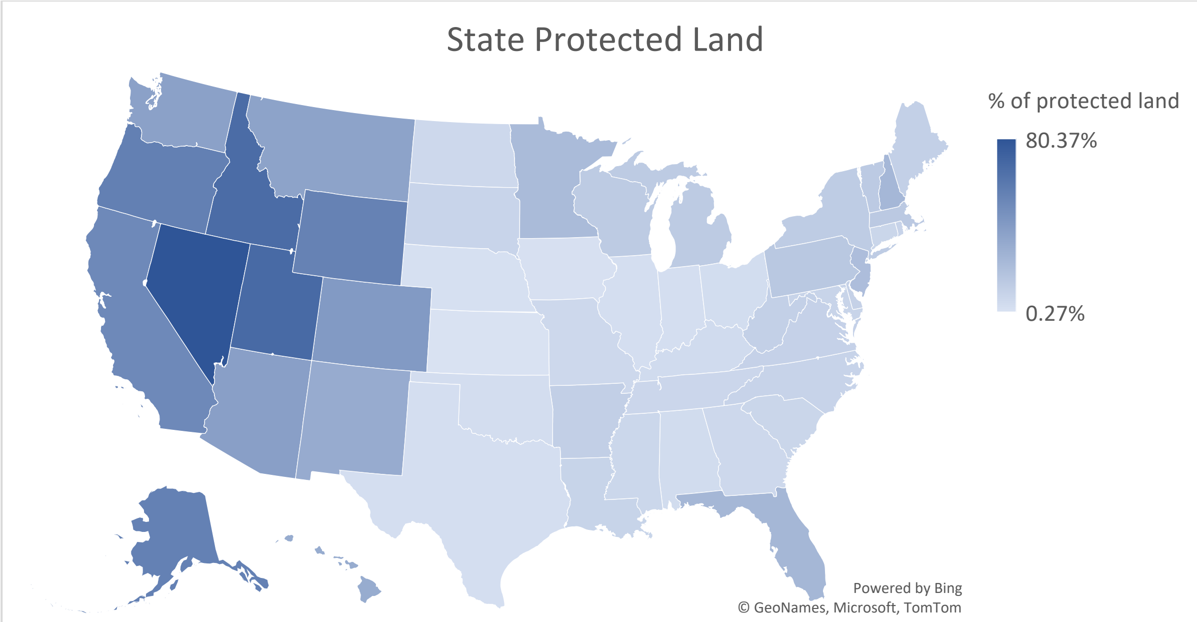


Source: dsireusa.org

Geographical. To gauge whether states are utilizing their available land and weather patterns, the models will also consider including the following geographical variables: % state protected land, average peak sun hours, and average wind speed.

State protected land is included in the model because states that have less protected land will likely have more available land to build things like utility scale solar and wind plants on. Additionally, states with less protected land likely have fewer environmental protection policies in place likely making it easier for new renewable power plants to be approved and produced. Data on protected land was acquired through the U.S. Department of the Interior's National Inventory of Protected Areas (Mantz, 2018). Figure 3.5 demonstrates that western states have much greater amounts of protected land than eastern states.

Figure 3.5: State Protected Land



Source: pubs.usgs.gov

The final two independent variables directly measure state weather patterns. Average peak sun hours is used as an independent variable to measure states' solar potential. States with longer average peak sun hours should be able to generate more solar power than states with less hours. Data for peak average sunshine hours was accessed through TurbineGenerator (TurbineGenerator, 2018). In addition to measuring sunshine, states average wind speed will also be used as an independent variable. States with higher average wind speeds should yield greater generation results from onshore wind farms so long as states are actively constructing and producing utility-scale farms. Data for average wind speeds was acquired through Usa.com (USA.com, 2014). All the independent variables are summarized in Table 3.1.

Table 3.1

Summary of Independent Variables

Variable Name	Measure	Hypothesized relationship with dependent variables
NoCollege	% of population not completed college	+
StatePopulation	State population	+
Pop. Density	# of people per square mile of land area	+
PovertyRate	Mean family income divided by poverty thresholds. Poverty thresholds vary based on family size and age but do not vary across states.	_
ProtectedArea	% of land that is protected by the state	_
PeakSun	Solar insolation an area receives when sun's intensity is highest for a specific # of hours	+
WindSpeed	Average wind speed	+
RegisteredDemocrat	% Registered Democrat	+
NORPS	No standards or goals	_
RPStandards	Renewable Portfolio Standards	+
REIncentives	# of incentives per state	+
MedianAge	Median age per state	_

Models

Four models will be employed to analyze the impacts these specific variables have on states' ability to generate RE and convert to EVs. For each dependent variable, RE generation and per capita EV registrations, two models, one linear regression and one logit model, will be used to test the hypotheses for similar sets of independent variables. The four models with their respective dependent variables and independent variables are displayed in the equations below:

$$\text{Energy Generation from Renewables} = \beta0 + \beta1{*}\text{College} + \beta2{*}\text{Statepopulation} + \beta3{*}\text{Povertyrate} + \beta4{*}\text{Protectedarea} + \beta5{*}\text{Peaksun} + \beta6{*}\text{Registereddemocrat} + \beta7{*}\text{REincentives} + u \tag{3.1}$$

$$\text{Likelihood that renewable energy generation is greater than mean renewable energy generation for all states} = \beta0 + \beta1{*}\text{College} + \beta2{*}\text{Statepopulation} + \beta3{*}\text{Povertyrate} + \beta4{*}\text{Protectedarea} + \beta5{*}\text{Peaksun} + \beta6{*}\text{Registereddemocrat} + \beta7{*}\text{REincentives} + u \tag{3.2}$$

$$\text{\# EV Registrations Per Capita} = \beta0 + \beta1{*}\text{College} + \beta2{*}\text{Statepopulation} + \beta3{*}\text{Povertyrate} + \beta4{*}\text{Protectedarea} + \beta5{*}\text{Peaksun} + \beta6{*}\text{Registereddemocrat} + \beta7{*}\text{REincentives} + \beta8{*}\text{NoRPS} + \beta9{*}\text{RPStandards} + u \tag{3.3}$$

$$\text{Likelihood that EV registrations per capita are greater than mean EV registrations per capita for all states} = \beta0 + \beta1{*}\text{Statepopulation} + \beta2{*}\text{Povertyrate} + \beta3{*}\text{Protectedarea} + \beta4{*}\text{Registereddemocrat} + \beta5{*}\text{REincentives} + \beta6{*}\text{NoRPS} + \beta7{*}\text{RPStandards} + u \tag{3.4}$$

These four final models exclude the independent variables population density, wind speed, and median age. These variables were excluded for several reasons. Population density was excluded because in regressions where both state population and population density were included, population density never had any statistical significance while state population was always significant. Through a process of testing down, it was determined that the variable was not significant enough to be included given a limited amount of 51 observations. Similarly, in regressions where wind speed was included, the variable never had any statistical significance while other geographical variables did show statistical significance in numerous models. Through the same process of testing down, it was determined that average wind speed was not a significant predictor given a limited amount of 51 observations. Additionally, data for average wind speed was not consistent across sources and was outdated. The final variable, median age, was excluded for similar reasons. Throughout regression models, median age lacked statistical significance and was dropped through process of testing down. While median age was not a significant predictor in these models or this data set, existing literature does suggest that it plays a role in states' ability to generate renewable energy and register electric vehicles.

Results

This final chapter will discuss the regression analysis results of the empirical models listed above. The results from four different models, two linear regressions and two logit models, will be presented. The first model will look at the effects the independent variables have on state generation of renewable energy, excluding hydroelectricity. The second model will examine the marginal effects the independent variables have on states' likelihood to produce greater than the mean amount (across all fifty states) of net renewable energy generation. The third model will look at the effects the independent variables have on state electric vehicle registrations per capita. The final model will examine the marginal effects the independent variables have on states' likelihood to produce greater than the mean amount of per capita electric vehicle registrations.

The results of the first regression model using renewable energy generation as the dependent variable (Eqn. (3.1) above) are listed in Table 4.1. The model has a moderate R-squared score of .510, indicating that 51% of the variation in the dependent variable is explained by variation in the independent variables included in the regression. Mean renewable energy generation across all states and the District of Columbia (totaling 51 observations) was 1024.922 thousand megawatts. The high F-test value of 6.398 allows us to reject the null hypothesis that all coefficients on the independent variables are equal to 0 with 99.999% confidence.

Table 4.1

Renewable Energy Generation: Linear Regression

REGeneration	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
NoCollege	-49.778	5119.692	-0.97	.336	-15302.656	5347.03	
StatePop	.09	.038	2.37	.022	.014	.167	**
PovertyRate	27.185	9410.91	0.29	.774	-16260.365	21697.451	
ProtectedArea	-24.271	1060.489	-2.29	.027	-4565.745	-288.386	**
PeakSun	502.851	266.706	1.89	.066	-35.013	1040.714	*
RegisteredDem	-8.811	4051.063	-2.17	.035	-16980.47	-640.975	**
REIncentives	19.412	9.604	2.02	.05	.044	38.779	**
Constant	4401.107	4407.059	1.00	.324	-4486.575	13288.789	
Mean dependent var		1024.922	SD dependent var			1675.128	
R-squared		0.510	Number of obs			51	
F-test		6.398	Prob > F			0.000	

**** p<.01, ** p<.05, * p<.1*

The results from the model indicate that five of the seven explanatory variables were significant at either the .05 or .1 level. State population demonstrated a positive linear relationship with renewable energy generation at the .05 level of significance. As state population increases by one unit, renewable energy generation increases by .09 thousand megawatt hours. In addition to state population, the number of renewable energy incentives demonstrated a positive linear relationship with renewable energy generation at the .05 level of significance with a coefficient of 19.412. This result suggests that renewable energy generation increases by roughly 19.5 thousand megawatt hours with each additional renewable energy incentive. Among all explanatory variables, average peak sun hours was the only variable that demonstrated a positive linear relationship with renewable energy generation at the .10 level of significance rather than at the 0.05 level. As average peak sun hours increase by one unit, the amount of renewable energy generation increases by 502.851 thousand megawatt hours. While state population, renewable energy incentives, and average peak sun hours had positive relationships with renewable energy generation, two variables, protected area and registered democrat, had negative linear relationships. State protected land had a negative linear relationship with renewable energy generation at the 0.05 level of significance with a coefficient of -24.271. This result suggests that as protected land increases by one acre, renewable energy generation decreases by an average of 24.271 thousand megawatt hours. Additionally, the number of registered democrats had a negative linear relationship with renewable energy generation at the 0.05 level of significance with a coefficient of -8.811. This suggests that as the percentage of registered Democrats increases by one percent, renewable energy generation decreases by an average of 8.811 thousand megawatt hours. When looked at collectively, these results suggest that state population, renewable energy incentives, and average peak sun hours increase renewable energy generation, while state-protected land and the percentage of registered Democrats decrease renewable energy generation.

A second model was tested that used a binary variable (=1 if the amount of renewable energy generation> sample mean; otherwise = 0) as the dependent variable (Eqn. (3.2)). Upon being implemented, the logit model below had a Wald Test distributed chi-squared with 7 degrees of freedom of 20.204. The probability of getting a chi-squared score greater than this 20.204 is 0.005. This means that the model is an appropriate fit for the data. Table 4.2 displays the effects of each explanatory variable on states' likelihood of generating greater than the sample's mean amount of renewable energy generation.

Table 4.2

Renewable Energy Generation: Logit Regression

NGMean	Dy/dx	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
NoCollege	.0144	16.597	0.53	.593	-23.657	41.403	
StatePop	5.65e-0	0	0.35	.725	0	0	
PovertyRate	-.0496	27.491	-1.11	.266	-84.493	23.271	
ProtectedLand	-.0098	2.781	-2.18	.029	-11.514	-.614	**
PeakSun	0.239	.664	2.22	.026	.173	2.774	**
RegisteredDem	-.0213	9.067	-1.45	.147	-30.91	4.633	
REIncentives	0.008	.025	1.95	.052	0	.096	*

Mean dependent var	0.294	SD dependent var	0.460
Pseudo r-squared	0.327	Number of obs	51
Chi-square	20.204	Prob > chi2	0.005
% Correctly Predicted	82.35	Link Test	Significant

**** p<.01, ** p<.05, * p<.1*

In addition to the high chi-squared value, this model correctly predicted 82% of renewable energy generation cases for all 50 states and the District of Columbia. The Pseudo r-squared value was 0.327, which suggests that the model is a good fit for the data. A link test was conducted after the logit regression, and both the predicted value and predicted value squared were significant. This means that misspecification was present, which makes sense considering many other variables are likely statistically significant predictors for renewable energy generation.

Among all explanatory variables, peak sun hours had the greatest effect on states' likelihood to generate renewable energy greater than the mean and was significant at the .05 level. An increase of one hour in the number of peak sun hours would increase the likelihood of generating renewable energy greater than the mean by 23.9%. Additionally, states' amount of land protected was a significant predictor of generation greater than the mean at the .05 level of significance. An increase in the amount of protected land decreases the likelihood of generating renewable energy greater than the mean by .98%. Among all predictor variables, RE incentives had the smallest linear effect on the likelihood of generating renewable energy greater than the mean and was significant at the .10 level. As RE incentives increase by one incentive the probability of generating renewable energy greater than the mean increases by .80%. These results suggest that increasing peak sun hours and the amount of renewable energy incentives are the best ways for states to produce an increased amount of renewable energy. Additionally, they suggest that having less protected land leads to an increased amount of renewable energy generation.

To further understand states' willingness to participate in the energy transition, two additional models were employed that used per capita electric vehicle registrations as the dependent variable. The results of the linear regression model using per capita electric vehicle registrations as the dependent variable (Eqn (3.3)) are listed in table 4.3. The model has a strong R-squared score of .748, indicating that 75% of the variation in the dependent variable is explained by variation in the independent variables included in the regression. Mean per capital electric vehicle registrations across all states, and one district totaling 51 observations was .003 electric vehicles. The high F-test value of 13.534 allows us to reject the null hypothesis that all coefficients on the independent variables are equal to 0 with 99.99% confidence.

Table 4.3

Per Capita Electric Vehicle Registrations: Linear Regression

EVPerCap	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
NoCollege	.003	.006	0.42	.674	-.01	.015	
StatePop	1.47e-07	0	3.27	.002	0	0	***
PovertyRate	-.028	.012	-2.37	.022	-.052	-.004	**
ProtectedLand	.006	.001	4.82	0	.004	.009	***
PeakSun	.001	0	1.82	.076	0	.001	*
RegisteredDem	.025	.006	4.28	0	.013	.037	***
REIncentives	-4.51e-06	0	-0.39	.701	0	0	
NORPS	-.001	.001	-0.92	.364	-.002	.001	
RPStandards	-.001	.001	-1.71	.095	-.003	0	*
Constant	-.01	.005	-1.79	.081	-.021	.001	*

Mean dependent var	0.003	SD dependent var	0.003
R-squared	0.748	Number of obs	51
F-test	13.534	Prob > F	0.000

*** *p<.01*, ** *p<.05*, * *p<.1*

The linear regression model results indicate that six of the nine explanatory variables are statistically significant. Like the model examining renewable energy generation, state population demonstrated a positive linear relationship with per capita electric vehicle registrations at the .01 level of significance. In addition to state population, the amount of protected land had a positive linear relationship with per capita electric vehicle registrations at the .01 level of significance with a coefficient of .006. This result suggests that per capita electric vehicle registrations increase by .006 as the amount of protected land increases by one percent. The independent variable registered Democrats was the final variable that demonstrated a positive linear relationship with per capita electric vehicle registrations at the .01 level of significance. As the percentage of registered Democrats increases, per capita electric vehicle registrations increase by .025. The last variable that demonstrated a positive linear relationship with per capita electric vehicle registrations was average peak sun hours, however, this was only significant at the .10 level. As average peak sun hours increase by one unit, per capita electric vehicle registrations increase by an average of .001. Two variables, poverty rate and renewable portfolio standards, exhibited negative linear relationships with per capita electric vehicle registrations. Poverty rate was statistically significant at the .05 level with a coefficient of -.028 suggesting that as a state's poverty rate increases by one unit, the amount of per capita electric vehicle registrations decrease by an average of .028. Lastly, renewable portfolio standards displayed negative linear statistical significance at the .10 level with a coefficient of -.001. These results suggest that increasing state population, the amount of protected land, average peak sun hours, and the percentage of registered Democrats will increase the amount of per capita electric vehicle registrations. Additionally, they suggest that an increase in states' poverty rate and having renewable portfolio standards decrease per capita electric vehicle registrations.

Once again, a second model was tested that used a binary variable (=1 if the amount of per capita electric vehicle registrations > sample mean; otherwise = 0) as the dependent variable. The logit model results shown in Table 4.4 had a Wald Test distributed chi-squared with 7 degrees of freedom of 42.154. The probability of getting a chi-squared score greater than 42.154 is 0.000. This means that the model is an appropriate fit for the data. Table 4.4 displays the effects of each explanatory variable on a state's likelihood to generate greater than the mean amount of per capita electric vehicle registrations.

Table 4.4

Per Capita Electric Vehicle Registrations: Logit Regression

EVPerCapMean	Dy/dx.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
StatePop	0.000	0	1.54	.125	0	.001	
PovertyRate	-.0412	30.33	-1.81	.07	-114.306	4.586	*
ProtectedLand	.0130	7.512	2.30	.021	2.582	32.028	**
RegisteredDem	.0405	23.202	2.32	.02	8.458	99.409	**
REIncentives	-0.003	.037	-1.17	.244	-.114	.029	
NORPS	-0.155	4.496	-0.69	.49	-11.914	5.711	
RPStandards	-0.360	4.614	-0.70	.487	-12.251	5.837	
Mean dependent var		0.314	SD dependent var			0.469	
Pseudo r-squared		0.664	Number of obs			51	
Chi-square		42.154	Prob > chi2			0.000	
% Correctly Predicted		90.20%	Link Test			Not Significant	

**** p<.01, ** p<.05, * p<.1*

In addition to the high chi-squared value, this model correctly predicted the dependent variable values for 90% of the observations. The Pseudo r-squared value was 0.664, which suggests that variation in the independent variables explain 66% of the variation in the model's dependent variable. A link test was conducted after the logit regression and both the predicted value and predicted value squared were not significant. This means that misspecification was not present.

Among all explanatory variables, poverty rate had the greatest effect (largest estimated marginal effect) on states' likelihood to generate greater than the mean amount of per capita electric vehicle registrations and was significant at the .10 level. An increase in poverty rate by 1% would decrease the likelihood of having greater than the mean amount of per capita electric vehicle registrations by 4.12%. Two explanatory variables, registered Democrat and the amount of protected land, were significant linear predictors of having electric vehicle registrations greater than the state's mean at the .05 level of significance. An increase in the amount of protected land by 1% increases the likelihood of having greater than the mean amount of per capita electric vehicle registrations by 1.3%, while an increase in the number of registered democrats by 1% increases the likelihood of having greater than the mean amount of per capita electric vehicle registrations by 4.05%. These results suggest that increasing the amount of protected land and the number of registered Democrats increases electric vehicle registrations. Additionally, the results suggest that having a lower poverty rate leads to an increased amount of electric vehicle registrations.

Discussion and Conclusions

First, I will summarize the results and findings from the models that used renewable energy generation as the dependent variable. In the linear regression model, state population, renewable energy incentives, and average peak sun hours were statistically significant and increased renewable energy generation. These results directly support the hypotheses.

The linear regression model demonstrated that renewable energy incentives aimed at climate change mitigation and converting to sources of clean energy increase renewable energy generation by an average of 19.5 thousand megawatt hours. The results from the logit model coincided with the linear regression model and showed that a one-unit increase in renewable energy incentives increases the likelihood of generating renewable energy greater than all states' mean by .80%. These results support the original hypothesis and previous literature. They suggest that the number of renewable energy incentives does matter for states that are trying to increase their renewable energy production.

The model also demonstrated that an increase in state population increases renewable energy generation by an average of .09 thousand megawatt hours. This suggests that state size plays a significant role in the ability to generate renewable energy from all sources excluding hydroelectricity.

The variable average peak sun hours was statistically significant in both models. In the linear regression model, an increase in average peak sun hours increased state renewable energy generation by 502.851 thousand megawatt hours per one-hour increase. In the logit model, an increase in average peak sun hours caused the likelihood of generating renewable energy greater than all states' mean to increase by 23.9%. This marginal effect is the largest produced in the entire logit model. These results directly support the hypothesis that states with greater amounts of sunshine will likely have increased amounts of renewable energy generation. Although states cannot directly control the amount of peak sunshine hours they receive, it is encouraging to see that states with more sunshine are using the natural resource appropriately to produce more significant amounts of solar energy.

The linear regression model found that an increase in the percentage of protected land in acres subsequently decreased renewable energy generation by 24.27 thousand megawatt hours. The results from the logit model for renewable energy production further supports these results. The logit model found that an increase in the amount of state-protected land would subsequently decrease the likelihood of generating renewable energy greater than all states' mean by .98%. This result directly supports the hypothesis that states with a greater amount of protected land have less renewable energy generation. This is likely due to a lack of available land for new generation projects and transmission projects to be constructed.

The most surprising result of the linear regression for renewable energy generation came from the variable registered Democrats, as the model found, with statistical significance, that an increase in the percentage of registered Democrats would decrease renewable energy generation by 8.811 thousand megawatt hours. This result refutes the hypothesis that Democratic leaning states would have greater renewable energy production and suggests that an increased amount of Republican voting share could result in increased generation. While prior literature and studies have demonstrated mixed results with Republican and Democratic leaning states, existing political beliefs and ideologies imply that blue states favor renewable energy production over red states. One potential reason for this negative relationship is because of the state of Texas (see Figure 3.1). Texas is a Republican state and produces 10337 thousand megawatts of renewable energy, the most out of any state. If Texas were not included in the model, the Democratic relationship could no longer be negative, or have a smaller negative coefficient.

The variables included to measure educational attainment and state wealth and/or poverty were insignificant in this model. For this reason, the hypothesis that increased wealth and educational attainment increase renewable energy generation is not supported, at least by the data employed here.

The last two models used per capita electric vehicle registrations as the dependent variable and offered supporting and different results for states' ability to participate and excel in the energy transition. In the linear regression model, the state population demonstrated a significant positive relationship with the number of per capita electric vehicle registrations. While the coefficient was extremely small, this result logically makes sense considering states with more people will likely have more people interested in owning and operating electric vehicles.

In both the linear regression model and the logit model, poverty rates were a statistically significant variable. For the linear regression model, poverty rate negatively affected per capita electric vehicle registrations by an average of .028. For the logit model, an increase in poverty rate decreased the likelihood of having greater than the mean amount of per capita electric vehicle registrations by 4.12%. Both results directly support the hypothesis that an increased amount of state wealth leads to an increased amount of electric vehicle registrations per capita. States with lower poverty rates possess populations that have more disposable incomes and can likely afford the initial increased expenses associated with purchasing new electric vehicles. Increased government incentives and tax credits for electric vehicles can help limit these costs, however, in both per capita electric vehicle regressions, renewable energy incentives were insignificant.

Similarly, in both the linear regression and logit models, the amount of protected land was statistically significant. In the regression model, an increase in the amount of protected land by 1% positively increased per capita electric vehicle registrations by an average of .006 cars per capita. In the logit model, an increase in state-protected land increased the likelihood for states to have greater than the mean amount of per capita electric vehicle registrations by 1.3%. These results refute the original hypothesis and suggest that states with higher amounts of protected land have higher electric vehicle usage. One potential reason for this is that states with greater amounts of protected land could generally possess populations that care more for their environment and natural resources than states with less protected land. For this reason, those populations could be more inclined to switch to electric vehicles to release less greenhouse gas emissions and preserve their natural environments.

The final variable that exhibited statistically significant results in both models was the percentage of registered Democrats. In both models, the percentage of registered Democrats increased per capita electric vehicle registrations. The linear regression model demonstrated an average increase of .025 cars per capita, while the logit model increased the likelihood for states to have greater than the mean amount of electric vehicle registrations by 4.05%. Unlike the results exhibited in the models using renewable energy generation as the dependent variable, these models do support the hypothesis that states with increased percentages of registered Democrats are more likely to take part in the energy transition and electric vehicle adoption.

The last variables worth discussing are average peak sun hours and renewable portfolio standards, as both were statistically significant in the linear regression model. The coefficients for both variables were extremely small, at .001, however, average peak sun hours was positively correlated with per capita electric vehicle registrations, while renewable portfolio standards were negatively correlated. The result for average peak sun hours does support the original hypothesis; however it is not likely that the amount of sunshine hours actually increases electric vehicle registrations. The previous models demonstrated that an increased amount of sunshine increases the amount of renewable energy produced in any given state, so it could be the case that states with greater amounts of renewable energy are more favorable to electric vehicle adoption due to communities who support the energy transition, although additional research would need to be done to determine if this is true. The result for renewable portfolio standards does not support the hypothesis that states with renewable portfolio standards have greater amounts of electric vehicle registrations, however, the coefficient is extremely small and the t-value does not indicate statistical significance, suggesting that renewable portfolio standards don't make much of a difference.

Limitations. The major limitations of this study come from a limited sample size and a limited amount of explanatory variables. One of the logistic models had a significant link test, which means that omitted variable bias is present. More specifically, this indicates a high probability of finding another statistically significant explanatory variable outside of your model. One particular variable that was left out of the model was a variable regarding attitudes about environmentalism, renewable energy and electric vehicles in general. States with populations who are very pro-environment likely have increased amounts of renewable energy generation and electric vehicle registrations. Future studies should consider this behavioral variable and utilize the advantages of collecting personal-level surveys and data from different political communities across the United States to test these potential relationships.

Another primary limitation of this study is that it possessed limited observations. Having only 50 states and one district in the United States meant that the models would be limited to only 51 observations. A limited sample size can limit the amount of statistically significant variables as well as the number of explanatory variables tested. For this reason, the models could not include every possible variable that affects renewable energy generation and electric vehicle registrations.

The final limitation of this study is that there was a time constraint. Multiple additional models and data would likely need to be produced in order to fully understand the predictors and variables that increase renewable energy generation and electric vehicle registration.

Implications. Although this study does possess limitations, the results do offer practical implications for states and policy makers across the United States. Renewable energy generation and electric vehicle adoption are two of the largest ways our nation can work toward reducing our carbon footprint and keeping global warming below the 2-degree Celsius benchmark, so it is crucial to know what factors benefit or hinder the broader energy transition. The first major takeaway from these results is that political standing does not necessarily hinder or benefit renewable energy generation and electric vehicle adoption. Results for the variable registered Democrats varied based on the dependent variable, suggesting that the energy transition is applicable in both Republican and Democratic leaning states. Voting share is likely a less significant predictor than other potential political variables like the ability to get new legislation passed and general attitudes about environmentalism, conservation, and renewable energy.

The second major takeaway from these results is that geographical variables, the amount of protected land and sunshine, play a large part in a state's ability to generate renewable energy. While this may seem obvious, it is important to specify that certain states are automatically more favorable to renewable energy generation than others. As a nation, we cannot expect states with a limited amount of sunshine to generate equal amounts of renewable energy as states with increased amounts of sunshine until battery energy storage technology becomes more widely available and accepted as a means to store and transmit clean sources of energy.

A third and final implication of this study is that renewable energy incentives do matter when trying to increase renewable energy generation. Policymakers, governors, and other elected officials across the United States should advocate for more renewable energy incentives and tax credits to increase total generation and the speed at which generation can occur. Without making renewable energy favorable from a monetary perspective, engineering procurement and construction companies, banking firms, and governments, in general, will likely not fully immerse themselves in the transition and will continue to hold on to old-gen fossil fuel assets. As a nation, we can no longer partially commit to renewable energy. Providing states and their respective populations with necessary and favorable incentives will help the United States collectively see increased amounts of renewable energy generation.

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