2017

Assessing Renewable Energy Policy Effectiveness: Price & Quality Instruments

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Spring 5-12-2017

SESSING RENEWABLE ENERGY POLICY EFFECTIVENESS: PRICE VS. QUANTITY INSTRUMENTS

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College Honors Thesis

May 2017

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Abstract

This study is an empirical assessment of the effectiveness of state renewable energy policies at increasing renewable energy generation. The theory of externalities explains that renewable energy will be under-produced by the market without government intervention, justifying the importance of increased understanding of the effectiveness of various policy instruments. Economic theory suggests that both command and control (CAC) and market-based incentive (MBI) policies can be used to address this market failure and can be equally effective under perfect information and perfect enforcement. In practice, standard setting and enforcement differ, and empirical evidence has shown that the effectiveness of the two types of policies differ. Additionally, it is possible that increased renewable energy generation is not only driven by energy policies, but also by certain economic, demographic, and political factors.

In this study two research questions are investigated: Which policy is more effective in promoting increased renewable energy generation: market-based or command and control policies? And, what other factors affect renewable energy generation in a state? Any and all insights gained through the investigation of these two questions will contribute to answering the overarching question asked by economists, environmentalists, political scientists, and ultimately policymakers of which types of policies can most effectively be used to promote renewable energy generation?

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Introduction

This study is an application of environmental economic theory and econometric methods to the environmental issues associated with the underproduction of renewable energy. In 2015, 35% of CO_2 emissions released into the atmosphere in the U.S. were a consequence of the burning of fossil fuels in the electricity generation industry (U.S. EPA 2017). Replacing electricity generated from fossil fuels with electricity generated from renewable sources would address this environmental problem. However, because renewable energy is a good with positive externalities it is being under produced in the market. Currently, only about 8% of electricity generated in the US comes from non-hydro renewable sources, while over 66% comes from polluting fossil fuels ("EIA's Energy in Brief: How Much U.S. Electricity Is Generated from Renewable Energy?" 2016). Because the root cause of this environmental problem is a market failure in the renewable energy industry caused by a positive externality, environmental economic theories and methods can be used to correct this market failure and, consequently, the environmental issue. Specifically, environmental economic theory can be used to model how government intervention, in the form of renewable energy policies, can provide a number of possible solutions to this problem.

This study aims to evaluate the effectiveness of various state energy policies at increasing renewable energy generation. Specifically, the effectiveness of price and quantity instruments, both suggested by environmental economic theory to be viable policy solutions, will be explored. The quantity instrument, or command and control policy, analyzed in this study is a Renewable Portfolio Standard, hereafter referred to as an RPS policy. These common state-level policies "require utilities to use or procure renewable energy or renewable energy credits to account for a certain percentage of their retail electricity sales or a certain amount of generating capacity" typically by a goal year (DSIRE, 2017). RPS policies are currently in place in 37 states; Table 1 provides information on the existing RPS policies, their implementation dates, their renewable energy goals, and their goal year.

To evaluate the effectiveness of price or market based instruments, this study uses a theoretical tax on fossil fuels. It is through prices that taxes (e.g., a carbon tax based on carbon content of fossil fuels) operate and influence firm behavior. This tax is theoretical because, unlike RPS policies, no such input tax exists in the United States. This unique approach uses fossil fuel prices as proxies to measure MBI effectiveness instead of using data from existing MBI policies because of their heterogeneous natures. The specific methodology used to evaluate policy solutions will be explained in depth later in the paper. However, it is important to note that the approaches used for the two different policies are distinct in one key regard. The CAC policy analysis in this study employs real policy data and can be used to conclude whether current policies are effective. Conversely, the analysis of the effectiveness of MBI policies is theoretical, and can inform only whether this type of policy would be effective if implemented. Finally, to isolate the effects of energy policies, the appropriate econometric methods are used to analyze renewable energy policies while controlling for several other factors that could lead to the differing percentages of renewable energy between states.

The findings of this study will add to the ever-growing body of literature evaluating state-level renewable energy policy effectiveness. While the empirical methods utilized are an extension of previous works, this study is unique in three significant regards. First, this paper will evaluate the current policies using the most up-to-date data available, whereas much of the existing literature was published four to eight years ago. This gap is significant because renewable energy policies have been adopted at a rapid rate; over 800 policies have been added to the DSIRE database since 2011. At the same time, the market for renewable energy is evolving rapidly. Second, in addition to including all the recent policies in the data set, this study also includes a unique set of control variables and estimation methods found to be significant in previous literature. These two elements, as well as an in-depth discussion and comparison of the results with hypotheses based in environmental economic theory, distinguish this paper from the existing literature.

Improving the understanding of renewable energy policies is critical to the design of effective policies that attain their intended goals. Without effective policies, renewable energy will continue to be under-produced in the U.S. electricity market. an outcome with catastrophic costs for both the environment and society. The benefits of renewable energy generation range from climate change mitigation to a more secure energy future. Impressive benefits such as these further increase the need for effective policies.

The goal of this study is to facilitate a deeper understanding of policy effectiveness by answering the following two research questions. Which policies emerge as more effective in promoting increased renewable energy generation: market-based (MBI) or command and control (CAC) policies? And, what other factors affect renewable energy generation in a state? The answers to these two questions will be hypothesized using a theoretical framework and tested empirically using rich data and econometric methods. The results of this study can be leveraged by policymakers to improve and promote effective policies that address the market failure of the underproduction of renewable energy and, ultimately, the environmental problem of CO_2 pollution.

Literature Review

As states continue to implement more energy policies, the body of literature evaluating their effectiveness is growing. Past empirical studies have evaluated the effectiveness of different types of policies, as well as the impact of non-policy factors on renewable energy. This study is most similar to the work of Shrimali and Kniefel (2011) who conclude that renewable capacity penetration is "driven by policy" using panel data from 1991 to 2007. This study applies similar methods to more recent energy policy data, but also considers the contributions of many other authors.

This study also aims to clarify the inconsistent results regarding policy effectiveness present in the literature to date. Carley (2009), for example, finds that RPS implementation is not a significant predictor of the percentage of renewable energy generation, while Yin and Powers (2010) conclude that RPS policies have a positive and significant effect on renewable energy. Finally, past work was leveraged to compile a thorough list of exogenous and non-policy factors to also consider in the model. Namely, Delmas and Montes-Sancho (2010) find all the non-policy factors they analyze to be positively and significantly related to renewable energy. The methodology used in the literature combines policy and control variables using panel data and then analyzes the data using a fixed-effects model (Shrimali and Kniefel 2011; Zhao, Tang, and Wang 2013). However, overall, the results in the literature regarding both the effectiveness of CAC and MBI policies as well as important non-policy factors are largely inconsistent, leaving many opportunities for further research.

First, Shrimali and Kniefel (2011) use a fixed-effects model with state-specific time-trends, including policy and non-policy explanatory variables. They model the "Nameplate Capacity," also referred to as "deployment" or "capacity of the different sources of Renewable energy" in a given state. A unique element of their work is that they use more than one dependent variable to measure the effects of policies on wind, biomass, geothermal, and solar capacity deployment separately. The policies they analyze in their model include: renewable portfolio standards (RPS), state government green power purchasing requirements, green power options, and clean energy funds (CEF). They predict that all policies will have a positive correlation with renewable energy deployment. The economic and political variables included are found to be “generally insignificant,” leading to the paper’s principle finding that “renewable capacity penetration is, to a large extent, driven by policy” (Shrimali and Kniefel 2011). They find that RPS are significant for each source, but negative for total energy. These surprising results are also found and explained further in other papers (Carley 2009; Yin and Powers 2010). They find CEFs to be positively significant, a result differing from previous works that find similar financing insignificant (Yin and Powers 2010; Menz and Vachon 2006). Green power options were found to be robustly significant, demonstrating the power of customer pull (Shrimali and Kniefel 2011). State government green power purchasing was also found insignificant, a result that is not yet fully understood.

There is also literature that evaluates just one policy’s effectiveness. Many articles are focused solely on RPS policies; this may be due in part to their puzzling negative and contradictory effects across studies, or their prevalence across states. Carley (2009) evaluates only RPS policies and finds them “not a significant predictor” of the percentage of renewable energy generation (Carley 2009). This is consistent with other findings that RPS are “ineffective” (Shrimali and Kniefel 2011) and that RPS have a “negative effect on investments in renewable capacity” (Delmas and Montes-Sancho 2011). Further studies of RPS by Yin and Powers (2010) including an “RPS stringency” variable to account for heterogeneity among states’ policies, reveal that more stringent RPS policies are positively and significantly correlated to renewable energy deployment. Other papers confirm this positive correlation when including stringency and controlling for other factors (Shrimali et al. 2015).

In the background of most of these studies are discussions of the significance and role of non-policy variables on renewable energy. Some papers find them insignificant (Shrimali and Kniefel 2011), while other papers find them significant (Delmas and Montes-Sancho 2011) at predicting renewable energy generation. In many papers, economic, political, and demographic variables are used only as controls in the model (Carley 2009; Shrimali and Kniefel 2011; Yin and Powers 2010). However, the study by Delmas and Montes-Sancho (2011) is unique in that it looks at only two policies in a state, allowing them to put a larger focus on the "natural, social, and policy context" under which policies are adopted. In doing this, Delmas and Montes-Sancho (2011) find resource endowment, democratic governance, and renewable association, all non-policy factors, to be positively and significantly related to renewable energy deployment. Delmas and Montes-Sancho (2011) also evaluate how economic factors like income per capita and unemployment affect policy implementation.

In addition to econometric models, other types of studies provide valuable insights that inform this study. For example, a synthesis article written by Krey and Clarke (2011) uses different scenarios to model the role of renewable energy in climate change mitigation. They investigate what future levels of renewable energy deployment are consistent with different CO_2 concentration goals. They conclude that "we should be planning for futures with substantially more… renewable energy than we have today" (Krey and Clarke 2011). This article and other similar works support the idea that renewable energy is a good with quantifiable external benefits that will not be produced at the socially optimal quantity without effective policy intervention.

Finally, theory also provides important frameworks for evaluating policy effectiveness. Environmental economic theory, as explained in environmental economic textbooks, provides the foundation for this study (Callan and Thomas 2013; Field and Field 2013). Theory will be utilized in this paper to make hypotheses, analyze the significance of the findings, and draw meaningful conclusions about how policy outcomes differ in theory and in practice. Overall, even a brief summary of the relevant past literature reveals many nuances in the methods and focuses of the previous works. The lack of consistent results prompt further research on this topic.

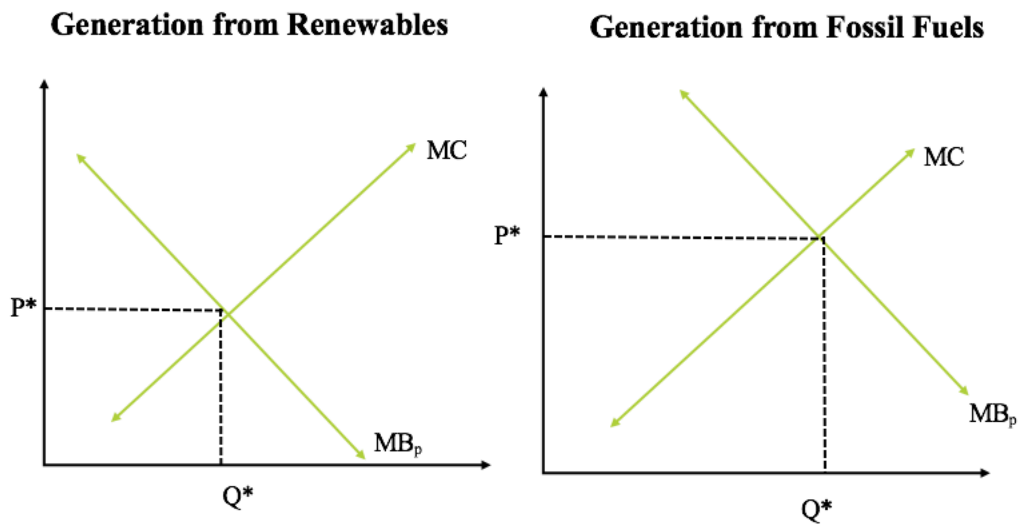
Theoretical Framework

Before any econometric analysis was conducted, a theoretical framework was constructed. This framework facilitates a better understanding of the electricity market, the environmental problem being addressed, and potential policy solutions. These models are constructed under the assumptions of perfect information and enforcement because they allow the models to represent the "socially optimal" level of renewable energy, even though this quantity is not known.

First, to construct a market model for the electricity market, a few additional simplifying assumptions were made. It is assumed that electricity can be generated from only two sources: fossil fuels sources and renewable sources. It is also assumed that electrical energy generated from renewable sources is a perfect substitute for electricity generated from fossil fuels. Lastly, it is assumed the amount of electricity generation remains constant and is equal to fossil fuel generation plus renewable energy generation, i.e., an increase in one source results in an equivalent decrease in the other. After these assumptions are made, the graphs seen in Figure 1 can be used to model the electricity industry.

The graphs shown in Figure 1 are representative of market graphs commonly used in environmental economics. Instead of supply and demand, they use MB and MC curves, but they represent the same underlying market relationships. The *x*-axis and *y*-axis represent the quantity and price of the good being modeled, respectively. In these graphs, the MC, or marginal cost curve represents the supply relationship, in which quantity supplied increases as price increases. The MB, or marginal benefit curve represents the demand relationship, wherein the quantity demanded is negatively related to price. The private market equilibrium is the point at which the two curves intersect, indicated by Q* and P*(Field and Field 2013).

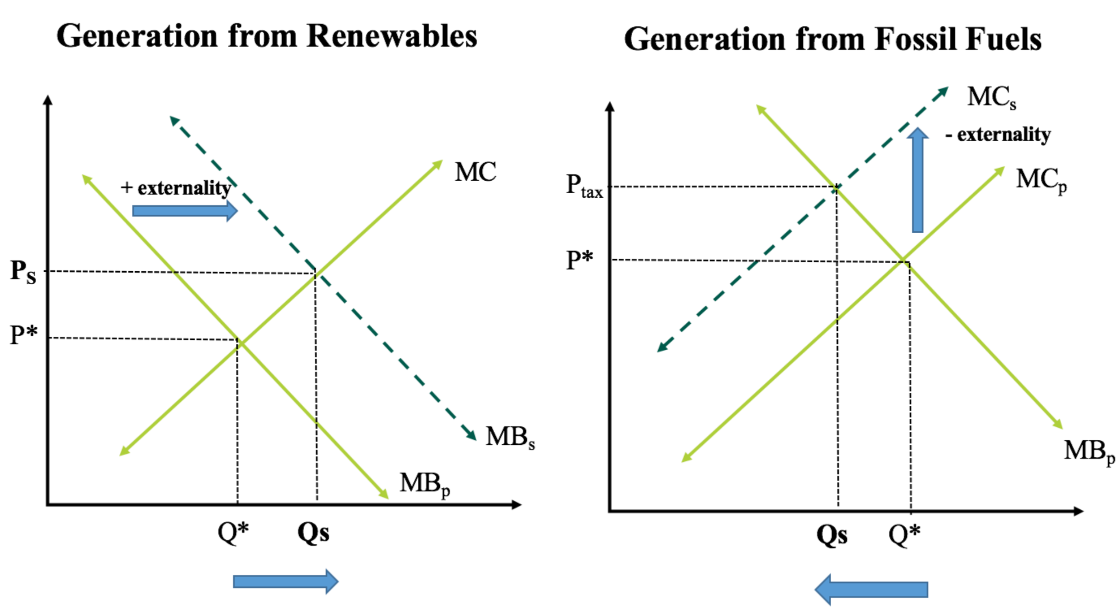
Figure 1



Now that a base model has been created, the environmental problem can be modeled using this framework. To do this, renewable energy is defined as a good with positive externalities. It can be classified this way because when electricity is generated from renewable sources, the negative environmental impacts of fossil fuel generation (greenhouse gases, namely CO_2) are forgone, which is a positive externality or "environmental benefit." The theory of externalities explains that a good with positive externalities will be under produced by the market (Field and Field 2013). This relationship can be seen in Figure 2.

In this figure, the external benefit is represented as a shift in the private MB curve (MB_p) to the social MB curve (MB_s) in the amount of the positive externality. The new socially optimal quantity is indicated by Qs. For renewable energy, it is less than the private quantity indicated by Q*. This shows that renewable energy is under-produced. The opposite scenario is modeled for fossil fuel generation, which is a good with a negative externality. This negative externality represents the environmental costs associated with the pollution that results from the burning of fossil fuels. This associated cost is represented as an upward shift in the MC curve from the private (MC_p) to the to the social MC curve (MC_s). Fossil fuels are overproduced (Q* < Qs) because the external costs are not captured in their price.

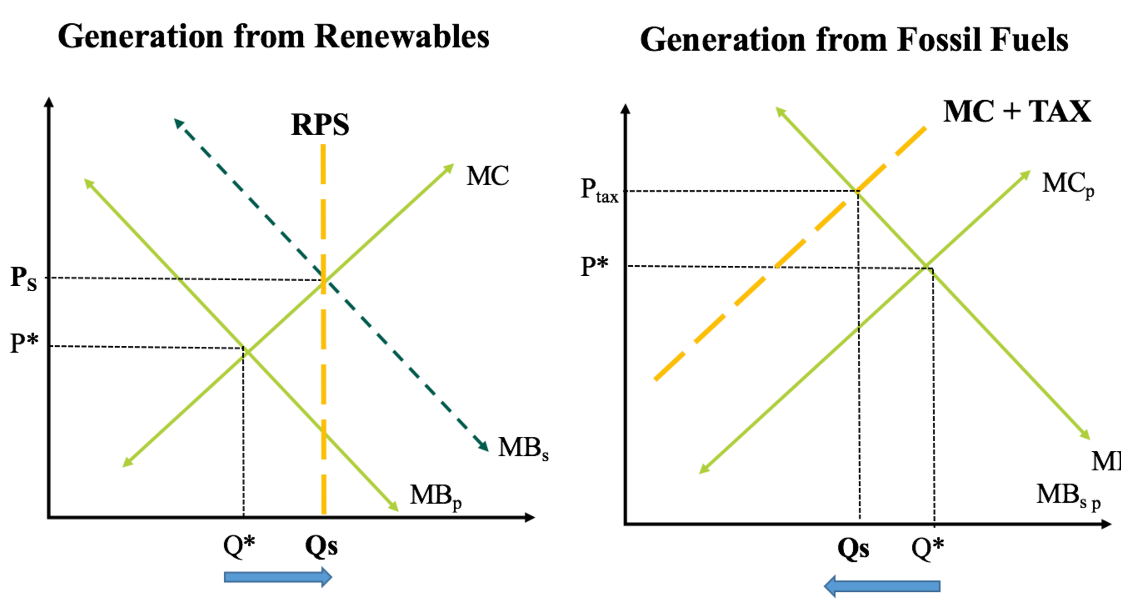
Figure 2



This framework helps to explain how policies can be used as a tool to correct market failures, thus increasing the quantity of renewable energy generation. Environmental policies are typically grouped into two main categories: quantity and price instruments. In this study, one of each is evaluated. Theoretical frameworks exist to explain how these two groups of policies can achieve their desired goals and, in the context of this study, increase renewable energy generation.

The category of quantity instruments can also be defined as command and control (CAC) or regulatory policies that mandate and enforce levels of desired behaviors. The example of a CAC policy evaluated in this study is a Renewable Portfolio Standard. RPS policies require a specific quantity or percentage of energy to be generated from renewable energy sources. Under perfect information, an RPS will be set at the optimal level of renewable electricity, thereby increasing renewable energy generation. If there is perfect enforcement, this quantity regulation can be depicted as a vertical line that intersects the social MB curve at the socially optimal level of Q*. While it is nearly impossible to know what the socially optimal level is without having perfect information, the goal of this study is simply to test if RPS policies, in fact, increase renewable energy from the market equilibrium towards this socially optimal level (Callan and Thomas 2013). RPS policies apply to the market for renewable energy generation and are shown in the graph on the left side of Figure 3.

Figure 3



The category of price instruments can also be called market based incentives (MBI) or financial incentives, wherein regulators influence prices, but firms make their own decisions about the quantity of energy to produce in light of market conditions. The example of this type of policy evaluated in this study is a theoretical input tax on fossil fuels. This tax would be applied in the market for fossil fuel-generated electricity because this is the good with the negative externality that policymakers seek to decrease. Graphically, the tax can be represented as an upward shift in the MC curve of fossil fuels by the tax amount that would result in a higher price of fossil fuels. The law of demand explains that if the price of a good increases, the quantity demanded should decrease. Therefore, a tax on fossil fuel should result in a reduction in quantity demanded for electricity from these sources. Under perfect information about the extent of the negative externality, the tax can be set such that the price increase will result in the socially optimal level of fossil fuels. Assuming the demand for all electricity remains the same, the decrease in generation from fossil fuels is translated to an increase in demand (MB) from renewable energy, via the substitution effect (Callan and Thomas 2013). This tax is applied in the market for fossil fuel generation, but the quantity increase can be seen in the market for renewable energy generation. This is shown in the graphs in Figure 3. Again, this study will not base policy effectiveness on the attainment of a specific socially optimal level, but rather on whether the policy moves the quantity of renewable energy generation in a positive direction.

Overall, these theories are critical to this study because they allow for the development of hypotheses regarding the effect of the policies of interest on the dependent variable. They also serve as a point of comparison for determining if a policy is effective or not, because the theoretical predictions about how a policy should work can be contrasted against what is observed in the data**.** This framework will be referenced throughout the study.

One shortcoming of these models, however, is that they rely on assumptions of perfect information and perfect enforcement, as well as simplifying assumptions about the renewable energy market. These assumptions are not realistic, which is why these models are only helpful in making hypotheses. However, in empirical analysis, additional factors need to be considered when analyzing renewable energy policy effectiveness. The inclusion of political, economic, and demographic variables serve the purpose of capturing these other factors in empirical analysis.

Data and Hypotheses

Data Structure

The empirical analysis in this study utilizes data on the variables listed below, collected for all 50 states from the years 2000 to 2014. Because the data exists and was collected for *n* different entities observed at *T* different time periods, it is called longitudinal or panel data. (Stock and Watson 2011). Data was successfully collected for each state for each year. Therefore, the panel is strongly balanced and there are 700 unique observations (n x T). Together, the 700 observations comprise a "short" panel with a large *n* of 50 states, compared to a relatively short *T* of 14 years (Park 2011).

Variable Definitions and Hypotheses

Below are descriptions of each of the variables used in this study and their hypothesized sign. Tables 1, 2, and 3 provide more detailed information about the variables. Table 2 contains variable definitions, units, transformations, sources and their hypothesized signs. Table 3 contains summary statistics. Table 1 contains details about RPS policies in different states to accompany the RPS policy variable.

<u>Dependent Variable</u>

The dependent variable in this study is denoted as REN. REN is defined as the logged percentage of net electrical energy generated in a state from renewable sources. Specifically, it is calculated by dividing the quantity of electricity generated from renewable sources (wind, solar, biomass and geothermal) in thousand megawatt hours by total net energy generation. This accounts for energy generated in all sectors; electric power (electric utilities and independent power producers), commercial, and industrial. It should be noted that hydropower is excluded because most of the existing capacity was installed between 1930 and 1980. There is less potential for growth in this industry compared to other renewables. Additionally, not all states' RPS policies define hydropower as a "renewable," affecting its eligibility in counting towards RPS goals (Uria-Martinez, O'Connor, and Johnson 2015). The exclusion of hydroelectric is common in the literature (Carley 2009; Shrimali and Kniefel 2011; Delmas and Montes-Sancho 2011).

Net Generation of Renewable Energy is used as the outcome variable because it is believed to be the best indicator of the increase in generation of electricity from renewable sources as a result of energy policies. It is also used as a dependent variable in a study by Carley (2009). Other authors have measured "renewable energy" using "capacity" variables that measure "the amount of capacity the generator produces under ideal conditions" or "the maximum rated output of all units owned per utility" (Delmas and Montes-Sancho 2011; Shrimali and Kniefel 2011). This variable is similar to this study's dependent variable REN in that it indicates if a state has increased renewable energy generation activities *within* that state, instead of attempting to comply with RPS policies by purchasing RECs or energy generated elsewhere. However, capacity is not guaranteed to equal generation. Even if infrastructure is in place in a state, it may not always be utilized to its full capacity, e.g., for cost reasons. This offers a justification for the use of net generation as a better indicator of renewable energy use in the day-to-day electricity market. Increasing renewable energy capacity is in line with policy goals. However, for renewable energy to make a difference in environmental issues, it must be used to replace generation from fossil fuels, which this variable does not capture. Some authors also use just the amount of generation from a given renewable energy source in megawatt hours (Carley 2009). This absolute generation variable is flawed because it may capture generation increases as a result of energy demands as time goes on, and will not indicate if the percent of energy coming from renewable sources has increased states' generation portfolios. This information is critical to achieve environmental goals, and is often specified by renewable energy policies like RPSs. For these reasons, the dependent variable REN, measuring the logged percent of net generation in a state from renewable energy is used.

Independent Variables

Policy Variables

There are three main policy variables included in the base model of this study. They include RPS, coal price, and natural gas price. RPS is the quantity instrument, the CAC variable. It is denoted as a categorical variable that takes on a value of 1 on the year it was adopted by the state in all succeeding years; it is 0 otherwise. In the first year of the study, 2001, nine states had RPS policies. By the end of the study, 37 states in the sample had adopted an RPS, meaning this variable captures 28 policy changes in various years (see Table 1). This variable is hypothesized to have a positive sign based on environmental economic theory and past results. While past results have indicated inconsistent support for the effectiveness of RPS policies, the hypothesis in this study is that they will be effective, because they are a command and control policy that, in theory, will result in increased renewable electricity generation within a given state if adopted, holding all other factors constant.

Coal price and natural gas price are proxies for price instruments, or MBIs. While there are many market-based instruments in practice such as Feed in Tariffs, Public Benefit funds, or other financial incentives, including tax incentives, grants, loans, rebates, and production incentives (Delmas and Montes-Sancho 2011; Menz and Vachon 2006), many of them are specific to one type of renewable (e.g., solar, wind) or are targeted to households and not to generators of electricity. Because current MBI policies are very heterogeneous across states, this study uses a different approach.

In the theoretical framework described earlier in this paper, the market for electricity has been defined as having two main inputs that are perfect substitutes: renewable sources and fossil fuels. Using this logic, environmental economic theory would suggest that an increase in price of either fossil fuel generation input (coal or natural gas) should result, via the substitution effect, in an increase in generation from renewable energy. Thus, coal price and natural gas price are the avenues through which fossil fuel taxes will be felt in the renewable and non-renewable markets.

A similar method of a counterfactual is used in a paper by Jaffe and Stavins, who model how a theoretical electricity tax affects green technology diffusion. The authors of this paper use price of a relevant good, electricity price, as a proxy for an MBI or tax. They interpret the responsiveness of the good in question to the change in a relevant price as the expected effect of a tax on that good (Jaffe and Stavins 1995). This method was employed instead of including a real tax variable in their model because one did not exist in practice. In the electricity market, while other MBI policies are in place, they are very heterogeneous across states and are difficult to model, resulting in inconsistent findings in the literature. In this study, like in the Jaffe and

Stavins (1995) paper, the tax in this study is a theoretical tax. However, it can still be used to gain an understanding of if and how the renewable electricity generation would react to a change in the price of fossil fuel inputs. In this study, the hypotheses being tested through the inclusion of the coal and natural gas price variables are that they are relevant prices in the renewable electricity industry and also that, according to environmental economic theory, a tax (MC increase) on these substitutes should result in an increase in renewable electricity generation. Put simply, we expect these prices to have a positive relationship with REN.

Four additional variables are added in later empirical analyses to further disentangle and explain the effects of these policy variables on renewable energy. They include RPS Experience, Lagged Fossil Fuel generation, Lagged Coal Generation, and Lagged Natural Gas Generation. These variables are included in the later models to allow for an even more in-depth analysis of CAC and MBI policy effectiveness.

The variable RPS Experience is an experience variable that simply takes the value of 1 the first year a state has a policy, then 2 the second, and so on, for all years the state has a policy. It is hypothesized to be positive and represent "learning by doing" or, that states get better at renewable energy the longer they have an RPS policy. The log of this variable is used to show that even though states may get better at renewable energy generation, the marginal return to each year of the policy diminishes as they approach their goal. The fossil fuel generation variables are included in later studies as additional controls for technological constraints facing the states in terms of switching from fossil fuel to renewable energy sources. They allow for testing the hypothesis that the quantity of a substitute used in the past could proxy for technological stickiness and can have a negative relationship with renewable energy. It should also be noted that these generation variables are *lagged* values and are expressed in terms of *absolute* generation or, thousand megawatt hours, while REN is the logged percent of renewable energy to avoid any collinearity problems.

Non-policy Variables

Due to imperfect information and imperfect enforcement, the comparison of CAC and MBI effectiveness also must include controls for other factors that may influence how these policies are designed or implemented. The non-policy variables included in this study can be grouped into three categories: economic, political and demographic. The economic variables include household income, population and electricity price. Their definitions are self-explanatory and they are hypothesized to be positive. The demographic variable Sierra Club Mem is the percentage of a state's population that are members of the Sierra Club. The Sierra Club is the nation's largest and most influential grassroots environmental organization and, therefore, is a proxy for how liberal and environmentally-minded a state's population is. It is hypothesized to be positively related to renewable energy (SCC 2016). Finally, the political variable in this study is LCV Score. The League of Conservation Voters, or LCV, is a political advocacy organization that computes and compiles annual scores based on a scale of 0 to 100 by dividing the number of pro-environment votes cast by the total number of votes scored (LCV 2016). These scores are based on "the most important issues of the year, including energy, global warming, public health, public lands and wildlife conservation, and spending for environmental programs" (LCV 2016). This score serves as a good indicator of how liberal and environmentally minded a state's government officials are and is hypothesized to be positive.

Methodology

All analysis in this study was done using the balanced panel data set described above and the statistical computing package STATA 14. Both time- and entity-fixed effects estimation methods were used to estimate models for analysis in this study. Employing the proper estimation method is especially critical to obtaining accurate unbiased results when dealing with panel data.

The time- and entity-fixed effects methods were chosen only after analyzing and comparing other panel data estimation methods and conducting statistical tests to uncover the nature of the relationships between variables in the unique data used in the study. These methods are also used widely by other authors who have conducted similar analyses on panel data, further validating this approach. Namely, various combinations of entity- and time-fixed effects are used by (Shrimali and Kniefel 2011; Carley 2009; Shrimali et al. 2015) in related studies.

Because selecting the correct estimation method was both critical to obtaining accurate results and informative about the relationships between variables in the data, the first sections of the results section, Results R.1 and R.2, recount and discuss the model selection process. Results R.1 includes the steps used in determining that Fixed Effects is more appropriate than pooled OLS (Ordinary Least Squares) or Random Effects estimation given the data. Results R.2 builds on the Fixed Effects model from the findings in Results Section R.1 and details how and why time Fixed Effects were included in future models.

Entity-Fixed Effects

Entity-Fixed Effects regression (also referred to as “Fixed Effects” or “state-Fixed Effects” in the context of this study) controls for time-invariant unobservable factors that vary across entities (states) over all time periods, (α_i) that may be correlated with the explanatory or independent variables of interest (Stock and Watson 2011). Fixed-effects examines individual differences as intercepts, assuming the same slopes and constant variance across states (Park

2011). Including entity-specific effects as part of the intercept is necessary when they are time-invariant and correlated with the regressors. When entity-effects of this nature are included in the model as part of the intercept rather than ignoring them (pooled OLS) or including them in the error term (Random Effects), the violation of key assumptions is avoided. Fixed effects estimation in this case allows the errors to remain independent and identically distributed with an expected value of zero and the other coefficients in the model to remain free from omitted variable bias (Park 2011).

There are many ways to control for fixed effects using different estimation techniques. This study uses the "within" effect estimation method. The "within" regression estimation technique uses the variation within each group entity from their mean over time, to capture and control for entity effects. This estimation technique yields the same result as the more common least squares dummy variable model (LSDV), wherein entity effects are controlled for by including entity dummies in the model. It was chosen in this study because it is simpler to compute than LSDV and yields the same coefficients without resulting in the loss of degrees of freedom that occurs when a large number of variables are included in the model. This is particularly important when the panel data is short and has a large "n" (number of states) because that means that 49 dummies variables would need to be included in every model.

The only limitation to using the within estimator instead of the LSDV method is that time-invariant variables are dropped from the model. They are not captured in this type of estimation because they have the same value over the entire sample, meaning they do not vary around their mean, $(x_i - \overline{x_i}) = 0$. Fortunately, this is not an issue in this study because this study does not include any strictly time-invariant variables. The only ramification of using the within estimator is that the RPS variable can only be interpreted for states that experience a policy implementation during the years included in the model in the study (28/37 states). This has a minimal impact because most of the states that have an RPS policy, implemented it during the time period analyzed in this study, see Table 1. The within regression estimator is equation is:

$$(y_{it} - y_i) = \beta(x_{it} - x_i) + (\varepsilon_{it} - \varepsilon_i)$$

Using this method to control for entity-effects allows the results to reflect the effect of the independent variables of interest (policy variables) included in the model on the dependent variable (REN) without confounding them with the effects of unobservable factors. In the context of this study the entity-effects we are controlling for are state-effects that are time-invariant unique characteristics of a state that are correlated with the outcome and/or predictor variables. One possible example of a time-invariant state-effect that would bias the model if not included could be state environmental preferences or natural resource endowment. (Carley 2009; Shrimali and Kniefel 2011). For example, if a state has plentiful coal resources this may be correlated with the dependent variable: REN making that state less likely to generate energy from renewable sources; and/or it could be correlated with one or many independent variables in the model, Coal price, for example. While it is impossible to say exactly what these state-effects are because they are unobservable; using the within fixed effects estimator includes them so they do not bias the other coefficients in the model.

Time-Fixed Effects

In a similar manner to how entity-fixed effects estimation controls for entity effects that are time-invariant but differ between entities, the use of time-fixed effects controls for variables that are constant across entities but evolve over time (Stock and Watson 2011). These time effects have the same impact on all states but change over the course of time, and, in the identical way entity effects do, they can bias the model by being correlated with the explanatory and/or independent variables of interest if not controlled for properly. Temporal variation in the dependent variable may be captured by simply including a "time" trend variable in the equation.

One example of a time-varying factor that affects all states equally is federal energy policy. If a federal energy policy, for example, a subsidy, was adopted in the middle of this study, it would represent a change in a time-varying factor that would apply to all states equally. Additionally, it would likely be correlated with the dependent variable REN and/or other independent variables. Technological change is also a good example of a time-varying factor; as time goes on, renewable energy technology improves and becomes more efficient and less expensive, affecting all states equally.

Base model estimation equation (Including both time and entity-fixed effects):

$$REN_{it} = \sum \beta_1 P_{CACit} + \beta_2 P_{MBIit} + \beta \sum Z_{it} + \lambda_t + (\alpha + \alpha_i) + u_{it}$$

REN_{it} - dependent variable: log percent of renewable energy generation
P_{cacit} - independent policy variable of interest: vector of RPS policy variables
P_{mbiit} - independent policy variable of interest: vector of coal and natural gas variables
Z_{it} - control variables: vector of economic, political, and demographic variables
$(\alpha + \alpha_i)$ – state specific intercept: entity-fixed effects
λ_t – time variable: time-fixed effects
i-state index
t -year index

Results

The results section of this paper is divided into three sections, Results R.1, R.2, and R.3. In results section R.1, the process for selecting an appropriate panel data estimation method through the analysis of the cross-sectional dimension of the panel is discussed. The results are in Table 4. The results of that table are discussed in detail below, but they suggest using the fixed-effects model. Table 5 displays only fixed-effects models and explores the role of time-varying factors by analyzing the time series dimension of the panel, described in detail in section R.2. Finally, section R.3 discusses and builds on the correctly-specified model, indicated from the specification tests explored in sections R.1 and R.2. These findings are reported in Table 6. All models in Table 6 properly control for both entity- and time-fixed effects. Therefore, the coefficients of the variables of interest are interpreted in context with the research questions and additional variables are added to further understand the significant finings.

Results R.1

In Table R1, four models explain REN, the log percent of renewable energy generation, as a function of the same independent variables RPS, coal price, natural gas price, population, median HH income, Sierra Club mem, and LCV score, respectively. These variables make up the base model and are the same in all four model specifications. However, the models differ in estimation method. Each of these models was used to gain a better understanding of the relationships in the data. Specifically, they specify what relationship, if any, exists between the unobservable entity or state effects and the independent and dependent variables.

Model 1 is the result of pooled OLS estimation. Pooled OLS estimation ignores the panel structure of the data by simply regressing the independent variables on the dependent variable irrespective of the state and year from which the data was collected. Pooled OLS is estimated using the following equation:

$$REN_{it} = \alpha + \beta_1 X_{it} + ... + \beta K_{xi} + u_{it}$$

OLS regression is an appropriate method to use with panel data only if certain assumptions are met. The standard OLS assumptions are critical to obtaining accurate results (Park 2011; Schmidheiny 2016; Stock and Watson 2011).

The OLS assumptions:

1. *Linearity*: the dependent variable (REN) is a linear function of the vector of independent variables plus a random error term u_{it}.

2. *Exogenous Error*: u_{it} is an idiosyncratic error term with and expected value of zero, $E[u_{it}] = 0$. It is not correlated with the explanatory variables, and most importantly u_{it} is uncorrelated with the individual specific effect. $E[\alpha_i] = 0$.
3. *Error Variance:* the variance of the errors (u_{it})…
    a. are homoscedastic, constant over the sample,
    b. and not auto-correlated , not related with one another.
4. *Independence:* All variables (Y_{it}, X_{it}) are independent and identically distributed (i.i.d); accomplished through random sampling.
5. *No Multicollinearity:* no exact linear relationship exists between independent variables.

These OLS assumptions will be true only if there are no entity-fixed (or time-fixed effects, discussed later) present in the data. If entity-fixed effects are present in the data but not controlled for in the model, they would be captured in the error term, resulting in the violation of assumptions 2 and 3. It is plausible that there would be some entity-fixed effects present in the model, given that the data is from 50 unique states over 14 different years; these state-fixed effects, if ignored, would result in the failure to meet the OLS assumptions. This suspicion can be objectively tested using the Breusch-Pagan Lagrange multiplier (LM) test. The null hypothesis of this test is that entity-specific error variance components are zero ($E[\alpha_i] = 0$), and the alternative is that they are not zero. Pooled OLS is appropriate only if the null hypothesis is true (Breusch and Pagan 1980; Park 2011).

The Breusch-Pagan Lagrange multiplier (LM) test was performed after estimating Model 2 using the Random Effects estimator, and can be found at the bottom of Table 4. The result of this test is a $chibar^2$ statistic of $chibar^2 = 1501.80$ with the corresponding p-value of $p<0.0001$.

The p-value is less than the alpha level of .05, so the null hypothesis is rejected, indicating that there are state-specific fixed-effects present in the data and random effects estimation is more appropriate than pooled OLS (Torres-Reyna 2007).

Once state effects were identified, further analysis was needed to identify the nature of the heteroscedasticity between states present in the data. Specifically, it must be determined whether the unobservable state effects are correlated with the explanatory variables or are not correlated with the explanatory variables. If the state effects are not correlated with the regressors they are considered “random” and can be modeled using a random effects model. When the model is estimated using random effects the individual-specific effects (αi) are random variables that are uncorrelated with the explanatory variables and (αi) state-specific effects become part of the error term $\mathcal{E}_{it} = (\alpha_i + u_{it})$ (Schmidheiny 2016; Park 2011).The random effects equation is:

$$REN_{it} = \beta_1 X_{it} + ... + \beta K_{xi} + \mathcal{E}_{it}, \text{ Where } \mathcal{E}_{it} = (\alpha_i + u_{it})$$

Model 2 shows the results of random effects estimation using the above equation. If the state effects are correlated with the *x*-variables, the random effects method is appropriate. However, if this is not true, fixed-effects estimation should be used. In fixed-effects estimation, the individual-specific effects (α_i) are not random and are correlated with the explanatory variables, instead of being part of the error term. The (α_i) state-specific effects should be included in the model as intercepts ($\alpha + \alpha_i$). Including unique state intercepts in the model is critical to avoiding omitted variable bias, because the α_i captures any leftover variation in the dependent variable that is not captured by the regressors (Xs) (Stock and Watson 2011). The equation used to estimate fixed-effects is:

$$REN_{it} = \beta_1 X_{it} + ... + \beta K_{xi} + (\alpha + \alpha_i) + u_{it}$$

In order to determine whether random or fixed-effects were more appropriate, a Hausman Test can be used. The Hausman test objectively determines whether state effects are correlated with the other variables in the model. The Hausman test accomplishes this by comparing the coefficients produced by both random and fixed-effects estimations of the same model and tests to see if the difference in the coefficients is systematic or random. The null hypothesis is that the difference in coefficients is not systematic, the errors are not correlated with explanatory variables, suggesting that random effects is appropriate. The alternative hypothesis is that the difference in coefficients is systematic, the errors are correlated with explanatory variables and fixed-effects should be used (Schmidheiny 2016; Torres-Reyna 2007; Park 2011).

The Hausman Test is applied to compare Models 2 (Random Effects) and Model 3 (Fixed Effects) and the result displayed at the bottom of Table 4 is a chi^2 statistic, $chi^2 = 83.53$ with the corresponding p-value of $p<0.0001$. The p-value is less than the alpha level of .05, so the null hypothesis is rejected, indicating that fixed-effects is the most appropriate estimator of state-fixed effects present in the panel data (detailed explanation in the methodology section). As a result of this finding, all future models will need to control for state-specific fixed-effects to yield accurate results.

There are a variety of estimation methods that control for entity-specific effects. The most common is the least squares dummy variable model (LSDV) where state dummy variables are included to control for the state-effects. This is problematic for panels with large “n” or number of groups (50 states), which is very large compared to only 14 years. The consequence of including a large number of variables in the model is loss of degrees of freedom, as well as the “incidental parameter problem which causes coefficients of individual effects to be inaccurate while the estimates of regressors are consistent” (Park 2011; Baltagi and Chang 1994). While

LCVD may not be ideal for samples with large "n," it is simple to estimate, and can be found in Appendix A.1 (note: the coefficients on the individual state dummies are likely to be incorrect, but the other coefficients are the same as the coefficients found when using other equivalent fixed-effects estimators). To avoid potential problems associated with the LSDV model, a method called the "within" estimator was employed in this study. This method of estimation of fixed-effects does not required dummies, but instead the variation is measured for each state separately compared to its mean (Park 2011) (see methodology for further details). Model 3 was estimated using the "within" fixed-effects estimator.

Finally, Model 4 is an even more refined version of Model 3. It is estimated using the "within" fixed-effects as well as robust standard errors. The use of cluster-robust standard errors controls for both heteroscedasticity and serial correlation of the error term that is often present when using fixed-effects estimators (Schmidheiny 2016). In order to confirm whether heteroscedasticity was present in the model, a Modified Wald test for group-wise heteroscedasticity was conducted. The null hypothesis of the test is that the error term is homoscedastic (Torres-Reyna 2007). The results of the test are displayed at the bottom of Table 4 and indicate that the null hypothesis should be rejected because the corresponding p-value of the chi^2 test statistic of $chi^2 = 4315.43$, is less than the alpha level of .05. In conclusion, Model 4 emerges as the most appropriate model to control for state-fixed effects as well as heteroscedasticity and will serve as the base model for all further analysis.

Analysis of the individual coefficients themselves will be reserved for when the model is completely specified. While Model 4 controls for state-fixed effects and is robust, this only addresses the "cross-sectional" dimension of our panel, leaving the "time series" dimension to be explored in R.2. The identification of the fixed-effects model as the most appropriate model leads to the conclusion that there are state-effects present in this type of data that effect the dependent variable (REN) or regressors in the model. The importance and policy implications of this finding will be interpreted in the context of the research questions in Results R.3.

Results R.2

Continuing to build on Model 4 from Table 4, Table 5 contains results from the models used to determine how to appropriately control for any time-fixed effects that may be present in the panel data (Model 4 in this table is identical to Model 4 from Table 4, simply reproduced for ease of comparison). In panel data, temporal effects are included in the model to control for variables that are constant across entities but evolve over time. First, in Model 5, a simple linear time-trend variable is included to test if any time-fixed effects are present, given the current base fixed-effects model. The variable is called "Trend," and it takes the value of 1 for the first year, 2 for the second, and so on, for all 14 years in the sample. The estimated coefficient of Trend is positive and significant, and its magnitude shows how much REN increases for every year that passes between 2002 and 2014, all other things held constant. This means that renewable energy generation would have increased over the time period captured in our sample, even if there was no change in the independent variables. Examples of time-varying effects that can apply to all states include exogenous technological change or federal policies. Thus, we need to control for these time effects, so as not to let them confound the effects of other variables on REN.

Using a linear time trend variable is an improvement on the base model, however it may be an oversimplification of the true effect of time on percent renewable energy generation. Including Trend to control for time is limiting, because it imposes that the effect of each year on REN is the same for each year, whereas, in reality, this may not be the case. The time-fixed effect may vary from year to year. In Model 6, this oversimplification is corrected for by including the 12 year dummies separately in the model. It should be noted that the first year in the study, 2001, is not included because it is lost to allow lagged independent variables. The year 2002 is omitted from this model to serve as a point of comparison for the other year dummy variables included in the model, and avoid perfect multicollinearity between the included year dummies. The coefficients on each year dummy variable can be interpreted as the time-fixed effect of that year on percent renewable energy generation.

A closer analysis of the coefficients in Model 6 reveals more information about the nature of the time trends. First, all year dummies that are significant are positive, confirming the positive time trend found in Model 5. But, it is also revealed that, in general, the time variables become positive and significant only in 2010 and subsequent years. This may indicate a break in 2010. As a result of this discovery in Model 7, only year dummy variables from "Period 2," years 2010 to 2014, are included, and the omitted time period is "Period 1," years 2003-2009. The remaining year dummy coefficients can now be interpreted as the change in percent renewable energy generation due to time-fixed effects with respect to the omitted time Period 1.

The inclusion of only the significant time dummy variables to control for the time-fixed effects present in the data was justified by performing a variety of linear hypothesis tests (F-tests) on Models 6 and 7 that confirmed three things:

1. All the year dummies are jointly significant as shown by a joint hypothesis test, and rejecting the null hypothesis that all the year dummies are equal to zero. The results are located in Table 5 below Model 6.
2. Period 1 year dummies are jointly insignificant as shown by a joint hypothesis test, and rejecting the null hypothesis that all the year dummies in Period 1 (2003-2009) are equal to zero. The results are located in Table 5 below Model 6.

3. Period 2 year dummies are jointly significant as shown by a joint hypothesis test, and failing to reject the null hypothesis that all the year dummies in Period 2 (2010-2014) are equal to zero. The results are located in Table 5 below Model 6.

Further, each of the year dummies in Period 2 have significantly different effects on REN and, therefore, should be included in the model separately. This was concluded after testing a number of hypotheses to determine that the Period 2 dummies are not only individually different from the omitted year (2002), but also generally from each other. Results are below Model 7.

In addition to being statistically justified, it is beneficial to the overall significance of the model to remove insignificant years because including extra insignificant variables in the model decreases the degrees of freedom making it harder to isolate the true significance of the independent variables of interest.

The conclusion reached in this result section is that Model 7 is fully and correctly specified and will be the base model for all further analysis in this study. To review, Model 7 employs the correct estimation method, within fixed-effects, to control for state-fixed effects. iIt includes the appropriate year dummies to control for time-fixed effect and it is corrected for cluster robust standard errors, allowing for accurate analysis of the coefficients on the independent variables of interest. Detailed analysis of the coefficients of interest included in the model will occur in the final results section R.3.

Results R.3

This section describes the results found in Table 6. Table 6 contains three new models and two models, Models 4 and 7, that have been previously discussed in the results sections R.1 and R.2, where they were used to determine the most accurate estimation method given the data. In this section, interpretations of the resulting coefficients will be discussed in the context of this study's research questions. The additional models that appear in Table 6 and Models 8, 9 and 10 are extensions that build on Model 7. In these models, additional variables are added to the base model in order to further examine the effectiveness of the command and control and market based policies being evaluated as well as promote a deeper understanding of the important forces at play in the market for renewable energy.

Overall, this empirical analysis yielded many significant results that, when interpreted, can be used to answer the research questions asked by this study. Altogether, the results reveal how the market for renewable electricity responds to a number of policy and non-policy forces. In this section, I will describe how the results above can be used to answer the following research questions: What types of policies emerge as more effective in promoting increased renewable energy generation, market-based or command and control policies? What role do state- and time-specific effects play in influencing how CAC and MBI policies explain REN? And, What non-policy factors affect renewable energy generation in a state?

State-and Time-Specific Effects

To begin, the findings from Models 4 and 7, used initially in determining the underlying patterns in the data, will be discussed as these models both demonstrate how appropriately controlling for state- and time-specific effects influences the magnitude, sign and significance of the coefficients of the CAC and MBI policy variables. Through the exercise of model specification, two important exogenous factors were identified, and each will be discussed in turn.

First, it is confirmed that state-level characteristics lead to differences in renewable electricity generation in between states. Model 4 is a fixed-effects model, which, after a series of tests, was selected over random effects and pooled OLS models. In the context of the study, finding fixed-effects present in the data indicates the importance of the contribution of unique state characteristics to determining a state's renewable electricity generation. These state-fixed effects affect renewable electricity generation in each state differently, whereas other variables have similar effects across states. This is not a surprising finding and confirms preconceived notions that U.S. states are different, and therefore might generate different levels of renewable electricity. While these factors are controlled for in this analysis, the finding has important policy implications. Because these state effects are not characteristics that policymakers can necessarily observe or measure about a state or directly change to promote renewable energy generation, it suggests that policies may work differently in each state because of these characteristics. It also provides an explanation as to why the current policy landscape may be dominated by heterogeneous state-level policies and fewer federal policies. Ignoring state-specific effects and ignoring heteroscedasticity in Table 4 (Models 2 to 3 versus Model 4) show that RPS has a higher coefficient, coal price has a positive and statistically significant coefficient, and that natural gas price has a negative and statistically significant coefficient. This suggests that if unobserved state-specific effects were unaccounted for, one may be led to believe that RPS is more effective than it really is and that coal is a substitute for renewable energy, but natural gas is a complement, when in reality in the properly specified model, we find the opposite relationship to be true.

Second, time-varying factors affect renewable electricity generation in all states equally. The analysis that led to the inclusion of specific time controls in Model 7 also revealed that time is the second important exogenous factor in explaining the increase in renewable electricity generation across all states. Specifically, our analysis indicates that something was happening in the renewable energy industry after 2009 that affected all states equally but was not captured by any other variables. It also implies that, even if all other variables in the model were held constant, renewable electricity generation would have increased due to time-fixed effects in these years. This is important for policymakers to note because it indicates that the list of variables in this study is not exhaustive and exogenous changes over time affect renewable energy. These fixed effects could potentially be capturing anything from federal policies to technological change. For example, the Renewable Electricity Production Tax Credit (RPTC) a federal policy was expanded in 2009 ("DSIRE" 2017). While this study cannot conclusively attribute the increase in renewable energy in the years following this policy change to the RPTC or any other federal policy changes, it alerts policymakers to notice how any number of macro-level factors may affect renewable energy generation in U.S. states equally. Falling technology costs in the renewable energy industry could also have affected renewable energy generation in these years ("Soft Costs | Department of Energy", 2017).

Even though state- and time-fixed effects are controlled for in this study to isolate the policy variables of interest, it is still a significant finding that they are, in fact, an important part of the story and should be considered. Inappropriately modeled time effects in Table 5 (Model 5 versus Models 6 and 7) show that RPS has a higher coefficient (though lower than in Table 4), and that the coal price coefficient is negative and only marginally significant, and natural gas price has a negative and statistically significant coefficient. These suggest that ignoring time-specific factors would lead one to believe that RPS is more effective than it really is, and that increasing the price of coal and price of natural gas may be counterproductive in promoting renewable energy.

Policy Variables

The key focus of the empirical analysis of this study was isolating the effect of different policies on percent renewable electricity generation in order to analyze their effectiveness. This is accomplished in the most basic way in Model 7 which controls for both time- and state-fixed effects. Model 8 further explores the effect of RPS policies on renewable generation through the inclusion of an experience variable and its interaction with RPS. Experience is defined as the log of the number of years a state has an RPS. (In results not shown, linear and quadratic RPS Experience terms were tested before settling on a logarithmic relationship). In Models 9 and 10, other variables are added as further controls.

Model 7 shows that RPS and Natural gas price are significant and have the correct sign. The coefficient on RPS is positive and significant at the 99% confidence level and natural gas price is significant at the 95% confidence level. The only unexpected result was that the coefficient on coal price was negative, instead of positive. This finding was only significant at the 90% confidence level in Model 7, and is diminished to insignificant with the inclusion of more variables in later models. Overall, the results that RPS policies have a positive relationship with renewable energy and natural gas price has a negative relationship with renewable energy are consistent with the hypothesized relationships of these variables based on environmental economic theory. To interpret the magnitude of the RPS coefficient in Model 7, the value can simply be exponentiated and stated as: on average, RPS adoption can be expected to cause a 1.50 percentage point increase in renewable energy. Indicating both CAC and MBI policies may be effective at increasing renewable electricity generation, spurring further analysis.

In Model 8, RPS*Experience is found to have a positive and significant coefficient at the 95% level. Also, it should be noted that when the interaction variable is included, the coefficient on RPS decreases in significance from 99% to 90%, and its magnitude decreases by about half.

The coefficients on RPS and RPS Experience are .171 and .201, respectively. The interpretation of the RPS and RPS Experience coefficients in Models 8, 9, and 10 are slightly more complicated because the marginal effect of RPS is always dependent on the level of experience. The marginal effect on REN can be calculated using the following formula E[REN/RPS=1, x]-E(REN/RPS=0, x]) or $= e^{\beta 1\ RPS + \beta 2\ RPS\ Experance * \ln(RPS\ Experance)}$ where β_1 is the RPS coefficient and β_2 is the RPS*Experience coefficient from each of the models (8,9,10). The resulting marginal effects of RPS are shown below Table 7. In other words, the marginal effect of RPS depends on how many years it has been adopted. Because RPS Experience follows a logarithmic trend each additional year of RPS Experience yields diminishing increases in percent renewable electricity generated in a state. This trend is illustrated in graphs below Table 7. For example, in Model 10, the year after a state implements an RPS they experience an increase in REN of 1.33% however the total increase in renewable energy as a result of an RPS policy in its fourteenth year is only 2.06%. One possible explanation for why this type of trend is observed is that RPS policies mandate a goal of renewable energy to be met by a certain year. It is possible that in early years of a policy, when a state is far from its goal, it increases renewable energy generation at a fast rate by investing in large projects, but, as it approaches its goal, it invests in fewer of these types of projects. Consequently, the rate of increase in renewable energy generation slows.

Models 9 and 10 help with the interpretation of the finding that the price of one fossil fuel, natural gas, was found to be positive as expected, but the other, coal, had the opposite sign. The coal and natural gas generation variables are used as controls because they are lagged variables that represent the fuel sources historically used in a state. It is expected that past fossil fuel generation is a good indicator of future fossil fuel generation because of the costs associated with the technological change needed to move to renewable energy. In Model 9, it is found that fossil fuel generation is negative, but in Model 10, when the two main fossil fuels sources are added separately, only natural gas generation is significant and negative. According to economic theory if the goods were both substitutes, their prices should both be positively related to renewable energy, and their quantities negatively related. However, the results of this study suggest natural gas is in fact a substitute for renewable energy but coal may not be related in this way. Not only does coal behave unexpectedly, it is also much less significant. In Model 9, when fossil fuel generation is added to the model, coal price is negative but significant only at the 90% confidence level. But when fossil fuel generation is further broken down into coal and natural gas generation in Model 10, neither the price or quantity of coal is significant. This suggests that a tax on natural gas may be more effective at increasing renewable electricity generation. One possible explanation for this is that natural gas is a much cleaner fuel than coal so it may be a transitional step for states to move from coal to natural gas, before moving to renewable energy. Additional research on the electricity market, and on the substitutability between coal, natural gas and renewable fuels is beyond the scope of this study, but would be needed to confirm this two-step transition story ("Coal-To-Gas Plant Conversions in the U.S." 2017).

The results of this paper indicate that natural gas is more likely to be a substitute of renewable energy than coal. Therefore, a tax on natural gas could be effective at promoting renewable energy generation. The effect of the price of natural gas can be interpreted as the responsiveness of the renewable electricity generation in a state to an increase in natural gas price. The results in this study suggest that the response to a one dollar per Btu increase in the price of natural gas could cause anywhere from a 1.29 (Model 9) to 1.17 (Model 10) percentage point increase in renewable electricity generation in a given state. This response is smaller in magnitude than the increase in renewable energy estimated for the first year a state has an RPS policy, which ranges from a 1.616 percentage point increase without controlling for past generation (Model 7) to 1.33 in the most controlled Model 10. In order to really compare these two policies to determine what would be more effective more information would be needed.

Overall this study was able to demonstrate how a CAC policy like RPS and an MBI policy like a tax on natural gas price may be used to promote renewable energy generation. The results also suggest that the effectiveness of an RPS policy may diminish over time and the use of MBI policies may require greater understanding of the technical substitutability between energy sources in order to be effective. Overall, the sign and significance of the RPS and natural gas price confirm the general hypothesis made about CAC and MBI policies using the theoretical framework.

Other Explanatory Variables

Finally, other non-policy factors that could potentially affect renewable energy were evaluated and controlled for in this study through the inclusion of a group of non-policy variables. The variables included in the base models were the economic variables of population and mean household income as well as the demographic variable of Sierra Club membership and a political variable, LCV score. Electricity price was added later in Models 8-10 as an additional economic control. These variables were chosen because other studies have found them to be related to renewable energy generation (Delmas and Montes-Sancho 2011) or because they were important controls to include in the model (Shrimali et al., 2015).

In this study, the economic variables included in the base model are found to be positive and significant as hypothesized. Specifically, the coefficient on population ranged from 3.209 in Model 8 to 3.747 in Model 10 both at the 99% confidence level. The coefficient on median household income was also found to be robustly significant across all models at the 95% confidence level. The final economic variable, retail electricity price was included because many other authors include it as a control. However, it is negative and insignificant in this study.

The demographic and political variables included in this study are both proxies for government and citizen liberalism in a state. They were expected to be positively correlated with renewable energy, however they were not found to be significant in any models. Sierra Club membership is positive as expected, but is not significant, and LCV score has the opposite sign as expected, but is insignificant. One possible explanation for this finding is that the effects of citizen liberalism and government ideals are better captured by the state effects that are controlled for when fixed-effects estimation is used. This means their effects are combined in the state-specific intercepts that are all captured in the constant term in the output rather than in the individual political and demographic variables. The state-specific effects or intercepts (α_i) and a summary of their values are reported in Appendix A.2 (values generated based on Model 10). The values can be interpreted as how the real percent of renewable energy generated in a state differed from what was predicted by the model ("Panel Data Models - Econometrics Academy" 2017). A quick glance at these values reveals that while they have a mean of about zero they are largely negative in less liberal states and largely positive in more liberal, environmentally minded states, generally indicating that some of these factors may be captured in this intercept term. Another potential criticism of the LCV variable that was found in this study and others to have a puzzling negative sign, is that while used widely in the literature, LCV score may not be the best indicator of state policies. The LCV score is based on votes made in the House and Senate regarding federal-level rather than local or state policies. Therefore, a state-level political variable may be better suited to capture political views that effect state-level legislation.

Conclusions and Discussion

While the body of knowledge on both the market for renewable energy in the U.S. and the effectiveness of different renewable energy policies were broadened by this empirical analysis, in closing, the principal findings in this study that should be highlighted moving forward include the following key discoveries. First, the results suggest that state-fixed effects, time-fixed effects and macroeconomic indicators influence the level of renewable energy in a state. Second, RPS policies were found to have a positive and significant effect on renewable energy generation in a state, holding all other factors constant, suggesting that the command and control method of regulation is effective at promoting renewable energy generation in the U.S.. It is also concluded that RPS policies with fixed goals experience diminishing returns the longer they are in place. Lastly, this study yields the unique fining that an MBI policy in the form of an input tax on natural gas may be effective at promoting renewable energy generation if implemented.

Overall, this study supports the idea that policy effectiveness at the state level can be successfully analyzed only by using models that include the correct controls and estimation methods that remove the many sources of bias that arise when modeling policy effectiveness across a heterogeneous sample of states over time. This study also provides evidence that under these conditions both CAC and MBI policies are found to be effective and have the expected result of promoting renewable energy as suggested by environmental economic theory.

The first finding of this study regarding the importance of controlling for non-policy factors is both informed by and informs other literature. Estimation methods similar to the ones employed in this study were used by other authors in the past (Shrimali et al. 2015; Shrimali and Kniefel 2011; Carley 2009; Yin and Powers 2010). Among these other papers, specific non-policy variables were largely used as controls and not found to have a significant effect on renewable electricity generation, the exception being that economic variables were found to be consistently significant and important to include as additional controls. An opposing viewpoint to this is suggested by Delmas and Montes-Sancho, who argue that non-policy factors play an important role in the renewable electricity market (Delmas and Montes-Sancho 2011). The results of this paper support the idea that controlling for exogenous factors using econometric methods should remove the significance of individual non-policy factors. This suggests that future analysis need not focus too heavily on non-policy variables such as demographic and political characteristics of states, but instead can simply control for them in the model through their estimation methods and focus on the primary goal further understanding renewable energy policy effectiveness.

In early literature, the results regarding RPS policy effectiveness were mixed. However, over time as the body of literature on this topic grew the estimation techniques used by authors became more sophisticated, moving from simple OLS with cross-sectional data (Adelaja et al. 2010) to very sophisticated panel data methods (Yin and Powers 2010; Zhao, Tang, and Wang 2013; Shrimali et al. 2015). Findings that RPS policies are effective have become more common. In the more recent literature, the finding that RPS policies are effective renewable energy policies is becoming more commonly accepted. Additionally, many authors suggest that a measure of RPS stringency is important to truly understand RPS policy effectiveness.

This study found RPS policies to be effective by simply differentiating between RPS policies using a dummy variable indicating implementation year and an experience measure, suggesting that the timing of a policy may be important to consider in further empirical work. This result is significant because it indicates that the RPS policies currently in place are effective at increasing the percent of renewable energy generated in a state, providing valuable feedback to policymakers. The finding that states experience an increase in renewable energy each additional year that a state has an RPS policy is confirmed by Carley (2009). This study adds that the returns of each year may diminish over time. The next step to extend this study would be to include a stringency measure. Many authors provide detailed methods for how this can be done and their results are strongly positive (Shrimali et al. 2015; Yin and Powers 2010). It would be an extremely valuable extension to this study to add a stringency measure that further differentiates policies by criteria more sophisticated than year experience in order to see if the results of this study remained robust as well as investigate how the RPS experience variable is affected.

Finally, the conclusion that an MBI policy in the form of an input tax on natural gas may be effective at increasing renewable energy generation is unique to this study. Related studies include results regarding the effectiveness of other MBI policies as well as some results regarding how coal and natural gas prices and quantities relate to renewable energy. With some creativity and caution, the MBI results from this study, although unique, may be compared to past finings. First, the previous finings regarding whether MBI policies are effective is largely mixed. Some authors find only some MBI policies to be effective; and the policies found to be significant differ between studies (Delmas and Montes-Sancho 2011; Shrimali et al. 2015). The findings in this paper add to these mixed results. It is even more difficult to find past results with which to compare the finding that an MBI policy in the form of a natural gas tax may be effective at increasing renewable energy generation because this is a unique approach. This is the first study that applies this method first used by (Jaffe and Stavins 1995) to the renewable energy industry. While various fossil fuel prices and quantity variables are included as controlled in many studies in the literature they are included in different forms (percentages, prices, absolute quantities, etc.) and should be compared with caution. The results regarding these variables are also inconsistent throughout the literature and further analysis will need to be conducted to confirm or nullify the finding that an MBI policy, such as the fuel tax proposed in this study, may be effective at promoting renewable energy if adopted in the U.S.

Overall, the empirical literature on this topic includes a wide range of studies that approach the problem of assessing the effectiveness of renewable energy policies uniquely. The results of this study make a significant contribution to the body of literature on this topic. The information gained in this study complements the existing literature and provides fresh insights that can also be considered by policymakers. Hopefully, the increased understanding of how economic policies can correct failures in the electricity market and effectively provide solutions to environmental problems will translate to a noticeable increase in the percent of electricity generated from renewable sources in the near future.

Tables

Table 1: RPS Policies

STATE	POLICY NAME	BASELINE % REN	POLICY IMPLEMENTATION YEAR	GOAL PERCENT	GOAL YEAR
IA	Alternative Energy Law	1.46% (105 mw)	1983*	2%	1999
MA	Renewable Portfolio Standard	3.41%	1997	15%	2020
NV	Energy Portfolio Standard	3.54%	1997	25%	2025
CT	Renewables Portfolio Standard	2.98%	1998	27%	2020
WI	Renewable Portfolio Standard	1.88%	1998	10%	2015
ME	Renewables Portfolio Standard	19.56%	1999	40%	2017
NJ	Renewables Portfolio Standard	1.42%	1999	20.38%	2020
TX	Renewable Generation Requirement	0.59% (5880MW)	1999*	4.4%	2015
HI	Renewable Portfolio Standard	4.66%	2001	100%	2045
CA	Renewables Portfolio Standard	12.71%	2002	50%	2030
CO	Renewable Energy Standard	0.53%	2004	30%	2020
MD	Renewable Energy Portfolio Standard	1.13%	2004	25%	2020
NM	Renewables Portfolio Standard	1.56%	2004	20%	2020
NY	Renewable Portfolio Standard;	1.25%	2004	29%	2015
PA	Alternative Energy Portfolio Standard	1.06%	2004	18%	2021
RI	Renewable Energy Standard	2.07%	2004	38.5%	2035
DE	Renewables Energy Portfolio Standard	0%	2005	25%	2026
MT	Renewable Resource Standard	0.26%	2005	15%	2015
AZ	Renewable Energy Standard	0.05%	2006	15%	2025
WA	Renewable Energy Standard	2.31%	2006	15%	2020
IL	Renewable Portfolio Standard	0.64%	2007	25%	2026
MN	Renewables Energy Standard	7.22%	2007	26.5%	2025
MO	Renewable Electricity Standard	0.27%	2007	15%	2021
NC	Renewable Energy and Energy Efficiency Portfolio Standard	1.29%	2007	12.5%	2021
ND	Renewable and Recycled Energy Objective	2.03%	2007	10%	2015
NH	Electric Renewable Portfolio Standard	4.82%	2007	24.8%	2025
OR	Renewable Portfolio Standard	4.05%	2007	50%	2040
VA	Voluntary Renewable Energy Portfolio Goal	3.27%	2007	15%	2025
MI	Renewable Energy Standard	2.25%	2008	15%	2021

OH	Alternative Energy Resource Standard	0.41%	2008	12.5%	2026
SD	Renewable, Recycled and Conserved Energy Objective	2.08%	2008	10%	2015
UT	Renewables Portfolio Goal	0.65%	2008	20%	2025
KS	Renewable Energy Goal	6.13%	2009	20%	2020
WV	Alternative and Renewable Energy Portfolio Standard	0.19%	**2009****	25%	**2025**
OK	Renewable Energy Goal	5.76%	2010	15%	2015
IN	Clean Energy Portfolio Goal	2.96%	2011	10%	2025
SC	Renewables Portfolio Standard	2.51%	2014	2%	2021
VT	Renewable Energy Standard	47%	2015***	75%	2032

* these states' RPS specify generation goals in MW vs. a percent, the percent was calculated based on their baseline renewable electricity generation in the year policy was implemented (Carley 2009)
** Repealed in 2015, but in place during the analyzed in this study
*** Implemented after the time period analyzed in this study

Table 2: Variable Definitions

VARIABLES	LABELS	UNITS and TRANSFORMATIONS *	SOURCE	HYPOTHESIS
Dependent				
REN	Percent of net generation from renewable energy sources (excluding conventional hydroelectric) out of all electrical energy generated in the state.	Logged Percent	EIA	_
Policy				
RPS	Dummy=1 for years where state has an active RPS Policy, otherwise = 0	Lagged 1 year	DSIRE	+
RPS Experience	The number of years a state has had an RPS policy, starting at 1 in implementation year and increasing by 1for each additional year a policy is in place.	Logged and Lagged 1 year		
Coal Price	Price of coal in the electric power sector	Logged and Lagged 1 year Dollars per million Btu	EIA	+
Natural Gas Price	Price of Natural Gas in the electric power sector	Logged and Lagged 1 year Dollars per million Btu	EIA	+
Fossil fuels Gen	Net electricity generation from fossil fuels, coal plus natural gas, All sectors	Thousand megawatt hours Lagged 1 year	EIA	+
Natural Gas Gen	Net electricity generation from Natural gas, All sectors	Thousand megawatt hours Lagged 1 year	EIA	+
Coal Gen	Net electricity generation from Coal, All sectors	Thousand megawatt hours Lagged 1 year	EIA	+
Economic				
Retail Electricity Price	Average retail price of electricity	cents per kilowatt-hour Lagged 1 year	EIA	+
Population	Resident Population Not Seasonally Adjusted	Logged Thousands of Persons	FRED	+
Median HH Income	Real Median Household Income	Dollars	FRED	+
Demographic				
Sierra Club	Percent of state population that is a	Logged Percent	SC	+

Mem	Sierra Club member.			
Political				
LCV Score	Average of Senate and House League of Conservation Voters Scores. Scores range from 0 to100, with 100 being the most pro-environment.	Range of numbers 1-100	LCV	+
Year	2001-2014			
StateID	1-50 US States Only			

* Some variables used in this study were transformed to improve the accuracy and interpretation of results. Variables were logged to improve their normality and others lagged to improve causality interpretation, some variables received both transformations.

Table 3: Summary Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Dependent					
REN	700	1.297	0.785	0	3.580
Policy					
RPS	650	0.480	0.500	0	1
RPS Experience	650	0.826	0.944	0	2.639
Coal Price	650	0.989	0.360	0	1.777
Natural Gas Price	650	1.837	0.382	0	2.550
Fossil Fuel Gen					
Natural Gas Gen	650	17,415	33,859	0	213,901
Coal Gen	650	37,272	36,298	0	157,897
Economic					
Retail Electricity Price	650	8.955	3.511	4.240	34.04
Population	700	15.13	1.012	13.11	17.47
Median HH Income	700	55,488	8,620	32,905	80,007
Demographic					
Sierra Club Mem	700	0.190	0.0965	0.0351	0.515
Political					
LCV Score	700	48	28.87	0	100
Time					
Year	700	2,008	4.034	2,001	2,014
StateID	700	25.50	14.44	1	50

Table 4: Results Models 1-4

VARIABLES	(Model 1) Pooled OLS REN	(Model 2) Random Effects REN	(Model 3) Fixed Effects REN	(Model 4) Fixed Effects Robust REN
Policy				
RPS	0.652***	0.605***	0.506***	0.506***
	(0.0630)	(0.0507)	(0.0478)	(0.119)
Coal Price	0.0914	0.809***	0.268**	0.268
	(0.0860)	(0.103)	(0.118)	(0.235)
Natural Gas Price	-0.0849	-0.124**	-0.140***	-0.140**
	(0.0729)	(0.0565)	(0.0526)	(0.0609)
Economic				
Population	-0.0968***	-0.0367	5.063***	5.063***
	(0.0287)	(0.0900)	(0.501)	(1.102)
Median HH Income	-1.44e-05***	1.56e-05***	2.03e-05***	2.03e-05**
	(3.88e-06)	(5.06e-06)	(5.05e-06)	(8.36e-06)
Demographic				
Sierra Club Mem	2.189***	-1.360**	-0.811	-0.811
	(0.398)	(0.534)	(0.593)	(1.047)
Political				
LCV Score	-0.00120	-0.00179	-0.00268**	-0.00268
	(0.00126)	(0.00127)	(0.00126)	(0.00242)
Constant	2.990***	0.499	-76.38***	-76.38***
	(0.468)	(1.378)	(7.550)	(16.72)
Observations	650	650	650	650
Number of stateID		50	50	50
Rho		0.749	0.996	0.996
R^2			0.836	0.836
Adjusted R^2			0.821	0.821
	Breusch and Pagan LM Chibar^2= 1501.80 Prob> Chibar^2 =<0.001	**Hausman Test** Chi^2 = 83.53 Prob>Chi^2 <0.001		**Modified Wald** Chi^2 = 4315.43 Prob>Chi^2 <0.001

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Results Models 4-7

VARIABLES	(Model 4) Robust FE Base Model REN	(Model 5) Time Trend REN	(Model 6) Time Dummy REN	(Model 7) Time Period 2 Dummies REN
Policy				
RPS	0.506***	0.434***	0.453***	0.480***
	(0.119)	(0.115)	(0.113)	(0.113)
Coal Price	0.268	-0.575*	-0.742**	-0.401*
	(0.235)	(0.291)	(0.330)	(0.218)
Natural Gas Price	-0.140**	-0.114**	0.259**	0.224**
	(0.0609)	(0.0551)	(0.115)	(0.0928)
Economic				
Population	5.063***	2.755**	2.799**	3.273***
	(1.102)	(1.322)	(1.297)	(1.112)
Median HH Income	2.03e-05**	2.06e-05**	2.54e-05***	2.24e-05**
	(8.36e-06)	(8.06e-06)	(9.09e-06)	(8.99e-06)
Demographic				
Sierra Club Mem	-0.811	0.305	1.357	0.372
	(1.047)	(1.206)	(1.388)	(1.168)
Political				
LCV Score	-0.00268	-0.00184	-0.00115	-0.000172
	(0.00242)	(0.00240)	(0.00267)	(0.00255)
Time				
Trend		0.0731***		
		(0.0218)		
Time Dummies				
Year = 2003			0.0579*	
			(0.0324)	
Year = 2004			0.00600	
			(0.0451)	
Year = 2005			-0.0529	
			(0.0815)	
Year = 2006			-0.0321	
			(0.112)	
Year = 2007			0.0455	

			(0.127)	
Year = 2008			0.169	
			(0.154)	
Year = 2009			0.291	
			(0.217)	
Year = 2010			0.530**	0.313***
			(0.229)	(0.0906)
Year = 2011			0.636**	0.410***
			(0.248)	(0.103)
Year = 2012			0.748***	0.499***
			(0.271)	(0.120)
Year = 2013			0.878***	0.621***
			(0.276)	(0.141)
Year = 2014			0.883***	0.641***
			(0.270)	(0.128)
Constant	-76.38***	-41.49**	-42.92**	-49.94***
	(16.72)	(20.03)	(19.63)	(16.79)
Observations	650	650	650	650
Number of stateID	50	50	50	50
Rho	0.996	0.988	0.989	0.992
R^2	0.836	0.852	0.861	0.855
Adjusted R^2	0.821	0.838	0.845	0.840
			Joint F-Test H_o: All years =0 F= 5.87 Prob > F < 0.0001	H_o: 2010.year =2011.year F= 11.81, Prob > F =0.0016
			Joint F-Test H_o: Time 1 =0 F= 2.81 Prob > F = 0.0154	H_o: 2011.year = 2012.year F= 9.08, Prob > F = 0.0041
			Joint F-Test H_o: Time 2 =0 F= 5.62 Prob > F = 0.0004	H_o: 2012.year = 2013.year F= 6.64, Prob > F = 0.0131 H_o 2013.year = 2014.year F= 0.01, Prob > F = 0.9097

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Results Models 4, 7-10

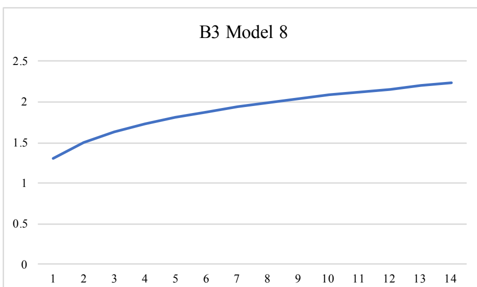
VARIABLES	(Model 4) Robust FE From R.1 REN	(Model 7) Robust FE Time Controlled From R.2 REN	(Model 8) Logged Experience REN	(Model 9) Logged Experience Generation FF REN	(Model 10) Logged Experience Generation Coal Natural gas REN
Policy					
RPS	0.506***	0.480***	0.271*	0.258*	0.283**
	(0.119)	(0.113)	(0.140)	(0.140)	(0.135)
RPS Experience			0.201**	0.191**	0.167*
			(0.0925)	(0.0909)	(0.0856)
Coal Price	0.268	-0.401*	-0.424*	-0.391*	-0.170
	(0.235)	(0.218)	(0.217)	(0.210)	(0.214)
Natural Gas	-0.140**	0.224**	0.231**	0.256***	0.160*
	(0.0609)	(0.0928)	(0.0943)	(0.0910)	(0.0821)
Fossil Fuel Gen				-7.22e-06**	
				(3.22e-06)	
Natural Gas Gen					-1.16e-05***
					(3.48e-06)
Coal Gen					4.63e-06
					(5.24e-06)
Economic					
Retail Electricity Price			-0.00843	-0.00980	-0.00771
			(0.0115)	(0.0115)	(0.0112)
Population	5.063***	3.273***	3.209***	3.644***	3.747***
	(1.102)	(1.112)	(1.105)	(1.151)	(1.112)
Median HH Income	2.03e-05**	2.24e-05**	2.11e-05**	2.10e-05**	1.76e-05**
	(8.36e-06)	(8.99e-06)	(8.84e-06)	(8.70e-06)	(8.17e-06)
Demographic					
Sierra Club Mem	-0.811	0.372	1.062	0.961	1.197
	(1.047)	(1.168)	(1.237)	(1.233)	(1.168)
Political					
LCV Score	-0.00268	-0.000172	-0.000274	-0.000348	-0.000339
	(0.00242)	(0.00255)	(0.00238)	(0.00234)	(0.00222)
Time					
Time period 2 Year		+***	+***	+***	+***

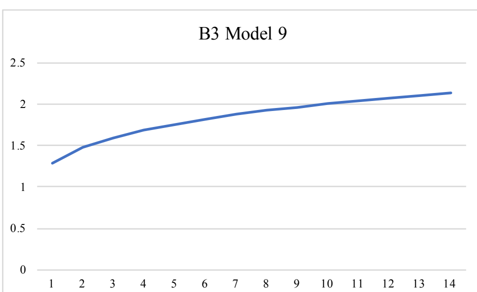
Dummies					
		(0.0906)	(0.0899)	(0.0921)	(0.0898)
Constant	-76.38***	-49.94***	-48.99***	-55.19***	-57.04***
	(16.72)	(16.79)	(16.68)	(17.30)	(16.70)
Observations	650	650	650	650	650
Number of stateID	50	50	50	50	50
R^2	0.836	0.855	0.860	0.862	0.870
Adjusted R^2	0.821	0.840	0.845	0.847	0.855

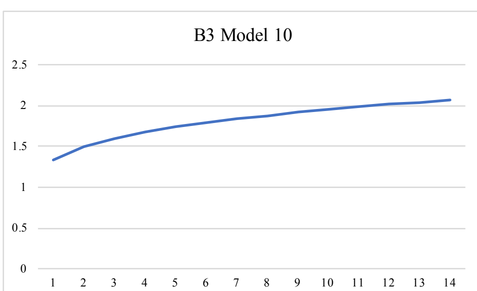
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7

Marginal effect of RPS for every year of Experience with RPS			
Year	Model 8	Model 9	Model 10
1	1.31%	1.29%	1.33%
2	1.51%	1.48%	1.49%
3	1.64%	1.6%	1.59%
4	1.73%	1.69%	1.67%
5	1.81%	1.76%	1.74%
6	1.88%	1.82%	1.79%
7	1.94%	1.88%	1.84%
8	1.99%	1.93%	1.88%
9	2.04%	1.97%	1.92%
10	2.08%	2.01%	1.95%
11	2.12%	2.05%	1.98%
12	2.16%	2.08%	2.01%
13	2.2%	2.11%	2.04%
14	2.23%	2.14%	2.06%







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Appendix

Table A.1

VARIABLES	(1) Fixed Effects within REN	(2) Fixed Effects LSDV REN	(3) Fixed Effects Robust FE Base Model REN
Policy			
RPS	0.506*** (0.119)	0.506*** (0.0530)	0.506*** (0.0530)
Coal Price	0.268 (0.235)	0.268** (0.110)	0.268** (0.110)
Natural Gas Price	-0.140** (0.0609)	-0.140** (0.0558)	-0.140** (0.0558)
Economic			
Population	5.063*** (1.102)	5.063*** (0.556)	5.063*** (0.556)
Median HH Income	2.03e-05** (8.36e-06)	2.03e-05*** (4.99e-06)	2.03e-05*** (4.99e-06)
Demographic			
Sierra Club Mem	-0.811 (1.047)	-0.811 (0.593)	-0.811 (0.593)
Political			
LCV Score	-0.00268 (0.00242)	-0.00268** (0.00130)	-0.00268** (0.00130)
group(abbreviation) = 2		-8.473*** (1.052)	
group(abbreviation) = 3		-5.556*** (0.796)	
group(abbreviation) = 4		-10.91*** (1.245)	
group(abbreviation) = 5		-17.75*** (2.260)	
group(abbreviation) = 6		-8.650*** (1.146)	
group(abbreviation) = 7		-7.772*** (0.926)	
group(abbreviation) = 8		-0.906*** (0.185)	
group(abbreviation) = 9		-15.41***	

	(1.818)
group(abbreviation) = 10	-11.96***
	(1.452)
group(abbreviation) = 11	-2.046***
	(0.424)
group(abbreviation) = 12	-5.535***
	(0.865)
group(abbreviation) = 13	-1.442***
	(0.500)
group(abbreviation) = 14	-13.97***
	(1.636)
group(abbreviation) = 15	-10.63***
	(1.235)
group(abbreviation) = 16	-5.598***
	(0.814)
group(abbreviation) = 17	-8.725***
	(1.012)
group(abbreviation) = 18	-8.056***
	(1.036)
group(abbreviation) = 19	-10.45***
	(1.274)
group(abbreviation) = 20	-10.35***
	(1.189)
group(abbreviation) = 21	-0.350
	(0.398)
group(abbreviation) = 22	-12.32***
	(1.490)
group(abbreviation) = 23	-8.174***
	(1.168)
group(abbreviation) = 24	-10.60***
	(1.203)
group(abbreviation) = 25	-5.853***
	(0.785)
group(abbreviation) = 26	-0.614**
	(0.267)
group(abbreviation) = 27	-12.26***
	(1.445)
group(abbreviation) = 28	1.647***
	(0.199)
group(abbreviation) = 29	-3.968***
	(0.566)
group(abbreviation) = 30	-1.890***
	(0.395)
group(abbreviation) = 31	-12.63***
	(1.413)
group(abbreviation) = 32	-3.905***

		(0.656)	
group(abbreviation) = 33		-5.288***	
		(0.755)	
group(abbreviation) = 34		-15.48***	
		(1.849)	
group(abbreviation) = 35		-13.95***	
		(1.566)	
group(abbreviation) = 36		-6.967***	
		(0.944)	
group(abbreviation) = 37		-6.554***	
		(1.016)	
group(abbreviation) = 38		-14.10***	
		(1.621)	
group(abbreviation) = 39		-1.155***	
		(0.354)	
group(abbreviation) = 40		-8.364***	
		(1.026)	
group(abbreviation) = 41		0.907***	
		(0.236)	
group(abbreviation) = 42		-10.26***	
		(1.211)	
group(abbreviation) = 43		-17.00***	
		(1.976)	
group(abbreviation) = 44		-6.438***	
		(0.777)	
group(abbreviation) = 45		-11.31***	
		(1.355)	
group(abbreviation) = 46		3.234***	
		(0.183)	
group(abbreviation) = 47		-9.946***	
		(1.299)	
group(abbreviation) = 48		-9.594***	
		(1.189)	
group(abbreviation) = 49		-4.476***	
		(0.552)	
group(abbreviation) = 50		2.683***	
		(0.202)	
Constant	-76.38***	-69.00***	-76.38***
	(16.72)	(7.507)	(8.449)
Observations	650	650	650
R-squared	0.565	0.836	0.836
Number of stateID	50		
Adjusted r2			0.821

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.2

VARIABLE	(1) N	(2) mean	(3) sd	(4) min	(5) max
αi	650	1.07e-08	3.815	-6.6125	7.324

Note: A state's renewable energy generation was underestimated by the model if it has a positive intercept (αi) and overestimated if it has a negative intercept (αi).

ABBREVIATION	α_i	AVERAGE LCV SCORE	SIERRA CLUB MEMBERSHIP PERCENT
WY	7.324900627	6	0.189
VT	7.284371376	94	0.505
ND	6.580777168	55	0.105
SD	6.387945652	42	0.104
ME	5.568994999	75	0.320
AK	5.520057201	16	0.242
MT	4.699974537	33	0.239
DE	4.595984459	83	0.203
ID	4.448876858	10	0.169
HI	4.276571274	87	0.352
NH	4.115595818	54	0.336
RI	4.01326561	91	0.244
NE	2.413386583	18	0.108
NM	2.26088953	61	0.364
MS	1.837480783	22	0.045
NV	1.753294349	47	0.184
WV	1.65626514	61	0.107
AR	1.600476623	43	0.090
KS	1.373980522	15	0.156
IA	1.216985941	46	0.183
OK	0.809846222	8	0.084
UT	0.500235558	15	0.166
OR	0.380505353	77	0.543
LA	0.316122293	25	0.073
AL	-0.446072966	15	0.074
CT	-0.447321892	88	0.281
SC	-0.521702886	25	0.119
MN	-0.789771199	66	0.350
CO	-1.302559614	48	0.396
KY	-1.401363373	15	0.114
WI	-2.036288261	68	0.252
WA	-2.160967827	77	0.416
TN	-2.211441994	26	0.107
MA	-2.327684641	87	0.343
MD	-2.58198452	87	0.264
AZ	-2.73140502	27	0.203

IN	-2.838331699	36	0.117
VA	-2.846674442	42	0.206
MO	-2.890740395	31	0.160
GA	-3.178275585	23	0.121
MI	-3.77175808	68	0.190
NC	-3.803062677	37	0.180
NJ	-3.918908119	80	0.226
FL	-4.897697926	48	0.163
TX	-5.403676033	19	0.096
IL	-5.404586315	62	0.193
PA	-5.414482594	44	0.203
OH	-5.49647665	39	0.160
NY	-5.500959873	82	0.207
CA	-6.612589359	77	0.471