Evaluating Renewable Energy Employment Impacts from Renewable Energy Policies

Thesis

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By

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Abstract

US policymakers at the local, state, and federal levels are considering policy mechanisms to promote renewable energy development and ensure a just transition to a clean energy infrastructure. These policies have the potential to both reduce greenhouse gas emissions and create jobs; however, the number of actual jobs created from these policy instruments is often disputed. In this study, I evaluate the direct non-hydroelectric renewable energy employment impacts from eight types of renewable energy policies: (1) subsidy programs; (2) corporate, (3) personal, and (4) other tax incentives; (5) performance-based incentives; (6) industry recruitment/support; (7) renewable portfolio standards; and (8) net metering. Using data from 3,035 US counties from 2001 to 2017, I employ Fixed Effects (FE) regression models controlling for calculated propensity scores, which address the potential selection bias in the model. The results indicate that three of the policy instruments (renewable portfolio standards, industry recruitment/support, and performance-based incentives) have positive and statistically significant impacts on direct non-hydro renewable energy employment at the county level. The policy type with the greatest positive impact was industry recruitment/support. Counties with industry recruitment/support policies present, on average, had 82 more direct non-hydro renewable energy jobs than counties that did not have industry recruitment/support present, holding all else constant. Critically, the results show the importance of addressing selection bias in analyses of renewable energy policy outcomes, as the models run without controlling for propensity scores led to an overestimation of employment impacts.

Dedication

I would like to dedicate this work to my wife, Anna, and our two pet rabbits, Apollo and Artemis.

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Chapter 1: Introduction

1.1 Summary and Rationale

The US must rapidly reduce our greenhouse gas (GHG) emissions to reach the climate targets set out in the 2015 Paris Agreement and avoid the most harmful impacts of climate change. This will require the electricity sector to transition its electricity generation from traditional fossil-fuel technologies to low- or no-carbon technologies. This transition to a clean energy infrastructure will engender a wide range of benefits and burdens. The primary benefits are increased energy security, reduced GHG emissions, and economic growth from employment/innovation opportunities (Wei et al., 2010). The primary burdens, on the other hand, are loss of employment in fossil-fuel related industries and a loss of tax revenue from fossil-fuel related economic activity. For the clean energy transition to be just and equitable, these benefits and burdens must be spread evenly across the US and across demographics (McCauley & Heffron, 2018).

The term *just transition*, first used in the US labor movement in the 1990s, addresses the questions of 'who wins, who loses, how and why' as they relate to the energy transition (Newell & Mulvaney, 2013). There are three primary tenets of a just transition discussed in the literature (Carley & Konisky, 2020; McCauley et al., 2013). First, *distributional justice* calls for the equal distribution of benefits and burdens on all members of society regardless of location or demographic. Second, *procedural justice* calls for equitable energy decision-making processes that engage all stakeholders who wish to participate. Third, *recognition justice* calls for understanding historic and ongoing inequalities and seeks to reconcile them. This just transition framework provides an equitable blueprint to decarbonization of the electricity sector, in the hopes that no one is left behind.

Communities that have historically relied on fossil-fuel based employment and tax revenue, specifically coal-based electricity production, are on the frontlines of the clean energy transition, meaning they are expected to lose jobs and tax revenue. Per unit of energy produced, carbon dioxide emissions from burning coal are about 40 percent higher than those from oil and 50 percent higher than those from natural gas (Pollin & Callaci, 2019). As a result, replacing coal as an energy source has been prioritized to reduce GHG emissions, and employment and tax revenue from coal-related activities have declined faster than those from oil or gas activities. Communities that have historically relied on coal-based employment and tax revenue have also been found to be less socio-economically resilient to the clean energy transition (Hincapie-Ossa, n.d.). Noteworthy, the fiscal impacts of this transition of energy sources only accounts for part of the cost, as many of these frontline communities have an 'economic identity' related to coal mining or coal-based electricity generation (Mayer, 2018).

Energy employment, both the loss of traditional fossil fuel jobs and the potential of job creation in renewable energy, energy efficiency, and grid modernization, has been a common political talking point related to the clean energy transition in recent US presidential elections (Healy & Barry, 2017). As a result, there has been significant research into the employment impacts of a clean energy transition. Garrett-Peltier (2017), for example, finds that each $1 million of investment shifted from fossil fuels to renewable energy or energy efficiency will create a net increase of 5 jobs. In addition, renewable energy and low carbon sectors generate more jobs than fossil fuel-based sectors per unit of energy delivered (Wei et al., 2010). Although these studies highlight the potential employment benefits of the clean energy transition, one key obstacle remains: there is a disconnect between where coal-based jobs are being lost and renewable energy jobs are being created. The choropleth maps in Figure 1 highlight the disconnect between renewable energy employment in shades of orange (panel A) and coal employment in shades of purple (panel B) in the year 2017.

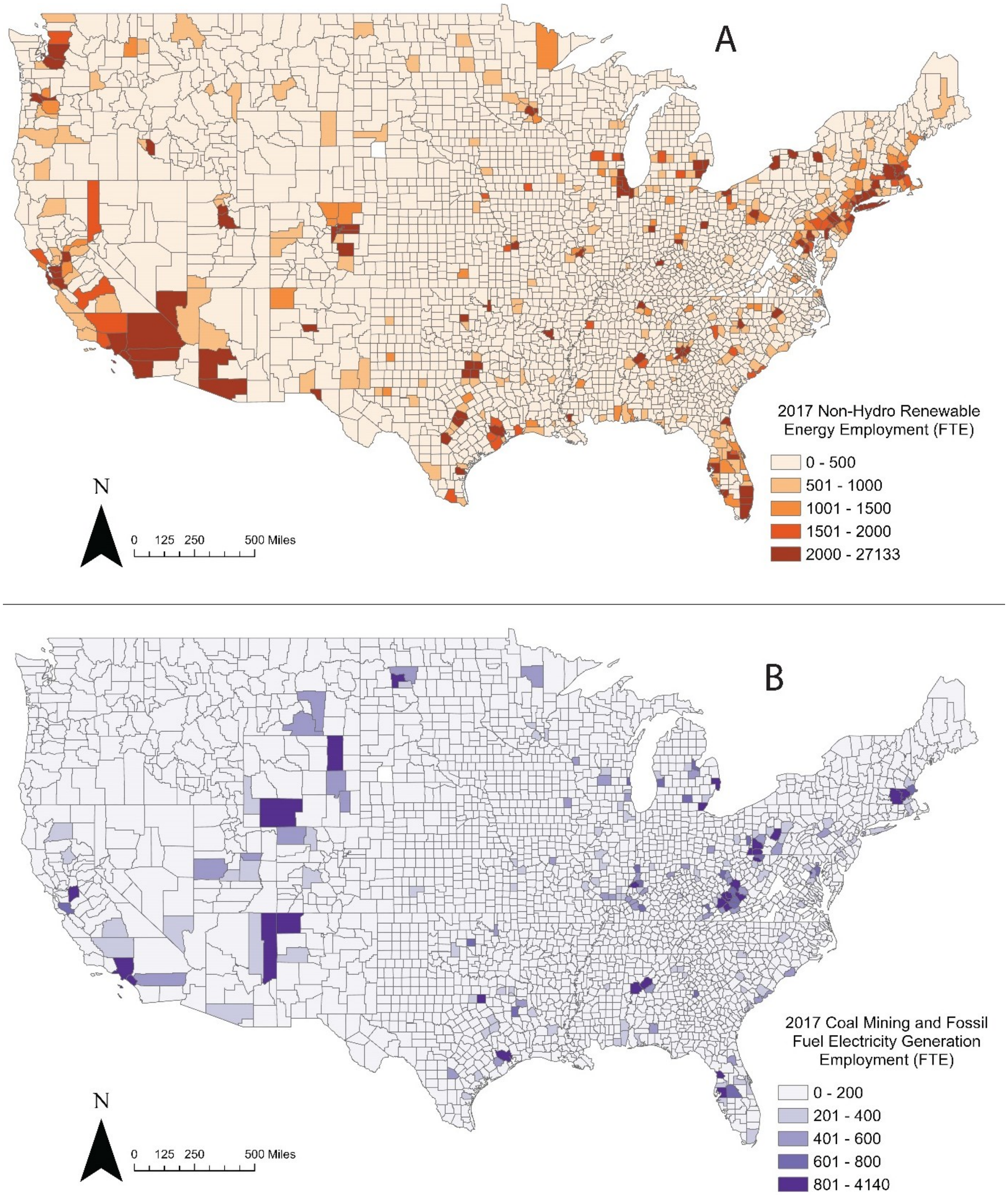

Figure 1: Geographic distribution of US renewable energy employment (Panel A) compared to coal employment (Panel B) in 2017

The renewable energy employment (orange) is mainly concentrated in California, Florida, and the northeast US as these areas have counties that have over 2,000 FTE in 2017 (dark orange). Coal employment (purple) is mainly concentrated in the Appalachian region, with pockets in Wyoming, Illinois, and Alabama having over 800 FTE in 2017 (dark purple). This figure shows that areas that have significant coal-related employment have a dearth of renewable energy employment, which is a concern for the distributional justice aspect of the clean energy transition. This disconnect may be due to a lack of renewable energy resources, political/cultural factors, or a lack of incentivizing policies for renewable energy.

1.2 Policy Intervention in the Energy Transition

Public interventions have the potential to address these distributional justice concerns and ease the employment burden felt by these frontline communities. Carley & Konisky (2020) discuss the following five types of efforts to address the disparities related to the clean energy transition:

1) Workforce and economic diversification programs,
2) Energy assistance and weatherization programs,
3) Expansion of energy technology access,
4) Collective action initiatives,
5) and new business development.

This list, though not exhaustive, helps frame the discussion around what will be needed to build adaptive capacity of frontline communities.

Historically, in times of sustained high unemployment, such as the Great Recession or Great Depression, policymakers have enacted programs to create jobs and invest in the nation's infrastructure. The American Recovery and Reinvestment Act of 2009 (ARRA), for example, devoted approximately $90 billion to energy projects to stimulate the economy and create jobs after the Great Recession (Carley, 2016). Similarly, the New Deal bolstered our nation's infrastructure while stimulating the economy and creating jobs after the Great Depression. Seeing as the negative employment impacts from the clean energy transition are much more localized, geographically targeted policy instruments are likely more prudent to address these distributional employment disparities. Examples of general targeted interventions include state enterprise zones, federal empowerment zones, and federal enterprise community programs. These programs use subsidies and tax credits to encourage employment development in disadvantaged labor markets and have been found to have positive and statistically significant impacts on the unemployment rate, poverty rate, wage and salary income, and employment (Ham et al., 2011). These programs, however, are not specific to energy or the energy transition.

These large federal investments in infrastructure have been rare in recent history, but two pieces of recent legislation will quickly change the federal infrastructure and energy policy landscape: the Infrastructure Investment and Jobs Act of 2021 and the Inflation Reduction Act of 2022. Prior to the passage of these bills, there was a lack of comprehensive federal energy policy (Byrne et al., 2007; Pischke et al., 2019). As a result, state and local governments implemented a variety of policy instruments meant to accelerate the clean energy transition by diversifying, decarbonizing, and decentralizing their electricity markets (Carley & Browne, 2013; Rabe, 2008). Examples of these renewable energy policies are subsidy programs, tax incentives, performance-based incentives, industry recruitment/support, Renewable Portfolio Standards (RPSs), and net metering (Abolhosseini & Heshmati, 2014; Menz, 2005). The following section will describe these six common types of renewable energy policies.

1.3 Description of Renewable Energy Policies

Subsidy Programs. Broadly speaking, subsidy programs are grants, rebates, or loans that help in the financing of residential, commercial, and community-scale renewable energy deployment, which can have high initial costs (Lantz, 2010). Each of these types of subsidies (grants, rebates, and loans) have similar goals, but slightly different mechanisms. Grants, which are usually competitive and must be applied for, are designed to lower the costs of eligible renewable energy systems or equipment by providing direct funds or discounts. Rebates, on the other hand, provide a refund from the cost of new renewable energy installations, and the amounts are usually based on the installed capacity of a system (Lantz & Doris, 2009). Renewable energy system loan programs often provide long-term, fixed rate loans and reduced consumer-transaction costs when compared to traditional lending. Loans can make investment in renewable energy projects more attractive by reducing up-front costs and lengthening the period over which installation costs are paid. Another type of subsidy program that is important to note is Property Assessed Clean Energy (PACE) financing, which allows property owners to finance renewable energy projects as a tax assessment on their property. These types of subsidy programs can incentivize increased renewable energy development, but are most effective as one element of a comprehensive renewable energy policy approach (Lantz, 2010).

Tax Incentives. Tax incentives, specifically at the state- and local-levels, can take different forms and target different entities. The forms of incentives include tax exemptions, tax deductions, and tax credits. Target entities can be corporations, individuals, property, and sales. The incentives can also be tied to investment, job creation, or research and development. A drawback of these policy instruments is that they are often tied to state and local government budgets, which can be fragile, especially in times of economic downturn. Additionally, tax incentives are often implemented in short periods of one- or two-years, which can lead to uncertainty about their availability. A benefit, on the other hand, is that they can be tailored to unique regional economic conditions and policy goals that promote renewable energy job creation (Garciano, 2010).

Performance-Based Incentives. Performance-based incentives (PBIs), also known as production-based incentives, award payment based on actual electricity produced from a qualifying renewable energy resource. These incentives are distinguished from capacity-based incentives, where payment is awarded based on installed capacity. Feed-in-tariffs are a popular type of PBI that provide fixed prices for the purchase of electricity that is generated from a qualifying renewable resource (Couture & Cory, 2009). These programs have been found to foster more rapid renewable energy project development, as they increase investor security by guaranteeing a reasonable rate of return (Butler & Neuhoff, 2008). One drawback of these policies, however, is that they do not address the high upfront costs of renewable energy systems, which is a common barrier to renewable energy projects. PBIs are used more commonly internationally than they are in the US.

Industry Recruitment/Support. In the hopes of promoting economic development and creating jobs, some jurisdictions employ industry recruitment/support policies targeted towards renewable energy industries (Doris et al., 2009). These programs are usually a combination of tax credits, tax exemptions, and grants, and they are meant to support industries in their early years. In most cases, the industry recruitment/support policies are temporary in the hopes that a given renewable energy industry will become self-sufficient within a certain number of years (Yusuf & Neill, 2013).

Renewable Portfolio Standards. The most studied of the renewable energy policy instruments, renewable portfolio standards require a certain percentage of a state's electricity generation to come from renewable energy sources by a target year (Carley, 2009). In their study on the impacts of RPSs on the green economies of states, Bowen et al. (2013) highlight four key attributes of the RPS: presence, duration, stringency, and increments. In addition to these attributes, RPSs differ in what energy sources they decide to qualify as "renewable." For example, Indiana includes "clean coal" technology as one of the energy sources that can qualify for their Clean Portfolio Standard Goal. They define clean coal technology as one that "directly or indirectly reduces airborne emissions of sulfur or nitrogen based pollutants associated with the combustion or use of coal" (DSIRE, 2022). Barbose et al. (2016a) point out that RPSs are not the most cost-effective way to reduce GHG emissions. The most cost-effective way would be to "internalize externalities" by pricing heavy GHG emitting activities with a carbon tax or cap-and-trade system. Finally, RPSs have been found to have a significant and positive effect on in-state renewable energy development, their primary policy goal (Yin & Powers, 2010).

Net Metering. Net metering is an electricity policy that allows utility customers to sell excess generated electricity back to the grid for retail price (Poullikkas et al., 2013). Most often used in small, distributed PV (photovoltaic) installations, this policy has the potential to benefit a utility, the utility customer, and the community at large. Utilities benefit by gaining additional capacity in their service territory paid for by their customers, utility customers benefit by lowering their utility bills, and communities benefit from additional business and employment opportunities. Net metering distinguishes itself from other renewable energy policies in the financing mechanism. The cost is passed to the utility companies, which can be increasingly important in times when state legislatures have tightening budgets (Stoutenborough & Beverlin, 2008). One potential concern for net metering policies is that they could impact the bottom lines of utility companies as distributed PV generation makes up more of the electricity generation in a jurisdiction. Another concern is that net metering can represent a subsidy from one group of consumers (consumers that do not generate electricity) to another group of consumers (consumers that generate electricity) without the approval of the former group.

Each of these renewable energy policies has the potential to influence renewable energy employment in their given jurisdictions; however, research into the extent of these policy impacts is lacking. To inform future policy formulation and implementation these employment impacts must be better understood.

1.4 Research Questions

As policymakers weigh which renewable energy policies to choose to incentivize the clean energy transition (if any), it is of paramount importance that they understand the impacts they may have on employment. This study aims to address the following research questions:

1) Which renewable energy policies (at the state- and local-levels) have created the most direct renewable energy employment from 2001 to 2017?
2) Do these policies have the potential to create jobs in jurisdictions with high unemployment and jurisdictions with high coal-related employment?

The first research question is focused on the retrospective comparison of job creation among renewable energy policies. Critically, this question is only focused on gross job creation in renewable energy industries. It does not consider economy-wide net employment impacts from these policies. The second question is more focused on the factors that may influence the employment in renewable energy industries. The answers to this question may be especially crucial for communities that are suffering high unemployment or are expecting job losses in traditional fossil-fuel industries.

Chapter 2: Evaluating County-Level Direct Renewable Energy Job Growth Due to Renewable Energy Policies

2.1 Introduction

The equal geographic distribution of employment benefits and burdens will be a key aspect of a just transition to a clean energy infrastructure. Currently, there is a disconnect between areas that are likely to lose employment in fossil fuel industries and areas that are likely to gain renewable energy employment (Figure 1). Several policy interventions have the potential to both accelerate the clean energy transition and create employment opportunities in renewable energy industries (Pollin et al., 2009). Among these are subsidy programs, tax incentives, performance-based incentives, industry recruitment/support, RPSs, and net metering. The employment impacts from these policies can be categorized as direct, indirect, or induced (Cameron & van der Zwaan, 2015). Direct employment is related to core activities such as construction, site development, installation, and operation and maintenance (O&M); indirect employment is related to the supply chain and support of the renewable energy industry at a secondary-level; and induced employment arises from the economic activities of direct and indirect employees, shareholders, and governments (via expenditures and associated tax revenues).

There has been extensive study on forecasting employment impacts of renewable energy policies using Computable General Equilibrium (CGE) models (Bohlmann et al., 2019; Mu et al., 2018), Input-Output (I-O) models (Bae & Dall'erba, 2016; Markaki et al., 2013), and analytical models (Wei et al., 2010). Computable general equilibrium models have the benefit of being able to account for direct, indirect, and induced employment impacts, but have significantly greater data and modeling requirements (Berck & Hoffmann, 2002). Input-Output models can account for both direct and indirect employment impacts but are limited due to their dependence on static coefficients (Lambert & Silva, 2012). Analytical models only account for direct employment impacts but are usually more transparent and easily understood than the other models. Models forecasting the employment impacts from renewable energy policies are useful for policymakers; however, the results of the studies are difficult to compare due to differing assumptions, system model borders, and modeling approaches (Meyer & Sommer, 2016).

In addition to forecasting employment impacts, it is important to evaluate which renewable energy policies have successfully created renewable energy jobs in the past, and the extent of that job creation. That being said, retrospective studies are far less common in the literature, and most studies focus only on the employment impacts of RPSs rather than studying impacts of several policies. Carley (2009) in her investigation into the impact of RPSs on the percentage of renewable energy electricity generation across states uses a subsidy index and a tax incentive index (in addition to RPS presence). This number of renewable energy policy variables (3) used in the same model is the most that I have found to date, but the study was focused on electricity generation rather than employment. Yi (2013) finds that both state and local clean energy policies have positive and statistically significant impacts on green jobs. His study utilizes an index of state-level clean energy policies to evaluate state-level action and International Council for Local Environmental Initiatives (ICLEI) membership to evaluate local action. Bowen et al. (2013) find that the presence of RPSs have no discernable effect on green job growth; however, their presence will help create green businesses if they are allowed to persist for several years. Barbose et al. (2016) find that renewable energy used to meet 2013 RPS compliance obligations is estimated to have supported nearly 200,000 US-based gross jobs.

To date, the analysis in this work represents a unique addition to this important field of study. First, this model allows for the direct comparison of the renewable energy employment impacts of eight different renewable energy policies. Additionally, the dataset used is more geographically resolved (by county rather than by state or Metropolitan Statistical Area (MSA)) and over a longer period (17 years) than previous studies of employment impacts of renewable energy policy instruments. This longitudinal dataset allows for the study of short-, medium-, and long-term employment impacts. Furthermore, to the best of our knowledge it is the first study to utilize both propensity scoring and fixed effects (FE) regression in concert to evaluate renewable energy employment. These methods have been used together in the fields of urban economics (O'Keefe, 2004), medicine (Mousteri et al., 2020), and education (Kvande et al., 2019) to addresses potential selection bias that could be present in models created alone.

This study evaluates and compares the direct renewable energy employment impacts of policies that incentivize the clean energy transition. Specifically, I hope to answer the question of which renewable energy policies (at the state-and local-levels) have created the most direct renewable energy employment from 2001 to 2017?

2.2 Methods

In this analysis, I evaluate different state- and local-level renewable energy policies to understand which has been responsible for the most direct renewable energy jobs. First, I collected county-level data on employment, renewable energy policies, and several other related control variables from 2001 to 2017. Then, I utilized FE regression models to evaluate and compare the direct employment impacts that are associated with renewable energy policies. Next, I calculated propensity scores and incorporated them into the FE models to address potential endogeneity. Finally, I interacted certain variables in our models to further understand their joint impact on county-level direct renewable energy employment.

2.2.1 Data Collection

To address the research question, I collected data from a variety of private and government sources.

Employment Data. The employment data used in the models is from the IMPact analysis for PLANning (IMPLAN) tool. This resource is a leading model for economic impact analysis (Bae & Dall'erba, 2016), and provides county-level employment data for 536 economic sectors (IMPLAN, 2018). I chose IMPLAN sectors from the 536-sector scheme to represent county-level direct renewable energy employment, the primary dependent variable in the analyses. The sectors I chose were 41, 44, 45, 46, 47, 48 representing electricity generation from renewable sources (hydroelectric, solar, wind, geothermal, biomass, and tidal). Sectors 49 and 54 were also included representing electricity transmission and power plant construction, respectively. I omit sector 41 (electricity generation from hydroelectric) in some models as hydroelectric renewable energy is excluded from several renewable energy policies (Carley et al., 2017), and its employment trend is different than the other renewable energy generation sectors (Appendix A). I also created coal employment and natural gas employment variables to investigate their impact on direct county-level renewable energy employment. The coal employment variable is the aggregate of employment in the coal mining (22) and electricity generation from fossil fuels (42) sectors. The natural gas employment industry is an aggregate of employment in the natural gas and crude petroleum extraction (20), natural gas liquids extraction (21), drilling oil and gas wells (37), support for oil and gas activities (38), and natural gas distribution (50) sectors. Detailed information on which IMPLAN industry sectors I aggregated to make each of the employment variables can be found in Appendix A.

Renewable Energy Policy Data. The policy data used in the analysis is from the Database of State Incentives for Renewables and Energy Efficiency, or DSIRE (DSIRE, 2022). This database has policies at several different geographic levels including the federal-, state-, county-, city-, utility-, and ZIP code-level. To get county-level policy data, I assigned state-level programs to all counties within a state, while the city, utility, and ZIP code programs were assigned to all counties that fall at least partially within those jurisdictions. I selected 18 programs as the most relevant to the transition to renewable energy, and I aggregated them into eight categories: (1) subsidy programs; (2) corporate, (3) personal, and (4) other tax incentives; (5) performance-based incentives; (6) industry recruitment/support; (7) renewable portfolio standards; and (8) net metering. Figure 2 shows the count of programs included in this study separated by type and implementing sector (state, utility, or local).

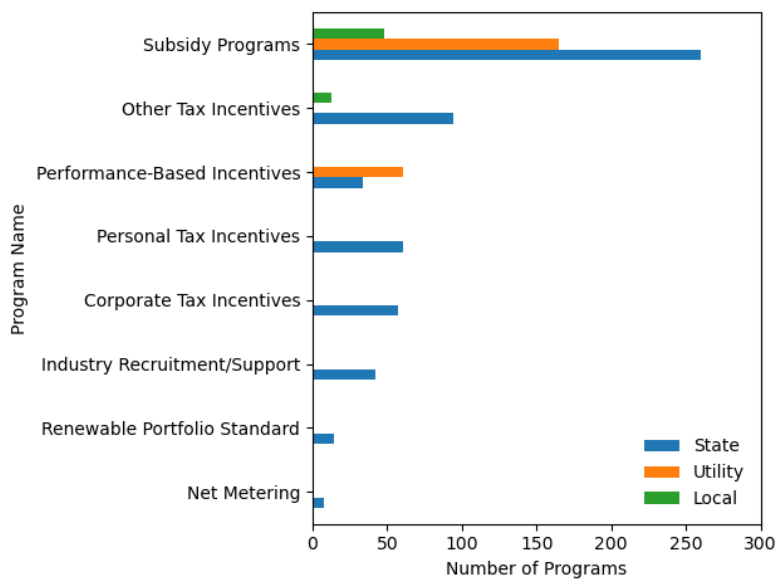

Figure 2: Programs separated by type and implementing sector.
Blue bars represent programs passed at the state level, orange bars represent programs passed at the utility level, and green bars represent programs passed at the local level.

Subsidy programs have the most programs of the eight types, while net metering is the least common. Noteworthy, most of these programs included in the models are passed at the state-level (blue bar). The program choices were based on previous research into renewable energy policy using the DSIRE database (Menz & Vachon, 2006; Yi, 2013). Detailed information on which DSIRE programs were chosen and their categories can be found in Appendix B.

Control Data. Control variables used in the models (e.g., county-level Gross Domestic Product (GDP), population, political preference, unemployment rate, solar resources, and wind resources) are from government and academic sources. The county-level GDP information comes from the U.S. Bureau of Economic Analysis (BEA), population estimates come from the U.S. Census Bureau, the political preference measure comes from the Massachusetts Institute of Technology (MIT) Election Data Science Lab, unemployment rates come from the U.S. Bureau of Labor Statistics (BLS), the wind resource variable comes from the Wind Integration National Dataset (Draxl et al., 2015), and the solar resource variable comes from the National Solar Radiation Data Base (Sengupta et al., 2018). I selected these control variables as they are consistently used as controls in the renewable energy policy literature (Bowen et al., 2013; Yi, 2013). Level of education has been found to have a positive relationship with state-level adoption of green electricity policies (Menz & Vachon, 2006); however, it was not included in our models due to a lack of available county-level education data. One final control variable included in certain models is the county-level propensity score, which is calculated in the next section of the analysis.

Table 1 highlights all variables, their measures, their predicted relationship to the primary dependent variable (non-hydro renewable energy employment) and their source. All policy variables are predicted to have a positive impact on county-level direct renewable energy employment due to the high labor intensity of renewable electricity production. Alternatively, coal employment and natural gas employment are predicted to have a negative relationship to direct renewable energy employment due to potential lobbying against the clean energy transition by incumbent energy companies. The literature remains inconclusive about this theoretical relationship (Vachon & Menz, 2006), but considering the potential impacts of lobbying pushed me to make this prediction.

Table 1. Variable names, measures, predicted relationships and sources.

VARIABLES	MEASURES	PREDICTED RELATION-SHIPS	SOURCES
Non-Hydro Renewable Energy Employment	The number of non-hydroelectric direct renewable energy jobs in county *i* at time *t*	N/A	(IMPLAN, 2018)
Coal Employment	The number of coal mining and fossil fuel electricity generation jobs in county *i* at time *t*	-	(IMPLAN, 2018)
Natural Gas Employment	The number of natural gas jobs in county *i* at time *t*	-	(IMPLAN, 2018)
Net Metering	Dummy variable representing if county *i* has net metering for renewable energy jobs at time *t*	+	(DSIRE, 2022)
Renewable Portfolio Standard	Dummy variable representing if county *i* has a renewable portfolio standard at time *t*	+	(DSIRE, 2022)
Industry Recruitment/ Support	Dummy variable representing if county *i* has industry recruitment/support present at time *t*	+	(DSIRE, 2022)
Other Tax Incentive	Dummy variable representing if county *i* has a sales or property tax incentive present at time *t*	+	(DSIRE, 2022)
Personal Tax Incentive	Dummy variable representing if county *i* has a personal tax incentive for renewable energy jobs at time *t*	+	(DSIRE, 2022)
Performance-based Incentive	Dummy variable representing if county *i* has a performance-based incentive present for renewable energy jobs at time *t*	+	(DSIRE, 2022)

Corporate Tax Incentive	Dummy variable representing if county *i* has a corporate tax incentive for renewable energy jobs at time *t*	+	(DSIRE, 2022)
Subsidy Programs	Dummy variable representing if county *i* has a subsidy program for renewable energy at time *t*	+	(DSIRE, 2022)
GDP Per Capita	Per capita GDP (in millions of chained 2012 dollars) in county *i* at time *t*	Control	(BEA, 2022)
Population	Population estimates in county *i* at time *t*	Control	(US Census Bureau, 2021)
Unemployment Rate	Percent of people unemployed in county *i* at time *t*	Control	(BLS, 2021)
Solar Resource	Average Direct Normal Irradiance (DNI) in county *i*	Control	(Sengupta et al., 2018)
Wind Resource	Average wind speed at 100 meters in county *i*	Control	(Draxl et al., 2015)
Political Preference	Political party (Republican or Democrat) that received a greater percentage of votes than the other in the last presidential election in county *i* at time *t*	Control	(MIT Election Data And Science Lab, 2018)
Propensity Score	Probability of having aggressive renewable energy policy in county *i* at time *t*	Control	N/A

Notes: Dependent variable: Non-Hydro Renewable Energy Employment, BLS: Bureau of Labor Statistics, BEA: Bureau of Economic Analysis, GDP: Gross Domestic Product.

This longitudinal dataset has observations for 3,035 counties in the contiguous US from the years 2001 to 2017. This number of counties is less than the current total number of counties (3,143) due to missing data, creation of new counties, and dissolution of counties over the sample period.

2.2.2 Fixed Effects (FE) Model

I employ a FE model (Figure 3) using both time and county fixed effects as it accounts for potential omitted variables that are county-specific and do not vary across time, as well as potential omitted variables that are year-specific and do not vary across counties. Figure 3 lists the factors that influence county-level direct renewable energy employment.

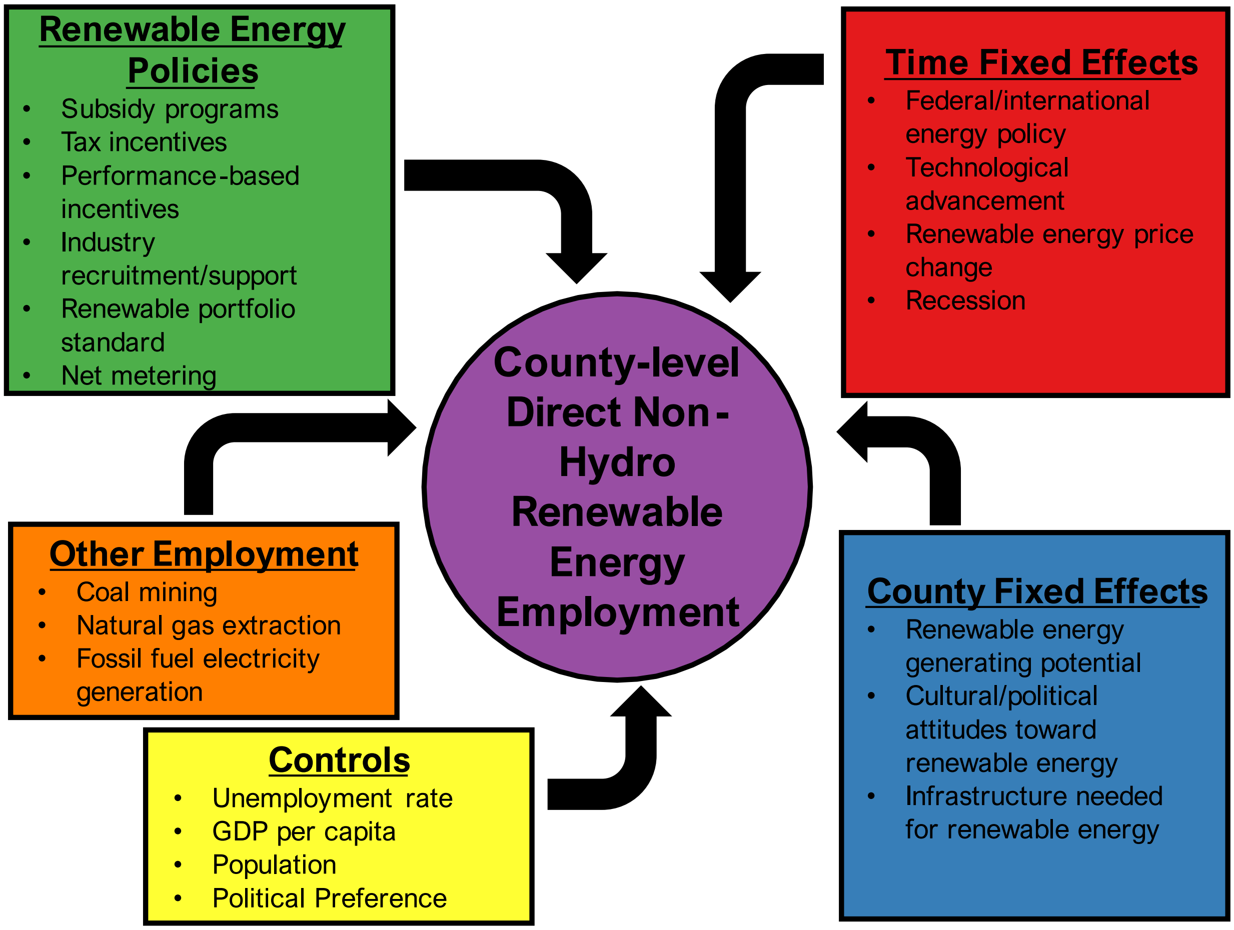

Figure 3: Factors influencing county-level direct renewable energy employment.

The FE model aims to account for all variables included in Figure 3 and is specified as follows:

$$\begin{gathered} JOBS_{i,t} = \beta_0 + \beta_1 NM_{i,t-1} + \beta_2 RPS_{i,t-1} + \beta_3 IR_{i,t-1} + \beta_4 PTI_{i,t-1} + \beta_5 CTI_{i,t-1} + \\ \beta_6 OTI_{i,t-1} + \beta_7 PBI_{i,t-1} + \beta_8 SP_{i,t-1} + \beta_9 GDP\_PER_{i,t} + \beta_{10} UNEMP_{i,t} + \\ \beta_{11} COAL\_EMP_{i,t} + \mathrm{a}_i + \lambda_t + \varepsilon_{i,t} \end{gathered} \tag{1}$$

where i is a given county, t is a given year, $JOBS_{i,t}$ is the dependent variable, the β values are the slope coefficients for each variable, β_0 is the constant, a_i is the county specific intercept, λ_t is the year specific intercept, and ε is the error term. The 12 variable names in Equation 1 have the following meanings:

- *JOBS*: direct non-hydro renewable energy employment,
- *NM*: presence of net metering,
- *RPS*: presence of renewable portfolio standard,
- *IR*: presence of industry recruitment/support,
- *PTI*: presence of personal tax incentive,
- *CTI*: presence of corporate tax incentive,
- *OTI*: presence of other tax incentive (property or sales),
- *PBI*: presence of performance-based incentive,
- *SP*: presence of subsidy program,
- *GDP_PER*: GDP per capita,
- *UNEMP*: unemployment rate,
- and *COAL_EMP*: coal employment.

The above equation addresses the temporal variability in the balanced panel dataset by lagging each of the eight renewable energy program variables by one year. This accounts for some of the potential policy lag that may come from the implementation of new policies in each county. The notation *t-1* denotes that a policy was present in a given county in the year prior to the observed year of the dependent variable. A similar policy lag was employed by Bowen et al. (2013) in their analysis of the influence of RPS programs on the green economies of states. I ran models with four different policy lag configurations (no lag, 1-year, 2-year, and 3-year) and the results can be found in Appendix C.

The FE models presented, like most regression models using panel data, was susceptible to many regression-related issues such as heteroskedasticity, multicollinearity, omitted variable bias, and autocorrelation. Heteroskedasticity was identified in the FE model using the modified Wald test for heteroskedasticity ($p < 0.0000$). Clustered robust standard errors were used in all models to address this heteroskedasticity and allow for more accurate tests of coefficients' statistical significance. To investigate possible multicollinearity in the FE models, I generated a correlation matrix of all variables (Appendix D). The only variables that had a pairwise correlation greater than 0.6 were coal employment and natural gas employment. To address this multicollinearity, the natural gas employment variable is omitted from the FE models. For more detailed information about the variable correlations and model specification tests see Appendix D.

2.2.3 Control on Propensity Scores

I calculated propensity scores to address potential selection bias in the model. Selection bias is likely present when proper randomization cannot be achieved. In this specific study, selection bias may be present if counties that have high renewable energy employment are more likely to implement renewable energy policies, thus introducing endogeneity to regression models of employment. Controlling for the county-level propensity score addresses selection bias by calculating the likelihood of policy adoption based on general county characteristics (political affiliation, renewable resources, renewable energy employment). This will allow for the calculation of an Average Treatment Effect (ATE) for each policy that can then be compared (Rosenbaum & Rubin, 1983). The specific method used to incorporate the propensity scores and address the potential selection bias is to include the propensity scores as an independent variable in the FE models (Caliendo & Kopeinig, 2008). This method leads to an efficient estimate of the average treatment effect. Because there are several different treatments available, I could not simply use the presence of treatment as a binary variable. As a result, I created an aggregation of all potential programs (Equation 2) to identify a variable differentiating more active counties from less active in each year.

$$total\_programs_{i,t} = NM_{i,t} + RPS_{i,t} + IR_{i,t} + PTI_{i,t} + CTI_{i,t} + OTI_{i,t} + PBI_{i,t} + SP_{i,t} \tag{2}$$

The average number of total programs per county was 2.78 per year and the median number of programs was 3 per year, so counties with 3 or more programs present in a given year were called *aggressive* for that year *(agg*=1) while those with less than 3 were not aggressive (*agg*=0). Then, I had to choose a representative year to calculate the propensity scores. I chose 2003 as it had the highest pseudo-R-squared (0.22) of the logistic regression runs for all years in the sample. Additionally, 2003 was a preferable choice as it is early in the panel dataset (2001-2017), before many of the renewable energy policies were enacted and their impacts felt. The logistic regression model used to calculate propensity scores is shown in Equation 3:

$$Log\left(\frac{agg_{i,2003}}{1-agg_{i,2003}}\right) = \beta_0 + \beta_1 NONHYDRO\_EMP_{i,2003} + \beta_2 COAL\_EMP_{i,2003} + \beta_3 GAS\_EMP_{i,2003} + \beta_4 POL_{i,2003} + \beta_5 POP_{i,2003} + \beta_6 WIND_{i,2003} + \beta_7 SOLAR_{i,2003} + \beta_8 UNEMP_{i,2003} + \beta_9 GDP_{i,2003} \tag{3}$$

where *i* is a given county, *2003* is the chosen year, $Log\left(\frac{agg_{i,2003}}{1-agg_{i,2003}}\right)$ is the dependent variable representing the log odds, the β values are the slope coefficients for each variable, and β_0 is the constant. The variable definitions are the same as those used in Equation 1.

This logistic model identifies the factors that influence a county being aggressive in terms of their renewable energy policy in the year 2003 and is used to calculate the county-level propensity scores (Caliendo & Kopeinig, 2008). Equation 4 shows the updated model, and itis identical to Equation 1, with an additional variable, *PSCORE*, as a control.

$$\begin{aligned} JOBS_{i,t} = {} & \beta_0 + \beta_1 NMP_{i,t-1} + \beta_2 RPS_{i,t-1} + \beta_3 IR_{i,t-1} + \beta_4 PTI_{i,t-1} + \beta_5 CTI_{i,t-1} \\ & + \beta_6 OTI_{i,t-1} + \beta_7 PBI_{i,t-1} + \beta_8 SP_{i,t-1} + \beta_9 GDP\_PER_{i,t} \\ & + \beta_{10} UNEMP_{i,t} + \beta_{11} COAL\_EMP_{i,t} + \beta_{12} PSCORE_{i,t} + a_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \tag{4}$$

The variables and symbols used in Equation 4 have the same definitions as Equation 1.

2.2.4 Interaction Terms

To provide further insight on the mechanisms contributing to or impeding renewable energy employment growth, I incorporated several interaction terms into the FE models. These terms allow for the estimation of more nuanced policy interventions, such as the presence of a renewable energy policy given some control variable (e.g., unemployment rate or political affiliation). First, because the natural gas employment variable had to be removed from the FE models due to its high correlation with coal employment, I included the interaction of coal employment and natural gas employment. Next, I interacted each of the renewable energy policy variables to see if they were more effective or less effective in counties with high unemployment. Finally, I interacted the renewable energy policy variables with coal employment to see if renewable energy policies were more effective or less in counties with high coal employment. Each of these interaction terms were added to the model individually using the "hit or miss method" (Caliendo & Kopeinig, 2008). If the coefficient of the added interaction term was found to be statistically significant (at the 5% level) it remained in the model. If not, it was removed.

2.3 Results

2.3.1 Descriptive Statistics

Table 2 contains the descriptive statistics of each of the variables included in the models, as well as their respective units.

Table 2. Descriptive statistics

VARIABLES	UNITS	DESCRIPTIVE STATISTICS			
		Mean	SD	Min	Max
Non-Hydro RE Employment	FTE	260.4	788.9	0	29,334
Coal Employment	FTE	63.00	263.0	0	9,944
Natural Gas Employment	FTE	325.8	2,302	0	132,581
Net Metering	Binary	0.115	0.319	0	1
Renewable Portfolio Standard	Binary	0.147	0.354	0	1
Industry Recruitment/Support	Binary	0.325	0.468	0	1
Property Tax Incentive	Binary	0.383	0.486	0	1
Corporate Tax Incentive	Binary	0.495	0.500	0	1
Other Tax Incentive	Binary	0.526	0.499	0	1
Performance-Based Incentive	Binary	0.286	0.452	0	1
Subsidy Program	Binary	0.513	0.500	0	1
GDP	Millions of chained 2012 dollars	4,814	19,133	6.311	662,419
Population	Ten thousand people	9.702	31.58	0.00400	1,009
GDP per Capita	Millions of chained 2012 dollars per person	0.0485	0.352	0.00772	45.66
Unemployment Rate	Annual average (%)	6.323	2.704	1.100	29.40
Solar Resource	DNI (W/m^2)	5.327	0.715	3.546	7.831
Wind Resource	m/s at 100m	6.668	0.791	3.312	9.452
Political Preference	Binary (1=dem, 0=rep)	0.213	0.409	0	1
Propensity Score	Probability (unitless)	0.313	0.236	0.000696	1

Note: 3,035 counties were included in this model over the 17-year period (2001-2017) meaning each variable has 51,595 observations. Detailed variable descriptions can be found in Table 1.RE: Renewable Energy, FTE: Full Time Equivalent, DNI: Direct Normal Irradiance

The dependent variable in the models, non-hydro renewable energy employment, has a mean of 260.4 FTE jobs per county with a standard deviation of 788.9. The minimum and maximum values of this variable show that some counties have zero non-hydro renewable energy jobs, and the county with the most non-hydro renewable energy jobs in the US has nearly 30,000 FTE. This is Harris County, Texas, home of Houston (the fourth largest city in the US by population and a hub of energy employment). The mean county-level coal employment (63 FTE) is less than non-hydro renewable energy employment while the mean natural gas employment

(325.8 FTE) is greater than non-hydro renewable energy employment. When looking at the eight binary policy variables, other tax incentives (such as property and sales tax incentives) are the most common (implemented in 53% of counties) while net metering is the least common (implemented in 11.5% of counties) from 2001 to 2017.

The GDP and population control variables were found to be highly correlated (see Appendix D). To avoid multicollinearity, I created a GDP per capita variable by taking the quotient of GDP and population. The units for GDP are millions of chained 2012 dollars to account for inflation over the 17-year dataset. The maximum value of the GDP per capita variable, remarkably, is 45.6 million chained 2012 dollars per person. This observation comes from Loving County, Texas in 2017 which had a relatively high GDP and a very small population. In that year, Loving County had the 447th highest GDP and the 2nd lowest population of all US counties. The county-level political preference is a binary variable showing which party received a greater percent of the popular vote in the last presidential election with 0 representing Republican and 1 representing Democrat. The mean (0.213) highlights the fact that a vast majority of counties had a greater percentage vote Republican than Democrat from 2001 to 2017.

2.3.2 Fixed Effects (FE) Model Results

The results of the FE models are mixed in their support of the hypotheses discussed earlier, as presented in Table 3.

Table 3. FE model results
Dependent variable: Non-Hydro Renewable Energy Employment

VARIABLES	COEFFICIENTS	
	County and Time FE	County and Time FE w/ Policy Lag
Net Metering	-8.323	-9.065
	(25.43)	(26.81)
Renewable Portfolio Standard	48.08**	61.43***

	(20.74)	(22.34)
Industry Recruitment/Support	16.47	13.23
	(10.25)	(10.26)
Personal Tax Incentive	-49.25***	-47.45***
	(8.184)	(7.944)
Corporate Tax Incentive	26.43**	22.95**
	(10.80)	(10.67)
Other Tax Incentive	5.138	5.813
	(8.352)	(8.281)
Performance-Based Incentive	33.33***	37.53***
	(7.177)	(8.239)
Subsidy Program	-15.28**	-13.22**
	(7.573)	(6.716)
Coal Employment	-0.304***	-0.323***
	(0.116)	(0.123)
GDP per Capita	-4.610***	-4.399***
	(1.321)	(1.285)
Unemployment Rate	-5.971***	-5.905***
	(1.507)	(1.589)
Political Preference	115.3***	115.0***
	(34.46)	(34.31)
Constant	229.1***	232.8***
	(13.15)	(13.98)
Observations	51,595	48,560
R-squared (within)	0.101	0.106
Number of Counties	3,035	3,035
County FE	Yes	Yes
Time FE	Yes	Yes
One-Year Policy Lag	No	Yes

Note: The model with the 1-year policy lag omits the observations from 2001 and has 3,035 less observations as a result. Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Of the eight policy variables included in the models, three were consistently found to have positive and statistically significant (at the 5% level) relationships with direct county-level non-hydroelectric renewable energy employment. RPSs had the greatest positive coefficient central values (48 to 61 FTE), followed by performance-based incentives (33 to 38 FTE), and corporate tax incentives (23 to 26 FTE). It is important to note that these results are only comparing the central values, and that there is overlap among these rankings of coefficients when the clustered robust standard errors are accounted for. The RPS coefficient interpretation for the non-policy lag model, for example, is that counties that have an RPS present have, on average, 48 more direct non-hydroelectric renewable energy FTE jobs than counties without an RPS present, *ceteris paribus.* Not all policy variables were found to have positive relationships with renewable energy employment. The coefficients of four policy variables (net metering, industry recruitment/support, other tax incentives, and subsidy programs) were statistically insignificant. As a result, no conclusions can be drawn from these coefficients. Personal tax incentive policies have a consistent negative and statistically significant coefficient central value across both models (-47 to -49).

The three control variables had statistically significant coefficients in the model with GDP per capita and unemployment rate associated with less non-hydro renewable energy jobs and democratic political preference associated with more non-hydro renewable energy jobs, holding all else constant. The inclusion of the one-year policy lag did not change the direction or statistical significance of any of the coefficients; however, the magnitude of the coefficients changed slightly as well as the within R-squared value. The coefficient of RPSs, for example, increased by 13 FTE upon the inclusion of the one-year policy lag. The within R-squared increased from 0.101 to 0.106 indicating a slight increase in the amount of variation accounted for in the model.

The full results of the models including the year coefficients can be found in Appendix E. Additionally, Appendix F contains results of FE models using different dependent variables (construction, generation, and non-hydro generation).

2.3.3 Control on Propensity Scores Results

After running the logistic regression to identify the factors influencing adoption of aggressive renewable energy policy and calculating the associated propensity scores for each county in each year, the same fixed effects regression was run with the propensity score included as a control variable. Results of the logistic regression can be found in Appendix G, and the calculated propensity scores averaged across the 17-year dataset can be seen in Figure 4.

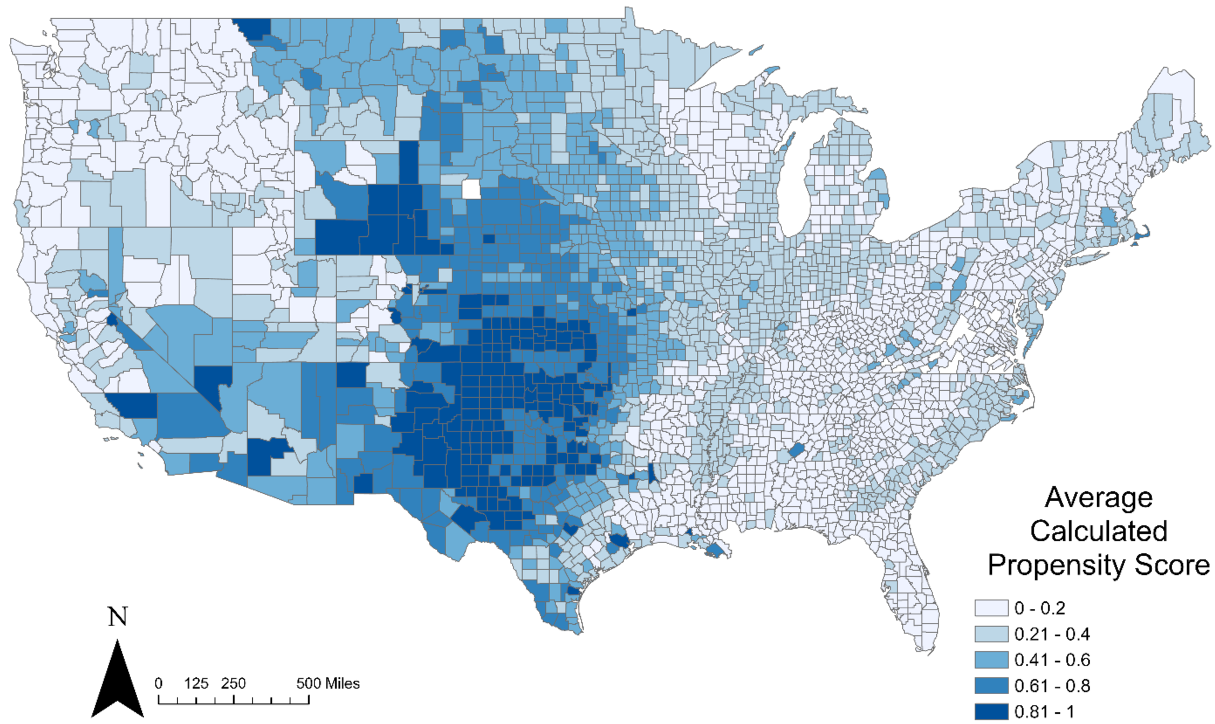

Figure 4: Average calculated propensity score by county

The higher probabilities of aggressive renewable energy policy (propensity score) in Figure 4 are shown using darker shades of blue. Most of the darker blue is concentrated in the Great Plains region and the southwest US, which highlights the importance of wind and solar resources in the calculation of propensity score. Results of the logistic regression can be found in Appendix G. Table 4 shows the results of the FE model including the propensity score control compared to the same model without it.

Table 4. FE model results with propensity score control
Dependent variable: Non-Hydro Renewable Energy Employment

	Coefficients	
VARIABLES	County and Time FE	County and Time FE w/ Propensity Score

Net Metering	-9.065	-19.00
	(26.81)	(19.91)
Renewable Portfolio Standard	61.43***	37.20**
	(22.34)	(17.73)
Industry Recruitment/Support	13.23	20.84**
	(10.26)	(9.274)
Personal Tax Incentive	-47.45***	-25.63***
	(7.944)	(6.311)
Corporate Tax Incentive	22.95**	17.81**
	(10.67)	(8.235)
Other Tax Incentive	5.813	2.380
	(8.281)	(7.902)
Performance-Based Incentive	37.53***	33.14***
	(8.239)	(7.217)
Subsidy Program	-13.22**	1.244
	(6.716)	(6.141)
Coal Employment	-0.323***	-0.589***
	(0.123)	(0.103)
GDP per Capita	-4.399***	-3.900
	(1.285)	(3.524)
Unemployment Rate	-5.905***	-51.38***
	(1.589)	(5.439)
Political Preference	115.0***	175.7***
	(34.31)	(33.39)
Propensity Score		3,410***
		(408.4)
Constant	232.8***	-511.6***
	(13.98)	(91.43)
Observations	48,560	48,560
R-squared (within)	0.106	0.249
Number of Counties	3,035	3,035
County FE	Yes	Yes
Time FE	Yes	Yes
One-Year Policy Lag	Yes	Yes

Note: Both models have a one-year policy lag, which omits the observations from 2001 and has 3,035 less observations as a result. Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

With the propensity score added as a control to the FE model, four of the eight policy variables have positive and statistically significant coefficients. These policies coefficient central values, in order from greatest to least, are renewable portfolio standards (37.2 FTE), performance-based incentives (33.1 FTE), industry recruitment/support (20.8 FTE), and corporate tax incentives (17.8 FTE). The coefficient on the propensity score variable (3,410 FTE) is statistically significant at the 0.01% level, but its interpretation does not have practical significance, as it represents a probability of being aggressive in terms of renewable energy policy. Personal tax incentives have a negative and statistically significant relationship with non-hydro renewable energy employment in both models, but the inclusion of the propensity score decreases the coefficient central value from -47.5 to -25.6 FTE. The sign and statistical significance of the control variables remain consistent across the two models, except for the GDP per capita variable which loses its statistical significance upon the addition of propensity score as an independent variable.

2.3.4 Interaction Terms Results

To further my analysis of some of the more nuanced impacts found in my models, I created a series of interaction terms to assess their direction and statistical significance. Table 5 shows the results of the models including interaction terms.

Table 5. FE model results with interaction terms
Dependent variable: Non-Hydro Renewable Energy Employment

VARIABLES	COEFFICIENTS	
	County and Time FE w/ Propensity Score	County and Time FE w/ Propensity Score and Interaction Terms
Net Metering	-19.00	47.06*
	(19.91)	(26.74)
Renewable Portfolio Standard	37.20**	45.78***
	(17.73)	(16.26)
Industry Recruitment/Support	20.84**	82.26***
	(9.274)	(13.96)
Personal Tax Incentive	-25.63***	18.90
	(6.311)	(12.57)
Corporate Tax Incentive	17.81**	-1.832
	(8.235)	(8.940)
Other Tax Incentive	2.380	-5.853
	(7.902)	(4.546)
Performance-Based Incentive	33.14***	19.39***
	(7.217)	(5.282)

Subsidy Programs	1.244	3.057
	(6.141)	(4.650)
Coal Employment	-0.589***	-0.635***
	(0.103)	(0.104)
Natural Gas Employment		0.148**
		(0.0749)
Coal Employment # Natural		4.45e-05***
Gas Employment		(1.21e-05)
Net Metering		-8.311***
# Unemployment		(2.093)
Industry Recruitment/Support		-6.840***
# Unemployment		(1.195)
Personal Tax Incentive		-2.882**
# Unemployment		(1.171)
Personal Tax Incentive		-0.186**
# Coal Employment		(0.0915)
Corporate Tax Incentive		0.226*
# Coal Employment		(0.117)
Performance-Based Incentive		0.269***
# Coal Employment		(0.102)
GDP per Capita	-3.900	-4.851
	(3.524)	(4.302)
Unemployment Rate	-51.38***	-26.93***
	(5.439)	(10.41)
Political Preference	175.7***	125.5***
	(33.39)	(14.09)
Propensity Score	3,410***	2,185***
	(408.4)	(694.3)
	(11.17)	(7.093)
Constant	-511.6***	-315.2**
	(91.43)	(130.5)
Observations	48,560	51,595
R-squared (within)	0.249	0.445
Number of Counties	3,035	3,035
County FE	Yes	Yes
Time FE	Yes	Yes
One-Year Policy Lag	Yes	No

Note: Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The first interaction term included in the FE models was the interaction of coal employment and natural gas employment. This was included as an interaction term because the natural gas employment variable was omitted from the other models due to multicollinearity. By interacting the two variables that are highly correlated, I avoid this multicollinearity issue. The interaction term has a negative and statistically significant coefficient, but its magnitude is small (0.0000455). This makes sense as the variable represents the product of coal and natural gas employment. Because it represents so many jobs, the marginal impact of a single job is far less.

The interaction of unemployment rate on each policy variable brought three additional significant variables into the model. The three policies that were found to have significant interaction terms with unemployment rate were net metering, industry recruitment/support, and personal tax incentives. Each of these has a negative coefficient.

Finally, the interaction of coal employment on each of the policy variables produced three statistically significant coefficients of interaction terms, two positives and one negative. The two positive coefficients were on the interactions with corporate tax incentives and performance-based incentives, while the negative coefficient was the interaction of coal employment with personal tax incentives.

The introduction of these seven statistically significant interaction terms into the model drastically changes the within R-squared and the coefficients of independent variables. The within R-squared increases from 0.249 in the model with propensity score control to 0.445 in the model that includes the interaction terms. The coefficient central value on industry recruitment/support policies, for example, quadruples from 20.84 to 82.26 FTE. The only three interaction terms between unemployment rate and renewable energy policies that are statistically significant have negative coefficients.

2.4 Discussion

2.4.1 Comparison of Policy Instruments

The hypotheses of a positive relationship between the renewable energy policies and renewable energy employment at the county-level were partially supported by the results of the analysis. The FE model including the propensity score control (Table 4) showed four renewable energy policies with positive impacts on county-level direct non-hydro renewable energy employment from 2001 to 2017. In order from largest impact to smallest, the policies with that led to renewable energy job creation were: RPSs, PBIs, industry recruitment and support, and corporate tax incentives. Net metering; other tax incentives; and grants, rebates, or loans were not found to have a significant impact on the dependent variable. Personal tax incentives were the only policy found to consistently have a negative and statistically significant relationship with county-level direct non-hydro renewable energy employment. These results provide an answer to my primary research question, but there are technical, financial, and political factors that must be considered by policymakers prior to implementation of these policies.

The primary technical factors that should influence renewable policy adoption are renewable energy potential and the existing infrastructure. If renewable energy potential is exceptionally rich in a given jurisdiction, policymakers may not need to incentivize renewable production. On the other hand, in jurisdictions with poor renewable energy potential, focus may need to shift to stimulating employment in other sectors. Financial factors will need to play a significant role in designing policy to accelerate the clean energy transition. The costs of RPSs, for example, are primarily passed down to the electricity consumers and can lead to increases in electricity prices (Palmer & Burtraw, 2005). Tax incentives are primarily funded through federal, state, or local government budgets, which can become exceptionally tight during times of economic downturn. Additionally, federal tax credits related to the clean energy transition have been found to disproportionately benefit higher income quintiles, and are likely to be less attractive on distributional grounds than market mechanisms to reduce GHGs (Borenstein & Davis, 2016). Lastly, political and cultural factors can come into play when renewable energy is simply unpopular in a given jurisdiction and implementing one of these policies would not be realistic. When these factors preclude a jurisdiction from passing one of the renewable energy policies studied, a county has the potential to capitalize on other parts of the clean energy transition. For example, energy efficiency, grid modernization, environmental remediation, and manufacturing of renewable energy components are all areas that can be capitalized on (Pollin & Callaci, 2019).

2.4.2 Importance of Controlling for Propensity Score

The inclusion of the propensity score as a control vastly changes the FE model (Table 4). First, it more than doubles the within R-squared value of the original model (0.106 to 0.249). Also, the coefficient for the propensity score is statistically significant at the 1% level. Finally, its inclusion caused the industry recruitment and support policy to change from being statistically insignificant to being significant at the 5% level. These changes show that the inclusion of the propensity score control led to a model that accounts for more of the variability in the dependent variable and has more accurate coefficients than a FE model by itself. Specifically, the inclusion of the propensity score reduced the magnitude of impact of each of the renewable energy policy variables that were found to be significant in the FE model. This fact shows that lone FE models can exaggerate renewable energy employment impacts from renewable energy policies. Furthermore, it reinforces the need for selection bias to be addressed in regression-based analyses of policy impacts, whether they be the use of PSM, controlling for propensity scores, weighting by propensity scores, or other methods.

2.4.3 Implications of Interaction Terms

Of the 17 interaction terms tested, seven were statistically significant and left in the model. Three of these were interactions of unemployment rate with policy variables, three were interactions of coal employment with policy variables, and one was the interaction of coal employment and natural gas employment. The coal and natural gas interaction term is key as it allows for the inclusion of natural gas employment, which was removed from other models to its high correlation with coal employment.

Interacting policies with unemployment rate is important as jurisdictions dealing with high unemployment may be especially interested in passing renewable energy policies to stimulate the economy and create new jobs. All three statistically significant coefficients on the interaction terms between unemployment rate and the policy variables were negative (net metering, industry recruitment/support, and personal tax incentives). This means that, on average, these policies have been counterproductive and are associated with a loss of non-hydro renewable energy employment in counties with high unemployment, *ceteris paribus.* The cause of these negative relationships is unknown; however, unemployment is a complex issue that impacts many facets of the economy. Therefore, it is believable that higher unemployment rates change the impacts of these renewable energy policies. These results show that a jurisdiction dealing with high unemployment should not look to these three incentivizing renewable energy policies.

The interacting of the policy variables and coal employment produced three statistically significant coefficients. Performance-based incentives and corporate tax incentives are associated with an increase in non-hydro renewable energy employment in counties with high coal employment. Property tax incentives, on the other hand, are counterproductive and associated with a decrease in renewable energy employment in areas of high coal employment. These results have especially poignant applications to the distributional justice aspects of the clean energy transition. Specifically, they show that even in jurisdictions with high coal employment, corporate tax incentives and performance-based incentives are viable policy options to stimulate employment growth. As coal-related employment declines in the coming years, non-hydro renewable energy employment can potentially be stimulated by the presence of these two policy instruments. Personal tax incentives do not show the same potential, as they have negative interactions with both coal employment and unemployment.

2.5 Conclusion

Although the results of the models seemingly provide a sufficient answer to the primary research question, there are several limitations to this study that need to be discussed. The first limitation of the model specification is that it does not account for policy heterogeneity. The use of binary variables to show the presence or absence of a policy each year is a crude representation of the policy environment and is ignoring key differences in policy designs across jurisdictions. A potential solution to this limitation that was not used for this study would be to add stringency and duration measures to the program variables rather than simply using binary variables. This technique is used in several studies looking into employment impacts of renewable portfolio standards (Carley, 2009; Wiser et al., 2008; Yin & Powers, 2010). Another issue facing the model is the potential for spillover impacts due to employees commuting to work from other counties; however, most policies were passed at the state level so this may only be a significant factor near state lines. A potential solution would be to run the same model at the MSA level to observe employment impacts in a larger geographic area.

The policy variables included in this study were taken from the DSIRE database which holds records of over 5,000 US incentives and regulations at different levels of government (federal, state, city, county, zip code). Of these policies, only 20 percent have documented start dates, and even less have documented end dates. This lack of temporal information led to the exclusion of several thousand policies from my analysis, which was a significant limitation of the study. Further information about the filtering process of policy variables and the number of programs that were included in the models can be found in Appendix B.

An additional limitation of this study can be seen in the dependent variable: *county-level direct non-hydro renewable energy employment*. This variable is an aggregation of seven IMPLAN industry codes, and it is likely picking up jobs that are not strictly renewable energy. This is a common limitation in many renewable energy employment-related studies, as jobs are rarely coded specifically by energy source. IMPLAN sector 54 is coded as construction of new power and communication structures but does not specify between construction of fossil-fuel power structures and renewable power structures (see Appendix A). This inclusion of non-renewable energy employment in the dependent variable likely influenced results, but data that is more disaggregated is not available.

The final limitation of this study is that it only accounts for part of the employment impacts from these policy instruments. This study is only focused on gross job impacts, meaning it does not factor in potential job losses in other sectors that could be influenced by these policies. Additionally, this study is only focused on direct employment, meaning indirect and induced employment that may be impacted by these policies is not accounted for. In order to account for indirect and induced impacts, a CGE model is preferred, but these models have significantly greater data and computational requirements than FE models.

The potential job creation from the clean energy transition, specifically renewable energy generation, is an often-debated topic among policymakers and researchers. Most studies only account for a few policies and are focused on projecting their impacts into the future. This study, in contrast, compares eight different types of renewable energy policies and is focused on evaluating the county-level job growth associated with these policies that took place from 2001 to 2017. Additionally, the calculation and control for propensity scores in this work allows for the estimation of coefficients that are more accurate than those in models that do not account for potential selection bias. Finally, I included statistically significant interaction terms in the models between unemployment rate and the policy variables and coal mining employment and the policy variables. These interaction terms illuminated more nuanced policy impacts and provided additional guidance into the potential factors that can influence employment impacts from these policy instruments.

Overall, the three renewable energy policies that were found to have positive and statistically significant relationships with non-hydro renewable energy from 2001 to 2017 were industry recruitment/support (68.3 – 96.2 FTE), renewable portfolio standards (29.5 – 62.0 FTE), and performance-based incentives (14.1 – 24.7 FTE).

Chapter 3: Conclusions and Future Work

The transition to a clean energy infrastructure will have a wide-ranging impact on US communities, families, and individuals. Some will enjoy the benefits and opportunities of this transition, while others are likely to bear much of the burden. A policy problem facing our federal, state, and local governments is how to equitably distribute these benefits and burdens. Employment is an often-debated aspect of the clean energy transition among both policymakers and scholars, yet the employment impacts from renewable energy policies are not fully understood. This work contributes to a growing literature studying the just transition by comparing employment impacts from more renewable energy policy instruments than have previously been studied, by controlling for selection bias (using propensity score control), and by investigating the interactions between renewable energy policies and key county-level factors.

3.1 Key Impacts

This work has several key impacts for policymakers and future study of employment impacts of renewable energy policy. The first is that it is, to the best of my knowledge, the first study to provide a direct comparison of county-level employment impacts from subsidy programs; corporate, personal, and other tax incentives; performance-based incentives; industry recruitment/support; renewable portfolio standards; and net metering. Of these, industry recruitment/support, renewable portfolio standards, and performance-based incentives were found to have positive and statistically significant relationships with non-hydro renewable energy employment. The other policy instruments were not found to have statistically significant relationships with direct non-hydro renewable energy employment.

The second key impact of this study is that it demonstrated the importance of addressing selection bias in studies of renewable energy employment. Specifically, by incorporating controls on propensity scores this study provides models that account for more of the variation in non-hydro renewable energy employment across counties. Additionally, it showed that when selection bias is not addressed, renewable energy policies can be shown to have exaggerated impacts on renewable energy employment.

Finally, by interacting unemployment rate and coal employment variables with renewable energy policies this study provided a nuanced look into what county-level factors can influence policy outcomes. I found that in counties with high unemployment rates, three renewable energy policies (net metering, industry recruitment/support, and personal tax incentives) were actually found to have a negative and statistically significant relationship with non-hydro renewable energy employment. In the case of interacting coal employment with renewable energy policy variables, there was a mixed impact on county-level renewable energy employment. Personal tax incentives were found to have a negative influence on direct non-hydro renewable employment as coal employment increased, while corporate tax incentives and performance-based incentives were found to be more effective in counties with high coal employment. This highlights the fact that specific county-level characteristics, like unemployment rate and coal employment, should be accounted for when formulating and implementing renewable energy policies.

It is important to note that renewable energy policies are only one approach to addressing the distributional justice issues presented by the clean energy transition. Some jurisdictions are not well-positioned to produce electricity from renewable energy sources due to technical, political, or social factors. In these areas, investing in other industries may be more beneficial to increase employment opportunities like energy efficiency, grid modernization, environmental remediation, and manufacturing of renewable energy components (Pollin & Callaci, 2019).

3.2 Future Work

Future work in this field should address the limitations discussed in section 2.5. First, the creation of a policy stringency measure for each of the renewable energy policy instruments included would address the policy heterogeneity of the US. This would lead to a more robust and accurate model than one using simple binary variables describing the presence or absence of a program. Next, employment data that is more resolved (by renewable energy source) would lead to more precise measurements of renewable energy employment and more accurate comparisons to fossil-fuel sectors. Specifically, in the cases of manufacturing and construction of new power sectors, the additional resolution would be extremely helpful. Finally, additional study into the temporal differences in employment impacts of these renewable energy policy instruments would be helpful to inform policymakers. For example, incorporating the duration of the policy into a model and investigating how the employment impacts of that policy vary across time.

The clean energy transition is a rapidly evolving field with intersections into the fields of economics, political science, environmental science, and engineering, to name a few. It is important to try to forecast and project policy impacts on future energy demand, electricity generation, GHG emissions, and economic factors, which is the focus of significant research. Equally as important is to understand the impacts of past programs to see how they have influenced the clean energy transition, and if they are achieving desirable outcomes (both intended and unintended). This understanding of retrospective impacts can inform and guide policymakers in their policy formulation and implementation. This is the space that I would like to focus my future work. Specifically, looking into demographic (e.g. race or income) distributional justice impacts of the clean energy transition to ensure that no one is left behind.

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Appendix A. IMPLAN Sector Aggregation

To isolate the direct renewable energy employment at the county-level, I identified and aggregated the eight IMPLAN industries that are most closely related to renewable energy production. Six of the eight industries focus on renewable energy generation from different sources (hydroelectric, solar, wind, geothermal, biomass, and other). The associated North American Industry Classification System (NAICS) descriptions of the "Electric power generation – All Other" industry (Table A1) show that it represents tidal electric power generation. The two additional industries included in the direct renewable energy employment were "Electric power transmission and distribution" and "Construction of new power and communication structures." It is important to note that these two industries include employment that is not strictly renewable energy; however, this industry aggregation scheme is the most resolved that I have found. Table A1 shows the IMPLAN industry codes used (with descriptions) and their associated NAICS codes and descriptions.

Table A1: IMPLAN industry codes aggregated to create dependent variables
Dependent Variable: Total and Non-Hydro County-level Renewable Energy Employment

IMPLAN 536 Index	*IMPLAN Description*	*2017 NAICS Code*	*NAICS Description*
41	Electric power generation – Hydroelectric	221111	Electric power generation, hydroelectric
41	Electric power generation – Hydroelectric	221111	Hydroelectric power generation
41	Electric power generation – Hydroelectric	221111	Power generation, hydroelectric
44	Electric power generation - Solar	221114	Electric power generation, solar
44	Electric power generation - Solar	221114	Power generation, solar electric
44	Electric power generation - Solar	221114	Solar farms
45	Electric power generation - Wind	221115	Electric power generation, wind
45	Electric power generation - Wind	221115	Power generation, wind electric

46	Electric power generation - Geothermal	221116	Electric power generation, geothermal
46	Electric power generation - Geothermal	221116	Geothermal electric power generation
46	Electric power generation - Geothermal	221116	Power generation, geothermal
47	Electric power generation - Biomass	221117	Biomass electric power generation
47	Electric power generation - Biomass	221117	Electric power generation, biomass
47	Electric power generation - Biomass	221117	Power generation, biomass
48	Electric power generation - All other	221118	Electric power generation, tidal
48	Electric power generation - All other	221118	Power generation, tidal electric
49	Electric power transmission and distribution	221121	Electric power control
49	Electric power transmission and distribution	221121	Electric power transmission systems
49	Electric power transmission and distribution	221121	Transmission of electric power
49	Electric power transmission and distribution	221122	Distribution of electric power
49	Electric power transmission and distribution	221122	Electric power brokers
49	Electric power transmission and distribution	221122	Electric power distribution systems
54	Construction of new power and communication structures	237000	Construction of Power and communication transmission lines
54	Construction of new power and communication structures	237000	Construction of Power plants

Upon further examination, it was found that the electricity generation from hydroelectric sector (IMPLAN code 41) demonstrated a different employment trend than many of the other renewable energy generation sectors. It decreases from 2001 to 2017, with a sharp decline in 2009. The other renewable energy generation sectors are similar across the 17-year period, with slight increases in 2017. Figure A1 highlights this difference and Figure A2 shows a comparison of the dependent variable when this sector is removed. The analyses in this study were performed excluding the hydroelectric sector.

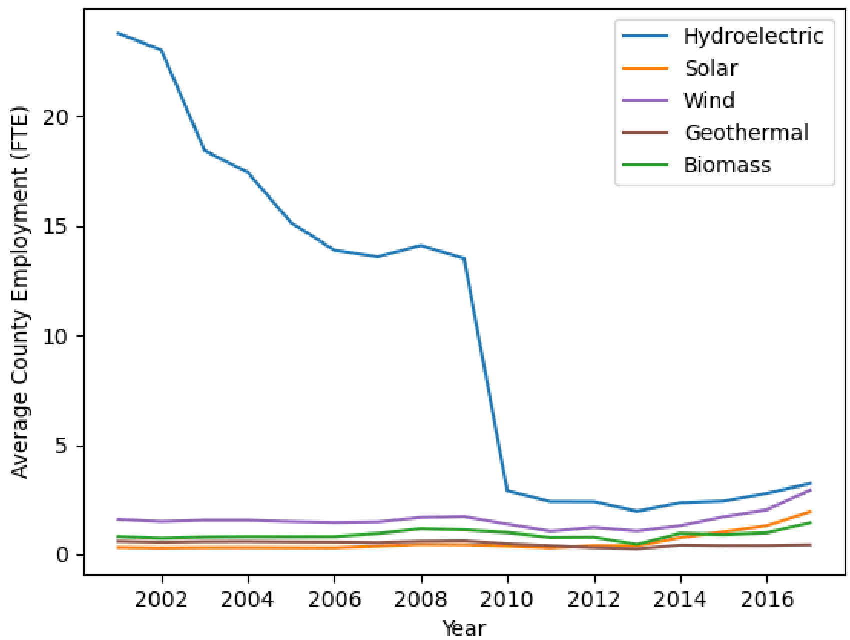

Figure A1: Average county employment of all renewable electric power generation sectors from 2001 to 2017.

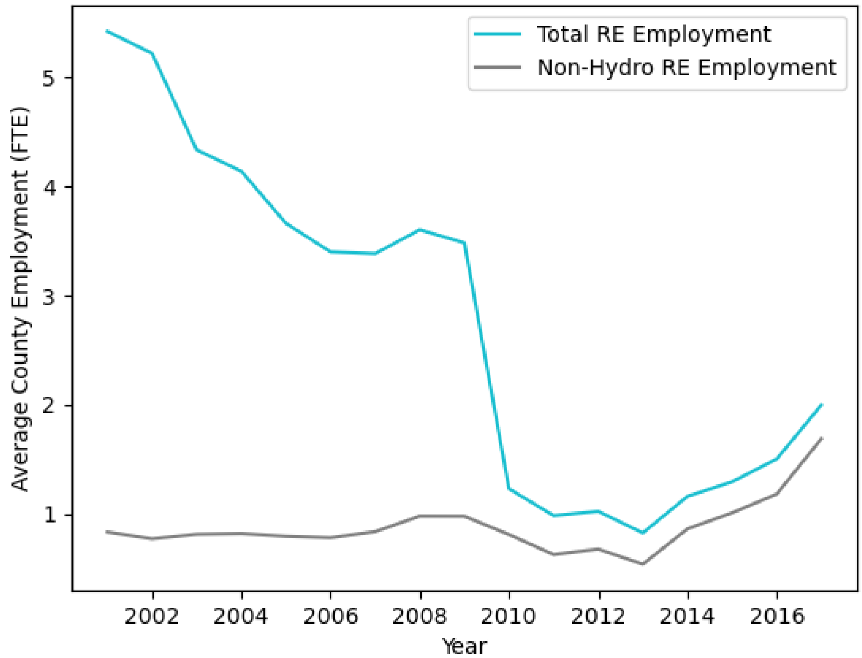

Figure A2: Average county employment aggregations including hydroelectric sector (Blue) and excluding the hydroelectric sector (Grey).

The construction sector is a significant driver of renewable energy employment. Omitting this sector would lead to an underrepresentation of renewable energy jobs, as nearly 80% of the jobs created by renewable energy projects are in the construction/installation phase (Bae & Dall'erba, 2016). The dependent variable is likely picking up jobs that are not solely renewable energy. The dependent variable broken down by type of job can be seen in Figure A3.

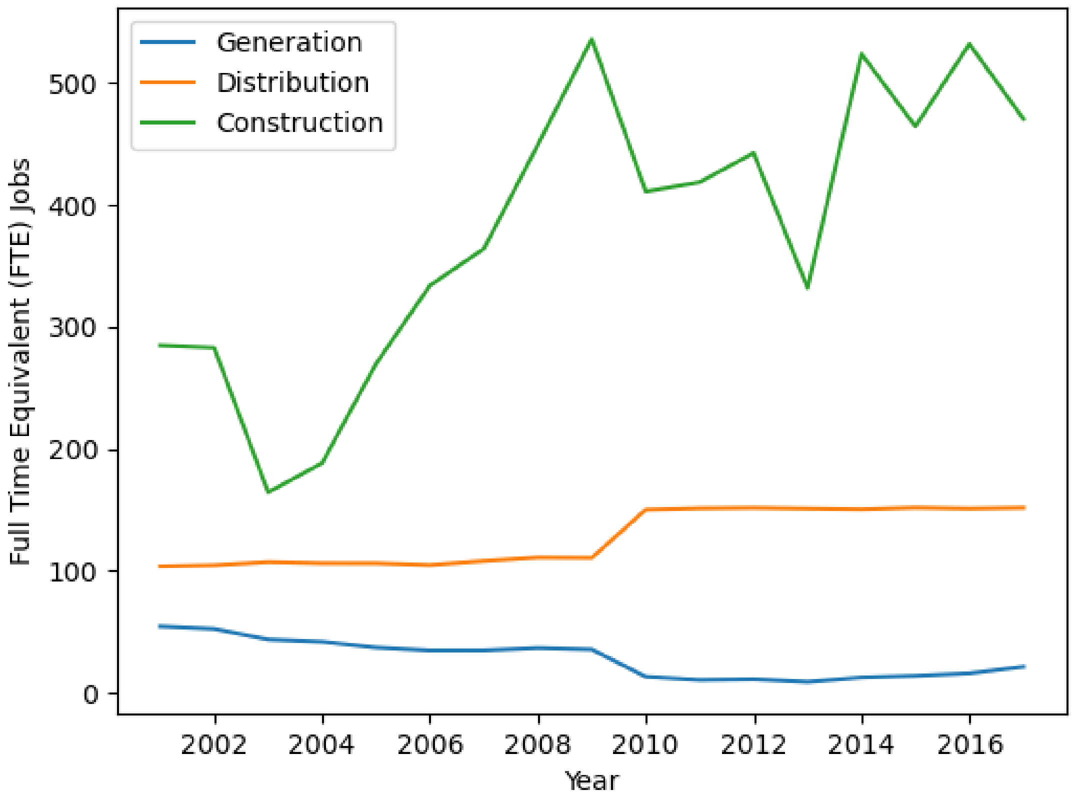

Figure A3: County-level renewable energy employment by type.
The dependent variable of all models by type of employment with the blue line signifying the generation employment, orange line representing distribution employment, and green line representing construction employment.

Construction jobs are the primary type of employment represented in the dependent variable, as seen in Figure A3. One potential solution is using another data source to account for the specific construction jobs desired such as County Business Patterns (CBP) data from the U.S. Census Bureau; however, this source has the same resolution as IMPLAN when it comes to that sector.

Appendix B. DSIRE Database Filtering and Categorization

To identify differences in employment impacts among renewable energy programs, I had to find what programs included in the database were most relevant to renewable energy. 18 relevant programs were chosen that were commonly mentioned or studied in previous studies of renewable energy policies. To make the interpretation of employment impacts easier, these 18 programs were placed into eight categories based on having similar characteristics and a similar mechanism. As three programs were not found in our sample period, there are fifteen program types that were studied for this analysis. Table B1 shows what programs were chosen and what category each program was placed in.

Table B1: Relevant DSIRE programs, program categories, and numbers of programs

Program	DSIRE Program Code	Number of Total Programs	Number of Relevant Programs
Personal Tax Incentives			
Personal Tax Credit	31	79	49
Personal Tax Deduction	32	17	9
Corporate Tax Incentives			
Corporate Tax Credit	18	85	49
Corporate Tax Deduction	19	6	2
Other Tax Incentives			
Property Tax Incentive	78	108	47
Sales Tax Incentive	81	88	46
Performance-based Programs			
Performance-based Incentive	13	160	75
Feed in Tariff	92	13	7
Subsidy Programs			
Grant Program	87	364	62
Rebate Program	88	2448	272
Loan Program	89	567	56
PACE Financing	76	70	16
Net Metering			
Net Metering	37	124	8
Renewable Portfolio Standards			
Renewable Portfolio Standard	38	60	14
Industry-specific Programs			
Industry Recruitment/Support	40	87	40

In addition to categorizing relevant programs, we had to filter the database based on several steps. Figure B1 highlights the steps involved in the filtering process that took us from the entire database (5,283 programs) and the programs we studied (752 programs). The largest removal of programs was due to lack of start dates in the database. A lack of end date in the database did not preclude a program from being studied, rather, all programs without an end date were assumed to continue until the end of our data (2017).

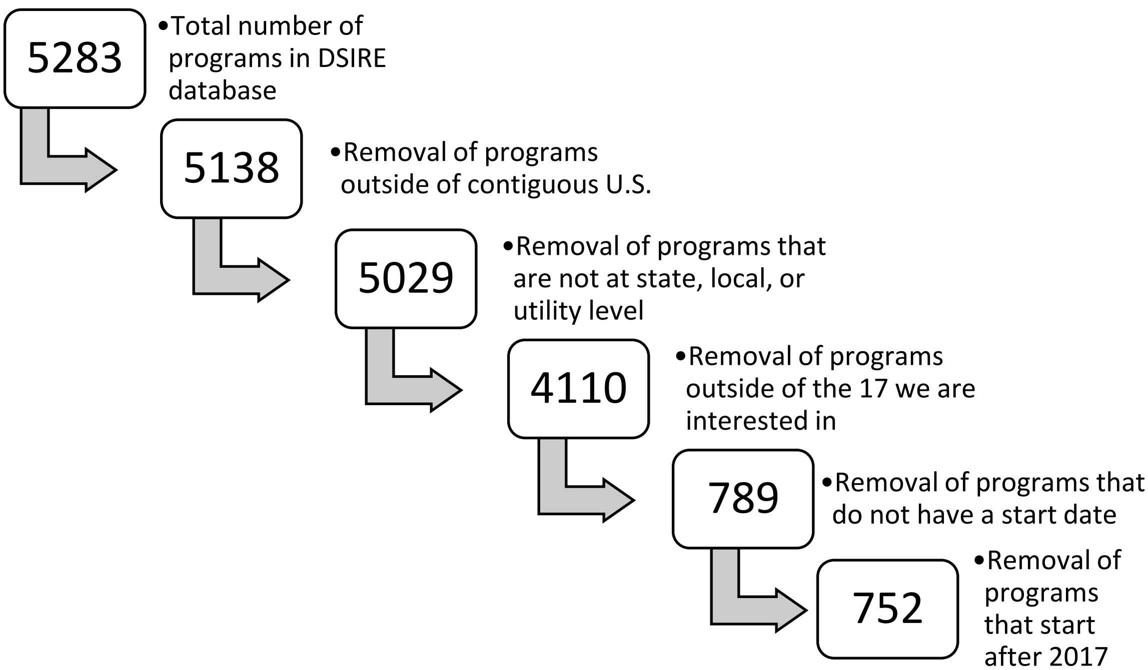

Figure B1: Filtering process of the DSIRE database

Appendix C. Comparison of Different Policy Lags

I ran models with four different policy lags and the results can be found in **Error! Reference source not found.**.

Table C1: FE model results with four different policy lags
Dependent variable: Non-hydro renewable energy employment

	COEFFICIENTS			
VARIABLES	No Policy Lag	One-Year Policy Lag	Two-Year Policy Lag	Three-Year Policy Lag
Net Metering	-31.56*	-19.00	-7.904	-4.161
	(18.97)	(19.91)	(20.55)	(17.80)
Renewable Portfolio Standard	37.68**	37.20**	43.76**	45.32***
	(17.05)	(17.73)	(17.65)	(15.24)
Industry Recruitment/Support	28.31***	20.84**	13.41	5.199
	(9.436)	(9.274)	(9.140)	(8.516)
Personal Tax Incentive	-31.70***	-25.63***	-23.80***	-20.34***
	(6.358)	(6.311)	(6.336)	(6.022)
Corporate Tax Incentive	25.68***	17.81**	12.38	5.692
	(8.387)	(8.235)	(8.223)	(7.416)
Other Tax Incentive	-1.615	2.380	4.761	2.111
	(8.126)	(7.902)	(6.769)	(5.446)
Performance-Based Incentive	30.62***	33.14***	25.25***	17.81**
	(6.114)	(7.217)	(7.985)	(8.244)
Subsidy Programs	-1.263	1.244	-0.727	-4.456
	(6.588)	(6.141)	(6.080)	(5.738)
Coal Employment	-0.574***	-0.589***	-0.568***	-0.533***
	(0.0976)	(0.103)	(0.103)	(0.0842)
GDP per Capita	-4.079	-3.900	-3.749	-3.704
	(3.511)	(3.524)	(3.647)	(3.324)
Unemployment Rate	-51.18***	-51.38***	-50.48***	-45.20***
	(5.538)	(5.439)	(5.419)	(4.697)
Political Preference	176.9***	175.7***	173.7***	156.4***
	(33.62)	(33.39)	(32.89)	(30.69)
Propensity Score	3,375***	3,410***	3,408***	3,054***
	(414.3)	(408.4)	(409.3)	(352.8)
year = 2002	0.0315			
	(1.850)			
year = 2003	-54.40***	-53.42***		
	(3.147)	(2.746)		
year = 2004	-45.70***	-46.41***	9.702***	
	(3.273)	(2.961)	(2.099)	
year = 2005	-14.91***	-19.78***	36.05***	30.55***
	(3.178)	(2.978)	(3.121)	(2.504)
year = 2006	6.182*	0.396	52.47***	49.70***

	(3.277)	(3.138)	(4.223)	(3.637)
year = 2007	15.80***	11.50***	62.99***	57.20***
	(4.319)	(3.748)	(4.922)	(4.318)
year = 2008	31.15***	30.31***	82.95***	79.42***
	(5.629)	(5.143)	(6.082)	(5.366)
year = 2009	67.22***	56.51***	110.3***	110.1***
	(12.32)	(10.60)	(11.56)	(9.370)
year = 2010	20.56	16.18	62.21***	65.94***
	(13.34)	(11.90)	(11.39)	(9.312)
year = 2011	28.13**	21.33*	74.70***	71.77***
	(12.24)	(11.81)	(11.70)	(8.751)
year = 2012	27.54**	21.88	74.70***	78.44***
	(13.55)	(13.48)	(14.73)	(11.87)
year = 2013	-4.934	-12.47	41.48***	43.60***
	(10.08)	(9.899)	(11.28)	(9.910)
year = 2014	52.84***	47.58***	100.7***	107.5***
	(12.68)	(11.89)	(13.70)	(13.19)
year = 2015	28.91***	22.81**	77.91***	82.58***
	(11.03)	(10.35)	(11.79)	(11.10)
year = 2016	70.97***	64.23***	118.8***	123.1***
	(13.25)	(12.53)	(14.23)	(13.60)
year = 2017	45.11***	36.75***	91.60***	94.98***
	(11.83)	(11.17)	(12.85)	(12.12)
Constant	-507.6***	-511.6***	-565.3***	-475.3***
	(92.29)	(91.43)	(91.79)	(77.84)
Observations	51,595	48,560	45,525	42,490
R-squared (within)	0.242	0.249	0.248	0.235
Number of Counties	3,035	3,035	3,035	3,035
County FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Note: Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Of all the policy lags, the one-year lag has the highest within R-squared, but there is not that much variation across the four models. As a result, the no policy lag and a one-year policy lag configuration were used most often in the paper.

Appendix D. Correlation Matrix of All Variables Included in Models and Model Specification Tests

To identify any potential multicollinearity in the models, I created a correlation matrix of all variables included in the models. Figure D1 is the correlation matrix, with green shades signifying positive correlation and red shades signifying negative correlation.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
(1) Total RE Employment	1.00	0.79	0.53	0.51	0.75	0.29	0.97	0.64	-0.03	0.06	-0.05	0.10	0.60	-0.02	0.00	0.08	-0.04	0.04	0.00	0.07	0.04	0.00	0.18
(2) Non-Hydro RE Employment	0.79	1.00	0.39	0.52	0.97	0.31	0.62	0.88	-0.01	0.03	-0.15	0.24	0.88	0.01	0.05	0.07	-0.04	-0.03	0.02	0.06	0.03	0.00	0.04
(3) RE Generation Employment	0.53	0.39	1.00	0.53	0.38	0.08	0.50	0.36	-0.01	0.00	-0.02	0.07	0.32	-0.01	0.01	0.03	-0.05	-0.01	-0.02	0.05	0.03	0.00	0.05
(4) Non-Hydro RE Generation Employment	0.51	0.52	0.53	1.00	0.49	0.11	0.46	0.45	0.01	0.05	-0.08	0.12	0.42	-0.01	0.01	0.03	-0.04	-0.04	-0.02	0.05	0.00	0.00	0.03
(5) RE Construction Employment	0.75	0.97	0.38	0.49	1.00	0.33	0.58	0.91	-0.01	0.04	-0.16	0.24	0.92	0.00	0.04	0.08	-0.04	-0.04	0.02	0.07	0.03	0.00	0.03
(6) Coal Employment	0.29	0.31	0.08	0.11	0.33	1.00	0.15	0.32	0.03	-0.03	-0.09	0.08	0.35	0.04	0.04	0.00	0.01	0.00	0.00	-0.03	-0.03	0.00	0.06
(7) Natural Gas Employment	0.97	0.62	0.50	0.46	0.58	0.15	1.00	0.47	-0.03	0.07	-0.01	0.04	0.42	-0.03	-0.02	0.08	-0.04	0.06	-0.01	0.07	0.04	0.01	0.21
(8) GDP	0.64	0.88	0.36	0.45	0.91	0.32	0.47	1.00	-0.02	0.04	-0.14	0.25	0.96	0.01	0.04	0.05	-0.04	-0.06	0.00	0.07	0.00	0.01	0.01
(9) Unemployment Rate	-0.03	-0.01	-0.01	0.01	-0.01	0.03	-0.03	-0.02	1.00	-0.06	-0.36	0.17	0.00	0.04	-0.01	0.18	0.01	-0.11	0.07	0.06	0.16	-0.03	-0.20
(10) Solar Resource	0.06	0.03	0.00	0.05	0.04	-0.03	0.07	0.04	-0.06	1.00	-0.07	-0.10	0.05	-0.31	-0.25	0.11	0.05	0.27	0.06	0.09	0.06	0.06	0.54
(11) Wind Resource	-0.05	-0.15	-0.02	-0.08	-0.16	-0.09	-0.01	-0.14	-0.36	-0.07	1.00	-0.08	-0.17	0.15	0.11	-0.08	0.02	0.19	0.04	0.04	-0.01	0.01	0.71
(12) Political Preference	0.10	0.24	0.07	0.12	0.24	0.08	0.04	0.25	0.17	-0.10	-0.08	1.00	0.24	0.04	0.14	-0.03	0.00	-0.12	0.02	0.00	0.05	-0.01	-0.14
(13) Population	0.60	0.88	0.32	0.42	0.92	0.35	0.42	0.96	0.00	0.05	-0.17	0.24	1.00	0.01	0.04	0.06	-0.04	-0.06	0.00	0.07	0.00	0.00	-0.01
(14) Net Metering	-0.02	0.01	-0.01	-0.01	0.00	0.04	-0.03	0.01	0.04	-0.31	0.15	0.04	0.01	1.00	0.57	-0.07	0.04	-0.13	-0.04	-0.07	0.01	-0.01	-0.08
(15) Renewable Portfolio Standard	0.00	0.05	0.01	0.01	0.04	0.04	-0.02	0.04	-0.01	-0.25	0.11	0.14	0.04	0.57	1.00	-0.08	0.17	-0.13	0.09	-0.18	0.15	-0.01	-0.07
(16) Industry Recruitment/Support	0.08	0.07	0.03	0.03	0.08	0.00	0.08	0.05	0.18	0.11	-0.08	-0.03	0.06	-0.07	-0.08	1.00	-0.18	0.03	0.06	0.33	0.24	0.03	0.07
(17) Personal Tax Incentive	-0.04	-0.04	-0.05	-0.04	-0.04	0.01	-0.04	-0.04	0.01	0.05	0.02	0.00	-0.04	0.04	0.17	-0.18	1.00	0.52	0.20	-0.29	0.01	-0.02	0.04
(18) Corporate Tax Incentive	0.04	-0.03	-0.01	-0.04	-0.04	0.00	0.06	-0.06	-0.11	0.27	0.19	-0.12	-0.06	-0.13	-0.13	0.03	0.52	1.00	0.10	0.03	0.10	0.03	0.33
(19) Other Tax Incentive	0.00	0.02	-0.02	-0.02	0.02	0.00	-0.01	0.00	0.07	0.06	0.04	0.02	0.00	-0.04	0.09	0.06	0.20	0.10	1.00	0.00	0.18	0.01	0.08
(20) Performance-Based Incentive	0.07	0.06	0.05	0.05	0.07	-0.03	0.07	0.07	0.06	0.09	0.04	0.00	0.07	-0.07	-0.18	0.33	-0.29	0.03	0.00	1.00	0.00	0.04	0.12
(21) Subsidy Programs	0.04	0.03	0.03	0.00	0.03	-0.03	0.04	0.00	0.16	0.06	-0.01	0.05	0.00	0.01	0.15	0.24	0.01	0.10	0.18	0.00	1.00	0.03	0.06
(22) GDP per Capita	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	-0.03	0.06	0.01	-0.01	0.00	-0.01	-0.01	0.03	-0.02	0.03	0.01	0.04	0.03	1.00	0.05
(23) Propensity Score	0.18	0.04	0.05	0.03	0.03	0.06	0.21	0.01	-0.20	0.54	0.71	-0.14	-0.01	-0.08	-0.07	0.07	0.04	0.33	0.08	0.12	0.06	0.05	1.00

Figure D1: Correlation matrix of all variables included in the models

The independent variables with the strongest pairwise correlations were *population* and *GDP* (0.96), *net metering* and *renewable portfolio standards* (0.57), and *property tax incentives* and *corporate tax incentives* (0.52). As a result, the *population* and *GDP* variables were removed from all models; however, the quotient of *GDP* and *population* was used as a new variable:

county-level *GDP per capita*. Allison (1999) asserts that correlations greater than the 0.6 threshold are a concern for the model. As such, we left the policy variables that were relatively-highly correlated in the models as they were 0.6 or less.

To support that a FE model was an appropriate model choice a Hausman test was performed (Hausman, 1978). The null hypothesis of this test is that the difference of the coefficients of the Random-Effects (RE) model and the FE model is not systematic. This null hypothesis was rejected (0.0007), therefore the result of this model specification test showed that a FE model was more appropriate than a RE model in this case.

Appendix E. Full Model Result Tables with Years Included

I ran four FE models without control for propensity score. Two of them had total direct renewable energy employment as the dependent variable, rather than non-hydro employment, and two had a one-year policy lag. The results, with the added year coefficients, can be seen in Table E1.

Table E1: Full model results with years included
Dependent variables: Signified by title of models

VARIABLES	COEFFICIENTS			
	Non-Hydro RE Employment	Total RE Employment	Non-Hydro RE Employment	Total RE Employment
Net Metering	-8.323	-72.48*	-9.065	-81.84**
	(25.43)	(37.95)	(26.81)	(39.96)
Renewable Portfolio Standard	48.08**	7.234	61.43***	31.03
	(20.74)	(36.92)	(22.34)	(39.47)
Industry Recruitment/Support	16.47	-34.91	13.23	-33.89
	(10.25)	(27.77)	(10.26)	(26.99)
Personal Tax Incentive	-49.25***	-160.6***	-47.45***	-164.4***
	(8.184)	(29.79)	(7.944)	(29.94)
Corporate Tax Incentive	26.43**	64.26***	22.95**	57.32**
	(10.80)	(23.63)	(10.67)	(23.07)
Other Tax Incentive	5.138	49.78*	5.813	45.66*
	(8.352)	(25.86)	(8.281)	(24.01)
Performance-Based Incentive	33.33***	48.83***	37.53***	55.75***
	(7.177)	(15.68)	(8.239)	(19.07)
Grants, Rebates, or Loans	-15.28**	-47.01**	-13.22**	-48.76**
	(7.573)	(19.54)	(6.716)	(19.45)
Coal Employment	-0.304***	0.624***	-0.323***	0.586***
	(0.116)	(0.170)	(0.123)	(0.180)
GDP per Capita	-4.610***	3.091	-4.399***	3.917
	(1.321)	(12.07)	(1.285)	(11.97)
Unemployment Rate	-5.971***	-25.91***	-5.905***	-27.10***
	(1.507)	(4.644)	(1.589)	(4.997)
Political Preference	115.3***	226.9**	115.0***	225.4**
	(34.46)	(92.34)	(34.31)	(92.30)
year = 2002	0.120	-0.168		
	(1.954)	(3.946)		
year = 2003	-62.59***	-47.36***	-61.00***	-41.74***
	(3.892)	(6.732)	(3.646)	(5.131)
year = 2004	-54.65***	-49.92***	-53.11***	-49.40***
	(4.226)	(7.413)	(3.924)	(6.424)
year = 2005	-13.60***	5.118	-18.72***	-4.992

	(3.594)	(8.092)	(3.850)	(7.863)
year = 2006	17.77***	53.17***	11.81***	46.43***
	(4.328)	(10.39)	(4.305)	(9.784)
year = 2007	35.43***	95.86***	30.27***	84.74***
	(5.241)	(13.06)	(4.936)	(12.25)
year = 2008	69.90***	204.5***	70.92***	207.5***
	(5.955)	(19.19)	(5.799)	(17.28)
year = 2009	141.1***	342.8***	127.8***	313.7***
	(10.93)	(33.60)	(9.212)	(29.75)
year = 2010	93.57***	342.4***	86.66***	333.0***
	(11.54)	(38.34)	(9.900)	(36.33)
year = 2011	92.12***	316.3***	87.07***	319.0***
	(11.00)	(36.49)	(10.40)	(36.95)
year = 2012	101.6***	392.3***	99.69***	404.1***
	(11.54)	(42.72)	(11.47)	(44.59)
year = 2013	40.18***	259.5***	34.87***	266.0***
	(8.662)	(35.20)	(8.391)	(36.70)
year = 2014	128.1***	408.4***	124.4***	409.3***
	(11.55)	(40.46)	(11.02)	(40.61)
year = 2015	94.58***	355.5***	88.94***	354.1***
	(10.02)	(35.30)	(9.368)	(35.45)
year = 2016	131.6***	321.8***	127.1***	324.5***
	(13.37)	(33.54)	(12.98)	(34.10)
year = 2017	100.6***	292.9***	93.19***	289.2***
	(11.67)	(30.26)	(11.14)	(30.66)
Constant	229.1***	574.3***	232.8***	590.2***
	(13.15)	(26.84)	(13.98)	(29.02)
Observations	51,595	51,595	48,560	48,560
R-squared (within)	0.101	0.069	0.106	0.068
Number of Counties	3,035	3,035	3,035	3,035
County FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
One-Year Policy Lag	No	No	Yes	Yes

Note: The models with the 1-year policy lag omits the observations from 2001 and has 3,035 less observations as a result. Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The results show that most years were significantly significant in the model, with earlier years having negative coefficients and later years with positive. This highlights the fact that the time fixed effects are properly taking into account variation caused by price reductions, technological changes, and international policy on renewable energy.

Appendix F. Renewable Generation and Construction Model Results

I ran three models comparing the construction (short-term) and generation (long-term) impacts. The long-term impacts were then further disaggregated to total generation and non-hydro generation. The results of these FE models can be found in Table F1.

Table F1: Renewable generation and construction FE models
Dependent variables: Signified by title of models

VARIABLES	COEFFICIENTS		
	Construction Employment	Generation Employment	Non-Hydro Generation Employment
Net Metering	-50.49***	-26.61***	-1.048
	(12.30)	(7.996)	(2.202)
Renewable Portfolio Standard	40.04***	-14.95**	-2.717
	(11.58)	(5.910)	(3.126)
Industry Recruitment/Support	34.36***	2.492	-0.703
	(7.377)	(2.994)	(1.055)
Personal Tax Incentive	-29.17***	3.847**	-1.170*
	(5.079)	(1.588)	(0.677)
Corporate Tax Incentive	18.18**	-0.640	-1.253*
	(7.495)	(1.463)	(0.663)
Other Tax Incentive	2.176	-5.259**	-0.942*
	(5.511)	(2.590)	(0.514)
Performance-Based Incentive	25.13***	-0.601	0.842
	(4.252)	(2.423)	(0.576)
Subsidy Programs	5.713	7.243***	0.258
	(4.277)	(2.417)	(0.783)
Coal Employment	-0.212***	-0.0173	-0.00291
	(0.0471)	(0.0182)	(0.00355)
GDP per Capita	-3.834	0.463	-0.150
	(2.747)	(0.413)	(0.147)
Unemployment Rate	-37.50***	1.613***	-0.523**
	(4.514)	(0.517)	(0.203)
Political Preference	134.2***	-18.58	2.657**
	(21.19)	(11.52)	(1.174)
Propensity Score	2,492***	-51.73	45.79***
	(347.0)	(40.63)	(13.02)
year = 2002	-1.027	-1.757	-0.0190
	(1.349)	(1.263)	(0.611)
year = 2003	-58.27***	-6.743***	0.241
	(3.058)	(2.169)	(0.833)
year = 2004	-47.69***	-5.962**	0.581
	(2.720)	(2.413)	(1.183)

year = 2005	-13.75***	-7.273***	0.455
	(2.061)	(2.398)	(1.025)
year = 2006	10.52***	-7.598***	0.460
	(2.400)	(2.558)	(0.797)
year = 2007	19.27***	-7.878***	0.682
	(2.936)	(2.740)	(0.744)
year = 2008	37.36***	-3.310	1.281
	(4.296)	(2.489)	(0.900)
year = 2009	73.68***	-7.070**	0.828
	(9.225)	(3.496)	(0.879)
year = 2010	8.804	-21.05***	0.175
	(9.167)	(5.553)	(0.964)
year = 2011	14.99*	-21.72***	-0.412
	(8.091)	(5.344)	(0.879)
year = 2012	18.55**	-20.65***	-0.0968
	(8.935)	(5.427)	(0.893)
year = 2013	-18.59***	-21.47***	-0.505
	(6.456)	(5.043)	(0.890)
year = 2014	50.18***	-18.17***	0.498
	(8.353)	(4.952)	(0.844)
year = 2015	24.02***	-17.17***	1.276
	(6.933)	(4.646)	(0.863)
year = 2016	65.56***	-16.18***	1.993**
	(8.078)	(5.199)	(0.870)
year = 2017	36.63***	-12.91***	4.300***
	(6.824)	(4.879)	(0.931)
Constant	-398.0***	39.51***	-6.124*
	(80.08)	(8.144)	(3.639)
Observations	51,595	51,595	51,595
R-squared (within)	0.238	0.018	0.007
Number of Counties	3,035	3,035	3,035
County FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
One-Year Policy Lag	No	No	No

Note: Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The model with construction employment as the dependent variable was not significantly different from the main models presented in Section 2, whereas the generation models have very low within R-squared values and do not explain much variation in the dependent variable. As a result, no conclusions can be drawn from the comparison between the generation and construction models.

Appendix G: Logistic Regression Results

To calculate the propensity scores of each county having aggressive renewable energy policy, I calculated logistic regressions of each individual year of the panel dataset to see which would be the best measure using Equation 3. The year 2003 was found to have the best pseudo-R-squared (0.22) and was used to estimate the propensity scores for each county in every year of the sample. The results of that logistic regression model can be found in Table G1.

Table G1: Logistic regression results
Dependent variable: Aggressive renewable energy policy in 2003

VARIABLES	ODDS RATIOS DV: Aggressive RE Policy in 2003
Non-Hydro RE Employment	1.001*
Coal Employment	1.001***
Natural Gas Employment	1.001***
Political Preference	0.851
Population	0.984**
Wind Resource	4.068***
Solar Resource	2.704***
Unemployment Rate	1.100***
GDP	1.000
Constant	8.03e-08***
Observations	3,035
Pseudo-R-squared	0.22
County FE	No
Time FE	No

*Note: *** p<0.01, ** p<0.05, * p<0.1*

Coal employment, natural gas employment, wind resource, solar resource, and unemployment were the variables with statistically significant odds ratios greater than one. This means that they increased the probability of a county being aggressive in 2003, holding all else constant. Non-hydro RE employment, political preference, and GDP were not found to have significant odds ratios.