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Three Essays on Environmental and Energy Economics

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Abstract

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In this dissertation, three related topics are investigated about environmental and energy economics. The research in these essays utilize panel data and regression models. The overall theme of these essays is to explore the relationships between energy and the environment in the United States (U.S.).

In the first essay, using data from fifty U.S. states between 2012 and 2020, the impacts of three types of state level policies on electric vehicles (EV) adoption are examined: 1) policies that mitigate the environmental impacts from energy production, 2) policies that provide financial incentives to consumers for EV purchase, and 3) policies that provide publicly available EV charging infrastructure. With a dependent variable of EV registration per 100,000 population, impacts are assessed with a panel data, fixed effects model. Evidence is found that policies which either increase low greenhouse gas (GHG) energy through increasing the renewable and nuclear energy sources in the energy mix or reduce carbon dioxide (CO_2) emissions from electricity generation by reducing the reliance on fossil fuels in the electric sector result in statistically significant increases in EV adoption rate. Financial incentives are important as the presence of a state income tax credit positively impacts EV adoption rate. Comparable elasticities on EV adoption rate from statistically significant coefficients show that per capita income has the largest effect on adoption (+10.1), while impacts of low GHG energy and per capita CO_2 emissions elasticities are much smaller at + 0.64 and -1.0, respectively. Since state policies that enhance low GHG and provide tax credits positively impact EV adoption rates, our research demonstrates the need to nationalize both types of policies in order to uniformly improve adoption across all states.

In the second essay, the impact of climate change on U.S. electricity consumption, production, and efficiency is examined using annual state-level data for 48 states over 30 years (1990 – 2019). Research results show that an increase in averaged maximum ambient air temperatures increases electricity demand and decreases generation efficiency. The electric sector in the U.S. is found to be vulnerable to climate change, such that a rise in the ambient temperature increases demand for electricity and decreases supply and efficiency of power plants. On the demand side, the per capita electricity consumption at the state level is responsive to the climate change, such that when the averaged maximum ambient temperature increases by 1 $^{\circ}$F (0.56 $^{\circ}$C), the per capita electricity consumption increases by a 0.52%. However, the most powerful impact on the per capita electricity consumption was found to be from the electricity retail prices such that a one cent increase in average per kilowatt-hours (kWh) price will result in a decrease of 7.1% in the per capita electricity consumption.

On the supply side, power generation is also responsive to climate change such that increasing the average maximum temperature by 1 $^{\circ}$F (0.56 $^{\circ}$C) results in a reduction of 3.9% in the total electricity generation at the state level. Estimates for fossil fuels weighted average price consistently agree with law of demand as increasing fossil fuels weighted average price by $1 per million British Thermal Unit (MMBtu)[1] results in reduction of demand for fossil fuels and

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[1] In average, this increase is equal to an increase of 2 cents per short ton of coal, $1.02 per 1000 CF of natural gas, or 12 cents per gallon of petroleum.

accordingly will result in a reduction of electricity supply by 10.2%. Finally, the efficiency of fossil fired power plants decreases with increasing ambient temperature due to increased fuel consumption.

In the third essay, the existence of the Environmental Kuznets Curve (EKC) in the presence of low GHG energy consumption is empirically examined using state level data in the U.S. This research explores whether the per capita income still retains an inverted U shape impact on per capita CO_2 emissions in the presence of state level environmental and energy policies which promote reduced fossil fuel use in the electricity sector. An Autoregressive Distributive Lag (ARDL) econometric model is employed using panel data for 50 U.S. states during the period of 1990 to 2018. The findings provide statistically significant evidence for the presence of the EKC for CO_2 emissions at the state level. Regression estimates find a turning point of $50,766.5 in the relationship between per capita income and CO_2 emissions. For the Low GHG energy variable, increased primary energy consumption for electricity from renewable and nuclear energy sources has a negative impact on per capita CO_2 emissions. When the per capita average low GHG energy consumption increases by one MMBtu[2], per capita CO_2 emissions reduces by 0.05%. With these findings, the existence of the EKC hypothesis for CO_2 emissions at the state level is supported.

The conclusion from essay three is that implementation of new energy technologies serves to reduce CO_2 emissions. However, these technologies do not diminish the entire impact of increasing per capita income on reducing these emissions. Other factors, in addition to new energy technologies, are at work in reducing CO_2 emissions with increasing per capita income past the turning point. These factors may include changes associated with higher levels of per capita income including an economic structure more heavily dependent upon services involving renewable energy source and increasing the adoption of green technologies such as EV, movement of production locations to other locations with lower income in helps stimulating the economic growth which in turn has a positive impact on the reduction of CO_2, and enhanced consumer awareness about climate change and behavioral changes related fossil fuel consumption.

[2] One million Btu is equal to 293 kWh.

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CHAPTER 1

Background and Significance

1.1 Introduction

This dissertation consists of three essays that empirically explore connections between energy and environment in the United States (U.S.). The relationship between energy usage and greenhouse gas (GHG) emissions is considered a vital area of concern to all levels of society - governments, policymakers, environmental scientists and scholars, and the general public especially those impacted by climate change (Salari et al., 2021). Increasing GHG emissions is significantly contributing to increases in global temperatures and the resulting climate change. These emissions are generated as a result of human activities in various sectors of the economy, especially energy and transportation sectors (IPCC, 2021).

Since 1990, the U.S. GHG emissions have decreased by 7%. This fall in GHG emissions stems from changes in the economy. In general, this reduction was driven by the structural shift in electricity generation to relatively lower emissions generating sources such as natural gas and low GHG energy[3], improvements in power plant efficiency, and reducing the share of coal in the power generation sector (Mohlin et al., 2019; Feng et al., 2016). In 2020, for example, the U.S. Environmental Protection Agency (EPA) reported that the U.S. GHG emissions decreased 11% compared to 2019 levels. This sharp decline in emissions is mainly due to two reasons, the first is the reduction of carbon dioxide (CO_2) emissions accompanied with the coronavirus (COVID-19) pandemic which yielded fossil fuels consumption reductions due to declines in economic activities and transportation. The second reason is the continued endeavors to switch to clean energy resources in electricity generation including renewables.

Transportation and energy sectors are the main contributors to air pollution and environmental degradation in the U.S. In 2020, transportation sector was accounted for about

[3] Low GHG energy sources include renewable and nuclear energy sources. Renewable energy sources include solar, wind, hydropower, geothermal, and biomass (EIA, 2019).

28% of the U.S. total GHG emissions (EPA, 2022). With this percentage, the transportation sector can be considered as the most significant contributor to anthropogenic GHG emissions (Umar et al., 2021). Moreover, it consumes about 30% of the U.S. total energy resources and accounts for 92% of the energy demand for petroleum (EIA, 2022). With respect to the energy sector, electric power in 2020 accounted for about 25% of the total U.S. GHG emissions (EPA, 2022). About 79% of the energy used in the U.S. was produced through combustion of fossil fuels – petroleum, natural gas and coal. (EIA, 2022). These sectors together were responsible for 55% of the total GHG emissions in 2019, and for 52% in 2020 (EPA, 2022). Recently, transportation electrification, including the deployment of electric vehicles (EV), has gained significant importance, especially with the policymakers' vital role in switching into clean energy technologies. Although motivations among state policymakers vary, many states had set target dates to phase out the internal combustion engine vehicles (ICEV) from their fleet (Rapson and Muehlegger, 2021). This goal would be accomplished by implementing incentives to promote the adoption of EV (Al-Buenain et al., 2021).

Following the establishment of the International Panel in Climate Change (IPCC) in 1988, awareness concerning the negative impacts of CO_2 emissions has increased (Hargrove et al., 2019). Many countries, including the U.S., have adopted a combination of efforts to mitigate those impacts. Various efforts have been set up to focus on the energy and transportation sectors. While most of these efforts are driven by a need for decarbonization to reduce GHG emissions, their main goal is to switch from fossil fuels including coal, natural gas, and oil to renewable energy, nuclear energy, and biofuels. Reducing GHG emissions requires collaborative endeavors across many sectors of society: individual consumers, industries that produce goods and services, and state and federal governments. It also requires policies that increase the share of low GHG energy production in the energy mix. One approach is to support the electrification of the transportation sector in order to achieve the goals of reducing both air pollution and the reliance on fossil fuels for energy and transportation sectors.

1.2 Purpose of This Study

This dissertation aims to highlight empirically the importance of low GHG energy technologies in the transportation and energy sectors for better environmental quality. It also explores the impact of climate change on the energy sector demand and supply. This research is composed of three essays. Each essay employs a panel data structure in its analyses. Our selection for type of data structure is based upon several advantages that include: 1) combining time series and cross-sectional observations which provides more informative data and variability, 2) measuring the effects that cannot be observed in cross sectional or time series data, and 3) minimizing the bias that might result by aggregating individuals or states into broad aggregates.

1.2.1 Aim of essay 1: The Impact of State Policies on Electric Vehicles Adoption - A Panel Data Analysis

The first essay explores the impact of state level policies - represented by the low GHG energy technology adoption- on the EV adoption rate within the U.S. fifty states using state panel data for the period 2012 to 2020. State level study is worthwhile for investigation since states can act independently from each other in adopting regulations and policies. Purchases of EV have increased greatly over the past decade in the U.S. With about 1.2 million EV on U.S. roads in 2019 (Ou et al., 2021), EV are still with a small fraction with about 1.9% from the total number of vehicles registered in the U.S. (Jang and Choi, 2021).

Several studies have investigated factors influencing EV adoption including environmental concerns, tax incentives, and personal attributes. As examples, Diamond (2009), Zhang et al. (2011), Sierzchula et al. (2014), and Clinton and Steinberg (2019) examined tax incentives, Langbroek et al. (2016) included tax incentives and income, Soltani-Sobh et al. (2017) included variables of income, urbanization, and incentives, Egbue and Long, (2012) used charging stations, and Choi et al. (2018) examined electricity generation mix. Based on these studies' findings which supported the importance of policies on EV adoption rate, this study will examine the impacts of three state level policies on EV adoption rate. The three policies will be presented by: 1) those that mitigate the environmental impacts from energy production, 2) those that provide financial incentives to consumers for EV purchase, and 3) those that provide publicly available EV charging infrastructure. With a dependent variable of EV registration per 100,000 population, impacts are assessed with panel data, fixed effects regression models. State level environmental and energy policies impact on EV adoption. Increasing a state's renewable portfolio and reducing CO_2 emissions from electricity generation increases EV adoption. Other policies were also found to have positive impact on EV adoption such as increasing both state income tax credit and charging infrastructure. The study contributes to the research on the adoption of EV by providing empirical evidence of how state policies that promote a clean environment spur adoption rate of EV. This essay, in part, is currently being prepared as a manuscript for submission to the journal *Renewable and Sustainable Energy Reviews*.

1.2.2 Aim of essay 2: Climate Change Impacts on Fossil Fired Power Plants

The second essay examines the performance of power plants under climate change impacts. The main objective of this study is to examine the impacts of ambient temperature increase from climate change on the consumption and production of electricity, and the efficiency electricity generation from fossil fired power plants across 48 U.S. states. This study extends existing studies that analyze the impact of climate change on the electric sector. Using state level panel data for the period 1990 to 2019, climate change impacts on electricity generation from fossil fuels power plants will be empirically examined. For this purpose, electricity consumption, electricity generation, and efficiency of fossil fired power plants are examined in regression models using seemingly unrelated regression (SUR) methodology in order to improve understanding how climate change can affect patterns of electricity consumption, and generation. Through rising temperatures, climate change could affect the performance of the electricity generation from fossil fuels. It affects how much energy is produced, delivered, and consumed in the U.S.

The electric sector in the U.S. is found to be vulnerable to climate change, such that an increase in the ambient temperature will result in an increase in the electricity consumption and a decrease in the generation and efficiency of fossil fired power plants. The strongest impact is on electricity consumption when ambient temperature rises. Electricity retail price was found to have the most powerful impact on the per capita electricity consumption and increasing fossil fuels weighted average price (weighted by the total quantities for coal, natural gas, and petroleum consumed for electricity generation) resulting in reduction of electricity generation. While state governments have taken actions in response to federal policies to mitigate climate change, such as federal tax incentives for renewable energy and renewable portfolio standards (RPS) in the states, state level policies and regulations are required and important such that the state level impacts from climate change are worthy of investigation. A manuscript from this essay is targeted from submission to the *Energy Economics* journal.

1.2.3 Aim of essay 3: Examining the Existence of the Environmental Kuznets Curve After Accounting for Low-GHG Energy Use in the Power Sector

The third essay investigates the impact of low GHG energy state policies on per capita GHG emissions across fifty U.S. states using data for the period 1990 to 2018. The relationship between economic growth and the environmental degradation has been one of the most controversial topics in the economic literature since the late 1970's (Tjoek and Wu, 2018). One explanation for this relationship is the Environmental Kuznets Curve (EKC) hypothesis where an inverted U-shaped relationship is hypothesized between per capita income and environmental pollution.

Previous studies have investigated the existence of an EKC hypothesis among U.S. states. For example, List and Gallet (1999) used data on U.S. state-level sulfur dioxide and nitrogen oxide emissions from 1929–1994 to validate the existence of the EKC hypothesis. Likewise, Aldy (2005) has validated the existence of the EKC hypothesis using data on U.S. state-level CO_2 emissions for the period 1960 to 1999. Contrarily, Tzeremes (2018) did not find any evidence for this hypothesis when examining CO_2 emissions between 1960 and 2010.

The aim of this research is to expand and enrich the existing literature on EKC hypothesis analysis examining U.S. states. This analysis involves empirically testing the existence of the EKC at the state level in the U.S. in the presence of a new explanatory variable associated with environmental and energy policies, highlighting the impact of low GHG energy consumption on improving the environmental quality at the state-level.

To achieve this objective, a Pooled mean group (PMG) autoregressive distributive lag (ARDL) bounding testing approach is utilized followed by robustness check for short run and long run using models that include pooled ordinary least square (OLS), fixed effects (FE), and random effects (RE). The findings include that increased consumption of low GHG Energy generated from renewable and nuclear energy sources has a negative impact on per capita CO_2 emissions. This finding provides a statistically significant evidence to validate the presence of EKC for CO_2 emissions at the U.S. state level and to verify that implementation of new energy technologies serves to reduce CO_2 emissions but does not diminish the entire impact of increasing per capita income on reducing these emissions in the long run. A manuscript from this essay is being prepared for submission to the *Environmental Science and Pollution Research* journal.

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CHAPTER 2

Essay 1: The Impact of State Policies on Electric Vehicles Adoption – A Panel Data Analysis

2.1 Introduction

The adoption of electric vehicles (EV) addresses environmental quality concerns and reduces the dependence on internal combustion conventional vehicles (ICEV) (Vienneau et al., 2015). There is a consensus among scientists and researchers that EV are a green product (Kieckhäfer et al., 2017; Gallagher and Muehlegger, 2011; Wang et al., 2018), which are products with low environmental impacts (Janssen and Jager, 2002), and serve as a potential solution to mitigate air pollution (Austmann, 2020). As an alternative to ICEV, EV have greater benefits in areas with low carbon producing power plants (McLaren et al., 2016; Nanaki et al., 2013). Production in the EV industry has increased greatly over the last decade but moving towards a large-scale energy transition to achieve a public good is likely to require support from government policy. Policies are still needed to encourage buyers, manufacturers, and states to increase the adoption of EV (Shao et al., 2017).

In this research, the term EV refers to as a vehicle that has an electric motor, instead of the internal combustion engine, that is powered by an equipped battery charged by an electric source by plugging the vehicle in to a charging station (AFDC, 2014). U.S. sales of EV grew rapidly from 2012 to 2020. In 2017, EV annual sales increased fourfold compared to the figures in 2012, with over 195,580 vehicles sold (AFDC, 2019). While EV sales still represent only a small portion of the automotive market, comprising 1.2% of the total number of vehicles sold in 2017 (Davis and Boundy, 2021), the year 2020 show a significant increase and in line with the global EV market as the U.S. EV market growth have reached to 1.8% of all vehicles (Conway et al., 2021). Nationally, the statewide average of EV registered per 100,000 population was about 208 in 2020 with California having the highest density at about 1187 followed by Hawaii with

823 (Figure 2.1). Mississippi and North Dakota recorded the lowest densities of 22 and 31 per 100,000, respectively.

In the U.S., the transportation sector is the largest contributor to greenhouse gas (GHG) emissions at 28 percent of U.S. total GHG emissions, followed by electricity sector with a 27% share (EPA, 2019). The Electric Vehicle Transportation Center (EVTC) focused on EV as a vital technology needed to help reduce carbon dioxide (CO_2) emissions and local air pollution related to personal transportation (Coffman et al., 2015). Based on these environmental benefits, the Obama Administration announced a goal that makes the U.S. to be the first country to have a million EV on road by 2015 (DOE, 2011). This goal was not achieved as by the end of 2014 when fewer than 300,000 EV had been purchased in the U.S. (Coffman et al., 2015), but it was achieved by October 2018 (Schwertner, 2018).

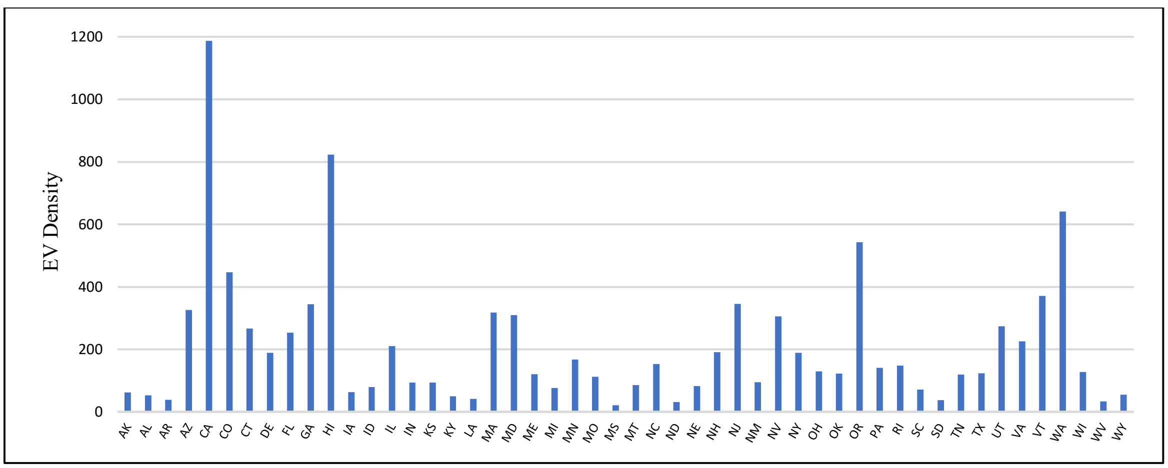

Figure 2.1: Distribution of the Registered Electric Vehicles per 100,000 People by State in 2020. The data used to create this figure was from the Advanced Technology Vehicle Sales Dashboard.

Many states have set goals to increase the sales and promote EV in the short run to reduce pollution in the long run (Linn and McConnell, 2019). States have implemented numerous policies to promote EV adoption both directly and indirectly. Direct policies include a variety of incentives, such as state income tax credits and rebates for vehicle purchases; sales tax exemption, home charging stations incentives and the direct investment to install public charging infrastructure (Narassimhan and Johnson, 2018). While the high prices of EV matters to consumers (Newbery and Strbac, 2016), the barriers to EV adoption are not solely financial. Carley et al. (2013) find that the willingness to buy an EV is low due to its limited driving range[4]. Since the driving range is identified as one of the primary barriers to make EV successful in the vehicles market (Kim et al., 2017), increasing the number of charging stations could spur people to purchase EV (Coffman et al., 2017).

Indirect policies that encourage EV adoption include those policies related to climate change and other environmental impacts of burning fossil fuels. Li et al. (2017) find that the increase in low GHG energy share in electricity generation lead to higher EV adoption between 2010 and 2015. Electricity generation from low GHG energy sources in the U.S. has nearly doubled in the last 20 years (EIA, 2020) and this increase in low GHG energy has been stimulated at the state level with Renewable Portfolio Standards (RPS). A state-level mandatory RPS requires a stated percentage of a utility's electricity to be from low GHG energy sources (NREL, 2021; Brannan, 2012; Lyon and Yin, 2010). The presence, magnitude, and structure of RPS vary across the U.S., starting in 1983 with the state of Iowa, RPS adoption has reached thirty states and the District of Columbia by 2019 (Pascaris, 2021; NCSL, 2020a).

The objective of this study is to examine and compare the magnitude of impacts from state policies on the EV adoption rate across all 50 states. These state level policies are represented by: (1) the percentage of electricity generated from low GHG energy sources from the total electricity generation and per capita CO_2 (CO_2pc) emissions from electricity generation,

[4]EV have a driving range of between 70 and 120 miles, with some vehicles now having ranges of 200–300 miles (Hardman et al., 2018). Driving ranges continue to increase, for example, 2020 Chevrolet Bolt EPA-rated range is about 417 km (259 miles) (O'Neill et al., 2020)

(2) financial incentives to purchase EV (state income tax credits and rebates on the purchase of EV), and (3) creation of charging infrastructure for EV. Statewide data on EV registration rates will be explained using econometric models with independent variables consisting of state policies on electricity generation from low GHG energy sources, CO_2 emissions, financial incentive to purchase EV, charging infrastructure and control variables.

Regression results show that a 1% increase in a state's low GHG energy share increases EV adoption rate by 1.7%, and the reduction of per capita CO_2 emissions from electricity generation by one metric ton (11.1% of the mean) increases EV adoption rate by 10.9%. U.S. government efforts are in line with the global efforts in meeting the climate change energy targets by reducing the dependence on fossil fuels and significantly reducing CO_2 emissions in transportation sector. These efforts are supported by several instruments and policies such as providing incentives for EV adoption. In addition, financial incentives for EV purchase are important as a $1000 increase in a state income tax credit (13% of the maximum tax credit) increases the EV adoption rate by 10.1%. Rebates did not have statistically significant impacts. While state energy policies positively impact EV adoption rates, the impacts of these state policies are substantially less than the impact of per capita income. These results lend support to efforts to provide tax credits and encourage the reduction of CO_2 emissions to create uniform incentives to adopt EV across all states.

The rest of the paper is organized as section 2 provides background information on sources of charging an EV and related GHG emissions, the future of EV, and the state incentives. Section 3 discusses the previous literature on three state level policies under investigation. In sections 4 and 5, methodology, empirical strategy, and data used in the analysis are presented. In section 6, empirical results are discussed, and finally, section 7 provides conclusions and policy implications.

2.2 Background

Unlike ICEV, EV are equipped with batteries storing energy that can be generated from a multitude of energy sources including high GHG emitting, such as fossil fuels, and low GHG emitting, such as renewables and nuclear (Buekers et al., 2014). While in operation, EV do not produce any emissions as ICEV do. Taking into consideration the sources of energy that EV are charged with, EV also are responsible for air pollution (Woo et al., 2017). Thus, an environment-friendly electricity generation mix is important in two aspects. First, it will enhance EV environmental performance in terms of GHG emissions. Second, it could promote EV adoption among consumers, especially for people who are concerned about human impacts on the environment. In this regard, Choi et al. (2018) find that changing the electricity generation mix to low GHG energy mix can reduce GHG emissions up to 5% and promote EV market share up to 10% and by 2026.

Many researchers have shown that a significant reduction in GHG emissions could be accomplished by the electrification of the transportation sector, especially if the electricity used for charging EV is mainly coming from a Low GHG energy source (Das et al., 2020). For example, Bahn et al. (2013) find that electrification in the Canadian transportation sector is a very important option for reducing GHG emissions as the penetration of EV is accompanied with a progressive phasing out of ICEV that rely on fossil fuels. Moro and Lonza (2018) find that using EV instead of ICEV in the European Union member states countries could save between 50% to 60% of GHG emissions in the transportation sector. Chen et al. (2015) and Smith (2010) also emphasize on the significant environmental benefits of transportation electrification.

Enhancing the quality of the environment by boosting EV on the road can also be maximized if it was accompanied with and supported by state level policies in respect to the source of electricity (Erickson, 2017).

Examining the relationship between low GHG energy share of electricity generation and EV adoption is important to consider the energy generation mix prior promoting EV adoption (Canals Casals et al., 2016). Many states rely on low GHG energy sources for electricity generation. Across the U.S., 2020 statewide average of low GHG share was about 41% with Vermont having the highest share of low GHG energy at about 100% from the total electric generation, followed by Washington at 84%.

As Table 2.1 shows, Vermont, Washington, South Dakota, Maine, and New Hampshire ranked as the top five states with the majority of electricity generation energy coming from conventional hydroelectric[5] and/or wind power, with the exception for New Hampshire, where the majority of its electricity coming from nuclear power generation. The lower panel of Table 2.1 shows the bottom five states in terms of low GHG electricity, where biomass and wind power contribute much of this energy. Delaware, West Virginia, Rhode Island, and Kentucky recorded the lowest share of low GHG energy sources at below 10%. This table demonstrates the potential for a positive relation between the share of electricity generation from low GHG energy sources and EV densities. Vermont and Washington show much higher than average EV density, while all bottom five states are below the U.S. national average.

[5] Hydropower is a potentially clean source of energy, while some projects produce GHG emissions (Rafael et al., 2019)

Table 2.1. Top and Bottom Five States in Low GHG Share and EV Density in 2020 (U.S. average EV density in 2020 was 207.98)*

	State	Low GHG Share of Electricity (%)	EV Density (Registration per 100,000)
Top Five	Vermont	99.82	371.22
	Washington	83.46	640.67
	South Dakota	80.50	38.20
	Maine	80.04	120.73
	New Hampshire	76.71	191.10
Bottom Five	Delaware	5.32	188.69
	West Virginia	6.22	34.01
	Rhode Island	6.95	148.23
	Kentucky	8.59	50.14
	Indiana	11.22	94.36

* Data Sources: U.S. Energy Information Administration and Alliance for Automotive Innovation: Electric Vehicles Sales Dashboard.

2.2.1 Vehicle Charging Source and Emissions

The growing interest in EV is also linked to the environmental concerns and the risk of emissions from ICEV which are threatening public health (Amjad et al., 2010). Worldwide, EV have been examined as a potential solution to transportation sector pollution (Smith, 2010). Several studies have performed life cycle assessments (LCA) to evaluate EV emissions. For example, Hawkins et al. (2013) show that EV have the lowest GHG emissions compared to all other vehicles, taking into consideration both the operation and production phases (Faria et al., 2013; Ma et al., 2012). In addition to their provision of environmental benefits by reducing GHG emissions, EV also have the potential to provide health benefits (Canals Casals et al., 2016) as they reduce humans exposure to pollutants from transportation sector. EV are still responsible for GHG emissions associated with their production and with the source of electricity generation needed to charge their batteries. Hawkins et al. (2013) find that the source of electricity charging EV is important for achieving EV global environmental benefits. As long as EV are charged by electricity generated from fossil fuels, they only can move emissions-generated from burning fossil fuels- away from the road rather than reducing them from the environment.

2.2.2 Electric Vehicles Fleet Future

Policies are necessary to push the transition from ICEV to EV (Dane et al., 2019). Globally, governments have introduced a wide range of policies to support the technological advancement in the transportation sector that will lead to a significant shift in the demand for EV in the near future (Lutsey, 2015). Both environmental and transportation policies promoting EV adoption will ultimately determine how much impact EV will have on the environmental quality in the future. Financial incentives, including tax credits and rebates for EV buyers, as well as taxes on carbon emissions, will have a positive impact on the EV share in the U.S. fleet (Weiller, 2011). Policies supporting EV production would also make EV to be seen as the future of the transportation system (Faria et al., 2013). One example of these advancements is that an EV can be used as an energy storage in the power system by releasing energy to grid (Aziz et al., 2015). So, EV are not only charged , but also, they can discharge their batteries and deliver the stored energy into the grid (Clement-Nyns et al., 2011; Mwasilu et al., 2014). By the end of 2018, more than five million worldwide registered EV were on the road. While China accounted for 47% of the worldwide EV, the U.S. had only 1.1 million EV on the road, representing 20% of the world stock (IEA, 2019). Several countries (e.g., France, China, Norway, Ireland, and other countries) have announced targets to phase out ICEV in the transition to EV (Ayetor et al., 2022; IEA, 2020; Meckling and Nahm, 2019). In the U.S., similar to other countries such as France, Germany, and Norway, President Biden has set a goal to push the U.S. forward on EV by replacing the government fleet of vehicles with EV to reach a target of 50% EV sales share by 2030 (U.S. Fact Sheet, 2021a).

2.2.3 Incentives

Governments at both federal and state levels have created incentives and regulations to encourage EV adoption. These incentives, both monetary and non-monetary, were created to promote EV adoption and increase the number of EV in the U.S. roads. At the federal level, the U.S. government provides financial incentives for EV buyers with the number and value of incentives varying by capacity of the equipped battery used to power the EV and the vehicle type (Jenn et al., 2018).

Incentive policies are attractive tools to promoting the purchase of EV. These policies have been categorized into two main categories: purchase-based and use-based (Lieven, 2015; Sierzchula et al., 2014). Purchase-based incentive policies comprise of financial incentives such as providing a subsidy for EV purchasers, offering a tax rebate when registering them, and providing registration fee exemption. Examples of use-based incentive policies are the allowance for EV users to use bus lanes and providing of free parking slots for EV (Langbroek et al., 2016).

The various types of state level EV adoption incentives are shown in Table 2.2. Non-monetary incentives vary between states, such as permitting EV drivers to use high-occupancy lanes. Despite the rapid expansion of charging infrastructure worldwide, the majority of charging stations in the period 2012 to 2020 were privately owned. This might indicate that EV owners were highly likely to charge their EV at home or the government have subsidized the home charging stations. In 2020, there were 7.3 million EV charging stations around the world , while the number of home charging stations was 6.5 million (IEA, 2021). The U.S. statistics show similar share of home charging stations from the total charging stations at about 89% (Wood et al., 2017). In California, 83% of EV drivers use home charging as a primary charging source (ICCT, 2020a) and 90% in San Francisco (ICCT, 2020b).

Table 2.2. Types of State Level Incentives for EV adoption in the U.S. 2012 - 2020

Incentive Type	**State**
Income tax credit	CO, GA, LA, MD, SC, UT, WV
Rebate	CA, CT, DE, HI, IL, MA, PA, TX
Sales tax waiver	NJ, WA
High Occupancy Vehicle Lane access	AZ, CA, FL, GA, HI, MD, NJ, NV, NY, SC, TN, UT, VA
Home charge installation discount	AZ, CA, CO, DE, GA, IL, IN, LA, MA, MD, MI, NC, NJ, OR, PA, SC, TN, TX, VA, WA
Home charging rate discount	AZ, CA, CO, HI, IL, IN, KY, MD, MI, MN, NV, NY, PA, VA
Parking fee exemption	AZ, CA, HI, NE
Excise tax waiver	AZ, NV, VA
Emission tax waiver	CO, ID, IL, MA, MI, MO, NC, NE, NY, OH, RI, VA, WA
Registration fee waiver	AZ, IA, IL, NE
Road use tax exemption	AZ

Note: This table is generated from information provided by the Alternative Fuels Data Center (AFDC, 2020), Santini et al., (2015), and Narassimhan and Johnson, (2018).

This research will focus on the impacts of monetary incentives for EV which vary widely between states (Canis et al., 2019). They include income tax credit, rebate, and sales tax waiver for the purchase of EV. Tax credits as a purchase-based incentive vary between states along with eligibility criteria. As one example, in order for Utah residents to be eligible for EV tax credit, the EV must be driven within the state with no less 50% of its mileage (AFDC, 2019). Between 2015 and 2020, Maryland offered tax credit calculated as $125 multiplied by the EV battery power up to $3000. The state of Colorado offers its residents the right to claim a state credit of $6,000 at point of sale when they buy an EV. Connecticut offers reduced registration fees for EV with a biennial fee of $38 (NCSL, 2020b), compared to EV annual registration fees of $200 in

Alabama and West Virginia, and $100 in Oklahoma and Tennessee (Xu et al., 2020). This variation in the registration fees refers to that every state is considering state-level policies to collect EV annual registration fees as compensation for depleting gas tax revenues in road improvements, and as a highway funding sources for infrastructure, including the EV charging stations (Van Dyke et al., 2022). This registration fees as high as $200 in states such as Alabama that rely heavily on gas tax and registration fees (Xu et al., 2020).

Some states offer an EV purchaser up to $4,500 for buying a new EV as rebates through various reward programs that vary between states (Zhang et al., 2014). For example, New York offers rebates for buying or leasing a new EV of up to $2,000 (Stephens et al., 2018). The California Air Resources Board (CARB) offers $1,500 as a rebate when buying a new EV (Sheldon and Dua, 2019). Eligible EV must meet two requirements to be eligible for this rebate; the battery capacity must be greater or equal to 5 kilowatt-hours (kWh)[6] and the vehicle to be purchased from a participating retailer. In addition to EV required eligibility criteria, customers also must reside and register the EV in California to be eligible for the rebate (AFDC, 2019). Each state has a different set of rules and regulations for the financial incentives they provide. And these incentives are subject to frequent change (Lu et al., 2022; Chen et al., 2021). This might be explained by and seen by how the number of states offering financial incentives was declining over time as shown in Figure 2.2. For example, the number of states having rebate incentive for EV buyers has decreased from 16 in 2012 to 12 in 2020. And states that have income tax credit incentive for EV buyers have decreased from 10 in 2012 to 4 in 2020.

[6] Electric Vehicle battery varies based on the manufacturer and the driving range. For example, Audi 2021 e-tron car with 222-miles battery range, have a battery of 95 kWh size. On the other hand, Porsche 2021 Taycan car with a driving range of 225-miles, have a 240-kWh battery. For more details on battery sizes, visit https://www.nj.gov/dep/drivegreen/pdf/ev-availability-and-comparison.pdf.

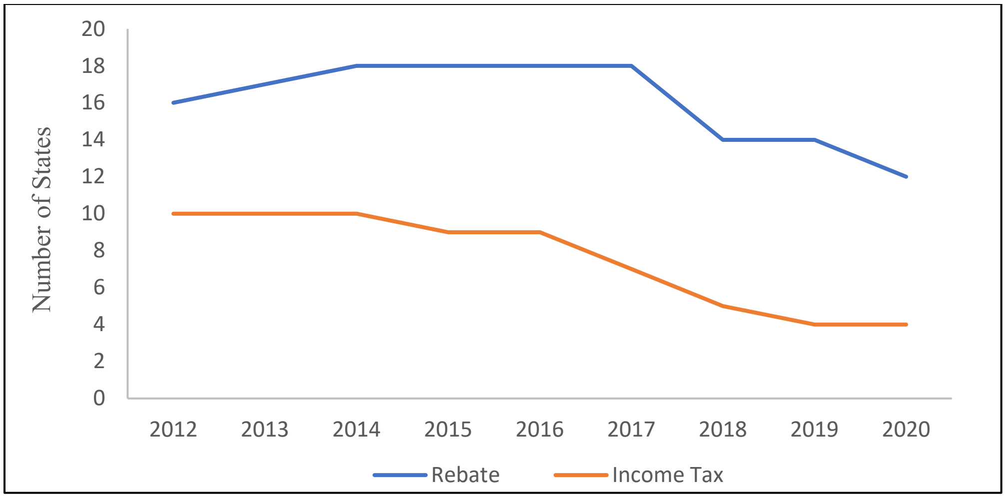

Figure 2.2: The decline in the number of states offering financial incentives (Income tax and Rebate) to EV buyers between 2012 and 2020. Data source: Alternative Fuels Data Center.

2.3 Literature Review

A willingness-to-pay for environmentally green products is associated with many factors that undergo personal assessment. Common factors of concern for EV consumers in many countries including the U.S. are the upfront cost, distance of travel, availability of charging stations, charging time, tax incentives policies, income, and overall knowledge of EV (Kim et al., 2017, Rezvani et al., 2015). Research has noted that the majority of EV owners in Norway have high income, despite that EV in the Norwegian market have a competitive price when compared to ICEV, which in turn makes the personal income less prominent predictor than incentives (Bjerkan et al., 2016). While Sierzchula et al. (2014) did not find links between income and EV purchase decisions in the U.S., they find that charging infrastructure and financial incentives impact EV adoption. Soltani-Sobh et al. (2017) find that income, urban roads (rate of urban roads to all road types), and government incentives have positive impacts on EV adoption in the U.S. In terms of price impacts, the demand for EV was nearly elastic (-0.92) in Switzerland (Glerum et al., 2014).

Technological advances and incentive policies have been shown to have positive impacts on EV adoption. An estimation of 2030 market share of EV in Beijing (China) by Zhang et al. (2017) showed that it will be less than 7% in the Chinese transportation market without technological advances and incentive policies in place. On the other hand, fast technological progress that led to lower battery cost and more charging stations, subsidies, and tax incentives could lead to 70% of the annual new vehicle sales being EV in China (Zhang et al., 2017). Coffman et al. (2015), based on an EV forecast and literature review on the impact of technological advances and incentive policies on EV adoption in Hawaii (U.S.), find that EV sales are projected to have 34% market share of new car sales in 2040.

In this study, the focus is on the factors that influence and impact the decision to purchase an EV in the American society. From a U.S. consumer standpoint, there are many factors that might influence the decision to purchase EV. These factors include affordability, concerns about driving range, charging infrastructure (Egbue and Long, 2012). In this regard, several studies have investigated the main factors that impact EV adoption, including environmental concerns, tax incentives, and personal attributes. Examples include Sierzchula et al. (2014), Zhang et al. (2017), and Langbroek et al. (2016) who find financial incentives to be significant and positively correlated to EV adoption. On the other hand, Clinton and Steinberg (2019) and Diamond (2009) find state income tax credits do not have a statistically significant effect on EV adoptions. Li et al. (2017) find percentage of renewable energies in electricity generation, number of charging stations have apparent and positive impacts on the EV adoption, while urbanization do not. In addition, Soltani-Sobh et al. (2017) find urban roads and government incentives are positively correlated with EV adoption. Finally, Choi et al. (2018) find increasing the low GHG energy share in the electricity generation mix can promote EV adoption.

2.3.1 GHG Emissions Reduction

For certain consumers in the U.S., environmental concerns positively impact their willingness to engage in actions that help to protect the environment (Egbue and Long, 2012). EV offers a possible and viable method that significantly reduces GHG emissions from the transportation sector (Soltani-Sobh et al., 2017). Buying EV is an action that has a positive impact on the environment given the potential to reduce the use of fossil fuels and the consequent GHG emissions in the transportation sector (Egbue and Long, 2012; Richardson, 2013). In addition to technological improvements and tax credits, people in European Countries are more willing to buy EV because of environmental reasons (Langbroek et al., 2016). Gong et al. (2020) examined the ways that stimulate the demand for EV in China by studying the impacts of tax relief and technology improvements and find that consumers' environmental awareness – mainly low carbon awareness- has positive impacts on the demand for EV. In addition, environmental concerns and the growing pro-environmental attitude among population are a key motivation behind the adoption rates of EV (Chellaswamy and Ramesh, 2017). Khaola et al. (2014) find that the environmental concerns have a strong impact on the decision to buy a green product in Lesotho (South Africa). In the same context, in California (U.S.), environmental concern can motivate pro-environmental behaviour and accordingly people with pro-environmental values are more likely weighing these values in their consumption decisions such as buying hybrid cars (Kahn, 2007).

2.3.2 Low GHG Energy Share

U.S. citizens characterized with pro-environmental attitude are more likely to behave in ways that they believe will benefit humans and the environment in general (Axsen et al., 2012). Using this line of reasoning, state adoption of environmental policies, such as RPS, can motivate residents to be aware of and account for their environmental attitudes in EV adoption decisions (Zhang et al., 2018). If consumers care about EV ownership because they want to reduce CO_2, then it makes more sense to adopt EV if the grid is relatively green. Increasing the share of low GHG energy can be stimulated by consumers environmental attitude (Lee et al., 2016). Intuitively, the pro-environmental attitude can be seen as a proxy for low GHG energy share in a state.

Examples of research on the links between environmental attitudes and EV adoption include Sanchez-Braza et al. (2014) who showed that municipal environmental commitments in Spain have positive impacts on promoting EV adoption. Lee et al. (2016) find that green electricity policies in the U.S. including RPS, net metering, and public benefit funds are examples of the links between environmental attitudes and EV adoption. They also find that pro-environmental attitudes by consumers accelerate green electricity policy adoption. Using a web-based survey in the U.S., Axsen and Kurani (2013) find that EV adoption will increase if the charging electricity comes from a low GHG energy source. Li et al. (2017) employed panel data from 14 countries, including the U.S., between 2010 and 2015 to find that a 1% increase in low GHG energy use would lead to a 2% to 6% increase in EV demand.

In addition, there is a growing literature focused on assessing the overall GHG emissions from green energy technologies including solar photovoltaic systems, wind turbines and EV by applying a life-cycle assessment (LCA) method. Recently, LCA has become an important tool for assessing potential cradle-to-grave environmental impacts of different technologies. For the relation between the energy source and GHG emissions, Van Vliet et al. (2011) find that GHG emissions generated from driving EV in Netherlands depend on the fuel type that is used in the generation process of electricity used for charging. For example, they find that it has a range between 0 gram (g) of CO_2 equivalent[7] per kilometer (km) when using renewable source of electricity to 155 g/km when using electricity generated by burning Coal or Natural Gas. In line with Van Vliet et al. (2011), Faria et al. (2013) in their life cycle assessment for EV in Portugal find that the electricity mix used to charge EV must be known with a high degree of certainty in order to assess the correct environmental impact of EV. That is why the overall GHG emissions are strongly related to the energy source used for electricity generation.

2.3.3 Financial Incentive Policies

Impacts of financial incentive policies on EV adoption have previously been studied based on empirical data with different forms of econometric analysis or simulation. Numerous researchers (Chandra et al. 2010 ; Diamond 2009; Gallagher and Muehlegger 2011; Jenn et al. 2018; Jenn et al. 2013; Sierzchula et al. 2014; Williams and Anderson (2022); and Zhang et al. 2014) have examined the impact of incentives provided by the government to promote EV adoption. For instance, Zhang et al. (2014) analyze the relationship between the policies and the adoption of EV across countries including the U.S., China, and the United Kingdom (UK) and find incentive policies have positive impact on EV adoption. Melton et al. (2017) considered incentive policies to be the main contributor to the highest EV market share in California. Sierzchula et al. (2014) examined the relationship between financial incentives and EV adoption across 30 countries and find them to be a significant predictor of EV adoption. Bjerkan et al. (2016) revealed that for a large number of EV users in Norway, incentive policies are the primary deciding factors for EV adoption. Moreover, Kim and Heo (2019) analyzed the factors for EV adoption from 2013 to 2017 in Korea. They find that financial incentives positively

[7] CO_2 equivalent is a term describing different GHG in a common unit. For any quantity and type of GHG, CO_2 equivalent signifies the amount of CO_2 which would have the equivalent global warming impact (Brander and Davis, 2012).

impact EV adoption. On the other hand, Diamond (2009) used data of the U.S. states between 2001 and 2006, he examined the impact of government incentives on Hybrid EV (HEV[8]) adoption and finds incentives to have a small effect on EV adoption. Jenn et al. (2018) and Jenn et al. (2013) also had drawn similar result in their study of the impact of government incentives on accelerating EV adoption in the U.S. While these incentives are different between countries, each country should employ effective policies based on its situation.

2.3.4 Charging Infrastructure

Studies suggest the availability of EV charging stations is an important contributor to EV adoption. In Norway, Mersky et al. (2016) find that the number of charging stations is a strong predictor of EV sales. In addition, increasing charging stations serves as an incentive to encourage consumers to adopt the EV in the U.S. (Hardman, 2019). Higueras-Castillo et al. (2020) find that charging infrastructure availability is a major factor increasing potential EV buyer's confidence and eliminating their hesitation of adopting EV. In line with the previous findings, Sierzchula et al. (2014) come to a similar conclusion with respect to the per capita number of charging stations at the national level. Tran et al. (2013), Egner and Trosvik (2018), and Egbue and Long (2012) each find that charging infrastructure has significant and positive effect on EV adoption.

Unlike all previous literature results, Kim et al. (2017) find statistically insignificant results, while Funke et al. (2019) in their review of the evidence and international comparison of

[8] Hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), and all-electric vehicles (EV)—also referred to as battery electric vehicles (BEV)—all use electricity to improve vehicle efficiency. HEV are powered by an internal combustion engine and an electric motor that uses energy stored in a battery. The vehicle is fueled with gasoline to operate the internal combustion engine, and the battery is charged through regenerative braking, not by plugging in. PHEV are powered by an internal combustion engine and an electric motor that uses energy stored in a battery. To enable operation in all-electric mode, PHEV require a larger battery, which can be plugged in to an electric power source to charge.

how much charging infrastructure is needed find that public charging infrastructure can increase EV sales but still have a minor effect. Hidrue et al. (2011) also provide evidence that a person's propensity to buy an EV increases with youth, green lifestyle, and the easy access to EV charging stations in the U.S. On the other hand, Lin and Greene (2011) did not find any evidence on that increasing charging stations alone will lead to EV adoption increase in the U.S.

2.3.5 Gasoline Prices

While changing gasoline prices in Lebanon are considered as one of the leading factors that affect the automobile sector (Marrouch and Mourad, 2019), there is no consensus in the literature on the impact of gasoline prices on consumer behavior. Some studies examined the impact of gasoline prices on EV adoption. Li et al. (2017); Beresteanu and Li (2011); and Diamond (2009) find the increase in gasoline prices contribute significantly to the increase in EV adoption in the U.S. On the other hand, there are studies that investigate the impact of gasoline prices on EV sales which argued that the effect of the increase in gasoline price does not promote EV sales. Soltani-Sobh et al. (2017) and Sierzchula et al. (2014) find gasoline prices to have negligible effects on EV demand in the U.S. and Adepetu et al. (2016) did not find any evidence for gasoline prices to be considered as an effective factor in promoting EV sales in San Francisco (U.S.). On the contrary with previous literature, Ni (2020) and Bushnell et al. (2022) find that gasoline prices have a negative relationship with the demand for EV in the U.S. and California (U.S.), respectively. Bushnell et al. (2022) referred this to the underlying correlations between unobservable patterns in the demand for EV and energy prices. These unobservable patterns include commuting patterns, local EV charging infrastructure density, and other factors that might influence EV adoption. After conditioning on time-invariant unobservables at the census block[9]-group level in California, the gasoline price coefficient turns to positive.

2.4 Methods and Models

A panel data structure has many advantages over a cross-sectional data set: (1) panel data can capture both time and cross-sectional variations (Baltagi, 2005), and (2) panel data allow for examination and control of unobserved heterogeneity by estimating both cross-sectional effects and time effects (Das, 2019). In a panel data regression analysis, there are three conventional models typically utilized: Pooled ordinary least squares (OLS), Fixed Effects (FE), and Random Effects (RE). All three model estimates will be reported in order to explore the three traditional panel data analysis models. However, in order to evaluate the impact of state level policies on EV registration, the FE model is utilized for interpretation due to its suitability for panel data analysis and its consideration of within entity (state) variation (Kennedy, 2008).

For the regression models, the dependent variable is electric vehicle density (EVD) on an annual basis which represents the number of EV registrations per 100,000 people in each state. The impact of state policies towards promoting green electricity follows the environmental commitment factor used by Sanchez-Braza et al. (2014), where they used the number of registered EV in the municipality as a factor which measures the environmental commitment due to their belief that it is a suitable variable to measure how inhabitants of the municipalities are environmentally concerned and engaged. Previous research results are used to guide explanatory variable decisions (Egner and Trosvik, 2018; Kim et al., 2017; Li et al., 2017; Sierzchula et al., 2014; Soltani-Sobh et al., 2017; and Qiu et al., 2019). These variables include the percentage of

[9] There are roughly 23,000 Census Block Groups (CBGs) in California, each comprised of approximately 600 to 3,000 people, or 200 to 1,000 households.

low GHG energy within a state's electricity generation, CO_2 emitted from electricity generation, tax and rebate incentives adopted to promote EV purchase, and infrastructure development by measuring charging stations availability.

The variables (i.e., CO_2 and Low GHG energy) used in this analysis are part of energy policies designed to increase the share of clean energy sources in the energy mix and reduce the consumption of fossil fuels, or part of climate policies designed to control GHG emissions. Bahn et al. (2013) find that GHG reduction target will impact the transportation sector. Choi et al. (2018) also find that energy policies targeting the electricity generation mix have effect on the consumer adoption behavior of EV.

Previous studies used panel data regression methods for studying EV adoption. Many of those studies employed FE models to examine the factors which have impact on EV adoption, Li et al. (2017) included low GHG energy sources and charging stations density, Egner and Trosvik (2018) included charging stations density in urban areas, and income, and both Soltani-Sobh et al. (2017) and Sierzchula et al. (2014) included gasoline prices in their models. Other studies employed RE to examine the factors which have impact on EV market share through panel data analysis. Kim et al. (2017) included charging infrastructure, and Soltani-Sobh et al. (2017) included urban roads and government incentives, while Qiu et al. (2019) included purchase subsidy policy in their model.

The econometric model for the EVD_{it} is established as:

$$\begin{aligned}\boldsymbol{EVD_{it} = \beta_1 Low\ GHG_{it} + \beta_2 CO2pc_{it} + \beta_3 Taxinc_{it} + \beta_4 Rebate_{it} + \beta_5 ChargingD_{it}} \\ \boldsymbol{+ \beta_6 Income_{it} + \beta_7 Urbanization_{it} + \beta_8 GasPrice_{it} + \gamma_i + \delta_t} \\ \boldsymbol{+ \varepsilon_{it}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{2.1})\end{aligned}$$

The coefficients $\beta_1, \beta_2 \ldots, \beta_8$ describe the direction and magnitude of impacts between EVD and the explanatory factors used to determine EVD in the regression model. FE variables are included for states (γ_i) and for years (δ_t). The error term is ε_{it}, and the subscripts i and t represents i^{th} state and t^{th} year, respectively.

To check for heteroskedasticity, two statistical tests are performed: 1) the Breusch-Pagan Test and 2) the White Test (Wooldridge, 2016) in the linear model in equation (2.1). With a null hypothesis of a constant variance among the residuals, the chi-square statistic has a probability value less than 0.05 – thus rejecting the null hypothesis of a constant variance. Hence, heteroskedasticity is present in the residuals. Accordingly, natural logarithms are employed for both the EVD, income, and gas price variables (equation 2.2) in order to correct for heteroskedasticity (Barreto and Howland, 2013). The Breusch-Pagan and the White Tests show that heteroskedasticity is corrected with this procedure given that the chi-square statistic has a probability value above 5%.

$$\boldsymbol{Ln(EVD_{it}) = \beta_1 Low\ GHG_{it} + \beta_2 CO2pc_{it} + \beta_3 Taxinc_{it} + \beta_4 Rebate_{it} + \beta_5 ChargingD_{it} + \beta_6 Ln(Income_{it}) + \beta_7 Urbanization_{it} + \beta_8 Ln(GasPrice)_{it} + \gamma_i + \delta_t + \varepsilon_{it}} \quad \textbf{(2.2)}$$

Endogeneity bias can lead to inconsistent estimates, provide misleading conclusions, and bias that might lead to coefficients having the wrong sign (Ullah et al., 2018). In order to assess potential endogeneity problems from EV adoption, renewables, per capita CO_2, and charging density in equation (2.2), we used two methods: 1) a Lagged Dependent Variable method, and 2) a Fixed Effects with Instrumental Variable method (FE-IV). These two methods are used with FE models when potential problems of endogeneity might exist (Egner and Trosvik, 2018). Results from these methods show the lack of endogeneity between the charging infrastructure and other variables in the model. More details about these results are available in Appendix I.

2.4.1 Percentage change on the dependent variable calculation

The regression model in eq. (2.2) includes logarithm format dependent variables and it includes both level and logarithm format independent variables. In the case of a level independent variable, the percentage change on the dependent variable will be represented in the following semi-elasticity models (log – level). Following Wooldridge (2016), percentage change on the dependent variables ($\%\Delta\boldsymbol{Y}$) resulted from the regression coefficient (β) and elasticities ($\boldsymbol{\varepsilon}$) were calculated based on the following equations:

$$\%\Delta Y = 100 \times (\beta)\ \Delta X$$

While, in the case of a logarithm independent variable, the percentage change on the dependent variable will be represented in the following elasticity models (log – log)

$$\%\Delta Y = \beta\ \%\Delta X$$

2.4.2 Elasticity calculation:

Elasticity represents the percentage change on the dependent variable divided by the percentage change on the independent variable, and it has the following formula:

$$\varepsilon = \frac{\%\Delta Y}{\%\Delta X}$$

Applying this formula to the two types of models (log-level and log-log), the following for elasticities are found for models (log – log):

$$\boldsymbol{\varepsilon} = \beta$$

and for the semi-elasticity models (log – level):

$$\boldsymbol{\varepsilon} = \beta \times \bar{X}$$

where Y is the dependent variable, X is the independent variable, and $\bar{X}$ is the independent variable mean.

2.5 Data

The EV adoption rate is measured as EV density across the fifty states in the U.S. between 2012 and 2020. Variables and data sources are listed in Table 2.3. EVD is the total registered number of EV per 100 thousand people. The eight independent variables include the percentage of electricity generated from low GHG energy sources, per capita CO_2 produced from electricity generation, state incentives for EV buyers represented by income tax incentive and rebate, the number of charging stations per 100 miles of road in states, per capita personal income, and the urbanization.

Table 2.3. Variables Description and Sources

Variable	Description	Source
EVD	The EV density variable represents the amount of EV's registered per 100,000 people.	Alliance for Automotive Innovation: Electric Vehicle Sales Dashboard
LowGHG	The percentage of renewables and other low GHG emitting forms of generation (nuclear) in a state's total energy generating portfolio	U.S. Energy Information Administration
CO_2pc	Represents the amount of CO_2 in metric tons annually produced by electric power plants in a given state on a per capita basis	U.S. Energy Information Administration
Taxinc	EV buyer maximum available income tax credit in thousand USD	Alternative Fuels Data Center
Rebate	EV buyer subsidy as the maximum available rebate in thousand USD	Alternative Fuels Data Center
ChargingD	The total number of charging stations per 100 mi of road	U.S. Bureau of Transportation Statistics
Income	Per capita personal income in thousand USD adjusted for inflation over 9 years[10]	U.S. Bureau of Economic Analysis
Urbanization	The percentage of urban roads from the total road miles	U.S. Department of Transportation
GasPrice	Motor gasoline average price in USD per gallon adjusted for inflation over 9 years	U.S. Energy Information Administration

The number of registered EV within a state was turned into a density variable (EVD) by dividing the registered EV in a state and year by state population. Similarly, the variable for CO_2 generation within the electricity sector was turned into a per capita estimate (CO_2pc) by dividing

[10] Income and GasPrices variables are adjusted for inflation over the study period of 9 years (2012 – 2020).

CO_2 generation in tons by state populations. In addition, charging stations in a state were also turned into a density of charging stations (ChargingD) by dividing the number of charging stations by the state road length in miles. Including these variables along with other control variables such as personal income, urbanization, and gasoline prices creates a more accurate representation of what is involved in the choice of buying an EV.

To accurately compare both income and gasoline prices over time, these variables are inflation adjusted with a base year of 2020 over the study period (2012 – 2020). To do so, consumer price index for all urban consumers in the U.S. city average (CPI) was retrieved from the Federal Reserve Economic Data (FRED)[11]. For example, to inflation adjust gasoline prices (GasPrice) from 2012 dollars to 2020 dollars, the following formula was used:

$$\boldsymbol{Inflation - Adjusted\ GasPrice = 2012\ GasPrice \times \frac{2020\ CPI}{2012\ CPI}} \ldots\ldots\ldots\ldots\ldots (\mathbf{2.3})$$ [12]

Table 2.4 provides summary statistics of all variables used for the empirical analysis. Registered EV per 100,000 people (EVD) reflects EV adoption rate and had an average of 74.1 between 2012 and 2020. California in 2020 had the highest value at 1187.4 with Arkansas having the lowest value of 0.3 in 2012. The percentage of electricity generated from a low GHG energy source of the total electricity generated from Low GHG sources had an average of just under 38%. Vermont had the highest value at about 100% between 2012 and 2020 with Rhode Island having the least reliance on low GHG energy sources to generate electricity at below 1%. Per capita CO_2 emissions from electricity generation in metric tons (CO_2pc) have an average of 9.0 MT. Wyoming had the highest levels of per capita CO_2 emissions along the period from 2012

[11] CPI data available at FRED: https://fred.stlouisfed.org/series/CPIAUCSL

[12] The same adjustment is used for Income.

to 2020 with the highest value of 87.1 MT in 2013 and Vermont had the lowest value below 1 MT. The state incentives for EV adoption, (Taxinc) was up to $7500 for Georgia between 2012 and 2015, and for the (Rebate) ranged up to $7500 in Oregon between 2012 and 2020. Charging stations (ChargingD) reflects the total number of charging stations per 100 miles of public road and have an average of about 0.3. Hawaii in 2013 had the highest value at about 3.6 with Alabama, Illinois, Montana, Nevada, and Wyoming in 2012 and 2013, respectively, having zero stations. Finally, the control variables of per capita income (Income), urban road share (Urbanization) , and Gasoline prices (GasPrice) have averages of 52.09, 32.3, and 2.9 respectively. Maximums are 77.66 for Connecticut in 2020, 86.7 for New Jersey in 2020, and 4.9 for Hawaii and Alaska in 2012, while minimums are 37.95 for Mississippi in 2012, 2.4 for North Dakota in 2012, and about 1.85 for Texas in 2020.

Table 2.4. Variables Summary Statistics for 2012 to 2020 (N=450)

Variable	Units	Ave	Min	Max	Standard Deviation
EVD	units/100,000	74.14	0.34	1187.36	128.3
LowGHG	percentage	37.27	0.92	99.91	23.23
CO_2pc	metric tonnes	9.04	0.01	87	12.23
Taxinc	1000 U.S. Dollars	0.44	0	7.5	1.25
Rebate	1000 U.S. Dollars	0.91	0	7.5	1.59
ChargingD	units/100	0.29	0	3.63	0.47
Income	1000 U.S. Dollars	52.09	37.95	77.66	7.99
Urbanization	person/sq mi	32.31	2.41	86.74	21.24
GasPrice	USD/Gallon	2.98	1.85	4.91	0.69

In Table 2.5, correlation coefficients are provided for all variables. Between a pair of independent variables, the largest cross-correlation coefficient is 0.48. Accordingly, there is no serious linear correlations between regressors.

Table 2.5. Variable Correlation Coefficients

Variable	EVD	LowGHG	CO_2pc	Taxinc	Rebate	ChargingD	Income	Urbanization	GasPrice
EVD	1								
LowGHG	0.16	1							
CO_2pc	-0.21	-0.38	1						
Taxinc	0.03	-0.07	-0.05	1					
Rebate	0.26	0.19	-0.13	0.04	1				
ChargingD	0.6	0.05	-0.22	-0.03	0.22	1			
Income	0.36	0.24	-0.05	-0.01	0.25	0.30	1		
Urbanization	0.28	-0.16	-0.36	0.01	0.25	0.48	0.44	1	
GasPrice	-0.15	-0.03	0.01	0.02	0.08	0.14	-0.11	0.03	1

2.6 Results

Table 2.6 reports the regression results for three linear models which examine the relationship between state level policies and other socioeconomic variables on EV adoption rate. Compared to the Pooled OLS model 2, results for models 1 and 3 show that adjusted R^2 values increased from 0.62 to 0.77 and 0.73, respectively. To choose the most appropriate model among the three models, two statistical tests are used: (1) a Chow test is used to determine the model of whether Pooled OLS (Model 2) or FE model (Model 1) is most appropriately used in estimating panel data, and (2) a Hausman test is used to choose between FE and RE model (Model 3). Results from Chow test show that the p-value is below 0.05 so a fixed effect model is better for this data. The results from the Hausman test show that the p-value is below 0.05 so a fixed effect model is better for this data. Based on the results from the Chow and Hausman tests, the FE model is the most appropriate model among the three methods. Models 2 and 3 are included in order to fully report the estimates from the different regression models. Table 2.7 reports computed elasticities at the mean for variables from the FE model coefficients.

Table 2.6. Estimation Results for Regression Coefficients (N=450)

Dependent Variable	**Ln(EVD)**		
	Model 1 FE	Model 2 Pooling OLS	Model 3 RE
LowGHG	0.017** (0.008)	0.003 (0.003)	0.005 (0.005)
CO_2PC	- 0.109*** (0.024)	- 0.027*** (0.005)	- 0.040*** (0.010)
Taxinc	0.091* (0.052)	0.108*** (0.037)	0.054 (0.049)
Rebate	0.028 (0.048)	0.081** (0.032)	- 0.009 (0.043)
ChargingD	0.486*** (0.184)	1.405*** (0.117)	0.961*** (0.164)
Ln(Income)	10.081*** (0.894)	2.094*** (0.398)	5.316*** (0.66871)
Urbanization	0.043*** (0.014)	0.001 (0.003)	-0.001 (0.006)
Ln(GasPrice)	- 2.226*** (0.212)	- 3.628*** (0.208)	- 3.434*** (0.178)
Adjusted R2	0.77	0.62	0.73

Note: Values within parentheses are the standard errors, *** p<0.01, ** p<0.05, *p<0.1

In general, regression coefficients show consistent signs and significance along the three models. Our coefficient estimates for Low GHG energy, charging density, and income are all positive and statistically significant. Coefficient estimates for per capita CO_2 emissions are negative and statistically significant. Coefficient estimates for income tax credit and urbanization are positive and statistically significant, but they become insignificant when state random effects are considered. Rebate incentives regression coefficient was insignificant when including state fixed and random effects. Gasoline prices are statistically significant in the three models, but with unexpected negative signs. FE Model 1 regression results will be used to interpret the impact of independent variables on EV adoption rate.

With EV adoption rate represented by Ln(EVD), the regression coefficient estimate for the Low GHG variable is positive and statistically significant. This result means that state policies which increase the percentage of low GHG energy sources as part of electricity generation portfolio will positively impact the EV adoption rate within states that implement these policies. When holding all other factors constant, a 1% increase in low GHG energy share in total electricity generation within a state results in a 1.7% change increase in EV adoption rate. This result is at the low end of the range (2% to 6%) found by Li et al. (2017). Thus, electricity generation from low GHG energy has a positive but inelastic impact on EV adoption rate (elasticity = 0.64). This result represents how people living within a state respond in EV adoption rates when more electricity is produced from low GHG energy, thereby lessening the environmental impact of electricity generation.

Table 2.7. EV Demand Elasticities based on FE Model Coefficients

Variable	% Change in Y*	Elasticity
LowGHG	1.7	0.64
CO2pc	-10.9	-1.0
Taxinc	9.1	0.0
Rebate	2.8	0.0
ChargingD	48.6	0.1
Ln(Income)	10.1	10.1
Urbanization	4.3	1.4
Ln(GasPrice)	-2.2	-2.2

* Dependent Variable

Per capita CO_2 emissions variable has a statistically significant negative impact on EV adoption rate. The estimated coefficient tells us that reducing the average per capita CO_2 emissions from all electricity generation plants by one metric ton per capita would result in a percentage change increase in EV adoption rate by 10.9. For example, TX in 2020 had about 7 MT per capita and WY had 64.5 MT per capita, so in order to reduce one MT per capita in the two states, TX needs to reduce 29,217,653 MT and WY needs to reduce 577,267 MT from the total CO_2 emissions. So, the larger the population, the more CO_2 that would need to be reduced. This result shows that the responsiveness of EV adoption to the reduction of CO_2 per capita is higher than the low GHG energy and is a unit elastic (elasticity at the mean = -1.0).

For the financial incentives, the income tax variable has a statistically significant coefficient. Holding all other factors constant and increasing the income tax credit to $1,000 results in an increase in EV adoption rate by 9.1% change. This result shows the responsiveness of EV adoption to tax credit variable despite being inelastic (elasticity at the mean below 0.1). On the other hand, the rebate variable has a statistically insignificant coefficient. A few previous research studies have also reached this conclusion about the impact of state financial incentives. Zhang et al. (2011) and Clinton and Steinberg (2019) did not find any evidence for state incentives' impact on EV adoption, while Sierzchula et al. (2014) find them to have a small positive impact. Williams and Anderson (2022) referred this negligible impact to the lack of consumers awareness of the rebate.

Considering the charging stations density (ChargingD), it has a positive and statistically significant coefficient. Holding all other factors constant and increasing one unit of charging stations per 100 miles of road results in an increase in EV adoption rate by 48.6% change. For example, in 2020, CA had 396,540 miles of roads with 7,671 public charging stations and WV had 80,167 miles of roads with 93 public charging stations. So, increasing one charging station per 100 miles of road is to increase the public charging stations total number by 4,000 in CA and 800 in WV. A positive coefficient means that increasing charging stations density leads to higher

EV adoption rates. Our result for charging station density impact is consistent with the literature focused on the importance of investment on charging infrastructure in order to promote EV adoption. Examples of these literature are Egner and Trosvik (2018), Li et al. (2017), Mersky et al. (2016), and Sierzchula et al. (2014) who find that increasing the number of charging stations has a significant and positive impact on EV adoption.

Our results show that income elasticity for EV adoption rates (10.1 from Table 2.7) was much higher than that for either low GHG or per capita CO_2 emissions variable impacts (+0.6 and -1.0, respectively). One possible explanation is that a large price difference between EV and ICEV overwhelms consumer concerns about such environmental issues as low GHG energy. The initial cost of an EV is significantly higher when compared to ICEV and this cost increases with battery size or the driving range of the EV. Hardman et al. (2021) stated that the average starting price of an EV model in 2020 is $61,889 compared to $42,145 in 2012; and the sales weighted average starting manufacturer suggested retail price (MSRP) of EV increased from $39,531 in 2012 to $52,558 in 2020. One of the reasons behind this increase in price was the development and improvement that have been made in the EV driving range. Van Velzen et al. (2019) show that future retail prices of EV might not be reduced when compared to the prices of ICEV. Moreover, EV might be more expensive than ICEV for the next 7 to 9 years (Soulopoulos, 2017). Later on, consumers who were willing to buy EV found themselves in need to pay between $8,000 and $16,000 above comparable ICEV (Breetz and Salon, 2018).

Given the large income effect on EV density, financial incentives, especially income tax credits, work to offset the impact of EV versus ICEV price differences. This adds to the explanation that personal economic factors have larger impacts than environmental attitudes on consumer decisions to buy EV (Egbue and Long, 2012). The price differences between EV and

ICWV as noted above make it more affordable for higher income consumers to purchase EV and provides an extra explanation of the strong impact of income on EV adoption rate, thereby maintaining EV as a niche market (Tran et al., 2013).

2.7 Conclusions and Policy Implications

Using regression analysis with data between 2012 and 2020, the following conclusions are drawn from the results: the EV adoption rate is highly responsive to personal income, which is more impactful than any state policies; state environmental policies have positive impacts EV adoption rates such that when the percentage of a state's low GHG energy increases by 1%, the percentage change in EV adoption rate is 1.7; and when reducing average CO_2 emissions in electricity generation by one metric ton per capita, there is a 10.9% change in EV adoption rate. Thus, state policies focusing on increasing the share of low GHG energy in electricity generation have positive, but inelastic impacts on EV registration. In line with this, policies focusing on decreasing the level of per capita CO_2 emissions positively impact EV adoption and have a unitary elasticity.

Financial incentives are found to have differing impacts on EV adoption rate depending upon the type. Regression estimates results show a statistically significant impact of tax credit on EV adoption rate such that an increase of the tax credit by $1000 results in a 9.1% change increase in the EV adoption rate, representing a very responsive impact of financial incentives on EV adoption. On the other hand, regression estimation results show insignificant impacts of rebates on EV adoption. Since rebate incentives are classified as taxable income in some states (such as New York, Connecticut, and Vermont) (TrueCarAdvisor, 2021), this may disincentivize high-income individuals from being motivated to become EV owners relative to tax credits based upon tax considerations. With rebate incentive showing no impacts on adoption in this research, the broadening of EV ownership to market segments beyond the high income, early adopters may make more publicly available charging infrastructure an influential part of EV adoption decisions. Monetary incentives need to be reviewed in a way that encourages EV owners to highly weigh the value of the rebate incentive while taking the decision of EV purchase.

Infrastructure policy also shows significant positives impacts. Both charging infrastructure and urban public road share have a positive impact on EV adoption rates. This may also be supported by the limited driving ranges of most EV during the data period. Hence, EV owners are more likely to be urban due to availability of more amenities, such as entertainment and shopping, within short driving distances compared to rural areas. Based on the time period examined in this research (2012-2020), charging infrastructure showed high importance in the EV adoption rates relative to the other policies in this study. These results demonstrate that EV consumers between 2012 and 2020 have the tendency to be committed to environmental goals and accordingly more spurred to purchase EV based on these commitments compared to financial incentives.

With respect to gasoline prices, the negative relationship between gasoline prices and EV adoption rate might be due to that higher gasoline prices may result in reduction in automobile sales in general, including EV. People tend to reduce their gasoline consumption either by using public transportation, reducing their travelling miles, or commuting together instead of a single person driving a single car. In addition to that, wealthier consumers are less sensitive to changes in gasoline prices (Busse et al., 2009; Gillingham, 2011), and that the EV price is the main attribute governing vehicle purchase decision between the years 2012 and 2020.

Based upon our findings that CO_2 reduction policies are impactful at the state level, increasing EV adoption rate more uniformly across all states requires federal level actions to achieve GHG emission reductions and promoting energy sources with lower GHG emissions in the energy mix. In this regard, the Biden Administration has announced a goal of a CO_2 emissions free power sector by 2050 (Choi, 2021). The Build Back Better plan[13] allocates $174 billion in tax credits and investments in EV to help in the transition away from conventional fossil fuels and includes a commitment to deploy half a million EV charging stations nationwide (U.S. Fact Sheet, 2021b; Crews, 2021). Current federal efforts to support EV markets will be expanding EV ownership beyond high income, early adopters to broader markets. Our research findings support efforts to provide tax credits and to support the collaborative state level endeavors that target the reductions in CO_2 emissions from electricity generation given their positive impacts EV adoption rates.

Finally, with the three separate groups of state level policies that are examined in this research – environmental, financial, and infrastructure, regression analysis and elasticity computations reveal that energy related policies and regulations by reducing CO_2 emissions from the electricity generation sector and increasing the low GHG energy technologies in the states' energy mix were with higher elasticities (+0.6 and -1.0, respectively) than the other policies. With this finding, switching to a cleaner environment by reducing GHG emissions from the energy sector should take precedence in a resource limited world, along with taking the advantage of the available supportive presidential and federal plans for the development of the financial and infrastructure policies.

[13] Building Back Better is a popular as a catch-phrase following the 2004 Indian Ocean Tsunami where it was recognized that the time period following a disaster is an optimal time to make changes in a community by introducing new technologies and methods (i.e. EV and renewable energy) to improve on pre-disaster conditions.

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2.9 Appendix I

In the first method, lagged dependent variable (LDV), we introduce a lagged-dependent variable ($\boldsymbol{EVD_{i,t-1}}$) term, representing the registrations density that happened in the previous time period and its natural logarithm (**LnEVD$_{it-1}$**) is used in the model. Regression results for this method are listed is Table A.1. below. Estimated regression coefficient results show a positive and significant relationship between low GHG energy and EV adoption. Supporting our results from FE model in equation 2.2.

In addition to the LDV method, we also used the fixed effects with instrumental variable (FE-IV) method. We introduced coal consumption for electricity generation in short tonnes (coal)[14] - which has no direct or indirect connections to EV adoption- as an instrumental variable and it is replacing the low GHG energy variable in the model in equation 2.2. Both estimation approaches indicate that we do not have a problem of endogeneity.

Table A.1 Estimated Results for Regression Coefficients

Dependent Variable	Ln(EVD)	
	LDV	FE-IV
Ln(EVD$_{-1}$)	-0.1399*** (0.025)	
(Coal=EVD)		0.00013*** (0.0004)
LowGHG	0.0177** (0.007)	0.0148* (0.007)
CO2PC	- .127*** (0.024)	- 0.114*** (0.024)
Taxinc	0.905** (0.049)	0.090* (0.051)
Rebate	0.016 (0.046)	0.027 (0.047)
ChargingD	0.529** (0.177)	.299* (0.195)
Ln(Income)	12.191*** (0.939)	8.256*** (1.110)
Urbanization	0.033** (0.013)	0.038** (0.013)
Ln(GasPrice)	- 2.058*** (0.207)	- 2.346*** (0.215)
Adjusted R2	0.81	0.80

Values within parentheses are the standard errors, *** p<0.01, ** p<0.05, *p<0.1

[14] Coal consumption for electricity generation in short tons. Data were retrieved from U.S. Energy Information Administration (EIA).; https://www.eia.gov/electricity/data/state/

CHAPTER 3

Essay 2: Climate Change Impacts on Fossil Fired Power Plants

3.1 Introduction

Climate change involves alterations of the state of the climate over an extended period of time that negatively impact both economic and environmental aspects of hundreds of millions of people across the world. Climate change has become a paramount concern to the international community since it has been observed to have increasingly more impacts on human health, energy use, agriculture, transportation, industry, environmental quality, and other aspects that affect human's quality of life (IPCC, 2021). For example, the global average land and sea surface temperature have increased by 0.85 °C (1.53 °F)[15] over the period 1880 to 2020. Since 1880, the earth's temperature has risen by 0.08°C (0.14°F) per decade, and for the averaged across land and ocean, the 2020 surface temperature was 0.84°C (1.51°F) warmer than the twentieth-century annual average of 13.9°C (57.0°F) (Lindsey and Dahlman, 2020). The vast majority of previous research have focused on the impacts of climate change associated with a warming of 2 °C or more and their estimate for future warming revealed that if there are no actions to reduce greenhouse gas (GHG) emissions, global surface temperature would be likely to increase in 2100 between 3.7 °C (6.66 °F) and 4.8 °C (8.64 °F) above the average for 1850-1900 (Brunner et al., 2020; Colón-González et al., 2018).

The U.S. is characterized by a wide variation in climate conditions and mixtures of energy sources (Khan et al., 2021). Temperature variations in the U.S. are mainly due to changes in latitude, and a range of geographic features, including mountains and deserts. For example, in the Western U.S., Donovan and Butry (2009) find that Sacramento has 73 days a year over 32°C (89.6°F). Phoenix's climate is much hotter and drier, with a daily average temperature of 19.5°C (67.1°F) in December and 41.4°C (106.6°F) in July. Phoenix averaged 109 days each year

[15] Temperature in Fahrenheit degree value = (Temperature in Celsius degree value * 9/5) + 32

between 1979 through 2006 with temperatures exceeding 37.7°C (100°F) (Hartz et al., 2013). For example, the number of days where the temperature in Phoenix[16] was at 37.7°C (100°F) or higher was 107 in 1980, 112 in 1991, and 128 in 2018 (ASU[17], 2022; NOAA, 2022). Sailor (2001) finds that sensitivities of the sectoral demand for electricity significantly varies between states. For example, Table 3.1 summarize the percentage increase in per capita electricity consumption of selected states resulting from a 2°C (3.6°F) temperature increase. With the baseline of 18.3°C (65°F) for all states, a temperature increases of 2°C (3.6°F) is associated with 11.6% increase in residential per capita electricity consumption in Florida, a 5.6% increase in Texas, and 1.9% increase in Ohio. These differences on impact show that there is a wide range of potential climate change impacts depending upon the region (state).

Table 3.1. Impacts of Temperature Increase by 2°C on the Annual per capita Consumption in Selected States

State	Residential Sector Impacts (%)	Commercial Sector Impacts (%)
California	4.1	4.8
Florida	11.6	5.0
Illinois	3.8	1.9
Louisiana	1.6	3.0
New York	0.9	1.6
Ohio	1.9	2.5
Texas	5.6	2.3

Note: This table is generated from information provided by (Sailor, 2001)

The table also shows that the residential sector is more sensitive to temperature change than the commercial sector, especially in the warmer states. For example, a 2°C (3.6°F)

[16] Phoenix Sky Harbor Airport, AZ at Latitude 33.43° North, Longitude 112.00 West°
[17] Arizona State University. Available at https://www.public.asu.edu/~aunjs/ClimateofPhoenix/wxpart2.htm.

temperature increase in Florida and Texas increases per capita electricity consumption by 11.6% and 5.6%, respectively, in the residential sector, while it is only 5% and 2.3%, respectively, in the commercial sector. In line with the previous findings, Scott et al. (1994) find that a 3.89°C (7°F) increase in the daily temperature is associated with 35.3% increase in cooling energy use in Phoenix and 93.3% in Seattle. Based upon previous research findings and the nature of climate change, research on climate change impact on electric system should be at the state level, rather than generalizing results, as it is anticipated to have geographically distinct impacts.

In the previous decades, energy production and consumption have been considered the main factors contributing to climate change (Chontanawat, 2020). Climate change is also affecting the economy via many different channels in many different sectors including but not limited to energy production and use. The energy sector is one of the sectors of the economy most impacted by climate change (Ciscar and Dowling, 2014). These impacts occur mainly within the supply side throughout energy generation with conventional energy systems that includes effects on energy production as well as its transmission and distribution, keeping in mind that both demand and supply are dynamic and intersecting, so changes in one will affect the other (Beecher and Kalmbach, 2012). Extreme weather including high winds, heat waves, and extreme rainfall can severely disrupt electricity generation and cause damage for its production and distribution (Zamuda et al., 2018). Climate change impacts also include changes to renewable energy supply (Cronin et al., 2018). These impacts include the wind speed, availability and intensity of solar and hydropower resources, and transmission line losses due to temperatures increase (De Lucena et al., 2010; Schaeffer et al., 2012). Transmission lines is a system that comprises many electrical components that are exposed to the weather and can experience faults due to weather events, faults can be either by losing part or all of the electricity that is delivered through the faulty component (Ward, 2013). In both cases, the fault will impact the reliability of the electrical grid and restrain its capability to transmit the electricity from the generating units to the distribution centers where it is delivered to consumers.

On the consumption side, climate change impacts such as the seasonal patterns, increased weather variability and more frequent and extreme weather events result in more electricity consumption for cooling when the ambient temperature increases (Ebinger and Vergara, 2011). Climate change impacts such as warmer winters and summers will increase electricity demand. Warmer temperatures affect residential indoor temperature and thermal comfort conditions. Consumers in warmer winter rely more on electricity than heating fuels (natural gas, heating oil, or other sources of fuels burned for heating purposes), people in areas with warmer summers are also more likely to use electricity for cooling. This seasonal warming occurrence will increase energy consumption (primarily electricity) in areas under warming effects (Zhang et al., 2019).

A 5 °C (9 °F) increase in ambient temperature has been estimated to create annual U.S. welfare losses of $57 billion in 2100. These losses measure the change in household income necessary to keep utility constant or the cost of maintaining the interior comfortable temperature given climate change (Mansur et al., 2008). An estimate for the U.S. economic impacts from global warming in a detailed focus on the energy cost, Ackerman and Stanton (2008) find that due to the rise in temperatures, higher demand for air conditioning and other cooling requirements in the U.S. will increase energy costs and this will result in an additional cost in the energy sector up to more than $141 billion annually in 2100 due to climate change. Therefore, studying and identifying the impacts of climate change on the electricity sector is important in order to address and evaluate these impacts.

From an engineering perspective, climate change has impacts on the energy sector in a number of ways, such as the increases in peak demand due to higher cooling requirements in hotter summers and interruptions of electricity supply due to electricity transmission damages or changes in the efficiency of power plants (Ciscar and Dowling, 2014). According to Wilbanks et al. (2008), climate change impacts, such as the increase in the average ambient temperature, is expected to occur in most regions in the U.S. and this will have implications for energy production, use, transmission, distribution, and also decrease the overall thermoelectric power generation efficiency. The decreased power generation efficiency has a negative impact on the environment as it increases the emissions of CO_2 (Wang et al., 2021; Ponce and Khan, 2021; Grant et al., 2014). Reduced power generation efficiency, mainly fossil fired power plants, due to ambient temperature increase lead to an increase in fossil fuel consumption required to generate a specific amount of electricity as if there was no ambient temperature increase. This increase in the amount of fossil fuels consumed increases the level of CO_2 emissions in the environment.

Several studies have discussed the impacts of climate change on electricity sector in the U.S. and in other countries as well. Most of these studies had discussed the impacts on one side of the electricity sector such as electricity consumption, supply, transmission, or on the residential sector electricity consumption. For example, in the consumption side, Baxter and Calandri (1992) examined the impact of the increase in the ambient temperature on California electricity use under two scenarios. When the temperature increases by 1.9°C (3.4°F), the statewide requirement for electricity will increase by 2.6%, and when the temperature increase by 0.6°C (1.1°F) it will increase by 0.6%. Ali et al. (2013) find that the electricity consumption in Pakistan increases with the increase in the monthly average maximum ambient temperature. Almuhtady et al. (2019) also find that the electrical system in Jordan has experienced the failure to respond to increased demands induced by the increase in the ambient temperatures which is increasing from a year to another.

On the supply side, Cronin et al. (2018) review the literature on the impacts of climate change on the energy supply system by summarizing the regional coverage of studies, trends in their results and sources of disagreement and conclude that the electricity supply systems are subject to climate change impacts. Hamududu and Killingtveit (2012) find that the global hydropower generation in 2050, based on the generation level in 2005, will be reduced in many countries of the world. As climate change impacts would result an increase in the electricity demand and a reduction in the supplied electricity due to transmission faults, Bartos et al. (2016) find that by mid-century (2040–2060), increases in ambient air temperature may reduce average summertime transmission capacity in the U.S. by 1.9%–5.8% relative to the 1990–2010 reference period. This reduction is mainly attributable to thermoelectric power plants, knowing that most of these facilities do not account for climate impacts in their development plans, meaning that they could be overestimating their ability to meet future electricity requirements (Bartos and Chester, 2015). For Arizona power grid, Burillo et al. (2016) find that a 1°C increase in the ambient air temperatures due to climate change could result power outages to occur often.

Similarly, Farzaneh-Gord and Dashtebayaz (2011) investigate the effect of the ambient temperature on the Khangiran (Iran) gas turbines thermal efficiency and find that the increase of ambient air temperature negatively impacts their efficiency. They recommend cooling down the inlet air for power plants fueled by natural gas in order to mitigate the climate change impacts.

Geng et al. (2017) and Soytas et al. (2007) had also investigated this relationship between energy consumption and carbon dioxide (CO_2) emissions and find that it is one of the main causes of CO_2 emissions in the U.S. Based on these findings of previous research, it is rational to assume that any endeavors towards climate change mitigation must include the electricity sector as a central focus area (Chandramowli and Felder, 2013). With the existence of federalism[18] within the U.S. plus state level regulation of the electricity sector, state governments have taken considerably more actions in response to policies to mitigate climate change than the federal government, such as renewable portfolio standards for electric utilities, which mandates that electric utilities provide a stipulated percentage of their electricity from renewable energy sources (Schelly, 2014). Kirshen et al. (2008) analyze interdependencies of the impacts of climate change and adaptation strategies upon infrastructure systems in the Metro Boston urban area in the northeastern U.S. and find that with respect to taking difficult policy steps in response to threats of climate change, the federal and state governments have done relatively little. In addition to the absence of a federal policy on climate change (Kaswan, 2007; Baker et al., 2012), state level policies and regulations are important such that there is an importance for studying and examining the state level impacts from climate change.

To the best of our knowledge, no previous empirical research examines the aggregate impacts at the state level from climate change all multiple aspects of the electricity sector that can attributed to the ambient temperature increases - the performance of power generation, electricity consumption, and fossil fuel consumption for electricity generation. Thus, the main objective of this study is to examine the impacts of ambient temperature increases on the supply of and demand for electricity along with the associated change in the fossil fuels consumption for electricity sector across all 48 U.S. states. This study will be additional to very few studies

[18] Federalism is a system of government in which the same territory is controlled by two levels of government. Federalism is a system of government that is comprised of multiple interacting governing units (Ostrom and Allen, 2008). It is characterized by semi-autonomous states in a regime with a common central government (Wheare 1964, Riker 1964, Elazar 1987). The interaction between these governments produces system-level properties that are not properties of any individual unit on its own (Bednar 2009).

analyzed the impact of climate change on the electric sector. Using state level panel data for the period 1990 to 2019, climate change impacts on electricity generation from fossil fuels power plants will be empirically examined including supply side, demand side, and power plants efficiency. This allows us to take advantage of variation across states as well as across time.

The rest of the paper is organized as section 2 discusses the previous literature on the influence of ambient air temperature increase on performance, demand, and supply of electricity generation from power plants fueled by fossil fuels, renewables, and nuclear energy sources, and the technological adaptation methods for this effect. In sections 3 and 4, methodology, empirical strategy, and data used in the analysis are presented. Section 5 discusses empirical results, and finally, section 6 provides conclusions and policy implications.

3.2 Literature Review

Electric power is one of the key foundations of a developed society and it is considered as the backbone of the U.S. economic sectors. Electricity, environment, and society are linked together, such that understanding the interrelationship between them becomes important due to its impacts on the wellbeing of humanity. Ahmad et al. (2014) find that electricity access has a significant positive impact on human wellbeing in India, and Phoumin and Kimura (2019) confirmed that the lack of access to electricity in Cambodia has a negative impact on human wellbeing, including health, schooling, and earning ability outcomes. Worldwide, energy and electricity consumption are both essential for improving human wellbeing (Mazur, 2011), and higher energy consumption reflects a higher living standard (Bedir and Yilmaz, 2016). Markandya and Wilkinson (2007) in their study of the health impacts of the electricity generation in the developing and developed countries, went beyond these perspectives and considered access to electricity as a pre-requisite for improving human health, while the lack of access to it is one of the principal barriers to the fulfilment of human wellbeing.

Climate change is one of the most important concerns facing the international community due to its negative impacts on the economy, environment, and humans. The average global surface temperature is rising, and this increase in global temperature is a consequence of an enhanced greenhouse effect caused by the human activities that emit GHG (Kweku et al., 2018; Henderson et al., 2018). Energy production, that largely relied on fossil fuels, has led to a rapid increase in GHG emissions (Gebremeskel et al., 2021; Li and Haneklaus, 2021). In 2018, global energy-related CO_2 emissions rose 1.7% relative to 2017 (Xue et al., 2021), with an increase in the emissions from all fossil fuels. The energy sector was responsible for about two-thirds of global CO_2 emissions in 2018 (IEA, 2019). In addition to energy production, energy consumption has also been considered one of the main factors contributing to climate change in the previous decades (Chontanawat, 2020). Geng et al. (2017) conducted literature review for studies published between 1997 to 2016 and related to residential energy consumption and corresponding GHG emissions. Based on their revision, they considered the residential sector as the key contributor to energy consumption and GHG emissions which will continue to increase due to the rapid development and increasing incomes. In the U.S., Soytas et al. (2007) had investigated the linkages between energy consumption and CO_2 emissions (the largest component of GHGs in the U.S.) and find that energy consumption is the main cause of CO_2 emissions.

For several decades, the relationship between demand and supply of energy and the increase of CO_2 emissions into the environment was, and still, considered a vital area of concern for governments, policy makers, and environmental scientists and scholars (Salari et al., 2021).

CO_2 is the most important GHG that is generated as a result of human activities in various sectors of the economy such as transportation and electricity generation. In 2020, the majority of GHG emissions came from burning fossil fuels for energy use, fossil fuel combustion for energy accounted for 73% of total U.S. GHG emissions (EIA, 2021a), and power plants were the largest contributor to GHG emissions in the U.S. (EPA, 2021). In addition, CO_2 emissions were responsible for more than 80% of the total GHG emissions in 2018 (EPA, 2020), which significantly contribute to increasing global temperatures associated with climate change (Matthews et al., 2018).

Power plants are the industrial facilities used to generate electricity from different energy sources. These sources are categorized as renewable and non-renewable or exhaustible and non-exhaustible. Non-exhaustible or renewable sources of energy include solar, wind, geothermal, and hydropower facilities, while exhaustible or non-renewable sources include fossil fuels such as petroleum, natural gas, and coal. A conventional type of power plant burns fossil fuels to produce electricity. In 2020, a total of 60% of the electricity generated in the U.S. were from fossil fuels (19% from coal, 40% from natural gas, and 1% from petroleum) (EIA, 2021b). The most traditional types of power plants are the thermal power plants (also called thermoelectric[19]), where the thermal energy of the burned fuel is converted to mechanical/rotational energy (Tatar, 2017). Thermal power plants could be operated with gas turbines, steam turbines, or a mix of the two types in a layout of the combined cycle power plant.

[19] Thermoelectric or Thermal power plants for electricity production include fuels such as coal, oil, natural gas, nuclear, and other lesser-used methods, such as geothermal and burning waste material.

3.2.1 Influence of ambient air temperature on power plants performance

The performance (efficiency and output) of gas turbines is influenced by the inlet air ambient temperature (Kakaras et al., 2006). As the ambient temperature rises, the air density decreases (Maulbetsch and DiFilippo, 2006). Since the suction capacity of the compressor is fixed, when ambient air temperature increases less air is entering the turbine to be mixed with fuel in a specific predesigned ratio for combustion, resulting in a reduction in the mas flow rate of the entering air and then the gas turbine output reduces (Kehlhofer et al., 2009). Since the ambient air is used directly as working fluid in the gas turbines, gas turbines are most likely to be the most affected systems in all conventional power plants (Oyedepo et al., 2014). The International Organization for Standardization (ISO) in its Gas Turbine Acceptance Test ISO-2431-009, has defined the standard reference conditions for all gas turbines included that the inlet air temperature should be 15 $^{\circ}$C (59 $^{\circ}$F) with a relative humidity of 60%. Since the output power of gas turbine is a function of fuel content, inlet air conditions -mainly temperature and humidity-, and turbine capacity, air should be entering the gas turbine through the air compressor with specific conditions such as, mass flow rate, temperature, and humidity. Schaeffer et al. (2012) studied the impacts that climate change might have on energy systems, and they indicated that performance of thermal power plants varies according to weather conditions including pressure, humidity, air and water temperature. The effects of changes in ambient temperature on electricity generation efficiency in the thermal power generation such as fossil fuels and nuclear power plants are similar. Higher temperatures reduce thermal efficiency and the generating output of conventional power plants (Zamuda et al., 2018). Thermal plant production losses increase when temperatures exceed standard design criteria.

A 10°C (18°F) rise in ambient temperature from the ISO condition resulting in more than 6% output power reduction (Kim and Ro, 2000). Mohanty and Paloso (1995) while studying the impact of ambient conditions on power plants output in Bangkok (Thailand) find that reducing the inlet air temperature to the ISO condition at 15°C (59°F), would result an additional 11% of the output power from a similar gas turbine power plant, and typically, an increase of 1°C (1.8°F) in the ambient temperature results in 1% drop from the gas turbine rated capacity. In line with the previous literature, Ameri and Hejazi (2004) studied the impact of climate change on the Chabahar power plant in Iran and presented an overview of different cooling methods used to enhance the performance of gas turbines and find that the increase of 1°C (1.8°F) in ambient air temperature resulting in 0.74% drop in the power output. De Pascale et al. (2014) considered ambient temperature as the main influencer to gas turbine performance and Chaker et al. (2006) find that an increase of 1°C (1.8°F) resulting in a power loss of about 0.5 – 0.9 %. Similarly, Bartos and Chester (2015) studied the impacts of climate change on the summertime electric power supply in the Western U.S. and find that power generation capacity will reduce by 1.1% to 3% due to higher ambient temperatures. Empirical evidence from very recent studies by Petrakopoulou et al. (2020) and Carcasci et al. (2020) showed that both coal and natural gas power plants output power and efficiency decrease with increasing ambient air temperature. Another recent study for Hamedani et al. (2021) confirmed that the efficiency and output of a gas turbine power plant located in Asalouyeh (Iran) are negatively affected by ambient air temperatures. They stated that, at ambient temperature 40°C (104°F), the power plant efficiency and output power will decrease by 2% and 12.5% respectively. This might be an indication to the future planning how conventional power plants might be facing climate related losses, and that peaking power plants[20] may not be as able to meet the peak electricity demand at locations with hot climates and with demand increasing.

In addition, electricity generation facilities are negatively affected by impacts related to extreme weather events (Kopytko and Perkins, 2011), transmission capacity is also vulnerable to air temperature increase. Bartos et al. (2016) estimated the impacts of rising ambient air temperatures on electric transmission ampacity for 121 planning areas in the U.S. and find that by mid-century (2040–2060), an increase in the ambient air temperature may reduce average summertime transmission capacity by 1.9 – 5.8 % relative to the 1990–2010 reference period.

3.2.2 Influence of ambient air temperature on renewable and nuclear power

While power plants that use fossil fuels to generate electricity are impacted by higher ambient temperatures, other energy sources are also impacted by climate change. Low GHG[21] energy has become a research focus due to links with climate variables such as precipitation, temperature, irradiation, and wind (Contreras-Lisperguer and de Cuba, 2008). Nuclear power plants, for example, are subjected to climate change impacts. Technically, the average efficiency of the nuclear power plant is lower than conventional types (Gingerich and Mauter, 2015), for this reason, it is considered vulnerable to climate change. Linnerud et al. (2011) examined the impact of climate change on nuclear power supply for the period 1995 to 2008 in seven European countries (Belgium, Finland, France, Germany, Spain, Sweden, and the United Kingdom) and find that with an ambient temperature increase of 1 °C (1.8 °F), nuclear power plant production is reduced with 0.7 percent.

[20] In general, power plants are categorized into two groups: base load and peaking power plants. A peaking plant is a reserve plant and only generates electricity in the event of power outages or high demand (See and Coelli, 2012).
[21] Low GHG energy comprises of renewable and nuclear energy sources. Renewable energy sources include solar, wind, hydropower, geothermal, and biomass (EIA, 2019).

Climate change impacts are expected throughout the renewable energy systems too (Gernaat et al., 2021). As one of the most important of renewable energy sources, solar energy is sensitive to climate change, such that the electrical efficiency of the photovoltaic (PV) module depends on ambient temperature, and it reduces when the temperature increases (Vokas et al., 2006; Solaun and Cerda, 2019). Makrides et al. (2012) analyzed the effects of temperature on the performance of PV systems installed in Cyprus and find that the ambient temperature rise resulting in an average loss of solar output power between 5 – 9 %, depending on the solar panels technology. Similar to solar, wind turbines are also penalized by climate change, where increasing air temperature resulting in decreasing the density of air[22] (Oyedepo et al., 2014). Accordingly, wind turbine power production declines (Pryor and Barthelmie, 2013). Moreover, the projection of future climate change impacts on wind energy indicates a decrease in the output capacity of wind energy production (Roshan et al., 2015).

3.2.3 Technological adaptation – Gas Turbine inlet air cooling

Previous literature discussed the negative impact of gas turbines inlet air temperature on the power generation performance. This had led to seeking methods that improve the air inlet conditions to gas turbine. The continuous supply of air into the gas turbine is mainly for three purposes; to be mixed with fuel in the combustion process, to cool the turbine blades, and for sealing[23] (Owen, 1988). Different methods have been developed to counteract gas turbine performance reduction due to ambient temperature rise. Several methods were examined by Farzaneh-Gord and Dashtebayaz (2011), Kehlhofer et al. (2009), Jonsson and Yan (2005), and

[22] Cooled air is denser, it gives the machine a higher air mass flow rate and pressure ratio, resulting in an increase in output.

[23] The cooling and sealing air system provides the necessary air flow from the gas turbine compressor to other parts of the gas turbine to prevent excessive temperature buildup in these parts during normal operation and for sealing of the turbine bearings.

Kakaras et al. (2006), including evaporative cooling, fogging, evaporation compressor cooling, and mechanical chiller. They showed a consensus that installing any of these cooling methods is necessary for enhancing the performance of the gas turbine especially during summertime when the ambient temperature is high. Amongst these methods, evaporative cooling and mechanical chilling systems were the most frequently used methods (Alhazmy and Najjar, 2004).

While electricity generation from gas turbines is sensitive to climate change and suffers from the rise in ambient air temperature (Abubaker et al., 2021) and also penalized by a power output loss, cooling methods to reduce the temperature of the inlet air become necessary, but they are resulting in power output loss (El-Shazly et al., 2016; Kakaras et al., 2006). While these methods might be important and economically effective for hot and dry climate regions, Ibrahim et al. (2011) note that the main disadvantage of this technique is not associated with high capital cost nor with the space required, but with its high consumption of electricity which reduces the potential power output increase of the gas turbine generator since part of the generated output will be consumed for the cooling system. In contrast, Popli et al. (2013) state that the mechanical chiller (one of the gas turbine inlet air cooling methods) may not be economically justified due to its high capital cost. Ibrahim et al. (2011) show that all methods of inlet air cooling are energy consuming and will reduce the total output of the gas turbine. Such air-cooling systems require an electric capacity for the cooling compressor of between 40 to 50 kW per MW capacity, which will reduce the potential output of the power plant (Ibrahim et al., 2011).

With respect to cooling methods capital costs, a study by the U.S. Department of Energy (DOE) in 1996 found that installing a cooling system for gas turbine will cost between $150 – 250 per kW of capacity (Hasnain, 1998). Bakenhus (2000) in his study of the effectiveness of one cooling method used in the U.S. find similar results concluding that it is not feasible because the installation cost for a cooling method is almost 55% of the installation cost for a new unit of gas turbine at $300 per kW. Based on the weather conditions, such as high relative humidity, this investment might not be returned during the lifetime of the installed cooling system (Lyu et al., 2018). Evaporative cooling techniques can be effective in hot and dry areas, but they are not in humid areas (Zadpoor and Golshan, 2006). Accordingly, installing an evaporative cooling method to mitigate the hot weather impact on power plants running by gas turbines might not be cost effective in all areas. For example, in humid areas, the economic benefit of the cooling system may not be offset by the total investment cost (Lyu et al., 2018).

The literature on climate change impacts on power sector reveals that climate change does not threaten power sector at the generation stage only, it also considered as a threat to all U.S. electric power system, including transmission and consumption (Ralston Fonseca et al., 2019). These challenges make the power sector more vulnerable to climate change, especially with the fact that the majority of the U.S. power plants are thermal type (Van Vliet et al., 2012).

3.2. 4 Influence of ambient air temperature on electricity consumption

While several empirical studies have discussed the relationship between the rise in ambient temperature and the degradation of electricity generation performance, other studies found that increased ambient temperatures also have a relationship with the increases in electricity consumption. In the U.S., climate change will increase peak electricity demand by 10–20% more than current peak demand (Craig et al., 2018). An estimate for the increase in the Midwest region electricity demand associated with climate change (mainly ambient temperature increase) could exceed 10 GW[24] (Gotham et al., 2012). Higher summer temperatures are expected to result in an increase in the net energy demand in Indiana commercial sector by about

[24] Gigawatt (GW) = 1,000 Megawatt (MW) = 1,000,000 Kilowatt (kW) = 1,000,000,000 watt

5% by 2050 (Raymond et al., 2020). Baxter and Calandri (1992) find that a 1°F (0.56°C) increase will result in 2.6% to 3.7% increase in California's electricity consumption, while Zhang et al. (2019) find it at about 0.015%. Similarly, Burillo et al. (2019) examined the effects of rising air temperatures on annual energy consumption and peak demand within Los Angeles County and found that increases in ambient air temperature due to climate change are projected to increase peak demand by 4–8% by 2060.

Auffhammer et al. (2017) stated that the southern U.S. states experiences the greatest load increases as a result of climate change, and climate change is projected to have severe impacts on the peak electricity demand across the U.S. Climate change impacts can also be challenging for other countries. A rise in the ambient temperature by 1°C (1.8°F) will result in 3% to 4% increase in electricity consumption in Singapore and 4% to 5% in Hong Kong (Ang et al., 2017). In Pakistan, Ali et al. (2013) find that the electricity consumption starts to rise up from March to August and is maximum in July and August, and their prediction equation shows that for an increase of 1°C (1.8°F) increase in ambient temperature, electricity consumption will increase by 109.3 Gigawatt-hour (GWh).

3.3 Methods and Models

This study identifies the impacts of climate change resulting in the electricity generation sector due to rising ambient temperatures. These impacts include: 1) the increase in electricity consumption, 2) the loss of electricity generation, and 3) the decreased performance of electricity generation in fossil fuels power plants. Previous work used different approaches for panel data analysis, including multiple regression models to estimate the demand and supply of energy. Some of those multiple regression models were used to identify the climate change impact on energy demand. For example, Considine (2000), Amato et al. (2005), and Fan et al. (2019) used the two-stage least squares (2SLS) method including the instrumental variable (IV) for the regression analysis to study the impacts of climate change on electricity demand based on panel data. Ruth and Lin (2006) used similar methodology with fixed effects modelling.

In this study, using data from all 48 conterminous U.S. states[25] from 1990 to 2019, the impacts of climate change on electricity consumption, generation, and efficiency are examined using a Seemingly Unrelated Regression (SUR) model. SUR was first developed by Zellner (1962), also known as the multivariate regression. A SUR model will improve understanding how climate change impacts can affect patterns of electricity consumption and generation, and how this in turn these impacts could affect the efficiency of the electricity generation from fossil fuels. When two or more dependent variables are correlated, a joint estimation provides a better estimation of the climate change impacts across these dependent variables. When the error terms in individual regressions are correlated, which is quite likely if the dependent variables are correlated, separate estimation of each regression will neglect this correlation. The SUR method, on the other hand, considers this correlation in estimating the between-equation covariances. Individual OLS regressions will neither produce multivariate results nor will they allow us to test coefficients across equations. Considering intercorrelations across equations, more efficient parameter estimates may be obtained. A SUR model estimates the parameters of the system, accounting for heteroskedasticity and contemporaneous correlation in the error terms across the three equations of this analysis (Khan et al., 2014). SUR results in greater efficiency of the parameter estimates, due to the additional information that is used to describe the system (Cadavez and Henningsen, 2012). Accordingly, SUR method has become a convenient econometrics approach that is more efficient than the single equation estimation (Binkley and

[25] Alaska and Hawaii are excluded from this analysis because data on cooling degree days (CDD) and heating degree days (HDD) data are not available for these states.

Nelson, 1988). As a robustness check for the SUR model, the pooled ordinary least square (OLS) model will also be presented in this analysis along with the SUR estimates.

Following previous studies, especially those that examined the impact of climate change, or the ambient temperature rise on the electric system, annual data are used for all the variables in the empirical analysis as this follows previous studies in selecting our independent variables used in the regression models. Previous research results are used to guide explanatory variable decisions. Ralston Fonseca et al. (2019) find that electricity average peak demand values during the summer in the U.S. can increase by more than 10% as a result of climate change, and Ali et al. (2013) studied the relationship between extreme temperature and electricity demand in Pakistan and find that the electricity consumption increases with mean monthly maximum temperature. Amato et al. (2005) investigate the implications of climate change for electricity demand for Massachusetts (U.S.A) and find heating degree days (HDD) and cooling degree days (CDD) have positive impact on per capita electricity generation. Fan et al. (2019) find positive effects of the per capita Gross Domestic Product (GDP) and the HDD and CDD on the per capita electricity demand in China. Previous studies (Siqueira et al., 2019; Menyah and Wolde-Rufael, 2010) used renewable and nuclear energy in their empirical models in order to examine their impact on climate change.

In this research, the amount of electricity generated from low GHG energy sources (renewables and nuclear) on a per capita basis is used as a measure for the degree of the energy transition for a given state. Low GHG energy has been targeted as an important area of several studies as it has environmental benefits and contributes to reducing CO_2 emissions from the atmosphere (Wei et al., 2010; Gyamfi et al., 2021). Electricity price is one of the factors affecting electricity consumption. Consumer demand for electricity decreases as electricity prices increase (Staffell and Pfenninger, 2018). Alberini et al. (2011) studied the demand for electricity at the nationwide household-level data for the period of 1997–2007 and find that electricity price elasticity of demand is at -0.81. Alberini and Filippini (2011) and Burke and Abayasekara (2018) used an empirical analysis of the electricity demand in the residential sector using annual aggregate data at the state level for 48 U.S. states from 1995 to 2007 and 2003 to 2015, respectively, and find that electricity prices have a negative impact while per capita income have a positive impact. Maulbetsch and DiFilippo (2006) find that the increase of ambient temperature will result in a reduction in electricity generation. Finally, using real data for HABAS, a natural gas fired power plant in Turkey, Şen et al. (2018) find that the power plant efficiency reduced by 0.6 % (30.4 MW) when the ambient temperature increased from 8°C (46.4°F) to 23°C (73.4°F), as its electricity generated reduced from 227.7 MW to 197.3 MW. Similarly, Petrakopoulou et al. (2020) also have reached to similar results, for coal fired power plants when ambient temperature increases by 10°C (18°F), electricity generation efficiency decreases by 0.5 - 0.7%.

The three dependent variables are: 1) TCpc: annual electricity consumption per capita in Megawatt-hour in a state (MWh/person/year) which is used to examine the influence of increased ambient temperatures on electricity consumption, 2) TG: net[26] electricity generated in Terawatt-hour[27] in a state (TWh/year) which is used to examine how ambient temperature increases influence electricity generation, and 3) Eff: efficiency of power generation at fossil fuel fired power plants as a percentage of the energy output from the energy input to analyze the impact of climate change on the performance of fossil fired power plants. Annual electricity consumption per capita provides an indication of electricity attributed to the population in the

[26] Net electricity generation is equal to gross electricity generation minus the consumption of power plants auxiliary services (i.e. lighting, heating, cooling, etc).
[27] Terawatt-hour (TWh) = 1,000,000 Megawatt-hour (1 million MWh) = 1 trillion Wh

state. While the net electricity generation is a measure of the annual net electricity generated from power plants and transmitted through the grid in its way to be dispatched to customers. For the Eff variable, data from U.S. Energy Information Administration (EIA) for electricity generation from fossil fuels and heat input of fossil fuels are used for electricity generation with the calculated based on the following formula:

$$\boldsymbol{Efficiency}\,(\%) = \mathbf{3412}\frac{\boldsymbol{Btu}}{\boldsymbol{KWh}} \times \frac{\boldsymbol{Energy\ Output}\,(\boldsymbol{KWh})}{\boldsymbol{Heat\ Input}\,(\boldsymbol{Btu})} \times \mathbf{100}\%$$

The linear specification of the multiple equations with panel data are:

$$\boldsymbol{Electricity\ Consumption\ Equation}: \boldsymbol{TCpc_{it}}$$
$$= \boldsymbol{\alpha_0 + \alpha_1 Tmax_{it} + \alpha_2 CDD_{it} + \alpha_3 HDD_{it} + \alpha_4 LowGHGpc_{it} + \alpha_5 GDP_{it}}$$
$$\boldsymbol{+ \alpha_6 EP_{it} + \varepsilon_{it}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{3.1})$$

$$\boldsymbol{Electricity\ Generation\ Equation}: \boldsymbol{TG_{it}}$$
$$= \boldsymbol{\beta_0 + \beta_1 Tmax_{it} + \beta_2 CDD_{it} + \beta_3 HDD_{it} + \beta_4 LowGHGpc_{it} + \beta_5 FP_{it}}$$
$$\boldsymbol{+ \beta_6 HI_{it} + \delta_{it}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{3.2})$$

$$\boldsymbol{Efficiency\ Equation}: \boldsymbol{Eff_{it}}$$
$$= \boldsymbol{\mu_0 + \mu_1 Tmax_{it} + \mu_2 CDD_{it} + \mu_3 HDD_{it} + \mu_4 HI_{it} + \gamma_{it}} \ldots\ldots (\mathbf{3.3})$$

where Tmax is the state annual averaged maximum temperature in Fahrenheit (°F) represents the increase of ambient temperature resulted from climate change impact and it has impacts on electricity consumption, generation, and performance. CDD is the cooling degree-days in °DF which is a measure of how hot the temperature was on a given day or during a period of days and it reflects the demand for energy to cool houses and businesses, HDD is the heating degree days in °DF which is a measure of how cold the temperature was on a given day or during a period of days and it reflects the demand for energy to heat houses and businesses (both CDD and HDD calculations are explained in the data section), LowGHGpc is the net annual electricity generated from renewable and nuclear energy sources per capita in Megawatt-hour per person (MWh/person/year), GDP measures the value of the final goods and services produced in the U.S. without double counting the intermediate goods and services used up to produce them and it is measured in $1,000 per capita, EP is the retail electricity price in cent per kWh (¢/kWh), FP is the weighted average for the consumed fossil fuels for electricity generation purposes (petroleum, natural gas, and coal) prices in U.S. dollars per million British Thermal Unit ($/MMBtu), finally, HI is the heat input[28] for all fossil fuels used for electricity generation in Trillion Btu.

After collecting the data of fossil fuels (coal, natural gas, petroleum) prices in $/MMBtu and the consumed quantities for the three fossil fuels consumed for electricity generation available at the detailed state data from EIA, these data are transformed into three quantities, based on the EIA energy conversion calculations[29], into MMBtu and then calculated the weighted average price of fossil fuels using equation 3.4.

$$\boldsymbol{FP = \frac{CP \times CQ + NP \times NQ + PP \times PQ}{CQ + NQ + PQ}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{3.4})$$

where FP is the weighted average price for fossil fuels in $/MMBtu, CP is the coal price in $/MMBtu, CQ is the coal consumption for electricity generation in MMBtu, NP is the natural gas price in $/MMBtu, NQ is the natural gas consumption for electricity generation in MMBtu, PP is the petroleum price in $/MMBtu, PQ is the petroleum consumption for electricity generation in MMBtu.

[28] Power plant heat input is measured by the heat available in fuels burned for electricity generation in British Thermal Units (Btu).

[29] One short ton of coal = 19.26 MMBtu, 1000 cubic feet (Mcf) of natural gas = 1.037 MMBtu, and one barrel of petroleum = 5.80 MMBtu.

The coefficients $\alpha_1, \alpha_2 \ldots, \alpha_6$, $\beta_1, \beta_2 \ldots, \beta_6$, and $\mu_0, \mu_1 \ldots, \mu_4$ describe the directions and strengths of the relationship between the three dependent variable and the explanatory factors used to determine TCpc, TG, and Eff in the regression models. The subscripts i and t are representing the state and time, respectively. The subscript i = 1, …, N denotes the state (our sample counts 48 states) and t = 1, …, T denotes the time period (our time frame is 1990 - 2019), with the error terms ε_{it} , δ_{it} , & γ_{it}.

Natural logarithms are used for the electricity consumption per capita and per capita GDP variables in order to improve the fit of a regression model and reduce error (Zhang et al., 2019). Moreover, taking logarithm of electricity demand will lead to a better statistical result (Goel and Goel, 2014). To validate the use of natural logarithms for these variables, the Shapiro Wilk (SW) test is used for testing the normal distribution for three variables; per capita electricity consumption (TCpc), net electricity generation (TG) and per capita GDP (GDP). Results of the SW test are listed in Table 3.2.

Table 3.2. Shapiro Wilk Normality Test Results (N=1,450)

Variable	W	V	Z	Prob > Z
TCpc	0.93256	59.301	10.258	0.00000
TG	0.80412	172.244	12.937	0.00000
Income	0.96450	31.218	8.646	0.00000
Ln(TCpc)	0.93256	59.301	1.684	0.0461
Ln(TG)	0.80412	172.244	-1.059	0.8553
Ln(Income)	0.96450	31.218	-0.752	0.7739

Table 3.2 results show that the three variables were not normally distributed, and after applying the natural logarithm they became normally distributed variables.

In addition to the SW test, normal distribution of these three variables are validated using the histograms shown in Figure 3.1. The upper panel includes histograms, from left to right, for the per capita electricity consumption (TCpc), the middle panel is for the net electricity generation (TG), and the per capita GDP (GDP), respectively. Clearly, variables do not appear to be normally distributed, and all looks right skewed. And the lower panel includes the three variables in the natural logarithm forms. Histograms also validate the variables in the natural logarithm form are normally distributed.

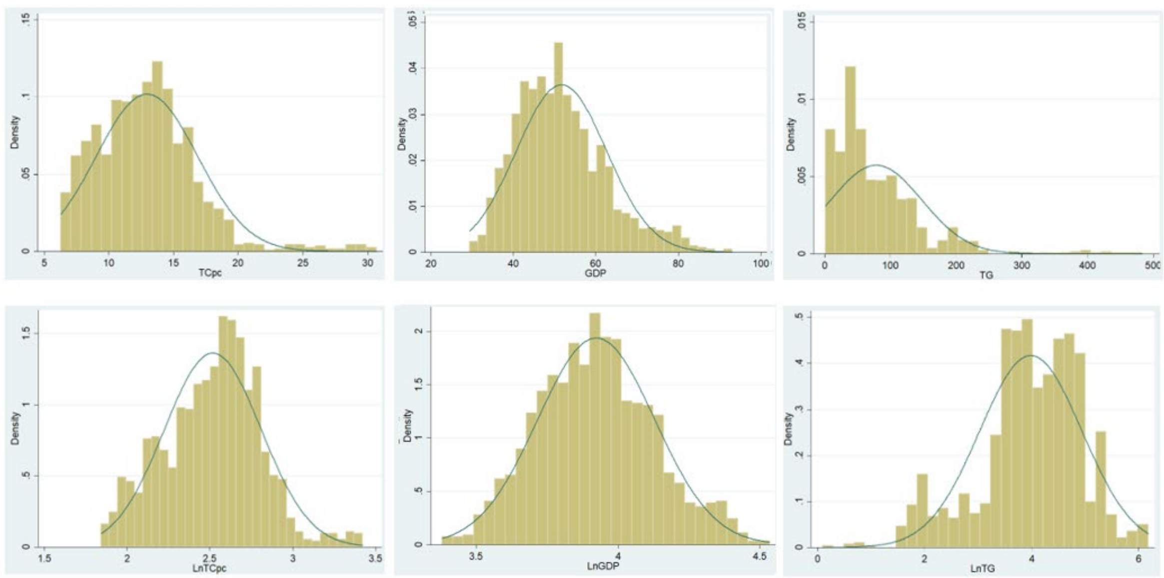

Figure 3.1: Normal Distribution Histograms for per capita electricity consumption (TCpc), per capita GDP (GDP), and net electricity generation (TG), and their natural logarithm forms.

Applying the natural logarithm also eliminates the heteroscedasticity that may exist in the variables (Fan et al., 2019). After all, logarithmic transformations are applied for per capita electricity consumption (TCpc), net electricity generation (TG) and per capita GDP (GDP) variables in Eq (3.1) and Eq (3.2), the resulting panel data linear specifications are:

$$\boldsymbol{Ln(TCpc_{it}) = \alpha_0 + \alpha_1 Tmax_{it} + \alpha_2 CDD_{it} + \alpha_3 HDD_{it} + \alpha_4 LowGHGpc_{it} + \alpha_5 Ln(GDP_{it}) + \alpha_6 EP_{it} + \varepsilon_{it} \ldots\ldots (3.5)}$$

$$Ln(TG_{it}) = \beta_0 + \beta_1 Tmax_{it} + \beta_2 CDD_{it} + \beta_3 HDD_{it} + \beta_4 LowGHGpc_{it} + \beta_5 FP_{it} + \beta_6 HI_{it} + \delta_{it} \quad (3.6)$$

Descriptions and sources for all dependent and independent variables of the previous models in Eq (3.3), Eq (3.5), and Eq (3.6) are listed in Table 3.3. All these variables are state level and annual.

3.4 Data

Data across the 48 states in the U.S. between 1990 and 2019 were collected from different sources listed in Table 3.3. For this type of empirical analysis, impacts on three dependent variables are evaluated: TCpc is the annual amount of electricity consumption in megawatt-hours (MWh) on a per capita basis. TG is the annual net amount of electricity generated in Terawatt-hours (TWh) in a state. Eff is the efficiency of power plants electricity generation. The other seven independent variables include the annual averaged maximum temperature, cooling and heating degree days, per capita GDP in 1000 U.S. dollar, retail electricity prices, weighted average annual fossil fuels price, and average annual heat input from all fossil fuels consumed for electricity generation.

Data on statewide averaged maximum temperature (Tmax), heating and cooling degree days (CDD and HDD) were provided by the National Oceanic and Atmospheric Administration's (NOAA) National Center for Environmental Information (NCEI). These data are based on temperature measurements from weather stations overseen by NOAA's National Weather Service (NWS). There are 344 climate divisions in the U.S. (Vose et al., 2014). For each climate division, monthly station averaged maximum temperature values are computed from the daily observations. The divisional values are weighted by area to compute statewide values, then the annual averaged maximum temperature for a state is the average of the monthly averaged maximums.

CDD and HDD estimates over the calendar year were calculated directly from NCEI daily data by summing the number of degrees that a day's average temperature was above (for CDD calculations) or below (for HDD calculations) a base temperature of 65°F using the following formulas:

$$\boldsymbol{CDD = \sum_{i=1}^{N} (T_i - T_{base})\,, T_i > T_{base}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (\mathbf{3.8})$$

$$\boldsymbol{HDD = \sum_{i=1}^{N} (T_{base} - T_i)\,, T_i < T_{base}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (\mathbf{3.9})$$

where N is the number of days in a year, T_i is the daily average temperature of the day i, and T_{base} is the base temperature (65°F).

Both CDD and HDD calculations assume that when the ambient temperature is 65°F, there will be no need for cooling or heating. They are calculated from equations (3.8) and (3.9) by dividing the sum of the highest and lowest temperature in a day by 2 to find T_i. Then, if T_i was above 65°F (T_{base}), then subtract 65°F from T_i to find the CDD, and if T_i was below 65°F, then subtract T_i from 65°F to find the HDD (Arguez et al., 2012; Almuhtady et al., 2019).

Annual data were used in this analysis mainly for two reasons. First, daily or monthly data were not available for the majority of the variables in the study. Second, while most previous literature has assumed that the largest impacts from climate change are seasonal (mainly summer), some authors have utilized annual data for empirical analyses. Examples include Deschênes and Greenstone (2007) who use annual variation in temperature and precipitation data in the U.S. to estimate the impact of climate on U.S. agricultural output. Ruth and Lin (2006) had also estimated the impacts of climate change on energy demand in the state of Maryland and concluded that there are noticeable annual impacts of climate change. Mirasgedis et al. (2007) studied the potential upcoming impacts of climate change in the 21st century on electricity demand where they used annual data for the empirical analysis, and also concluded that annual impact of climate change on energy sector are noticeable.

Table 3.3. Variables, Data Description, and Sources

Variable	Description	Source
TCpc	Annual electricity consumption per capita in Megawatt-hour per person (MWh/person/year)	U.S. Energy Information Administration (EIA)
TG	Net electricity generation in Terawatt-hour per year (TWh/year)	U.S. Energy Information Administration (EIA)
Eff	The efficiency of electricity generation from fossil fuels in % ($3412\,\frac{Btu}{KWh} \times \frac{Energy\ Output\ (KWh)}{Heat\ Input\ (Btu)} \times 100\%$)	U.S. Energy Information Administration (EIA)
Tmax	State averaged maximum temperature in Fahrenheit (°F)	National Centers for Environmental Information (NCEI)
CDD	Cooling degree-days in Fahrenheit (°DF) (reference point is T*=65°F; CDD=Tmax-T*, 0)	National Centers for Environmental Information (NCEI)
HDD	Heating degree-days in Fahrenheit (°DF) (reference point is T*=65°F; HDD=T*-Tmin, 0)	National Centers for Environmental Information (NCEI)
LowGHGpc	Net annual electricity generated from renewable and nuclear energy sources per capita in Megawatt-hour per person (MWh/person/year)	U.S. Energy Information Administration (EIA)
GDP	Per capita GDP in 1000 U.S. dollar ($k) adjusted for inflation to 2019 dollars[30]	U.S. Bureau of Economic Analysis (BEA)
EP	Retail electricity prices in cent/kWh (¢/kWh) adjusted for inflation to 2019 dollars	U.S. Energy Information Administration (EIA)
FP	Weighted average fossil fuels prices in U.S. dollars per million Btu ($/MMBtu) adjusted for inflation to 2019 dollars	U.S. Energy Information Administration (EIA)
HI	Heat input for all fossil fuels used for electricity generation in Trillion Btu	U.S. Energy Information Administration (EIA)

To accurately compare per capita GDP and other prices such as electricity retail prices and weighted average fossil fuels prices in this study over time, 2019 inflation adjusted dollars

[30] GDP, EP, and FP are adjusted for inflation over the study period of 30 years (1990 – 2019).

are used over the time period (1990 – 2019). To do so, consumer price index for all urban consumers in the U.S. city average (CPI) was retrieved from the Federal Reserve Economic Data (FRED)[31]. For example, to inflation adjust a value (X) from 1990 dollars to 2019 dollars, the following formula was used:

$$\boldsymbol{Inflation - Adjusted\ X = 1990\ X \times \frac{2019\ CPI}{1990\ CPI}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{3.10})$$

where X applied for GDP, EP, and FP.

Table 3.4 provides summary statistics of all variables used for the empirical analysis. Statistics from the table show the wide variation between states, GDP, energy consumption and generation, electricity prices, and weather.

Table 3.4. Summary Statistics for Annual State Level Variables, 1990 to 2019 (N=1,440)

Variable	Units	Ave	Min	Max	Standard Deviation
TCpc	MWh/person/year	12.95	6.31	30.69	3.91
TG	TWh/year	78.65	1.11	483.20	69.59
Eff	Percentage (%)	35.96	10.45	50.74	6.46
Tmax	Fahrenheit (°F)	63.86	47.40	83.60	8.07
CDD	Degree Day in Fahrenheit (°DF)	1,092.06	42.00	4,156.00	816.44
HDD	Degree Day in Fahrenheit (°DF)	5,222.29	430.00	10,810.00	2,096.15
LowGHGpc	MWh/person/year	4.78	0.01	19.72	3.76
GDP	1000 U.S. Dollars /person	51.68	29.40	93.13	10.94
EP	¢/kWh	10.94	5.97	21.53	3.09
FP	U.S. Dollars/MMBtu	3.59	0.02	22.06	2.28
HI	Trillion Btu	511.07	0.04	3,796.77	539.15

Note: GDP, EP, and FP are all in real dollars (adjusted for inflation)

[31] CPI data available at FRED: https://fred.stlouisfed.org/series/CPIAUCSL

Per capita total annual electricity consumption in a state in MWh (**TCpc**) had an average of 12.9. Wyoming in 2011 had the highest value at 30.7 with Rhode Island having the lowest value of 6.3 in 1992. Net annual electricity generation in a state in TWh (**TG**) had an average of 78.6. Texas in 2019 recorded the highest value at 483.2 with Rhode Island having the lowest value of 1.1 in 1990. The efficiency of electricity generation from fossil fired power plants (**Eff**) in percentage (%) had an average of 35.9. Fossil fired power plants located in Maine recorded the highest efficiency at 50.7 in 2019 with plants in Vermont having the lowest efficiency at 10.5 in 1996. The annual averaged maximum temperature in a state (**Tmax**) in °F had an average of 63.9. Florida has the highest value at 83.6 in 1990 with North Dakota having the lowest value of 47.4 in 1996. Finally, the per capita net annual electricity generated from renewable and nuclear energy sources (**LowGHGpc**) in MWh had an average of 4.8. Washington has the highest value at 19.7 in 1997, while Rhode Island and Delaware have the lowest values below 0.01 in 2005 and 1991 respectively.

3.5 Results

Table 3.5 reports the regression results for three models in equations (3.5), (3.6), and (3.3), respectively. Both SUR and Pooled OLS regression estimates for three models are included in table 3.5 in order to validate the robustness of the results and to fully report the estimates from the different regression models. SUR regression results will be used to interpret the impact of independent variables on per capita electricity consumption, electricity generation, and power plants efficiency. In general, for both SUR and Pooled OLS, regression coefficients show consistent signs and significance along the three models. This consistency emphasizes the robustness and reliability of SUR estimates for the three equations.

The coefficient estimates for equation (3.5) shows that annual averaged maximum temperature, cooling degree days, heating degree days, state per capita electricity generation from renewable and nuclear sources, and per capita GDP all have positive and statistically significant coefficients. An increase in these variables is resulting in an increase in state level electricity consumption. On the other hand, the coefficient for electricity prices is negative and statistically significant.

Table 3.5. Regression Coefficient Estimates (N=1.440)

Dependent Variables	**Ln(TCpc)**		**Ln(TG)**		**Eff**	
Independent Variables	Pooled OLS	SUR	Pooled OLS	SUR	Pooled OLS	SUR
Tmax	0.0052116** (0.0020625)	0.0051658** (0.0020571)	-0.0399527*** (0.0072921)	-0.0394493*** (0.0072553)	-0.6112162*** (0.0644405)	-0.6111424*** (0.0643285)
CDD	0.0000933*** (0.0000114)	0.0000932*** (0.0000292)	-0.0003564*** (0.0000418)	-0.0003613*** (0.0000417)	-0.0040371*** (0.0003859)	-0.0040358*** (0.0003852)
HDD	0.0000295*** (0.00000725)	0.0000292*** 0.00000723)	-0.0003867*** (0.0000258)	-0.000387*** (0.0000256)	-0.0048793*** (0.0002257)	-0.004879*** (0.0002253)
LowGHGpc	0.0134804*** (0.0011628)	0.0135731*** 0.0011598)	0.0397067*** (0.0041499)	0.0472343*** (0.0040205)		
Ln(GDP)	0.1024134*** (0.0216221)	0.1093212*** (0.0215225)				
EP	-0.0708527*** (0.0015131)	-0.0712632*** (0.001507)				
FP			-0.0997088*** (0.0070372)	-0.101998*** (0.0068081)		
HI			0.0011702*** (.0000328)	0.001183*** (0.0000326)	-0.0008471*** (0.0002957)	-0.0008614*** (0.0002952)
Constant	2.2379*** (0.1937924)	2.219461*** (0.193178)	8.516186*** (0.5806687)	8.45672*** (0.5769507)	105.3138*** (4.999701)	105.3086*** (4.991011)
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R-squared	0.70	0.70	0.64	0.64	0.33	0.33

Note: Values within parentheses are standard errors, *** p<0.01, ** p<0.05, *p<0.1

For the electricity generation model (equation 3.6)), coefficients for annual averaged maximum temperature, cooling degree days, heating degree days, and fossil fuels weighted average price are all negative and statistically significant. While coefficients for state per capita electricity generation from renewable and nuclear sources and the heat input for all fossil fuels used for electricity generation are positive and statistically significant. Finally, for the efficiency model of equation (3.3), coefficients for annual averaged maximum temperature, cooling degree days, heating degree days, and heat input for all fossil fuels used for electricity generation are all negative and statistically significant.

For the demand side, the increase in the maximum ambient temperature has a statistically significant and positive impact on the demand for electricity, while this variable has negative impacts on electricity generation performance measures of efficiency and output. An increase in annual maximum temperature leads to more electricity consumption. One explanation is that an increasing average annual maximum temperature leads to a higher use of air conditioners and other cooling devices. On the contrary, for the supply side, results show that average annual maximum temperature is negatively impacting the electricity generation and led to more heat input (HI) available in fossil fuels to be used. This is so-called derating power generation due to climate change, where the generating unit consumes more fuel to produce the same amount of electricity. Due to this derating, the efficiency or performance of a generating unit is said to be reduced or degraded.

SUR regression estimates show that average maximum ambient temperature has a statistically significant coefficient in each of the three models with a positive impact on per capita electricity consumption and negative impacts on both the generated amount of electricity and efficiency of electricity generation from fossil fuel power plants. These impacts lead to increasing the consumption of fossil fuels to generate the same amount of electricity as if no increase in the temperature occurred.

Regression coefficients from SUR models and their impacts on the dependent variables are shown in Table 3.6. For the first two models, consumption and generation, where the dependent variables (Y) are in the logarithm format, following Wooldridge (2016), these coefficients are interpreted as the percentage change on the dependent variables ($\%\Delta\boldsymbol{Y}$) resulted from the regression coefficient (β) and elasticities ($\boldsymbol{\varepsilon}$) are calculated based on the following:

When the dependent variable is in the logarithm format, and the independent variable (X) is in the level format, the percentage change on the dependent variable is:

$$\%\Delta Y = 100 \times (\beta)\ \Delta X$$

and when both the dependent and independent variables are in the logarithm format, the percentage change on the dependent variable becomes:

$$\%\Delta Y = \beta\ \%\Delta X$$

With respect to the elasticity which represents the percentage change on the dependent variable divided by the percentage change on the independent ($\varepsilon = \frac{\%\Delta Y}{\%\Delta X}$), we calculated the elasticities for two different types of models. When both the dependent and independent variables are in the logarithm format, the elasticity is equal to the coefficient estimate ($\boldsymbol{\varepsilon} = \beta$), and when the dependent variable is in the logarithm format, and the independent variable is in the level format, the elasticity is equal to the result of multiplying the coefficient estimate by the independent variable mean ($\boldsymbol{\varepsilon} = \beta \times \bar{X}$).

Table 3.6. SUR Estimates and percentage change in the three dependent variables

	Ln(TCpc)		Ln(TG)		Eff	
Variable	**Coefficient**	**% Change in Y**	**Coefficient**	**% Change in Y**	**Coefficient**	**% Change in Y**
Tmax	0.0051658	**0.517**	-0.0394493	**-3.945**	-0.6111424	**-0.611**
CDD	0.0000932	**0.009**	-0.0003613	**-0.036**	-0.0040358	**-0.004**
HDD	0.0000292	**0.003**	-0.000387	**-0.039**	-0.004879	**-0.005**
LowGHGpc	0.0135731	**1.357**	0.047234	**4.723**		
Ln(GDP)	0.1093212	**0.109**				
EP	-0.0712632	**-7.126**				
FP			-0.101998	**-10.200**		
HI			0.001183	**0.118**	-0.0008514	**-0.001**

Results from the SUR models reveal that a rise in ambient temperatures will positively impact electricity consumption within states. From the electricity demand model, when holding all other factors constant, a 1-degree Fahrenheit increase in Tmax (about 1.6% change in Tmax) within a state results in a 0.52% increase in the per capita electricity consumption. Thus, a rise in the averaged maximum ambient temperature has a positive impact on the per capita electricity consumption due to increased electricity consumption, mainly for cooling purposes.

Cooling and heating degree days (CDD and HDD) have the same direction of impact as averaged maximum temperature such that increasing CDD or HDD by one hundred degree-day (°DF) (about 10% and 2% change in CDD and HDD, respectively) results in 1% and 0.3% in electricity consumption, respectively. These results show that CDD have a stronger impact on electricity use when ambient temperature rises. One explanation that that electricity is generally the only option for cooling (Eskeland and Mideksa, 2010). Apparently, in the hot weather, consumers need for air conditioning seems to depend solely on electricity, while consumers can use other alternatives such as oil and natural gas for heating (Mirasgedis et al., 2007).

Per capita GDP and electricity prices coefficients show that increasing per capita GDP by 1% ($517 on the average) increases the per capita electricity consumption by 0.11%, while increasing electricity prices by one cent per kWh (about 10% change in electricity retail price) will result in a -7.12% change. Results show that the elasticity of per capita GDP for per capita electricity consumption in the U.S. (0.11) which show electricity to be less income elastic than has been traditionally found, reflecting in part the period studied. The income elasticity from this study is lower than estimates of 0.23 found in Branch (1993) and very close to 0.14 found in Houthakker (1980). The results for elasticity of electricity prices in the U.S. (- 0.78) reveals that demand for electricity is less responsive to its price change. This result is also very close to what both Alberini et al. (2011) and Burke and Abayasekara (2018) found -0.81 and -1.0 respectively.

For the electricity generation model, results show that the rise in the ambient temperature will negatively impact electricity generation capacity within states. When holding all other factors constant, a 1-degree Fahrenheit (°F) increase in Tmax (about 1.6% change in Tmax) within a state results in a -3.95% change in electricity generation. Thus, a rise in averaged maximum ambient temperature has a negative impact on the net electricity generation capacity. This result seems to be consistent with previous research focused on climate change impact on the electricity supply side. Van Vliet et al. (2012) investigated the impact of climate change on thermoelectric power production in Europe and the U.S. Their findings suggest that a summer average decrease in capacity of power plants of 4.4% –16% in the U.S.

Cooling and heating degree days (CDD and HDD) coefficients have the same sign as coefficients for the averaged maximum temperature variable. Thus, increasing CDD or HDD by one Fahrenheit degree-day (°DF) results in decreases the net electricity generation by 0.036% and 0.039%, respectively. The fact that both CDD and HDD variables both have the same impact is not contradictory. Knowing that the standard reference temperature condition for all gas turbines is inlet air temperature should be 15°C (59°F), and by looking to how HDD is calculated in equation (3.9), then HDD is counted, for example, for days with maximum temperatures between 60°F (16°C) and 70°F (21°C), both above the standard reference temperature for gas turbines of 59°F, and minimum temperatures between 30°F (-1°C) and 40°F (4°C) so that the HDD on those days count 20°DF and 10°DF, respectively. These results for CDD and HDD show that both having the same impact stems from differences in standard temperatures (59°F versus 65°F) between gas turbines and human comfort.

The weighted average fossil fuels price coefficient show that a one U.S. dollar increase per MMBtu (about 30% change) will result in a -10.20% change in the net electricity generation. From this result, fossil fuels price (weighted average) elasticity of supply was calculated to be about - 0.37. Thus, the electricity supply curve is inferred to be inelastic relative to changes in fuel prices. Estimates for fossil fuels weighted average price consistently agree with law of demand. The rise in price resulted in a decrease in quantity. Fuel costs make up approximately half of the total costs of electricity generation at fossil fuels power plants (Steenhof and Fulton, 2007). This seems to be reflected by the high impact of increasing fossil fuels weighted average price by one U.S. dollar per MMBtu on electricity supply reduction by 10.2%. The heat input also has statistically significant coefficient such that increasing the consumption of fossil fuels by 10 trillion Btu (about 2% change) will result in 1.2% change in the net electricity generation. The relationship between inputs of energy (fossil fuel input) to the output (generated electricity) is not a one-to-one relationship, losses exist when energy is converted. There are some factors those have an impact such as the efficiency of the used technology (turbines or generating units), the type of burned fossil fuel (natural gas, petroleum, coal), and also the quality (energy content) of each fuel which may differ based on the fuel source.

The results from the Eff model provide empirical evidence that climate change will negatively impact the efficiency of electric generation within states. When holding all other factors constant, a 1 degree Fahrenheit (°F) increase in Tmax (about 1.6% change in Tmax) within a state results a degradation of 0.61% in power plant efficiency. Thus, a rise in averaged maximum ambient temperature has a negative impact on the efficiency of electric generation and its performance. Cooling and heating degree days (CDD and HDD) have the same direction of impact as averaged maximum temperature such that increasing CDD or HDD by one hundred units (°DF) resulting in a decrease of 0.4% and 0.5% in the efficiency, respectively.

Values and signs for all independent variables are reasonably stable across the two estimation techniques (Pooled OLS and SUR). Based on the data for the period 1990 to 2019, the average MWh use per capita in the U.S. is 12.95 MWh. For a unit increase in CDD (one-degree Fahrenheit, one day), electricity demand changes by 0.12 MWh per year per capita, and for a unit increase in HDD, the demand increases by 0.04 MWh per year per capita. In the context of energy use, 0.12 MWh amounts to the yearly energy used by 15-watt lamp for 24 hours.

Using Excel, projections of linear trend are made for electricity consumption in TWh, electricity generation in TWh, and the averaged maximum temperature in °F until the year 2050. All three variables were aggregated at the U.S. national level. Values from these projections are shown in Table 3.7. Using the forecasting linear trend from Excel, the 2050 values for electricity consumption, electricity generation, and averaged maximum, temperature are found to be

5168.85, 5524.65, and 65.38 respectively. These values show percentage changes from 2019 to 2050 of 37%, 34%, and 3% respectively.

Table 3.7. Variables Linear Projection Results

	2019	2015	2019 - 2050	Percentage Change (%)
Tmax (F)	63.37	65.38	2.11	3.34%
TC (TWh)	3,784.85	5,168.85	1384.00	36.57%
TG (TWh)	4,111.86	5,524.65	1412.79	34.36%

If climate change as reflected by averaged maximum temperature, continues to increase in the future, reaching 65.38 °F (an increase of 2.11 °F higher than the 2019 value) in 2050, the impacts on electricity demand and supply will be enhanced. Without climate policy intervention, an increase of 2.11 °F by the year 2050 will lead to an increase in the annual total electricity consumption in the U.S. by 53 TWh and a reduction of 460 TWh from the U.S. annual net electricity generation. These results are showing that the electricity sector in the U.S. is vulnerable to climate change impacts. Values from this projection are very close to Steinberg et al. (2020) projections of temperature and electricity generation in the U.S. in 2050 (1–2 °C (1.8 – 3.8 °F) and 5000 TWh)).

3.6 Conclusions and Policy Implications

In this study, the impacts of climate change on the U.S. electricity consumption, production, and efficiency are examined using annual state-level data for 48 states over 30 years (1990 – 2019). The results of this study show that an increase in averaged maximum ambient air temperatures increases electricity consumption and decreases generation efficiency. From these findings, the electric sector in the U.S. is vulnerable to climate change, such that the rise in the ambient temperature will result in an increase in the electricity demand and decreases supply and efficiency of power plants.

On the demand side, the per capita electricity consumption at the state level is responsive to the climate change, such that when averaged maximum ambient temperature increases by 1 °F (0.56 °C), per capita electricity consumption increases by a 0.52%. The most powerful impact on the per capita electricity consumption was found to be from electricity retail prices such that a one cent increase per kWh will result in a decrease of 7.1% in the per capita electricity consumption. Elasticity for per capita GDP of per capita electricity consumption (0.11) shows that it has less impact on consumption than electricity prices and climate conditions. CDD and HDD capture the number of days on which the average temperature is below or above the thresholds (65 °F) of cold and heat, and by how many degrees the temperature has deviated from the thresholds. Regression estimate for the CDD is much larger than that of HDD, showing the stronger impact of weather in electricity demand when ambient temperature rises. This result reflects the dominance of electricity as a main source for cooling purposes.

On the supply side, power generation from fossil fired power plants is negatively impacted by changes in either ambient temperature or weighted average fossil fuels price. These results show that as ambient temperatures increase in the future with climate change power generation capacities will decrease.

With respect to the impact of climate change on efficiency, findings from this study are consistent with previous research findings. The efficiency of fossil fired plants has been shown to decrease with increasing ambient temperature due to increased fuel consumption (Petrakopoulou et al., 2020). This research showed that fossil fired power plants efficiency declines upon increases in ambient temperatures. Thus, the power generation system, while producing less electricity using the same amount of fossil fuels due to the negative impacts of ambient temperature increases, will be faced with the need to produce more electricity due to consumption changes with climate change.

Findings of this study have important policy implications related to increases in maximum temperatures having negative impacts on both electricity generation and efficiency of fossil fired power plants, while increasing electricity consumption. This is important since future temperature increases will lead to increased electricity demand which will also be accompanied by decreased ability to supply electricity, leading to possible electricity shortages. Taking into consideration the variation between states' energy mix, state and federal governments need mitigation plans for climate change impacts and to meet the future challenges in the electricity sector. These plans might include restricting and limiting the continuity of fossil fired power plants expansion (Fofrich et al., 2020), especially for states those still relying on fossil fuels to generate electricity. One example of these restrictions is to allow only for repairs and corrections in the existing fossil fired power plants, but not to allow for future expansions or new projects.

New electricity generation projects need to rely only on low GHG energy sources which reduce CO_2 emissions and help mitigating the negative impacts of climate change. Adopting this perspective in future plans will duplicate the environmental effect as they it will help reducing GHG emissions resulting from the new low GHG energy sources and also from the retirement or decreasing the generation from fossil fired power plants. In addition, policymakers might need to revise the renewable portfolio standards (RPS) in order to allow for the soonest switching from fossils to renewables in each state (Fischlein and Smith, 2013).

Although this study has examined the impact of climate change on electricity demand, supply, and efficiency at the state level in the U.S., some limitations still exist. For example, the annual averaged data on the maximum temperature were collected on a daily basis and averaged annually which may not fully reflect the impact of seasonal fluctuations of the climate on the electricity sector. In addition, there is unavailability of data at lower frequency such as hourly, daily, or monthly for the majority of the control variables. Therefore, future research might need to collect more detailed data, hourly, daily, or monthly to address these limitations.

3.7 References

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CHAPTER 4

Essay 3: Examining the Existence of the Environmental Kuznets Curve After Accounting for Low-GHG Energy Use in the Power Sector

4.1 Introduction

Air quality and environmental deterioration are concerns around the world due to the severe impacts of air pollution on human's quality of life (IPCC, 2021). These concerns have motivated economists and researchers to study the reasons behind this deterioration and to address its consequences. Environmental deterioration has been linked to the early stages of economic development (Dinda, 2004). For example, relationships have been established between economic growth, energy consumption and carbon dioxide (CO_2) emissions (Saboori and Sulaiman, 2013). In general, air pollution increases rapidly due to the use and growing demand for natural resources (Dasgupta et al., 2002). A primary motivation for natural resource extraction is to produce energy which is one of the main contributors to air pollution (Perera, 2018). Compared to 1990, the global total energy consumption in 2019 increased by approximately 60%, resulting in an increase in the global CO_2 emissions (considered as the main contributor to greenhouse gas (GHG) emissions) by about 63% (Erdogan et al., 2020).

The link between energy consumption and increased CO_2 emissions is considered a vital area of concern for governments, policy makers, and environmental scientists and scholars (Khan et al., 2019; Wang et al., 2018). CO_2 concentrations in the atmosphere are dramatically rising faster than ever in recorded history, which is expected to have severe impacts on the environment and humans (Peter, 2018). CO_2 is the most important GHG that is generated as a result of human activities in various sectors of the economy. GHG emissions contribute to increases in global temperatures and the resulting climate change (Matthews et al., 2018).

Primary sources of increased GHG concentrations in the atmosphere are from GHG emissions caused by human activity as a by-product of burning fossil fuels in transportation, energy, industry, agriculture sectors and other activities associated with fossil fuels combustion.

These GHG emissions include: 1) CO_2 from fossil fuel combustion, 2) Methane (CH_4) from landfills, coal mines, agriculture, and oil and natural gas operations, 3) Nitrous oxide (N_2O) from using nitrogen fertilizers and agricultural soils along with certain industrial and waste management processes plus burning fossil fuels, and 4) fluorinated gases such as Hydrofluorocarbons (HFCs), Perfluorocarbons (PFCs), Sulfur hexafluoride (SF6), Nitrogen trifluoride (NF3) (EPA, 2020). In the U.S., CO_2 emissions were responsible for about 80 percent of all U.S. GHG emissions in 2019 generated from human activities (EPA, 2020).

In the same context of linking human activities (mainly of energy production and consumption) and GHG emissions, population and economic growth were linked together and received the attention of economists since they are associated with climate change and environmental damages (Acheampong et al., 2019; Peterson, 2017). Increasing population within an area due to the process of population migration from rural to urban areas often means increased urbanization[32], which in turn causes changes such as conversion of forest and cropland for housing, increased transportation needs, and other commercial purposes (Lind and Espegren 2017; Alig et al. 2004).

Urbanization is also seen as a major factor of air pollution, especially in the early stages of economic development (Ouyang et al., 2019). Aslan et al. (2021) have investigated the relationship between urbanization and air pollution in Turkey and found that urbanization has a positive and statistically significant impact on CO_2 emissions, such that when urbanization increases by 1%, CO_2 emissions increase by 0.02%. As urbanization increases, energy consumption within urbanizing areas also increases (Wang et al., 2019). Several studies have

[32] Urbanization refers to the concentration of human populations into discrete areas. Urban refers to areas with population density ≥ 1,000 people per square mile, plus surrounding areas with population density ≥ 500 people per square mile (U.S. Census Bureau, for 2000 Census).

derived relationships between urbanization and CO_2 emissions in different regions. Al-Mulali et al. (2015) found that urbanization has a positive effect on the CO_2 emissions in Europe. Ali et al. (2019) found that urbanization in Pakistan enhancing CO_2 emissions both in the long run and short run. Shahbaz et al. (2014) found that urbanization had a positive impact on CO_2 emissions in the United Arab Emirates (UAE). Urban areas were responsible for about 75% of CO_2 emissions from global final energy use (UN-HABITAT, 2020). The U.S. is one of the countries that had experienced a rapid increase in urbanization through the 19th century (starting from the year1810). By 1900, 40 percent of the people were living in urban areas, reaching to about 80% by 2000 and about 83% by 2020 (CENSUS, 2021; World Bank, 2021).

Since the late 1970's, the relationship between economic growth and the environment is one of the most controversial topics in economic literature (Tjoek and Wu, 2018). This link has been explained in a theory that includes both environmental deterioration and improvement associated with increasing per capita income levels. An early 1990's hypothesis called the environmental Kuznets curve (EKC)[33] postulates that at a certain point in economic growth, environmental degradation starts to decrease. This EKC hypothesis defined the relationship between level of economic activity and the environmental degradation in an inverted U-shaped relation. In the early stages of development, environmental degradation increases, reaches a maximum point, and then decreases with higher levels of income (Dinda, 2004). The early stages of development are characterized with high priority to increase production, and people are more interested in goods, jobs, and income than clean environment (Dasgupta et al., 2002). Pollution became a by-product for those stages due to the extraction and use of natural resources- mainly fossil fuels- which in turn generate pollutants to the atmosphere resulting in an environmental

[33] https://www.nobelprize.org/prizes/economic-sciences/1971/kuznets/facts/

degradation. As income rises and people have a certain level of goods, they start seeking methods to reduce air pollution in order to improve the quality of the environment (Özokcu and Özdemir, 2017; Panayotou, 1993).

The main objective of this study is to examine the existence of the EKC hypothesis in the U.S. while incorporating the low GHG energy in the econometric model using an extended EKC regression model that including low GHG energy consumption as a new explanatory variable. Therefore, this study contributes to the literature by implementing a panel data, empirical study focusing on the state-level data for the sake of expanding and enriching the existing literature on EKC hypothesis analysis within the U.S. This research involves empirically testing the existence of the EKC within U.S. states while simultaneously examining the effect of low GHG energy consumption on the total CO_2 emissions within the same model by incorporating an explanatory variable associated with environmental and energy policies, highlighting the positive impact of low GHG energy consumption on improving the environmental quality at the state-level. To achieve this objective, we apply the ARDL approach, using the PMG model (PMG-ARDL).

The rest of the paper is organized as section 2 discusses the background of this study. Section 3 discusses the previous literature on the EKC hypothesis and validating it in the U.S. and highlighting the impact of low GHG energy consumption on the environmental quality. In sections 4 and 5, we present the methodology, empirical strategy, and data used in the analysis. In section 5, we present and discuss our empirical results, and finally, section 6 provides conclusions and policy implications.

4.2 Background

To obtain sustainable development, it is important that cleaner and green electricity sources be introduced into electricity systems in order to reduce the effects of climate change

(Marques et al., 2018). Yildirim et al. (2012) have studied this issue in the U.S. and found that renewable energy consumption contributes to economic growth. In 2019, U.S. annual renewable energy consumption was 11.5 QUADs (3,370.33 TWh)[34], recording the first time in over 130 years that renewable energy consumption surpassed coal consumption of 11.3 QUADs (EIA, 2021). The low GHG energy[35] has been targeted as a key area of study that has environmental benefits as they contribute to reducing CO_2 emissions from the atmosphere (Wei et al., 2010). U.S. data sources show that the increase in low GHG energy is accompanied with variations in the level of CO_2 emissions in the last period. From 1990 to 2018, GHG emissions had experienced ups and downs, for example, between 1990 and 2007, CO_2 emissions from energy related activities in the U.S. grew by 1% annually. On the other hand, after 2007 emissions start to decline with an annual average of 1.2%; though, 2018 emissions are 4.8% greater than in 1990 but 12% lower than in 2007 (EIA, 2020). One explanation of this reduction after 2007 is that the 2008 economic recession has reduced the CO_2 emissions since that period was characterized with less energy demand, less industrial and economic activity, and less vehicle miles travelled (Goodman and Mance, 2011; Vrekoussis et al., 2013).

In the U.S., several plans targeting energy production and improving the environment were set by the Environmental Protection Agency (EPA), such as the Clean Power Plan (Ross and Murray, 2016; NRDC, 2017). Recently, the Biden administration announced the climate plan -Biden Plan[36]- that will be put in place to allow the U.S. to meet its Paris Agreement commitments of GHG reductions. Biden plan had set a target to reduce the GHG emissions until

[34] QUAD is a unit of energy. 1 QUAD = 293,072,222,376.4 kWh = 293,072,222.3 MWh = 293,072.2 GWh
[35] Low GHG energy sources include renewable and nuclear energy sources. Renewable energy sources include solar, wind, hydropower, geothermal, and biomass (EIA, 2019).

[36] https://joebiden.com/climate-plan/

reaching a 100% carbon-free power sector by 2035 (Aiken, 2021; Boyle et al., 2021). Examples of ways to achieve this goal and reduce electricity emissions to net zero by 2035 is the use of more efficient appliances and more renewable sources of energy. His plan is not directed to the energy sector only, but also to the Housing and Urban Development Department. The latter is asked to make housing in low-income communities more energy efficient. While the Department of Energy is asked to redouble the efforts to accelerate efficiency standards for household appliances and equipment.

In addition to including renewable and nuclear energy consumption into the empirical analysis, the previous research examined the existence of EKC hypothesis assuming that both declines and improvements in environmental quality are attributed to income and the associated demand for products and energy. While the relationship between income and the quality of the environment depends on the technology used in the industry, states with similar economic growth might have different quality of environment based on the technology been adopted in their development stage. Energy sources and their importance to economic activities are also different between states. This can result in variation in the levels of energy production and consumption.

Previous research shows that there are differences in economic and socioeconomic characteristics such as income, trade, industry and types of goods and services being produced (Stern, 1998). These differences reflect variations between states in the level of pollution and GHG emissions such that poorest states incubate industries that are generating more pollution than other states, and high-income states are with industries adopting low GHG emitting technologies (Kaika and Zervas, 2013). Moreover, the level of GHG varies between states due to differences energy consumption, production, and environmental regulations across states (Salari et al., 2021). EIA in its annual energy outlook 2022 reports that renewable energy is the fastest growing through 2050 among all other energy sources, this is mainly due to policies and regulations those incentivize switching towards clean energy sources and the fall in technology costs (EIA, 2022a). Renewable energies have important role to reduce global CO_2 emissions in the long run and are the main attention for policymakers and governments due to the dependency on fossil fuels in energy generation, depletion of exhaustible energy sources, and the environmental deterioration related to GHG emissions from fossil fuels use (Salari et al., 2021). With this perspective towards increasing the production of renewable energy in the long run, investigating the impact of renewable energy consumption on CO_2 emissions in the EKC context is important for researchers and policymakers.

Based on the role of renewable and nuclear energy in reducing CO_2 emissions, we expect estimates to confirm the importance and significance of low GHG energy in the short- and long run. Income is expected to have a negative impact on the quality of environment with the existence and improvement of the low GHG technologies in the energy sector. Supported by the previous literature on EKC hypothesis, income is expected to have an important role in determining the quality of the environment. In the short run, both income and population density are expected to increase the level of air pollution by increasing CO_2 emissions in the atmosphere, while it is expected to reduce them in the long run.

4.3 Literature Review

Many economic and environmental researchers studied the relationship between environmental degradation and economic growth in the EKC hypothesis context. Of those researchers who examined the existence of EKC hypothesis the empirical studies of Grossman and Krueger (1991) and Panayotou (1993). They find an inverted U-shaped relationship between per capita income and environmental degradation. For investigation the existence of EKC hypothesis, many studies have applied empirical methods to examine the validity of this hypothesis. For example, Panayotou (1993) showed that environmental degradation is inevitable for an economy in the development stage, and it occurs in the early stages of a country's development path. Arguing that with more economic development, per capita income increases and at a certain level the environmental degradation starts to decrease. This rise and fall in the environmental degradation forms, in relation with income, what is so-called the inverted U-shaped EKC (Akbostancı et al., 2009).

In the early stages of economic development, where society needs more goods to produce to meet basic needs, the economy is at the resource intensive stage that relies on fossil fuels and other natural resources as a requirement for production. Once per capita income increases beyond a turning point, people tend to improve the environmental quality by adopting new technologies that allow them to use resources more efficiently in production in order to help in reducing the amount of emitted pollutants to the environment (Dinda, 2004). In addition to this tendency, Panayotou (1993) and Dasgupta et al. (2001) argued that higher per capita income is highly correlated with environmental regulation adoption. Using annual data on renewable energy consumption and income for 18 emerging countries[37], Sadorsky (2009) showed that income increases in the long run, and per capita CO_2 emissions are main drivers towards the renewable energy use. For the U.S. context, Feng et al. (2015) analyzed the factors affecting U.S. emissions from 1997 to 2013., They find that economic growth was the main driver for rising emissions before 2007, while after 2007, they find two main factors for decreasing

[37] The 18 emerging countries in Sadorsky (2009) study were: Argentina, Brazil, Chile, China, Columbia, Czech Republic, Hungary, India, Indonesia, South Korea, Mexico, Peru, Philippines, Poland, Portugal, Russia, Thailand, and Turkey.

emissions, those were the economic recession with changes in fuel mix or the energy sector decarbonization. Decarbonization of the energy sector includes switching from fossil fuels toward renewables and other low GHG emissions technologies such as nuclear energy. In line with the previous studies, Haar and Theyel (2006) showed that the U.S. economic growth and environmental regulations, especially those promote the reduction of CO_2 emissions, are considered as main drivers of renewable energy adoption.

Energy consumption increases with economic growth, as an indicator for economic development, resulting in increasing CO_2 emissions (Ang, 2007). Rahman et al. (2020) examined the effects of electricity consumption and economic growth on the CO_2 emissions of top 10 electricity consuming countries[38] including the U.S. and found that electricity consumption has a strong positive impact on CO_2 emissions. The growing importance of sustainable development enriched the research on low GHG energy impacts, though researchers became interested more in the impacts of renewable and nuclear energy consumption on economic growth (Omri and Chaibi, 2014). Yoo and Jung (2005) examined the causality relationship between nuclear energy consumption and economic growth for Korea and find that beside the economic factors that contribute to the economic growth, increasing the nuclear energy consumption is also a driver for economic growth. Similar result was also found by Payne (2011) by examining the causal relationship between biomass energy consumption and real gross domestic product (GDP) in the U.S. for the period of 1949–2007.

The literature on the impact of low GHG energy consumption on the environmental quality is vast and it has been debated for decades. For instance, (Shafiei and Salim, 2014; Lu, 2017; Paramati et al., 2017) find that production and consumption of low GHG energy are

[38] China, United States, India, Japan, Germany, Canada, Brazil, South Korea, France and the United Kingdom.

contributing to the reduction of GHG emissions, and accordingly improve the quality of environment by lowering air pollution in the long run. On the other hand, based on the EKC hypothesis, Ben Jebli et al. (2015) investigated the relationship between renewable energy and CO_2 emissions for 24 Sub-Saharan countries. Those countries have high potential for the use of different sources of renewable energy sources and the growth of renewable energy was very strong where the total production of electricity from renewable sources has increased by 72% (45 to 78 Terawatt[39] per year) between the period 1998 to 2008. They found that renewable energy consumption has a positive impact on reducing CO_2 emissions and concluded that there was no evidence to support the existence of EKC for those countries.

Bento and Moutinho (2016) used the ARDL bounds testing method to examine the varying causal link between CO_2 emissions and electricity production in Italy from 1960 to 2011. They revealed that per capita renewable electricity production reduces CO_2 emissions per capita. In line with the previous study investigating the impact of log GHG energy consumption and the reduction of CO_2 emissions, Apergis and Payne (2012) used the Generalized Method of Moments (GMM) methodology to test the EKC hypothesis by examining the correlation between renewable energy and CO_2 emissions in 11 South American countries from 1980 to 2010. Their results show that renewable energy is significant in improving environmental quality by reducing CO_2 emissions. Sulaiman et al. (2013) used the ARDL to validate the EKC hypothesis and to analyze the impact of renewable energy on the environment in Malaysia for the period 1980-2009. Their results show that renewable energy reduce CO_2 emissions. Mehmood et al. (2022) investigated the impact of renewable energy on CO_2 emissions in the context of EKC hypothesis in Pakistan, India, Bangladesh, and Sri Lanka using data from 1990 to 2017. He was

[39] Terawatt (TW) = 1,000,000 Megawatt (1 million MW) = 1 trillion Watt

able to validate the existence of EKC and confirm the importance of renewable energy in mitigating CO_2 emissions. Finally, using similar methodology to the latter, Bölük and Mert (2014) studied the connection between renewable energy and EKC hypothesis in Turkey from 1961 to 2010. Their results revealed that renewable energies have a negative and substantial long-run influence on CO_2 emission.

Many studies have been carried out to examine relationships between CO_2 emissions and energy consumption (Dogan and Ozturk, 2017; Amri, 2017; Attiaoui et al., 2017; Bildirici, 2017; Ali et al., 2016; Dogan and Turkekul, 2016; Farhani and Ozturk, 2015; Akhmat et al., 2014; Rafindadi et al., 2014). A few of these studies have examined the existence of the EKC hypothesis (Apergis and Ozturk, 2015; Lean and Smyth, 2010; Apergis and Payne, 2009; Halicioglu, 2009; Soytas et al., 2007). The majority of these studies relied on national and cross-country panel data analysis.

For the U.S., only a few studies that empirically studied the EKC at the state-level. The first was (List and Gallet, 1999) who used a panel data set on state-level sulfur dioxide and nitrogen oxide emissions from 1929–1994 to examine the EKC hypothesis. Their results validated the existence of EKC hypothesis at the state level, where the per capita emissions and per capita income were found to be in an inverted U-shaped relationship. The EKC hypothesis was also validated at the state level by Aldy (2005), using data on CO_2 emissions, annual heating and cooling degree days for the period 1960 to 1999. He analyzed the EKC hypothesis but did not incorporate energy within the explanatory variables in the empirical analysis but found that hotter summer states have higher per capita CO_2 emissions. A third study by Atasoy (2017) examined the existence of EKC hypothesis for 50 states between 1960 and 2010 using three methods. He finds that regression results are very sensitive to the method. With the Augmented

Mean Group (AMG) method, the EKC hypothesis was strongly validated, and it holds in 30 out of the 50 states. The Common Correlated Effects Mean Group (CCEMG) method provided weak evidence on the EKC hypothesis existence as it holds only in 10 states. On the other hand, pooled mean group (PMG) method estimators validate the EKC hypothesis with highly significant coefficients. Finally, Tzeremes (2018) empirically examined the relationship between CO_2 emissions, energy consumption, and economic growth to investigate the existence of EKC hypothesis for the 50 U.S. states between 1960 and 2010 using a time-varying causality approach. Results from this study do not support the validity of the EKC.

While energy plays an essential role in economic development and environmental pollution. Energy consumption in economic activities increases CO_2 emissions (Pata, 2018). With respect to energy consumption in the EKC testing literature, very few studies have included renewable energy as an explanatory variable in examining the EKC. The reason may be the small share or renewable energy production from the U.S. total energy production. According to EIA (2022b), the renewable energy production share in 2021 was at 13%. Balsalobre-Lorente et al. (2018) investigate the existence of EKC in five European countries (Germany, France, Italy, Spain, and the United Kingdom) for the period between 1985 and 2016 using Panel Least Squares method by exploring the relationship between economic growth and CO_2 emissions and incorporating renewable electricity consumption variable into their model. Their results validate the existence of an N-shaped relationship between economic growth and CO_2 emissions and show that renewable electricity consumption improves environmental quality. Hussain and Rehman (2021) studied the effects of renewable energy consumption on CO_2 emissions in Pakistan using data from 1975 to 2019 by employing an autoregressive distributive lag (ARDL) bound approach and find that renewable energy consumption reduces CO_2 emissions in the short and long run. Their conclusion seems to contradict with a previous study of Apergis et al. (2010) who examine the relationship between CO_2 emissions and renewable energy consumption in 19 developed and developing countries (including Pakistan) for the period 1984–2007. They find an insignificant effect of renewable energy on CO_2 emissions in the short run. This result might be due to the lack of adequate storage technology to overcome intermittent supply problems as a result the producers of electricity have to rely on energy sources that produce emissions to meet peak load demand (Apergis et al., 2010). Baek (2016) studied the effects of renewable and nuclear energy consumption on CO_2 emissions in the U.S. for the period 1960 to 2010 by employing ARDL bound approach and he concluded that nuclear energy consumption reduces CO_2 emissions at the short and long run, while renewable energy consumption does only in the short run. The author was not able to provide a justification for this result, however, the estimated coefficient for the renewable energy consumption variable is positive but statistically insignificant. This conclusion also seems consistent with Hussain and Rehman (2021) findings but contradicts with Apergis et al. (2010). Another study of Dogan and Ozturk (2017) aims to explore the influence of renewable energy consumption on CO_2 emissions for the U.S. in the EKC model for the period 1980–2014 find that the long-run estimates from the ARDL model show that the increase in renewable energy consumption mitigate environmental degradation. Baek (2015) used a panel cointegration analysis to quantify the effects of nuclear energy on CO_2 emissions in 12 major nuclear generating countries[40]. While no evidence was found to support the EKC for CO_2 emissions, the results show that nuclear energy reduces CO_2 emissions.

Other studies, such as (Ben Jebli et al., 2015; Zhang et al., 2019; Tjoek and Wu, 2018; Sun et al., 2017; Pata, 2021) used per capita energy consumption from renewable sources as

[40] The twelve countries include the United States, France, Japan, South Korea, Canada, Germany, United Kingdom, Sweden, Spain, Belgium, Switzerland, and Finland

independent variable in their empirical analysis regression models. Danish et al. (2017) and Baek (2016) have included renewable energy and non-renewable energy consumption as independent variables to examine the relationship between renewable energy consumption, non-renewable energy consumption, economic growth and CO_2 emission.

We also followed the previous literature in using the population density variable as it was one of the variables that previous research mostly focused on especially when examining the EKC hypothesis (Park and Lee, 2011). A number of studies suggest that population density is a variable that can explain the geographic differences in GHG emissions (Jones and Kammen, 2014). This variable influences the quality of the environment through the increase in energy demand and the transportation sector expansion (Ozcan and Ulucak, 2021). More energy consumption, represented in this study by burning fossil fuels such as natural gas use for electricity generation, along with the expansion in transportation sector increases CO_2 emissions. Du et al. (2012); Iwata et al. (2010); and Farhani and Ozturk (2015) find that population density variable found to be impactful in the literature examined the EKC hypothesis. Moreover, the population density is considered a good proxy for urbanization, and it is used as an index to analyze the urbanization effects (Chen et al., 2020; Hantak et al., 2021).

With respect to the electricity imports variable, Sarkodie and Ozturk (2020) assumed that an energy imports variable is less important in explaining environmental pollution, despite that it was documented in previous literature. On the other hand, Singer et al. (2014) show that electricity imports greatly vary between states, and it is associated with per capita CO_2 emissions. Finally, we used energy losses variable in the empirical model in order to account for the CO_2 emissions associated with generation, transmission, and distribution losses from the electricity grid (Brander et al., 2011; Harmsen and Graus; 2013)

4.4 Methods and Models

The research objective is to examine the impact of low GHG energy consumption on CO_2 emissions in the U.S. with the estimation of an extended EKC for the fifty U.S. states based on a panel data set. An extended EKC refers to the inclusion of a low GHG energy consumption as a new explanatory variable in the regression model. This extension is important for this paper and for policymakers as the increase in low GHG energy consumption has the potential to reduce CO_2 emissions even in the presence of a per capita income variable within an EKC model. Inclusion of a low GHG energy variable adds more insights into policies that aim to reduce GHG emissions within states that implement policies to encourage low GHG energy production and consumption along with the income effect.

The panel structure utilized in this research has several advantages over the cross-sectional data set. One of the main advantages is that it can capture the time variation in addition to the cross-sectional variation (Baltagi, 2005). Furthermore, a panel structure examines unobserved heterogeneity by estimating both cross-sectional effects and time effects, and it allows to control for unobserved cross-sectional heterogeneity (Das, 2019).

In addition, previous EKC literature is followed when using a panel data structure. Multiple works have used panel data in their econometric technique while examining the EKC hypothesis. For example, Narayan and Narayan (2010) utilized panel data to validate the existence of EKC in the Middle Eastern and South Asian panels. Dinda and Coondoo (2006) also were able to validate the existence of EKC in 88 countries. Finally, Du et al. (2012) find an inverted U-shaped relationship between per capita CO_2 emissions and economic development level in China. From previous literature we conclude that the panel data structure is vastly utilized and appropriate for this type of study.

The empirical method is based on the PMG-ARDL method due to several advantages over other methods. For example, it involves a single equation set-up which produces unbiased and efficient estimates since it avoids problems such as endogeneity and serial correlation (Jalil and Ma, 2008), and it also allows for outlier's correction (Marques et al., 2018; Martınez-Zarzoso and Bengochea-Morancho, 2004). This PMG-ARDL method captures the dynamic effects of the lagged dependent and the lagged independent variables (Tenaw and Beyene, 2021). Another important advantage of this method is that it can address the problem of endogeneity by including the lagged values of the variables (Tenaw and Beyene, 2021). Moreover, in the PMG-ARDL approach, the residual correlation is eliminated and accordingly the endogeneity problem is mitigated (Ali et al., 2016; Andrei, 2021). This method is also used to generate both long-term and short-term estimates simultaneously, and it controls the long-term parameters to be constant across individual states whilst allowing the short-term estimates and the variance of the errors to vary (Mensah et al., 2019). This makes the ARDL approach robust and more useful than the conventional panel data models.

Pesaran et al. (1999) developed the PMG model, which is based on a cointegrated ARDL approach for a panel data set. According to Pesaran et al. (1999), the PMG estimator is dependable, robust, as well as durable to lag orders and outliers. PMG-ARDL is model that allows the short-term parameters to differ between groups while imposing equality of the long-term coefficients between groups (Bangake and Eggoh, 2012). By utilizing this method of examining both short and long run relationships, a PMG-ARDL model tends to be more efficient to capture the long run relationship irrespective of whether variables are stationary, non-stationary, or even mutually cointegrated (Atasoy, 2017; Pesaran et al., 2001). Based on the above information and the number of empirical studies on EKC that employed the PMG-ARDL approach, the PMG-ARDL approach seems to be the most appropriate for our study and it is more efficient in the sense that it was developed for considering valid long run restrictions.

The basic model in the literature for investigating the EKC hypothesis is shown equation (4.1).

$$\boldsymbol{Pollution} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 Income} + \boldsymbol{\beta_2 Income^2} + \boldsymbol{\beta_3 X} + \boldsymbol{u_{it}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{4.1})$$

where $\boldsymbol{Pollution}$ is a measure for environmental degradation measured by the annual per capita CO_2 emission inventories from fossil fuel combustion in metric tons. CO_2 emissions serves as the dependent variable since it is the most widely used indicator of environmental degradation in the energy and environmental economics literature (Sinha et al., 2019). $\boldsymbol{Income}$ measures the income in thousand U.S. dollars per capita. The square of $\boldsymbol{Income}$ ($\boldsymbol{Income^2}$) is added to the model to test the non-linearity in the relationship between economic growth and CO_2 emissions. $\boldsymbol{X}$ is a matrix of control variables which affect CO_2 emission inventories, such as energy consumption and population density.

The EKC hypothesis holds if the coefficient of the income per capita ($\boldsymbol{\beta_1}$) is positive and the coefficient of the income per capita squared ($\boldsymbol{\beta_2}$) is negative, forming what is so-called the inverted U-shaped relationship. It shows that income has a positive impact on pollution in the short run, while it has a negative impact in the long run. At first, $\boldsymbol{Pollution}$ increases with $\boldsymbol{Income}$ at a decreasing rate until reaching a maximum point, after this point, $\boldsymbol{Pollution}$ decreases at an increasing rate. The point at which the curve attains its maximum is called the turning point, which is the point on the curve where CO_2 emissions are at a maximum. The EKC model implies that after the turning point is reached, economic growth can improve both living standards and environmental quality (Richmond and Kaufmann, 2006). This turning point is calculated by setting the first derivation of equation (4.1) equal to zero and solved for $\boldsymbol{Income}$.

$$\boldsymbol{\beta_1 + 2\beta_2 Income = 0} \quad \ldots\ldots \quad \mathbf{(4.2)}$$

$$\boldsymbol{Income^* = \frac{-\beta_1}{2\beta_2}} \quad \ldots\ldots \quad \mathbf{(4.3)}$$

$\boldsymbol{Income^*}$ denotes the turning point of $\boldsymbol{Income}$.

The proposed model in this research is specified to investigate the EKC relationship given with the presence of a low GHG energy variable. The basic model of EKC hypothesis in this study will be:

$$\boldsymbol{Pollution = \beta_0 + \beta_1 Income + \beta_2 Income^2 + \beta_3 LowGHG_{it} + \beta_4 X + u_{it}} \quad \ldots\ldots \quad \mathbf{(4.4)}$$

where $\boldsymbol{Pollution}$ is the dependent variable that will be $\boldsymbol{CO2_{it}}$ and it is measured by the by the annual per capita CO_2 emission in metric tons, and $\boldsymbol{LowGHG}$ is the per capita consumed energy[41] from a low GHG emitting source in a state. The set of variables ($\boldsymbol{X}$) will be control variables including population density, electricity imports, electricity losses, and natural gas consumed for electricity generation. Following previous studies cited in the literature review, especially those examined the EKC hypothesis, annual data is used for all the variables in the empirical analysis. In addition, results from previous studies focused on the relationship between environmental degradation and income and other economic activities related to energy production and consumption were used to guide explanatory variables selection. So, the basic model for estimation will be:

$$\begin{aligned}\boldsymbol{CO2_{it}} &= \boldsymbol{\beta_0 + \beta_1 Income + \beta_2 Income^2 + \beta_3 LowGHG_{it} + \beta_4 PopDen_{it} + \beta_5 Imports_{it}} \\ &\quad \boldsymbol{+ \beta_6 Losses_{it} + \beta_7 NG_{it} + u_{it}} \quad \ldots\ldots \quad \mathbf{(4.5)}\end{aligned}$$

[41] Total energy consumption by state is the consumption of primary energy from renewable sources such as solar, wind, geothermal, hydropower, biomass, and nuclear. More details in the link: https://www.eia.gov/tools/glossary/index.php?id=Primary%20energy%20consumption#:~:text=Primary%20energy%20consumption%20expenditures%3A%20Expenditures,energy%20used%20to%20generate%20electricity.

where $CO2_{it}$ is the per capita total CO_2 emissions from fossil fuels burned for electricity generation in metric tons in a state i and year t, $Income_{it}$ and $Income_{it}{}^2$ are the per capita income in thousand U.S. dollars and its squared value, $LowGHG_{it}$ is the per capita consumed energy from a low GHG emitting source in a state in MMBtu, $PopDen_{it}$ is the population density (average population per square mile), $Imports_{it}$ is the per capita imported electricity into a state in MMBtu[42], $Losses_{it}$ is the per capita total losses[43] in the electric energy in MMBtu, NG_{it} is the amount of natural gas used for electricity generation in MMBtu, and u_{it} is the error term which includes all other factors affecting CO_2 emissions.

In order to improve the fit of the regression model in equation (4.3), we applied the natural logarithm to the dependent variable CO_2. Generally, the transformation of data with natural logarithms improves the fit of a regression model and reduces error. Literature such as Solarin and Lean (2016); Sarkodie and Ozturk (2020); Bilgili et al. (2016); and Minlah and Zhang (2021) used the natural logarithm of per capita CO_2 as a dependent variable for their empirical analysis models. So, the regression model that will be estimated in this analysis will be in the following form:

$$\boldsymbol{ln(CO2_{it}) = \beta_0 + \beta_1 Income + \beta_2 Income^2 + \beta_3 LowGHG_{it} + \beta_4 PopDen_{it} + \beta_5 Imports_{it}}$$
$$\boldsymbol{+ \beta_6 Losses_{it} + \beta_7 NG_{it} + u_{it}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \boldsymbol{(4.6)}$$

where $lnCO2_{it}$ is the natural logarithm of per capita total CO_2 emissions from fossil fuels burned for electricity generation in metric tons in a state i and year t.

[42] A British thermal unit (Btu) is a measure of the heat content of fuels or energy sources. It is the quantity of heat required to raise the temperature of one pound of liquid water by 1 degree Fahrenheit at the temperature that water has its greatest density (approximately 39 degrees Fahrenheit). (Source: https://www.eia.gov/energyexplained/units-and-calculators/british-thermal-units.php)

[43] Losses represents the electrical system energy losses (energy conversion and other losses associated with the generation, transmission, and distribution of purchased electricity) (https://www.eia.gov/energyexplained/use-of-energy/).

To check the presence of EKC and cointegration among the introduced variables in equation (4.4), the PMG-ARDL approach is used to analyze the variables of interest and assess together the short and long run approximations (Pesaran et al., 1999). The general form of an autoregressive distributed lag structure that integrates lags of CO_2 and other control variables is shown by:

$$\boldsymbol{ln(CO2_{it}) = \beta_i + \sum_{j=1}^{p} \delta_{ij} LlnCO2_{i,t-j} + \sum_{j=0}^{q} \emptyset_{ij}(Income_{i,t-j} + Income^2{}_{i,t-j} + LowGHG_{i,t-j} + X_{i,t-j}) + u_{it}} \quad \ldots\ldots (\mathbf{4.7})$$

where $X_{it} = (PopDen_{it},\ Imports_{it}, Losses_{it},\ NG_{it})$ which is a vector of descriptive variables utilized in this analysis. i represents the number of states (1, 2, 3...,50), t is the number of years (1990-2018), β_i symbolizes the state-level fixed effects, δ_{ij} symbolizes slope of the lagged dependent variable ($LlnCO2_{it}$), p and q are the lag of dependent and independent variables, respectively , and $\emptyset_{i,j}$ symbolizes the slope of lagged control variables.

To validate the PMG-ARDL model results, a robustness check is performed by applying the dynamic panel-data estimation (DPE) by means of Generalized Method of Moments (GMM) approach. DPE approach is a suitable statistical method for robustness as it is used to investigate the dynamic relation between energy consumption and economic growth in the economic literature (Huang et al., 2008). The model in equation (4.4) was estimated in this robustness check.

4.5 Data

Annual data from 1990 to 2018 for the fifty U.S. states come from sources of the U.S. Energy Information Administration (EIA), U.S. Environmental Protection Agency (EPA), and

U.S. Bureau of Economic Analysis (BEA). Data include per capita total CO_2[44] emissions from burning fossil fuels (CO_2), per capita personal income (Income), population density expressed in persons per square mile (PopDen), the per capita low GHG energy consumption (LowGHG) as the amount of energy consumed from renewable and nuclear energy sources, (Imports) as the electricity imported into a state in MMBtu, (Losses) as the total electric system energy losses in MMBtu, and (NG) as the amount of natural gas consumed for electricity generation in a state measured in Quads[45]. Variables used in this study are described along with the source in Table 4.1. All these variables are measured at the state on an annual basis.

CO_2 emissions and personal income within a state are turned into per capita variables (CO_2 and Income) by dividing the total CO_2 emissions from burning fossil fuels and personal income in a state and a year by state population. In addition, state population is turned into a population density (PopDen) with the calculation: annual state population divided by land area in square miles for each state. Low GHG energy generated per state is turned into a per capita basis by dividing the consumed energy in a state and a year by state population. Imports were turned into a per capita basis by dividing the total electricity imported into a state and a year by state population. Losses were also turned into a per capita basis by dividing the total electric system energy loss in a given state by state population.

[44] Our analysis focuses on CO_2 emissions produced from burning fossil fuels in the U.S. states; emissions embodied in imports are not included.
[45] Quadrillion (Quad) = 10^{15} Btu = 1000,000,000 MMBtu

Table 4.1. Variables, Data Description, and Sources

Variable	Description	Source
CO2	Carbon dioxide (CO2) emission inventories from fossil fuel combustion, from commercial, industrial, residential, transportation, and electric power sectors, in metric tons of carbon dioxide (CO2) in a given state on a per capita basis annually.	U.S. Environmental Protection Agency (EPA)
Income	Represents the income people living in each state get from wages, dividends, interest, rents, and government benefits in 1000 of U.S. dollars per capita.	U.S. Bureau of Economic Analysis (BEA)
LowGHG	Represents the primary energy consumption from renewable and nuclear energy sources in a given state on a per capita basis annually.	U.S. Energy Information Administration (EIA)
PopDen	Represents the density of population living per square mile, calculated by dividing annual state population by the total land area of the state in square miles.	U.S. Bureau of Economic Analysis (BEA)
Imports	Represents the amount of electricity imported into a given state on a per capita basis annually.	U.S. Energy Information Administration (EIA)
Losses	Represents the total electric system energy loss in a given state on a per capita basis annually.	U.S. Energy Information Administration (EIA)
NG	Natural gas consumed by the electric power sector in a given state annually.	U.S. Energy Information Administration (EIA)

In order to accurately compare the Income variable over time, income data are adjusted for inflation to 2018 dollars over the time period of the study (1990 – 2018) using consumer price index for all urban consumers in the U.S. city average (CPI) retrieved from the Federal Reserve Economic Data (FRED)[46]. For example, to adjust income estimates for inflation 1990 dollars to 2018 dollars, the following formula was used:

$$\boldsymbol{Inflation - Adjusted\ Income = 1990\ Income \times \frac{2018\ CPI}{1990\ CPI}} \ldots\ldots\ldots\ldots\ldots\ldots \mathbf{(4.8)}$$

Table 4.2 provides summary statistics for all variables used for the empirical analysis. Per capita CO_2 emissions (CO_2) reflects the per capita CO_2 emissions from burning fossil fuels in

[46] CPI data available at FRED: https://fred.stlouisfed.org/series/CPIAUCSL

metric tons has an average of 24.98. Wyoming in 1992 has the highest value at 133.81 with New York having the lowest value of 8.31 in 2017. Per capita personal income is total personal income divided by total population (Income) has an average of $43,610. Connecticut in 2018 had the highest value at $73,929 with Mississippi having the lowest in 1990 at $25,666. Low GHG energy consumption (LowGHG) which represents the amount energy consumed from renewable and nuclear energy sources in per capita basis in a state has the average of 60.58 MMBtu. North Dakota in 2017 had the highest level of 218.27 MMBtu per capita while Delaware in 2002 had the lowest at 1.63 MMBtu per capita. Population density (PopDen) reflects the number of people per square mile of a state land area has an average of 186.98. New Jersey has the highest density at 1209.10 in 2018 while Alaska has the lowest density in 1990 at 0.97. The electricity imported into a state has an average of 1.24 MMBtu per capita. Vermont in 2013 had the highest per capita amount of imported electricity at 63.94 MMBtu. The electric system energy losses have the average of 93.44 MMBtu per capita. Wyoming in 2008 had the highest level of losses at 230.62 MMBtu per capita, while Vermont had the lowest at 10.78 MMBtu per capita in 2015. Finally, the natural gas consumed for electricity generation has an average of 0.14 Quads. Texas has the highest values through the study period (1990 – 2018) with a maximum of 1.85 Quads in 2000, while Hawaii did not record any natural gas use for electricity generation through the study period.

Table 4.2. Summary Statistics for Annual State Level Variables, 1990 to 2018 (N=1,450)

Variable	Units	Ave	Min	Max	Standard Deviation
CO2	metric ton/person/year	24.98	8.31	133.81	19.38
Income	Thousands of U.S. dollars ($)/person/year	43.61	25.67	73.93	8.19
LowGHG	Million BTU (MMBtu)/person/year	60.58	1.63	218.27	44.89
PopDen	persons per square mile (psm)	187.01	0.97	1,209.10	252.57
Imports	Million BTU (MMBtu)/person/year	1.24	0.00	63.94	4.93
Losses	Million BTU (MMBtu)/person/year	93.44	10.78	230.62	32.37
NG	Quads/year	0.14	0.00	1.85	0.27

In 2017, the data on per capita Income in Texas was $50,250 which was the same income level as Kansas, but per capita CO_2 emissions were different at 28.4 and 20.4 metric tons, respectively. This variation in CO_2 reflects the variation in consumption and production of energy sources per state. Data from the U.S. Energy Information Administration (EIA) show that in 2017, Texas state energy per capita consumption from low GHG energy sources was about 46.6 million British Thermal Unit (MMBtu) and the percentage of low GHG in the energy generating portfolio was about 25%, while Kansas state has higher consumption and production at about 113.5 MMBtu and 57%, respectively. Another example from 2012 data for Colorado and Vermont both had same level of per capita Income at about $49,860. Vermont state depends on low GHG energy sources more than Colorado in the production and consumption of energy. Data from EIA in 2012 show that Vermont state energy per capita consumption from low GHG energy sources was about 129.5 MMBtu and the percentage of low GHG in the energy generating portfolio was about 99%, while Colorado state has lower consumption and production at about 20 MMBtu and 14%, respectively. Consequently, per capita CO_2 emissions were different between Vermont and Colorado at 9 and 17 metric tons, respectively. These examples show the variation between states in the quality of environment and the technology been adopted in their energy utilization.

4.6 Results

Stationarity and unit root of panel data are checked to determine whether the possibility of running PMG-ARDL is feasible or not. We test for panel stationarity using the Levin-Lin-Chu test and then the Hadri LM test for the unit root. The Levin-Lin-Chu test assumes that panels contain unit roots across cross-sections, while the Hadri LM test assumes that all panels are stationary against some panels containing unit roots. These tests have become extremely popular and widely used over the last decade (Hlouskova and Wagner, 2006). For Levin, Lin and Chu tests, 1 lag is used with the null hypothesis that is the panel under consideration contains a unit root, while the alternative hypothesis states the panel is stationary. Panels means and time trend are included. For the Hardri LM tests, time trend is included. The null hypothesis is that the panel under consideration are stationary while under the alternative hypothesis the panel contains a unit root.

For the Levin–Lin–Chu bias-adjusted t statistics for all variables (e.g., adjusted t statistic for Ln(CO_2) is -2.3441) were significant at all the usual testing levels. Therefore, we reject the null hypothesis and conclude that the series is stationary. On the other hand, results for LM Hadri test are not all statistically significant, meaning that we cannot reject the null hypothesis and conclude that the panel is stationery. With these results of the two tests in Table 4.3 we conclude that the panel is stationery and there is no evidence for a unit root within the series and accordingly we can use the PMG-ARDL model for the panel.

Table 4.3. Stationary and Unit Root Test Results

Levin, Lin and Chu tests				Hardri LM tests			
Series	**Adjusted t**	**Series**	**Adjusted t**	**Series**	**Z**	**Sereis**	**Z**
Ln(CO_2)	-2.3441**	**ΔLn(CO_2)**	-12.4710***	**Ln(CO_2)**	67.8972***	**ΔLn(CO_2)**	-2.0509
Income	-1.7338*	**ΔIncome**	-9.3239***	**Income**	37.6712***	**ΔIncome**	4.0412***
Income^2	-1.2850*	**ΔIncome^2**	-11.0211***	**Income^2**	33.0496***	**ΔIncome^2**	3.4813**
LowGHG	-1.1435*	**ΔLowGHG**	-12.9621***	**LowGHG**	46.2235***	**ΔLowGHG**	-4.4479
PopDen	-6.3075***	**ΔPopDen**	-5.6015***	**PopDen**	83.5208***	**ΔPopDen**	23.4078***
Imports	1.7766*	**ΔImports**	-1.4204*	**Imports**	45.6067***	**ΔImports**	-2.7903
Losses	-0.6911*	**ΔLosses**	-12.0594***	**Losses**	69.3280***	**ΔLosses**	-3.4067
NG	1.3127**	**ΔNG**	-13.0145***	**NG**	48.3955***	**ΔNG**	-3.8503

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

The long- and short-run results from the PMG-ARDL model which examines the relationship between state socioeconomic independent variables on per capita total CO_2 emissions in the logarithm form are summarized in Tables 4.4. Except for the imported electricity (***Imports***) and the natural gas consumed for electricity generation (***NG***) variables in the short run, regression coefficients show consistent signs and significance, and each reflects the expected signs of the relationship with the dependent variable. Both in the long run and the short run path positive sign of the coefficient of income shows that per capita CO_2 emission increase with growing income. Income squared, however, has a statistically significant, negative relationship with per capita CO_2 emission both in the long run and short run. This means that per capita CO_2 emission increases and later it starts to decline after reaching a threshold point of income.

Table 4.4. PMG-ARDL Regression Results

Dependent Variable: $\ln(CO_2)$								
Long Run Estimates				**Short Run Estimates**				
Variable	**Coefficient**	**Standard Error**	**P > |Z|**	**Variable**		**Coefficient**	**Standard Error**	**P > |Z|**
Income	0.0541272	0.0164937	0.001	**Income**	**D1.**	0.0074156	0.0043157	0.086
$Income^2$	-0.0005331	0.0002036	0.009	**Income2**	**D1.**	-0.0001424	0.0000479	0.003
LowGHG	-0.002601	0.0009559	0.007	**LowGHG**	**D1.**	-0.0004889	0.0001792	0.006
PopDen	-0.0298307	0.0106376	0.005	**PopDen**	**D1.**	-0.0008736	0.000366	0.017
Imports	-0.092024	0.1578306	0.560	**Imports**	**D1.**	-0.0013948	0.0005415	0.010
Losses	0.0039657	0.0005246	0.000	**Losses**	**D1.**	0.002575	0.0002836	0.000
NG	-0.1608351	0.5199804	0.757	**NG**	**D1.**	-0.1143816	0.0603802	0.058

Since EKC hypothesis examines the effect of income levels on CO_2 emissions in the long run (Panayotou, 1993), income turning point from equation (4.3) is computed from the long run regression estimates for the general model in equation (4.4) and found to be \$50,766.5. This estimated income level represents the estimated peak of per capita CO_2 emissions. By 2018, 27 states have reached this turning point and 23 states have not reached it yet. A list of states with income below and above the turning point is shown in Appendix II. The existence of the turning point confirms that the EKC hypothesis holds and there is an inverted U-shaped relationship between income and environmental degradation in the presence of the low GHG energy variable. This result means that as per capita income levels increase, emission levels rise, but when per capita income levels reach the turning point, economies begin to experience reductions in per capita CO_2 emissions. In addition, this result can be interpreted as many U.S. states have already moved beyond the EKC threshold level of income (\$50,766.5) and hence per capita CO_2 emissions decline with per capita income growth in these states.

Per capita consumption of low GHG energy also has negative, statistically significant impacts on per capita CO_2 emissions, such that in the long run, an increase in average primary energy consumption per capita by one MMBtu (293 KWh) from renewable and nuclear energy sources results in a 0.05% reduction in per capita CO_2 emissions.

The amount of CO_2 emissions generated from burning fossil fuels is related to the amount of the burned fuel. For example, burning one MMBtu of coal (0.05 short tons) emits around 215 pounds of CO_2, petroleum (0.17 barrel) emit 160 pounds, and natural gas (960 cubic feet) emits 117 pounds (Zhou and Huang, 2021). So, on average, increasing low GHG energy consumption or replacing energy produced from burning fossil fuels with other low GHG energy sources will reduce CO_2 emissions by 164 pounds. Taking in consideration that one fuel of the three might be used less than the other two, we calculated the weighted average[47] reduction of CO_2 in the U.S. in 2020 and find it at 157 pounds per one MMBtu. On average, each home in the U.S. consumed 40.5 MMBtu (11,880 kWh)[48] of delivered electricity in 2020. Regression estimates show that if one household increased or switched to consume energy generated from low GHG energy sources by 2.5% (1 MMBtu ÷ 40.5 MMBtu), they will help reduce per capita CO_2 emissions by 0.05%. This impact diminishes overtime, as in the short run the impact was a reduction of 0.26%. This might refer to the future structure of the energy mix in U.S. states that will have more renewable energy sources replacing the nonrenewable sources.

Electric system energy losses, in both the long and short run paths, have statistically significant, positive impacts on CO_2 emissions. Model results show that per capita CO_2 emissions increase with increasing the per capita losses of energy system in a state. One MMBtu

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[47] Weighted average reduction of CO_2 in pounds calculated by multiplying each fossil fuel consumption in MMBtu by its CO_2 emissions per unit (pounds of CO_2/MMBtu), then divided the sum of the three products by the sum of all three fossil fuels consumption in MMBtu in 2020.

[48] https://www.eia.gov/outlooks/aeo/data/browser/#/?id=4-AEO2020&sourcekey=0

(about 1.1% change in losses) increase in the per capita energy losses will result in 0.26% and 0.39% increases in per capita CO_2 emissions in the long and short run, respectively. The amount of electricity imported into a given state on a per capita basis annually has a positive impact on increasing per capita CO_2 emissions in the long run path. A one MMBtu (about 80% change in electricity imports) increase in the per capita electricity imports will result in a 0.14% increase in the per capita CO_2 emissions in the long run. In the short run, the electricity imports estimate is statistically insignificant, so we find no evidence that electricity imports have any impact on the per capita CO_2 emissions in the short run path. This might refer to the fact that imports are coming from neighboring states that does not indeed increase the level of CO_2 emissions in the importing state, or the transfer of CO_2 emissions resulted from electricity generation will be impacting the importing state in a later time frame not the time when electricity imports took place.

The estimated coefficient of natural gas consumption for electricity generation is -0.114 in the short run, which is statistically significant at the 1% level. This data shows that the use of natural gas has a negative correlation with CO_2 emissions. The reason is that natural gas used in the electricity generation sector has a positive impact on the environment since it replaces coal and petroleum products. Due to its lower CO_2 emissions per unit of generated electricity than coal, natural gas has been recognized as a means of decarbonization in the U.S. power sector (Shearer et al., 2014). So, the negative sign of the natural gas variable coefficient is reasonable since the natural gas emits CO_2 when it is burned, but it reduces the overall level of CO_2 emissions from the environment.

Finally, population density estimates for both the short and long run were statistically significant but with different signs. In the short run path, population density has a positive impact on increasing the level of CO_2 emissions. Increasing the population density in a state by one person per square mile will result in a 2.9% increase in the per capita CO_2 emissions in the short run. This result shows that population density in the short run is very elastic at 5.47. This finding is consistent with that of Ohlan (2015) in the case of India, where a 1 % increase in population density gives 5.48 % rise in CO_2 emissions. In the long run path, the relationship between population density and the level of CO_2 emissions has a negative sign in which a one person per square miles increase will result in a reduction in the per capita CO_2 emissions by 0.09%.

Results for the robustness check regression model in equation (4.6) are shown in Table 4.5. We ran the dynamic panel-data estimation by means of Generalized Method of Moments approach as a robustness check to validate estimates of PMG-ARDL model.

Table 4.5. Robustness Check Regression Results (N=1,450)

Dependent Variable Ln(CO_2)			
Variables	**Coefficient**	**Standard Error**	**P>|z|**
Income	0.0107302	0.0028717	0.000
Income^2	-0.0001514	0.0000305	0.000
LowGHG	-0.0036379	0.0002207	0.000
PopDen	-0.0011888	0.0001872	0.000
Imports	-0.0015056	0.0032874	0.647
Losses	0.006158	0.0002429	0.000
NG	-0.1618265	0.0250371	0.000

Coefficient estimates from the DPE model are consistent with the PMG-ARDL regression results in terms of statistical significance and coefficient signs, with the exception of the imports which has a negative sing in the long run. This consistency emphasizes the robustness and reliability of the PMG-ARDL estimates.

4.7 Conclusions and Policy Implications

In this research, the EKC impact on CO_2 emissions is examined in the presence of zero to low GHG emitting energy resources such as renewables and nuclear energy (low GHG energy) within the power sector of the U.S. using a data set consisting of per capita CO_2 emissions using annual state-level data for 50 U.S. states over a 29-year period (1990 – 2018). The empirical analyses show that the signs of control variables' coefficient estimates are consistent with expectations. Our expectations relied on previous research that found environmental degradation and improvement are related to economic development stages as described by the EKC hypothesis. Both the short run and long run coefficient estimates for income impacts are positive and negative for income squared. These positive and negative signs for income effects on CO_2 emissions in the short and long run support the hypothesis that economic development in the early stages results in more pollution emissions, then when more economic development occurs past the turning point, pollution emissions decline.

In addition to income level, economic development processes that involve the adoption of new technologies in production or a change in the energy mix also have an impact on the quality of the environment. In both the long and short run, income and low GHG energy play important roles in reducing CO_2 emission among all independent variables in equation (4.6). While income, in the early stages of economic development, increases CO_2 emissions, after the long run income turning point is reached at the turning point of \$50,766.5 per capita income, CO_2 emissions start to decrease with per capita income increases. Since low GHG energy within the power sector plays an important role in the reduction of CO_2 emissions, we include an additional explanatory variable related to the per capita low GHG energy consumption in the model. A per capita primary energy consumption variable from renewable and nuclear energy sources consistently has negative impacts on per capita CO_2 emissions within the regression models. The estimation of the EKC model confirms the statistical significance of the low GHG variable along with supporting the inverted U-shaped EKC hypothesis. According to these empirical results, both short and long run results were able to confirm the existence of an inverted U-shaped EKC in the fifty U.S. states in the presence of a low GHG variable. These results support that policies to adopt low GHG energy sources contribute positively to the reduction of GHG emissions.

As this research finds that implementation of low GHG energy within the power sector acts to mitigate CO_2 emissions, it is important for states to adopt policies that promote low GHG by investing more in renewable energy sources to mitigate CO_2 emissions. Some states are still relying more on high GHG energy sources in their energy production, and they need to increase the share of renewable energy in their energy mix. We conclude that implementation of new energy technologies that serve to reduce CO_2 emissions within the power sector, but it does not represent the entire impact of increasing per capita income on reducing these emissions.

Other factors, in addition to new energy technologies, are at work in reducing CO_2 emissions with increasing per capita income past the turning point. These factors may include changes association with higher levels of per capita income including an economic structure more heavily dependent upon services, movement of production locations to other locations which have lower income in order to stimulate the economic development and growth which in turn has a positive impact on the reduction of CO_2, and enhanced awareness and behavioral changes related fossil fuel consumption. Our long-run estimates show that increasing low GHG energy consumption and income decreases CO_2 emission. This means that per capita income growth is impacting CO_2 emissions through more than just through low GHG energy usage for electricity. After controlling for energy consumption from low GHG energy sources, per capita income has negative impacts on per capita CO_2 emissions above the turning point of $50,766.5, which per capita income in all 50 states exceeds. This revealed that there are additional factors reducing CO_2 emissions at the state level beyond income. Thus, significant development in the energy sector and transition toward low GHG energy technologies such as renewables and nuclear energy could contribute to reduce the CO_2 emissions and sustain the long run economic growth.

Finally, this research provides important implications for state environmental policies to energy related emission abatement. With the existence of several endeavors to mitigate climate change impacts, policymakers need to consider states' individual characteristics such as their economic development level, energy mix, energy consumption patterns in their economic sectors to implement different regional policy tools rather than a single policy recommendation. For example, states which are most dependent on fossil fuels for energy and other manufacturing purposes need to implement policies that limit the use of fossil fuels and encourage the utilization of low GHG energy sources in both sectors. Electricity imports need to be administrated by a regulation that allows only for imports from low GHG energy sources. Further studies might be important to better understand the dynamics of interstate electricity flows. In addition, the existence of an inverted U-shaped relationship between income and CO_2 emissions suggests that after a certain threshold (turning point at $50,766.5), the economic activities and economic growth lead to mitigate the environmental deterioration in the long-run. These findings suggest that investment in low GHG energy to promote cleaner energy consumption and develop clean technologies creates substantial effects on CO_2 emission reduction.

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4.9 Appendix II

A List of State Below and Above the Turning Point of Income ($50,766.5) in 2018

Sates with income below the turning point	States with income above the turning point
Alabama	Alaska
Arizona	California
Arkansas	Colorado
Georgia	Connecticut
Indiana	Delaware
Iowa	Florida
Kentucky	Hawaii
Louisiana	Illinois
Maine	Kansas
Michigan	Maryland
Mississippi	Massachusetts
Missouri	Minnesota
Montana	Nebraska
Nevada	New Hampshire
New Mexico	New Jersey
Ohio	New York
Oklahoma	North Dakota
Oregon	Pennsylvania
South Carolina	Rhode Island
Tennessee	South Dakota
Utah	Texas
West Virginia	Vermont
	Virginia
	Washington
	Wisconsin
	Wyoming

CHAPTER 5:

Summary and Conclusions

Concerns about climate change have increased substantially in the last few decades as global temperature has increased by a about 1 °C (1.8 °F) since the age of the industrial revolution (IPCC, 2021). One of the main reasons behind this temperature increase is the result of increased carbon dioxide (CO_2) emissions in the environment (EPA, 2021a). Increased CO_2 emissions are mainly caused by burning fossil fuels such as coal, petroleum, and natural gas in both the energy and transportation sectors. These two sectors are the two largest contributors to the United States (U.S.) greenhouse gas (GHG) emissions. In 2020, transportation sector accounted for 27% followed by electricity generation sector at 25% of the total U.S. GHG emissions (EPA, 2021b). GHG emissions are one of the greatest market failures ever seen (Stern, 2022), and CO_2 emissions negatively affect human health (Khan et al., 2019). Thus, it is important to investigate and invest in mitigation strategies for climate change risks. For effective climate change mitigation, it is vital to understand how GHG emissions can be associated with specific technologies, especially those help reducing GHG emissions in the U.S.

With the existence of climate change impacts, this dissertation empirically provides examinations and highlights the importance of policies and technologies which help improve the quality of the environment and mitigating the impacts of climate change. This dissertation examines three aspects of environmental and energy economics: (1) the impact of adopting low GHG energy[49] and state incentives on electric vehicle (EV) adoption; (2) the impact of climate change on the electric sector; and (3) determining the existence of environmental Kuznets curve (EKC) in the presence of low GHG energy sources.

[49] Low GHG energy sources include renewable and nuclear energy sources. Renewable energy sources include solar, wind, hydropower, geothermal, and biomass (EIA, 2019).

Three essays utilize different econometric methods: fixed effects, seemingly unrelated regression, and autoregressive distributive lag, respectively. For each regression, panel data sets are used in each essay: the period 2012 to 2020 for essay one, 1990 to 2019 for essay two, and 1990 to 2018 for the third essay. The advantage of using panel data, rather than focusing on the national data, is that we can have greater efficiency in estimation, as panel data provides more information, more variability, and more degrees of freedom (Lean and Smyth, 2010). All observations are annual, which are collected from U.S. sources of data and information, such as the U.S. Bureau of Economic Analysis (BEA), the U.S. Energy Information Administration (EIA), and the U.S. Environmental Protection Agency (EPA).

5.1 Summary Results and Policy Implications

The first essay (Chapter 2) investigates the impacts of three types of state level policies on EV adoption rate, 1) environmental, 2) financial incentives for EV purchase, and 3) publicly available EV charging infrastructure. We find that policies that positively impact EV adoption rate include increasing low GHG energy provision, reducing CO_2 emissions from electricity generation, and state income tax credits for EV purchase. EV adoption rate elasticities were computed from statistically significant coefficients and show that per capita income has a much larger marginal effect than any of the policy variables. Since state policies that enhance low GHG and provide tax credits positively impact EV adoption rates, results demonstrate the need to nationalize both types of policies in order to uniformly improve EV adoption across all states.

In the second essay (Chapter 3), we examined the impact of climate change on the U.S. electricity sector, including consumption, production, and efficiency, Results show that an increase in the averaged maximum ambient air temperatures increases electricity demand and decreases generation efficiency. We find the electric sector in the U.S. vulnerable to climate change, such that the rise in the ambient temperature will result in an increase in the electricity demand and decreases supply and efficiency of power plants. On the demand side, the per capita electricity consumption at the state level is responsive to climate change. On the supply side, power generation is also responsive to climate change such that increasing the average maximum temperature resulting in a reduction in the total electricity generation in a state. With respect to power plants performance, the efficiency of fossil fired plants decreases with increasing ambient temperature due to increased fuel consumption.

The main goal of the third essay (Chapter 4) is to investigate the EKC hypothesis in the presence of zero to low GHG emitting energy resources such as renewables and nuclear energy (low GHG energy) within the power sector of the U.S. during the period 1990–2018. This goal is achieved by employing pooled mean group (PMG) autoregressive distributed lag (ARDL) model. Results show that both short run and long run estimates for per capita income are positive and negative for per capita income squared. Long run estimates show a turning point of $50,766.5, the per capita income level where CO_2 emissions begin to diminish. This in turn, supports the existence of an inverted-U shaped relationship between economic growth and CO_2 emissions. We also find that in both the long and short run, low GHG energy plays its expected role in reducing CO_2 emissions. The study highlights the importance of implementing new energy technologies that speed up the reduction of CO_2 emissions within the power sector.

With these three essays, we emphasize the importance of policies and regulations targeting both transportation and energy sectors in the U.S. These two sectors have become the leading and most-rapidly growing contributors to GHG emissions in the U.S. as well as globally. These sectors almost rely on fossil fuels which negatively impact human health, quality of the environment, and the performance of energy generation. GHG emissions cuts must be translated to further declines in GHG emissions intensities and inventories. In order to address the aggregate impact of the energy and transportation sectors on GHG emissions, an effective policy approach must address the three levels of society- individual, industry, and government. Incentive policies targeting consumers along with awareness endeavors highlighting the importance of low GHG energies. Policies and regulations targeting industries need to be aimed at reducing the reliance on fossil fuels and adopting new green technologies in their manufacturing and economic activities.

Results from this dissertation reveal that state level policies have positive impacts on consumers adoption for green technologies such as EV and electricity generated from low GHG emissions. These policies help mitigate climate change risks and reduce GHG emission from the atmosphere and benefit both the economy of a state and the people health as well. State governments need to help increase EV adoption rate across all states by taking actions to achieve GHG emission reductions and promoting energy sources with lower GHG emissions in the energy mix. This could be achieved by reviewing the monetary incentives in a way that encourages EV owners to highly weight the value of the rebate incentive while taking the decision of EV purchase. Moreover, switching to a cleaner environment by reducing GHG emissions from the energy and transportation sectors should be a priority for policymaker, especially with the ongoing efforts and support from the presidential and federal plans for the development of the financial and infrastructure policies to speed up achieving the goal of cutting the U.S. total GHG emissions.

Climate change abatement is not achieved by adopting one strategy or policy within one specific sector. There needs to be collaborative policies targeting multiple sectors. Research findings from this dissertation shows that to combat climate change, new technologies and policies reducing carbon emissions from fossil fuels consumption in the transportation and power sectors can be of those effective strategies. However, environmental policies promoting renewable energy development or adopting cleaner technologies can further contribute to the reduction of GHG emissions originating from the use of fossil fuels.

The U.S. is trying hard to reduce its CO_2 emissions by 50% from 2005 levels by 2030 in a way towards a green economy (U.S. Fact Sheet, 2021). The environmental policies and technologies inducted to improve the quality of the environment and make it free from GHG emissions are the efforts that have been put by the U.S. to reach the sustainability level. The adoption of green technologies in the transportation and energy sectors will have a positive effect on the reduction of GHG emissions. To minimize transportation related emissions, more consideration needs to be paid to the utilization of technologies, such as EV, powered by low GHG energy sources and make a widely spread network of charging infrastructure. Further, in order to duplicate the effect of environmental and energy policies, the ultimate goal of policies should be at switching from fossil fuels to a mix of low GHG energy sources. Finally, the research endeavors of the future can be targeted towards the development of a framework that can be helpful to further flourish the transportation and energy sectors in the U.S. towards a cleaner environment and better health quality.

5.2 References

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