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Watts Driving EV Demand? A Panel Data Study on Renewable Energy's Impact in the United States

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Abstract

Diese Masterarbeit untersucht, inwieweit der Anteil erneuerbarer Energieträger an der Stromerzeugung die Verbreitung von Elektrofahrzeugen (EVs) in den Vereinigten Staaten beeinflusst. Auf Grundlage von bundesstaatlichen Paneldaten für den Zeitraum 2016–2023 werden Fixed-Effects-(FE)-Regressionen geschätzt, welche für Kraftstoffpreise, Ladeinfrastruktur, Bevölkerungsdichte, Pro-Kopf-Einkommen und Bildungsniveau kontrollieren.

Die Ergebnisse zeigen, dass ein höherer Anteil erneuerbarer Energiequellen innerhalb eines Bundesstaates im untersuchten Zeitraum keinen statistisch signifikanten Einfluss auf die Verbreitung von Elektrofahrzeugen hat. Zusätzliche Schätzungen mittels Instrumentvariablen-(IV)-Regressionen bestätigen die Robustheit der FE-Ergebnisse, wobei lediglich eine Spezifikation einen signifikanten Zusammenhang zwischen dem Zugang zu erneuerbarer Energie und der Verbreitung von Elektrofahrzeugen aufweist. Unter den untersuchten Einflussfaktoren erweisen sich insbesondere der Benzinpreis sowie die Dichte der Ladeinfrastruktur als statistisch stark signifikant und prägend für die Entwicklung der EV-Adoption.

Diese Befunde deuten darauf hin, dass die Verbreitung von Elektrofahrzeugen in den Vereinigten Staaten im betrachteten Zeitraum nicht unmittelbar mit dem Zugang zu erneuerbarer Energie verknüpft ist, sondern vielmehr durch die Kosten der Energieträger und die Verfügbarkeit von Ladeinfrastruktur bestimmt wird. Ein zukünftiger Übergang hin zu einer breiteren Akzeptanz von Elektrofahrzeugen dürfte daher von einer koordinierten Zusammenarbeit zwischen Gesetzgebern und Energieproduzenten abhängen, um Rahmenbedingungen für einen nachhaltigen und verbraucherorientierten Wandel weg von Fahrzeugen mit Verbrennungsmotoren (ICEVs) zu schaffen.

Contents

1 Introduction

1.1 Introduction

This thesis will focus on the accessibility of renewable electricity generation and the demand for electric vehicles in the United States. The principle reason why individuals purchase electric vehicles is widely disputed; however, increased levels of environmental protectionism at the consumer level could provide insight to the growth of electric vehicles (EVs) sales in the United States over the past few years. The individual level effects of utilizing renewable energy to power electric vehicles are believed to be significant in deciding to buy an EV or internal combustion engine vehicle (ICEV). Thus, scholars believe that a state's primary method of electricity generation can impact a consumer's preference to purchase an electric vehicle. Additionally, champions of environmental activism may purchase an EV while charging on an electrical grid powered by carbon emitting fuel sources, limiting the carbon reduction ability of EVs . The thesis will attempt to show whether the relationship between renewable energy and EV sales is significant in determining consumer behavior in the United States. Concurrently, this thesis may show that there is a correlation between high levels of environmental activism and willingness to purchase an EV in a state with higher levels of renewable energy.

1.2 Motivation

The debate surrounding EVs in the United States centers on whether the vehicles genuinely contribute to environmental protection or simply provide a misleading perception of reducing carbon emissions. Unlike the European Union, which enforces strict emissions regulations and vehicle standards, the United States presents a unique landscape for examining the relationship between EV adoption and direct environmental impact.

The United States differs significantly from the European Union in terms of environmental attitudes, government intervention, electricity generation methods, and consumer behavior, particularly regarding automobiles. Political affiliation plays a key role in shaping these perspectives, with Democrats in the United States generally advocating for stronger environmental protections and Republicans often expressing skepticism toward climate change policies. While EVs are purchased by individuals across the political spectrum, the question remains: does buying an EV truly lower one's carbon footprint?

This thesis will explore the key question: Does access to renewable energy influence EV sales within a state? By analyzing regional variations in energy sources and consumer behavior, this study seeks to determine whether EV adoption aligns with environmental impact or remains dependent on a state's energy infrastructure.

2 Literature Review

2.1 Introduction

The transition from ICEVs to EVs represents one of the most significant shifts in modern transportation. The rise of EVs is part of a broader energy transition away from fossil fuels. Historically, energy transitions from wood to coal and ultimately to oil took significant time. The modern transition is marked by the increasing penetration of renewable energy sources into electricity markets alongside the adoption of EVs across the world. Some analyses draw parallels between the decline of coal in the early 20th century and a potential future decline in oil demand, driven by the rise of electric mobility and renewable power generation. While fossil fuel prices could influence the pace of the energy transition, there is a possibility of a faster shift compared to historical precedents, making the study of renewable energy and EV technology influencing energy usage shifts throughout the 2000s a widely relevant issue.

As concerns over climate change, energy security, and fossil fuel dependence grow, EV adoption is becoming increasingly intermingled with advancements in renewable energy infrastructure and policy incentives; however, the extent to which renewable energy availability influences EV demand remains an area of ongoing debate. Dissimilarly to previous research, the impact of renewables on EV demand will be examined empirically in a state level panel study in the United States within this thesis. Few studies have completed comprehensive empirical research on the relationship between EV demand and renewable energy access in the United States due to the presence of other consumer demand factors outside of renewable energy driving the majority of research.

This section examines the existing literature on the relationship between EV adoption and renewable energy availability, both working in tandem with underlying socioeconomic factors. Beginning with the theoretical foundation followed by the methodology utilized in the literature, this review aims to identify gaps in the literature and provide a foundation for analyzing state-level EV adoption trends from 2016 to 2023 in the United States, a time horizon that has not been examined in recent literature. Additionally, the economic diversity among the states in the United States should provide a clearer examination of the relationship between EVs and renewable energy access compared to cross-country analysis due to the heterogenous intricacies of each state interacting with overarching federal policies (Golove, 2014).

2.2 Socioeconomic Factors

Previous research has empirically examined the impact of renewable energy sources as a percentage of electricity generation on EV demands across the USA, China, Germany, the UK, France, Canada, Sweden, Norway, Italy, Spain, Portugal, Japan, South Korea, and New Zealand, countries which accounted for over 96% of global EV sales through the duration of their targeted time horizon (Li et al., 2017). Several studies have explored the role of socioeconomic factors in shaping EV adoption, though this particular study considers six socioeconomic factors alongside renewables in influencing EV demands. Another study analyzing data from 20 leading EV market countries between 2015 and 2019 includes household disposable income as a significant socioeconomic factor influencing EV market share and found that EV sales are positively impacted by gross domestic product (GDP) per capita (Yamaner, 2024). The consideration of socioeconomic factors on EV demand is shown to be significant as previous studies fail to account for all demand driving factors. Supporting the mentioned studies, other research found that socioeconomic issues are the most prevalent source of EV demand compared to all others (Bilotkach & Mills, 2012).

Furthermore, research on the demographics of decarbonizing transport in Nordic countries shows that demographic attributes such as gender, education, employment, occupation, age, and household size can shape knowledge, patterns, and preferences related to EVs (Sovacool et al., 2019). By including Nordic participants, the authors show that heterogeneous consumers are required to consider diverse demographic groups and their different views of EV adoption. In contrast, a study in the UK finds that consumers in colder parts of the country rarely purchase an EV as the lithium ion batteries used in EV batteries possess limited driving range in colder weather. Concurrently, colder areas of the county require additional carbon based energy output up to an additional 25% production to meet electricity demand, little of which comes from renewable energy sources. Within the same study, using Nordic countries as a consumer base may have biased results from the influence of colder temperatures (Koncar & Bayram, 2021).

2.3 Policies

Federal and state government incentives are shown to play an important role in driving EV adoption. Studies have examined the effectiveness of various types of incentives, including purchase subsidies, registration tax benefits, ownership tax benefits, and value-added tax (VAT) benefits. Research focused on the US market analyzed the impact of individual tax credits and rebates on EV registrations, finding them to be consistently positive and statistically significant (Jenn et al., 2018). Furthermore, high-occupancy vehicle (HOV) lane access, weighted by traffic density, is found to have a positive impact in their model, resulting in a 4.7% increase in EV sales derived from HOV lane density. Other studies considered other non-subsidized incentives affect the market, examining the non-monetary incentives of parking, charging discounts, and access to bus lanes using stated-choice experiments (Langbroek et al., 2015), while others consider non-financial incentives like road priority and waivers on fees, but their specific random effects model did not find these factors to be statistically significant (Xue et al., 2021).

Concurrently, the effect of Electric Vehicle Supply Equipment (EVSE) credits appeared insignificant in the US context. One study examines the effectiveness of electric vehicle incentives in the United States, with the authors compiling a database of 198 incentives across all 50 states, including subsidies for home and public EVSE (Jenn et al., 2018). Their regression analysis, which modeled new vehicle registrations as a function of various incentives and macroeconomic variables, found that EVSE credits did not show any statistically significant effect on the adoption of electric vehicles across any of the regression models they tested, though direct dealer to consumer subsidies did possess an effect.

Policy recommendations from the literature emphasizes the need for designed incentive programs to promote EV adoption. Separating the analysis of Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) is prevalent in multiple studies, as gasoline prices appear to have a more apparent impact on the demand for BEVs. One study differentiated between PHEVs and BEVs, noting gasoline price had a more apparent impact on the demand for BEVs compared to PHEVs after separating the two types of EVs (Li et al., 2017). In terms of electricity, additional research indicates that a decrease in the price of electricity regardless of the production method will spur electric car demand just as a comparable increase in the price of fuel would (Birnbaum, 2015). The literature indicates that policymakers may need to use different incentives tailored to these two types of EVs and the scope of this thesis will require a direct focus on BEVs instead of the combined EV market (Burnham et al., 2021). A consideration for this thesis is the supply of gasoline in the United States compared to other countries. As these studies are cross-country panel based, the United States may possess a dissimilar elasticity of the price of gasoline when contrasted with other EV markets such as the EU.

The effectiveness of policy instruments is shown to vary across the United States, with many states regulated similarly achieving differing results, with one study highlighting levels of regional consumer awareness impacting policy effectiveness (Borchers et al., 2022). Consumer awareness of these policies is deemed necessary for policy success, though the divide in American political thought regarding the environment limits future success across regions. Their study suggests future research should explore a wider range of potential policy instruments, such as improving home charging availability for those without dedicated parking, providing dedicated public EV parking, and other regulatory measures to expand further on the direct effect of policy. Going beyond their study, other researchers econometrically model EV sales at the state level in the United States to infer consumer demand responses. Their model directly estimates the price elasticity of EV demand with respect to policy incentives, finding that every $1000 increase in incentives leads to a 2.6% increase in sales, with the incentives directly applying to individual consumer vehicle purchases (Jenn et al., 2018).

Examining targeted governmental incentive policies, researchers analyze the impact of preferential treatments for PHEVs in fuel consumption and GHG (greenhouse gases) emissions regulations, including super-credits (Federal tax credits) and zero emissions tax credits for electric cars, quantifying the resulting increase in GHG emissions from the policies (Gan et al., 2021). They model the "dilution effect" of super credits and the "leakage effect" of omitting electricity generation emissions within previous research, both of which provide a significant result on GHG emissions when combined with other dominant demand driving factors. The research indicated the depth of the analysis, with factors like renewable energy, charger density, education, or population consistently showing positive and significant coefficients for both PHEVs and BEVs, similar to the analysis of combined EVs.

Their model reveals positive demand elasticities for these factors, suggesting that consumers prefer EVs when government policies are favorably targeted specifically to EVs. Additionally, the study supports previous literature that gasoline price affects the demand for BEVs more than PHEVs, indicating the presence of a substitution effect based on fuel costs perceived by consumers. (Blair & Swanson, 2017). Further research models the effect of charging infrastructure availability on EV demand finding a positive correlation, with charging infrastructure referred to as charging density in other models (Xue et al., 2021). These infrastructure levels are often influenced by government policies and investments, both on the state and federal level. The collection of literature supports that EV demand is influenced similarly to ICEV demand; however, in regard to socioeconomic behavior, charging infrastructure and education access go beyond ICEV demand determinants due to the fueling sources of each vehicle system.

Within one panel data analysis, a model of OECD countries shows that specific government incentives positively impact EV sales (Yamaner, 2024). Government incentives alone are shown to be influential on EV demand; however, supporting previously discussed literature, a lack of consumer knowledge of these programs can limit their effectiveness (Isik et al., 2024). The primary goal of these incentives are shown to gain increased exposure by increasing consumer awareness through information campaigns and media coverage. One study introduces the Climate Policy Uncertainty (CPU) Index in their analysis of CO2 emissions in the USA, examining the emissions knowledge of American consumers. Though targeting overall national emissions knowledge instead of strictly reviewing vehicle emissions data, their empirical findings indicate that rising uncertainty in climate policy in the USA does not directly affect particulate CO2 emissions in their model. Applying their index of direct modeling of policy-related uncertainty to EV demand, increased awareness of vehicle CO2 emissions may not directly lead to increased EV sales. This study is rather limited as it is a survey based study, forgoing socioeconomic analysis and direct consumer preferences in a state by state analysis (Isik et al., 2024).

Other studies forgoing the survey method show overall knowledge exposure surrounding EVs and renewable energy can impact demand. Other research introduced variables to quantify consumer knowledge of EVs and associated incentives, finding that raising consumer awareness is critical to the success of EV incentive programs (Jenn et al., 2018). The authors model the heterogeneity in state-level monetary incentives to uniquely determine the effect of consumer awareness of EV incentives, finding that greater awareness significantly enhances the effectiveness of monetary incentives on sales, highlighting the importance of information dissemination in shaping EV demand. In addition, several sources emphasize the combined role of socioeconomic factors in shaping consumer demand in tandem with established incentive policies, as seen in the econometric models of (Li et al., 2017), (Xue et al., 2021), (Yamaner, 2024). These models suggest that income, education, and urbanization levels influence the propensity to adopt EVs when combined with incentive programs. One study finds that most car users lack profound knowledge on electric cars, which may result in a discrepancy between survey results and future market development (Link et al., 2012). Another study states consumer knowledge additionally impacts EV sales through future choices of perceived EV infrastructure or price determinants in the future (Lee & Lovellette, 2011). Informed predictions on the future of EV accessibility or price points are shown to affect consumers attempting to save money by using EV over ICEVs, due to the uncertain future of gasoline prices. Further research includes a study that incorporates psychological constructs such as environmental perception, risk analysis, and producer innovativeness into choice models to uncover the motivations behind EV adoption (Liao et al., 2017). Returning to the Nordic model, the researchers show how demographic factors influence the importance respondents attribute to the environmental impact of a car when considering future purchases, illustrating that consumers of differing socioeconomic standing and overall demographics influence consumer level EV adoption due to the psychological aspect of saving money(Sovacool et al., 2019).

Financial or technical attributes, such as driving range and charging time, combined with overall EV infrastructure attributes are generally significant in consumer choices; however, the effectiveness of incentive policies combined with the influence of individual-related variables on preferences have shown less consensus across studies. Previously mentioned research illustrates the schism in the literature, specifically targeting the lack of clarity of non-targeted grid or individual tax benefits that impact EV charging, hinting that future studies should consider real-world EV usage patterns when designing choice experiments related to EV charging (Liao et al., 2017). One study shows positive and significant effects of charging stations, years of schooling, and GDP per capita on EV sales, implying that infrastructure, consumer awareness/preferences, and economic capacity drive demand. This study also noted a negative relationship between crude oil prices and EV sales, although the significance varied (Yamaner, 2024).

The common consensus within the literature is that policies aimed at increasing the number of fast-charging stations are paramount combined with regulatory mandates in order to improve and expand upon charging infrastructure. Multiple empirical researchers agree that policies requiring automakers to sell EVs in certain states increases sales while promoting future growth (Jenn et al., 2018)(Wesseling et al., 2015). The prominence of these factors, connected to socioeconomic demand determinants, the role of consumer awareness in climate uncertainty, and a clear analysis of one specific vehicle category (BEVs), provides necessary background for completing a study examining EV demand in the United States.

2.4 Business Policies

Looking to the producer side of EVs, the transition to EVs represents a race for technological innovation that can leave major producers behind when they fail to adapt to the growing EV market (Wesseling et al., 2015). In the United States, manufacturers with smaller market share can improve their position by adopting EV development before their competitors, promoting growth of EV development to enhance overall market capitalization. Additionally, the lack of Chinese competition in the American EV market may limit total competitive innovation of current US suppliers, leading to limited technical development due to a lack of free market competition(Earl & Fell, 2019).

The same study analyzes large car manufacturers between 1990-2011, finding that firms with a stronger incentive and a stronger opportunity were more likely to introduce more EVs during the primary EV adoption phase around the year 2007 (Wesseling et al., 2015). Regulatory pressures, such as the zero-emission mandate in California, was found to stimulate car manufacturers to develop EV related assets during the research and development period of the 1990s as found in one study, though a higher opportunity to innovate did not holistically translate to significantly higher EV sales, potentially due to strategic decisions to keep sales low while lobbying against advancing mandates. The study additionally identified first movers as having high incentive and opportunity, quick followers with a smaller blend of the two, and two types of laggards: those with high incentive but low opportunity, and those with no incentive but sufficient opportunity, both types failing to utilize the strengths of advancing EV policy (Wesseling et al., 2015). They additionally found that manufacturers regulated by the full emission mandate developed a stronger EV asset position during the research and development period, solidifying the position of companies such as Tesla and General Motors as the leading EV producers in 2024. The emissions mandates, particularly shown in California, are shown to increase overall EV technical development, with strict environmental policies shaping advances in components such as battery life and charging speed.

2.5 Charging

The availability and type of charging infrastructure are proved critical for the adoption of EVs in the global market. Studies have evaluated differences in residential, public, and workplace charging strategies, with the differences in their respective ease of charging combined with overall access influencing EV demand. As charging networks and their respective EV charging speeds vary depending on the state, some states or countries have a technological advantage regarding charging speeds. Bidirectional charging (V2G) technology, the fastest charging method for EVs, is not yet widely implemented in the United States due to infrastructure limitations and the availability of V2G-capable vehicles, which are predominantly heavier commercial vehicles (Yilmaz & Krein, 2023). Quality of life for EV owners is shown to be significant in another study, highlighting the time spent charging, the potential carbon offset of a particular grid, and overall cost of charging are as important as socioeconomic factors. The importance of these factors is shown by Tu et. al. (2020), stating if consumers believe that EV usage is beneficial on the individual, environmental, or national level, a positive attitude towards EVs is shown (Tu et al., 2020). Expansion of workplace charging and implementation of fast charging may increase the benefit upon the individual, leading to a greater ease of access driving increased EV adoption while the type of energy powering a charging station may impact the environment.

Further research explores the cost-benefit analysis of implementing light and heavy duty EV charging at the same workstation within a private energy grid, considering infrastructure and implementation costs to promote individual and commercial EV charging (Yusuf et al., 2023). Factors such as V2G availability and battery degradation further impact the overall cost-benefit for the grid owner (Carley et al., 2019). These studies include factors like energy cost savings and peak price reductions for different charging configurations, with net metering highlighted as a factor that can help recover initial investments in a shorter timeframe by combining different electricity generation methods to account for charging demand throughout the day. The availability of charging infrastructure is consistently modeled as a key factor influencing consumer demand, overshadowing the method of electricity generation of the charging stations. The positive coefficients for charger density in the models of multiple studies suggest that consumers are more likely to purchase EVs when they perceive adequate charging options, all of which are influenced by the type of power received from the electrical companies, be that renewable or fossil fuel produced (Li et al., 2017), (Xue et al., 2021), (Yamaner, 2024).

Advanced approaches to EV charging demand management are investigated throughout the literature for potentially enhancing the integration of renewable energy into the grid and optimizing the electricity market. Smart charging strategies may help consumers to align EV charging times with periods of high renewable energy generation and low demand, thereby maximizing the use of clean energy and reducing grid stress. A panel data analysis models EV market share while noting the impact of charger density, split between renewable energy dominant and fossil fuel powered grids, reinforcing that differing charging strategies may reliably decrease costs and promote charging infrastructure (Xue et al., 2021). A further distinction between advanced charging and the slower trickle systems is drawn within the study, with higher income areas possessing larger advanced charging density. Their results indicate a positive relationship between charger density and household income with EV adoption, suggesting that infrastructure availability and speed influence consumer decisions.

With the increasing number of EVs in the United States, managing charging demand is important for grid stability and efficient integration of renewable energy. Other approaches for EV charging demand management are being explored, including participation in electricity markets and strategies to enhance renewable energy integration, as shown by Tesla's Megapack grid battery. EVs can potentially benefit from grids participating in speculative and forecasted demand energy markets to maximize charging on renewable powered grids, with power companies potentially maximizing renewable energy generation during peak hours when EVs are being charged.

The consensus between the literature is that understanding consumer driven charging preferences is essential for designing effective strategies to promote EV adoption, with multiple studies highlighting consumer preferences as prominent factors within their studies. EV charging factors such as range anxiety, battery life, charging time, and vehicle efficiency are shown to influence consumer choices (Jenn et al., 2018), (Liao et al., 2017). Further research supports this claim, indicating that preferences for public charging vary based on household size and suggest that as EVs achieve price parity to ICEVs, the factor of perceived long charging times can deter consumers (Sovacool et al., 2019).

The majority of the sources model consumer demand effects through statistical analysis of actual sales data, direct elicitation of preferences via surveys, and the incorporation of a variety of economic, social, psychological, and infrastructural factors that are believed to influence consumers' decisions regarding electric vehicle adoption. The findings consistently point to the importance of price, vehicle attributes, infrastructure availability, and broader socioeconomic conditions in shaping the demand for EVs. Government policy influences each of these demand factors differently, though the studies support that targeted policies towards these factors are significant in increasing EV demand.

2.6 Renewable Energy

A central aspect of the adoption of EVs is their existing relationship with renewable energy. One study explicitly examines the impact of renewables on EV demands, which is the latest research in the literature to empirically study EV demands from the viewpoint of renewables (Li et al., 2017). Their findings indicated a positive and significant impact of the share of renewables in electricity generation on EV sales. This suggests that as countries increase their reliance on renewable energy, it can contribute to a greater demand for EVs, potentially due to increased environmental awareness or the perception of "greener" transportation. They implicitly model the environmental effects by including the percentage of renewable energies in electricity generation as a factor influencing EV demand. Their finding that a higher percentage of renewables leads to higher EV demand suggests a consumer preference for environmentally friendly electricity sources for their EV charging. Although the study is far from homogenous as a cross country panel study, a relationship between renewables and EV demand is economically significant when examining EV adoption across multiple countries.

Furthermore, the integration of renewable energy into EV charging networks is seen as an opportunity to advance sustainability and reduce carbon emissions. Innovations like smart grids are highlighted as ways to facilitate this integration and create EV infrastructure powered by cleaner energy sources. Multiple electrical utility companies offer renewable only EV charging options, highlighting a direct link in the market between renewable energy supply and EV usage, though this phenomenon is represented less in the United States (Rădulescu & Șerbănescu, 2023).

The environmental benefits of EVs are often cited as a key driver for their adoption, with the realized GHG emissions associated with EVs dependent on the electricity generation mix. A regional emissions analysis of EVs in the US, considering state-level generation mixes, found that in 2020, the median state had slightly higher total particulate matter (PM2.5) emissions for an EV compared to gasoline vehicles (Gan et al., 2021). As the grid incorporates more renewables, this difference is projected to decrease, with some states showing lower predicted emissions for EVs by 2050. The literature highlights that the decarbonization of the power sector is significant in maximizing the environmental benefits of electric vehicles. The same research quantifies the increase in GHG emissions using a well-to-wheels (WTW) analysis to compare the actual emissions with a scenario without greener electricity production mixes across the EU, United States, and China. The authors consider different GHG emission intensity scenarios for electricity generation based on projections from the International Energy Agency (IEA), finding that fossil fuel dependent states utilizing EVs may not always offset ICEVs. Another study performs a cradle-to-grave (C2G) life cycle analysis (LCA) to compare GHG and criteria air pollutant (CAP) emissions of EVs and ICEVs (Burnham et al., 2021). They use state-level electricity generation-mix data from the National Renewable Energy Laboratory (NREL) and emission factors from the GREET (Greenhouse Gases, Regulated Emissions, and Energy use in Technologies) model to generate state-level emission factors from 2020 to 2050. They calculate CO2 equivalents for three GHGs (CO2, CH4, N2O) using global warming potentials, highlighting that per vehicle, EVs produce less GHGs in their lifetime when excluding manufacturing and shipment (Burnham et al., 2021).

As the most influential area of this thesis, the regional variation of grid systems and their electricity mix illustrates the effects of EV adoption due to increases in renewable energy access. The environmental benefits of EVs can vary regionally depending on the composition of the electricity generation mix, with states such as West Virginia historically powering their grid exclusively with coal. In regions with a higher proportion of fossil fuels in electricity generation, the immediate greenhouse gas emissions reductions from EVs might be less significant compared to regions with cleaner energy sources as previously discussed. As a state's grid becomes greener with increasing renewable energy capacity, the emissions benefits of EVs are projected to improve across all regions regardless of outside changes. Analyses using state-level generation mixes in the United States show a trend towards lower overall emissions from EVs as renewable energy generation shares grow in the power sector.

Supporting the claim of increases of renewable energy access leading to increased EV adoption, the literature provides a clear direction for this study while simultaneously identifying primary exclusions for this thesis. Existing research has explored multiple factors driving EV adoption, including fuel prices, government incentives, charging infrastructure, and consumer behavior to uncover the complex relationship between renewable energy access, policy incentives, and socioeconomic factors in shaping EV adoption. While some studies suggest that increased renewable energy production encourages EV sales by potentially lowering electricity costs and reducing emissions concerns, others argue that consumer preferences, policy frameworks, and infrastructure development play a more dominant role. While the 14 country panel data analysis provides the closest proxy for this study, their research is focused on a cross country analysis using older data, targeting multiple countries with widely varied federal, regional, and individual opinions on the utilization of EVs (Li et al., 2017). Though relatively conclusive, their research fails to address the complete significance of the determinants discussed in this review when pertaining solely to the United States, a gap which this thesis will seek to explore. Additional components of this thesis will include a state by state analysis of not only the listed factors, but additional environmental products while utilizing a more recent time horizon, providing a clearer explanation of EV demand determinants in the United States in a more current study.

3 Data and Modeling

3.1 Introduction

In this section, EV demand is analyzed across the United States on a state level panel, including the District of Columbia (DC), with the time period between 2016 and 2023. Independent variables include renewable energy access, measured as the ratio of renewable energy production to total energy production, in addition to six consumer demand factors.

3.2 Data Collection

This study is a cross-state panel of the United States, with each of the 50 states and DC considered within the analysis. Each state possesses a positive value for renewable energy generation throughout the time period along with evolving changes in EV registrations. Due to limited public access to vehicle registration data, the analysis will measure the time period of 2016-2023.

Table 1 provides the data explanation and sources. All data used in this analysis is free-access via various government data collectors of the United States. Additional data explanation is available through their respective websites. All calculations for data transformation are completed by the author using Microsoft Office and RStudio.

For each state, EV purchases are reflected as the total number of registrations of BEVs by state, with standard BEVs and PHEVs treated separately within the study. The dependent variable of EV density is calculated as EV registrations per 100,000 residents; however, previous empirical literature indicates that EV density should be represented as a logarithm to avoid heteroskedasticity, along with the variables of gasoline price, population density, and income per capita (Li et al., 2017). With the exception of one state for 2016, all entries possess a non-zero value to ensure logarithmic integrity.

Renewable energy production is measured as the ratio of renewable energy production to total energy production. Clean energy production, which is included in the renewable energy calculation, is created by removing GHG producing generation methods from renewable energy production, while maintaining a ratio to total energy production. As such, any regression with the two variables will involve endogeneity and collinearity, driving the study to create separate models for the two variables. The other independent variables are identified in Table 1: price of gasoline, charger-density, population-density, income per capita, and active subsidies. The price of electricity may possess some endogeneity when included with the other independnent variables, though this is accounted for in other models. Gasoline price is organized by PADD region (New England, Central Atlantic, Lower Atlantic, Midwest, Gulf Coast, Rocky Mountains, West Coast) of the United States due to limited historical records for each state over the time period. Previous empirical literature noted that GDP per capita is insignificant for EV models, so income per capita is included to test significance (Hidrue et al., 2011).

Table 1: Variables and Sources

Variable	Data Description	Source
STATE-RENEW	Percent of total energy generated by renewable methods	US Energy Information Administration (2024) www.eia.gov
STATE-CLEAN	Percent of total energy generated by clean methods	US Energy Information Administration (2024)
EV-DENSE[a]	Number of EV registrations per state per 100k residents	Alternative Fuels Data Center (2024) afdc.energy.gov/data
GASPRICE	Average gasoline price (non-diesel, USD/gal)	US Energy Information Administration (2024)
CHARGER-DENSITY[b]	Charging stations per 100k residents	Alternative Fuels Data Center (2024) eia.gov/petroleum/gasdiesel/
EDUC	Percentage of college-educated residents aged 25+	US Census Bureau (2024) www.census.gov
LPOPULATION-DENSITY	Number of residents per square mile of land area	US Census Bureau (2024)
PERGDPI	Personal income per capita, PPP-adjusted	Bureau of Economic Analysis (2024) www.bea.gov
ACTSUBS	Active subsidies/incentives per U.S. state	Alternative Fuels Data Center (2024)
ELECPRICE	Average electricity price (¢/kWh, all sectors)	US Energy Information Administration (2024)

[a] EV registrations between 2016–2023 are sourced from AFDC (2024). Per 100k resident values calculated using U.S. Census population estimates.
[b] Total number of Level 1, Level 2, and fast chargers from AFDC (2024), adjusted by population estimates from the U.S. Census.

3.3 Modeling

The dependent variable is EV-DENSE, the number of EV registrations per 100,000 residents, and the independent variables are as follows: 1. STATE-RENEW (percent of renewable energy in total electricity generation); 2. GASPRICE (USD per gallon); 3. CHARGE-DENSE (number of EV charging stations per 100,000 residents); 4. EDUC (percentage of state population with a bachelors degree over 25 years of age); 5. LPOP-DENSE (number of residents per square mile of land area); 6. PERCAPI (income per capita); 7. ACTSUBS (number of active subsidies targeting EVs). The following Equation (1) shows the primary model.

$$\begin{aligned}\ln(EV\text{-}DENSE_{it}) = {} & \beta_1(STATE - RENEW_{it}) + \beta_2 \ln(GASPRICE_{it}) \\ & + \beta_3 \ln(CHARGE\text{-}DENSE_{it}) + \beta_4(EDUC_{it}) \\ & + \beta_5 \ln(LPOP - DENSITY_{it}) + \beta_6 \ln(PERCAPI_{it}) \\ & + \beta_7(ACTSUBS_{it}) + \gamma_i + \mu_t + \varepsilon_{it} \end{aligned} \tag{1}$$

For each variable, there is a regression β coefficient to be determined. The fixed effect for a state is γ_i, and for specific years is μ_t. The random disturbance term is ϵ_{it}. To reduce the level of heteroskedasticity, four independent variables are taken with natural logarithm, along with the dependent variable EV-DENSE.

3.4 Summary Statistics

In Table 2, the summary statistics are calculated and expressed. For EV density, the average is 273 EVs per 100,000 people with a minimum of 0 (North Dakota 2016) and a maximum of 3,205 (California 2023). In order to use logarithmic data, the EV density value of all US States is transformed by adding 1 additional EV registration to account for logarithmic tabulation, which turns the minimum value to 0.131 for North Dakota in 2016. Examining the primary independent variables of interest, every state possesses a non-zero value for renewable energy production, with the minimum value of 2.2% (Delaware 2016) and maximum value of 96.8% (Vermont 2016). Clean energy production averages at 37% of total energy production with the maximum of 84% (Washington 2018). For gasoline prices, the average is 2.8 USD per gallon with the maximum of 4.6 USD per gallon (West Coast 2022). For charger density, the average is 10.65 charging stations per 100,000 residents with a minimum of 0.4 (Alaska 2016) and a maximum of 58.73 (Vermont 2023).

Table 2: Summary Statistics of Key Variables

Variable	Max	Min	Mean	Standard Deviation
EV-DENSE	3205.722	0.131	273.211	367.1317
STATE-RENEW	0.96823	0.02169	0.40048	0.2227932
STATE-CLEAN	0.84376	0.01105	0.37523	0.205646
GASPRICE	4.595	1.869	2.797	0.6507485
CHARGE-DENSE	58.7321	0.4036	10.6467	9.133614
EDUC	65.90	20.20	33.46	6.806047
LPOP-DENSE	11267.607	1.285	420.194	1540.106
PERCAPI	105518	35638	57085	11464.09
ACTSUB	47.000	2.000	8.745	6.048431

For education, the mean is 33.46% of the population over 25 years of age possessing a bachelor's degree or higher with a maximum of 65.9% (District of Columbia 2023) and minimum of 20.50% (West Virginia 2017). Population density averages 420 residents per square mile with a minimum of 1.285 (Alaska 2023) and a maximum of 11,267.6 (District of Columbia 2023). Income per capita averages at 57,085 USD with a minimum of 35,638 USD (Mississippi 2016) and a maximum of 105,518 USD (District of Columbia 2023). For active subsidies, the mean is 8.745 with a minimum of 2 (Alaska 2016-2021) and a maximum of 47 (California 2023). Not included within the primary table, electricity prices average at 0.11 USD per kilowatt hour with a maximum of 0.39 USD/kwh (Hawaii 2022). The results are as expected, with maximum values reflecting increased EV adoption throughout the time period and low population density states possessing smaller values for charging availability, therefore limiting EV density.

3.5 Econometric Testing

In Table 3, the correlation coefficients between the primary variables are provided. Looking at the independent variables, the maximum value of the correlation coefficients is 0.81, meaning that no high magnitude linear correlations should impact the regressions.

Table 3: Variable Correlation Coefficients

	Variables							
	log(EV-DENSE)	STATE-RENEW	log(GASPRICE)	log(CHARGER-DENSITY)	EDUCATION	log(POPULATION-DENSITY)	log(PERGDP)	ACTSUBS
log(EV-DENSE)	1							
STATE-RENEW	0.21	1						
log(GASPRICE)	0.71	0.12	1					
log(CHARGE-DENSE)	0.81	0.34	0.59	1				
EDUC	0.54	0.4	0.3	0.66	1			
log(LPOP-DENSE)	0.25	-0.01	0.02	0.3	0.54	1		
log(PERCAPI)	0.69	0.3	0.61	0.68	0.78	0.32	1	
ACTSUB	0.42	0.13	0.21	0.34	0.32	0.32	0.35	1

To assess the stationarity of the variables, an Augmented Dickey Fuller (ADF) test is executed. The null hypothesis (H0) is the presence of a unit root or non-stationarity while the alternative hypothesis (H1) is presence of stationarity. The results of the compiled ADF test are tabulated in Table 4. The majority of variables are stationary, while EV density is likely non-stationary at baseline statistical threshold, meaning further augmentation on the variable EV-DENSE is required to proceed with regression analysis. The first transformation is a first-difference ADF on the variables, which is shown in the Appendix in Table 12.

Table 4: ADF Test Results for Stationarity

Variable	**Statistic**	**P-Value**	**Variable**	**Statistic**	**P-Value**
log(EV-DENSE)	-2.902182	0.1962	EDUC	-5.3244	0.0100
STATE-RENEW	-8.0387	0.0100	log(LPOP-DENSE)	-5.8033	0.0100
log(GASPRICE)	-3.3655	0.0599	log(PERCAPI)	-3.7447	0.0219
log(CHARGE-DENSE)	-3.4898	0.0436	ACTSUB	-5.3604	0.0100

Though EV-DENSE can not be considered stationary after differencing, an Engle-Granger cointegration test is performed on the initial EV-DENSE and GASPRICE, with both variables in logarithmic form, also shown in the Appendix in Table 13. With an ADF test performed on the residuals, the p-value of 0.01 rejects the null hypothesis, meaning the residuals are stationary and the variables are cointegrated. Though an error correction model (ECM) is considered, the primary goal of the study is focused on long-term trends with no intention of investigating short-run returns to equilibrium. With the rejection of the null hypothesis, the data can be used with standard panel data models.

4 Regression Results

4.1 Renewable Energy Regression

For a panel data study within the United States, three methodological options are available for modeling this analysis: fixed effect, random effects, and mixed effects. Utilizing the tabulated F-value and Hausman test, the fixed effects (FE) regression is determined to be the best modeling method for this analysis. The results are available in the Appendix, shown in Table 11. Multiple regressions are run within this study, with the primary considerations being the effect of renewable energy generation shares on EV density. Additional testing utilizes differing variables; however, the priority considerations are given to the previously specified independent variables. For expected coefficients, positive coefficient values are expected for renewable energy, gasoline prices, charging density, education, population density, personal income, and active subsidies. An increase in these independent variables should empirically reflect an increase in EV density. Figures 1 and 2 illustrate the change in the renewable energy ratio over the time period, showing a slight positive trend in renewable energy adoption throughout the evaluated time frame.

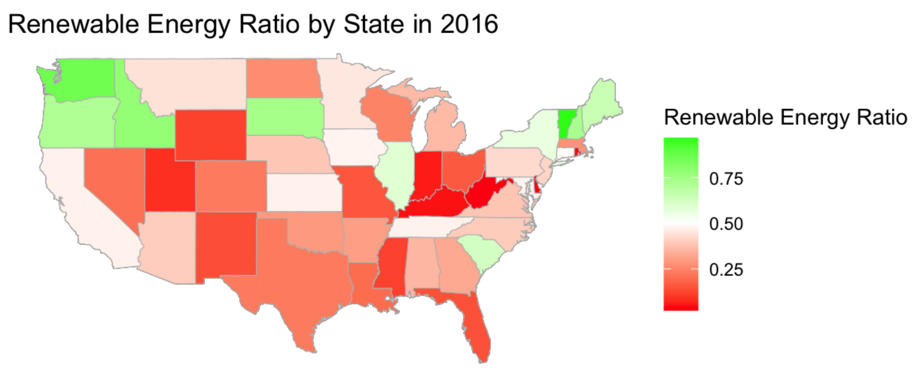

Figure 1: Renewable Energy Generation (2016)

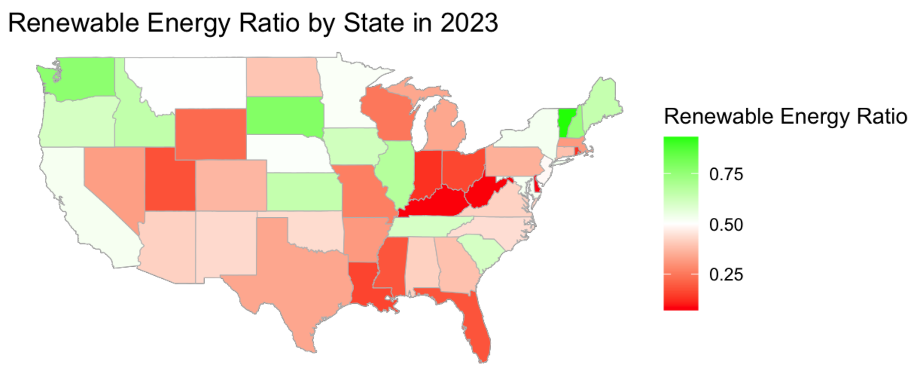

Figure 2: Renewable Energy Generation (2023)

Table 5 expresses the initial regression results using the renewable energy ratio as the primary independent variable. The four models reflect an R-squared value of 0.905 or higher, with a maximum of 0.920 for Models (3) and (4). Exclusively examining the R-squared values, Model (3) or (4) should reflect more efficient results than the earlier models; however, the inclusion of some variables in the models may be problematic.

Table 5: FE Renewable Energy

Dependent Variable:	**log(EV-DENSE)**			
	(1)	**(2)**	**(3)**	**(4)**
STATE-RENEW	1.498^{***}	1.455^{***}	$0.698^{\cdot}$	$0.687^{\cdot}$
	(0.426)	(0.428)	(0.407)	(0.408)
log(GASPRICE)	1.017^{***}	0.996^{***}	0.520^{***}	0.530^{***}
	(0.121)	(0.122)	(0.128)	(0.129)
log(CHARGE-DENSE)	0.814^{***}	0.819^{***}	0.495^{***}	0.502^{***}
	(0.069)	(0.069)	(0.077)	(0.077)
EDUC	0.228^{***}	0.219^{***}	0.097^{***}	0.099^{***}
	(0.017)	(0.018)	(0.023)	(0.023)
log(LPOP-DENSE)		1.475	-1.371	-1.433
		(1.213)	(1.180)	(1.183)
log(PERCAPI)			4.014^{***}	4.035^{***}
			(0.517)	(0.518)
ACTSUB				-0.013
				(0.016)
Observations	408	408	408	408
R-squared	0.905	0.906	0.920	0.920
Adj. R-squared	0.891	0.891	0.907	0.907
F-statistic	845.0	677.2	669.4	573.3

Note: All models use state and year fixed effects. Standard errors in parentheses.
${}^{\cdot}p < 0.1$, ${}^{*}p < 0.05$, ${}^{**}p < 0.01$, ${}^{***}p < 0.001$

Within the regression in Model (1), the state renewable energy ratio is shown to be statistically significant at the 99.9% confidence level. With a beta coefficient of 1.498, a 1% increase in the average renewable energy generation mix is shown to increase EV density by 0.6%. Though relatively unchanged in Model (2) with the addition of population density, the later models show that the state renewable energy mix is no longer statistically significant and results in a decreased magnitude, reducing the coefficient to 0.698.

Unsurprisingly, gasoline price, charging density, and education possess statistically significant beta coefficients at the 99.9% confidence level in the first two models, with the result being backed by the empirical literature. The addition of further regressors in later models results in these variables maintaining significance to the 99.9% confidence level.

Reviewing the expected coefficients for renewable energy, gasoline price, charging density, and population density, all values are positive in the first two models; however, in the later two models, population density expressed a negative coefficient with no statistical significance. Surprisingly, active subsidies also show a negative coefficient, though lacking large magnitude and statistical significance. The addition of active subsidies in Model

(4) results in little change of the previous coefficients, negating the concern of gross overspecification. Examining the variable ACTSUB, an overgeneralization of the variable may have occurred. Due to the dynamic nature of incentives and subsidies, where benefits appear through discounts or state/federal tax breaks, the number of incentives may not entirely encompass the cash value of each piece of legislation. Further research may be needed to explore the direct benefit of total subsidy impact; however, due to the changes in active governments and the sheer number of incentives, that may be difficult. Within this study, due to previously mentioned reasoning, the variable will remain omitted from the regression.

With the addition of income per capita in Model (3), renewable energy loses statistical significance above the 90% interval while gasoline prices and income per capita are still significant at the 99.9% level in both Model (3) and Model (4). Regarding final impressions of the renewable energy regression, both Model (3) and (4) possess the largest R-squared values of the various models at 0.920; however, due to the variable ACTSUB lacking significance or magnitude in addition to an unexpected negative value, Model (3) appears to be the best model for predicting EV buying behavior in respect to renewable energy ratios. Therefore, Model (3) will be discussed econometrically instead of the other models.

Using Model (3), state renewable energy production is shown to not be statistically significant with a beta coefficient of 0.698, where a 1% increase in the average renewable energy ratio would result in an approximate 0.3% increase in EV density. Examining real life data, a one percent increase in average renewable energy access in a state with an EV density of 100 EVs per 100,000 residents would increase EV density to 100.3 EVs per 100,000 residents, which is economically reasonable. However, due to limited statistical significance, this result can not be taken as a direct relationship between the two variables. Looking at the other independent variables which are statistically significant such as gasoline price, charging density, education, and income per capita, a clearer relationship can be examined. For gasoline prices, a 99.9% confidence interval highlights a result interpreted as a 1% increase in the price of gasoline would result in a 0.520% increase in EV density. Though low in magnitude, the result is economically sound, with the empirical literature supporting this result. Possibly the independent variable of most interest in this study, charging density is shown to be significant at the 99.9% confidence level, with an interpretation of a 1% increase in charging stations per 100,000 residents resulting in a 0.495% increase in EVs per 100,000 residents. This result, showing a positive relationship, is economically sound as increased access to charging points should increase EV ownership. Historically and empirically, the charging options in a state or region directly shape EV adoption as increased access to charging points influence the perceptions of ease of access for EV purchases. Looking towards education, a 99.9% confidence interval combined with an econometric interpretation of a 1% increase in state residents over 25 years of age possessing a bachelor's degree or higher results in a 9.7% increase in EV registrations per 100,000 residents. Following on from the previous trend, the relationship between education and EV density follows the economic literature, in which increased understanding of EV technology and environmental impacts relates to higher EV ownership rates. With the last of the significant independent variables, income per capita is significant at the 99.9% interval with an interpretation of a 1% increase in income per capita resulting in a 4.014% increase in EV registrations per 100,000 residents. Looking back along the time period in this analysis (2016-2023), EV access in the later 2010s remained somewhat limited due to the luxury status of EVs in the United States, with the most popular US based producer Tesla offering their Model S, their least expensive vehicle in 2016, at 70,000 USD for a stock model (most basic vehicle without additional packages)(Edmunds, 2017). Within the same year, the average cost for a vehicle in the United States was 34,077 USD, illustrating the price differential between the average vehicle market and EVs. Throughout the remainder of the time period, other companies introduced their own models, such as the Nissan Leaf, with the 2025 book price for a stock model starting at 29,280 USD, though the model was available throughout the entirety of the time period (Car and Driver, 2025). Returning to the interpretation of income per capita, the relationship between personal income and EV density is economically founded.

Finally, the interaction between land population density and EV density is slightly puzzling. Though previous empirical literature denotes a strong and significant relationship between the two variables, this model illustrates a weak and statistically insignificant relationship, interpreted as a 1% increase in land population density resulting in a 1.371% decrease in EV registrations per 100,000 residents (Li et al., 2017). Economically, as population density increases, EVs theoretically provide better quality of life as work commutes and daily tasks can be completed within the mileage limits of EV batteries. Additionally, PHEVs may gain increased prominence as population density increases, as the lower capacity batteries of PHEVs can cover smaller commute distances without needing to utilize the gasoline component of the hybrid engine. As previous empirical work analyzed the United States as an individual entity within cross-country studies, further research focused on the relationship between EV ownerships and population density may be required to fully comprehend their correlated effects through specific state or city research.

With the overall results of the regression, a state's renewable energy generation mix is not statistically correlated with EV adoption rates and can not be proven to have a significant effect. As the data in this analysis utilizes gross renewable energy production and public use charging systems, further analysis of personal consumer actions such as solar panel and home charger installation rates may reveal additional insight into the relationship as other options outside of primary electrical generation and charging methods become increasingly mainstream as time progresses. Shown through the model, the primary variables of significance for changes in EV adoption are the price of gasoline, charging density, and income per capita, supported by previous literature and economic principles.

4.2 Clean Energy Regression

Although the relationship between renewable energy access and EV ownership in the United States is not shown to be correlated within the confines of this study, further analysis investigating clean energy may provide new aspects to the interaction of electricity generation and EV adoption. Figures 3 and 4 illustrate the change in the clean energy ratio over the time period. Utilizing a FE regression similar to the previous analysis with substitution of state renewable energy mix for the state's clean energy mix, the new regression maintains the previous independent variables as the renewable energy regression due to their supported empirical significance, with the addition of clean energy generation potentially highlighting the impact on environmentally focused consumers more than the previous model. The expected signs of coefficients are identical to the previous model, with the expected coefficient for clean energy generation being positive and of higher magnitude than renewable energy.

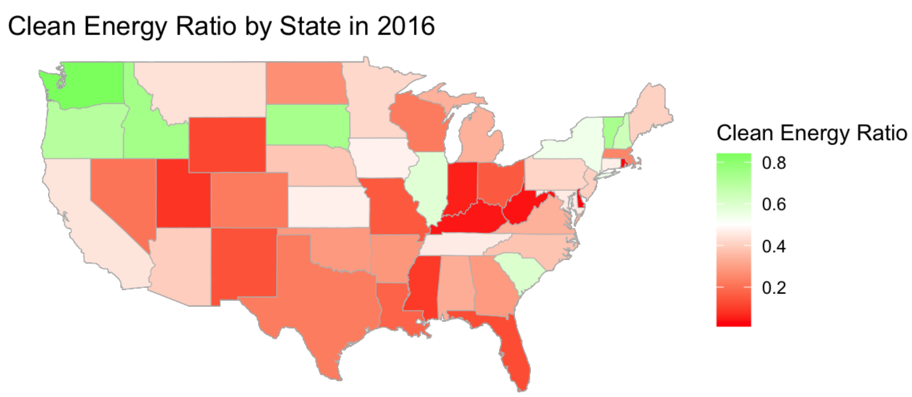

Figure 3: Clean Energy Generation (2016)

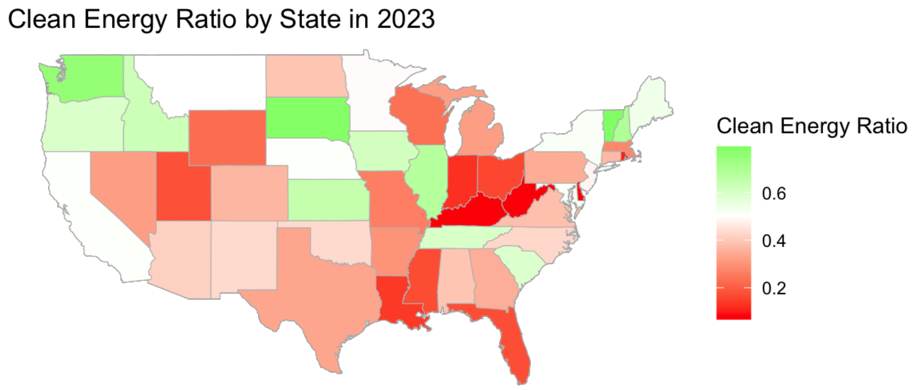

Figure 4: Clean Energy Generation (2023)

Table 6 shows the results of the clean energy regression. All variables including ACTSUB are included; however, following the methodology from the earlier renewable regressions, Model (3) will be discussed economically instead of the other models.

Table 6: FE Clean Energy

Dependent Variable:	**log(EV-DENSE)**			
	(1)	**(2)**	**(3)**	**(4)**
STATE-CLEAN	1.275**	1.282**	0.711	0.701
	(0.474)	(0.473)	(0.441)	(0.442)
log(GASPRICE)	1.019***	0.993***	0.510***	0.520***
	(0.121)	(0.122)	(0.128)	(0.128)
log(CHARGE-DENSE)	0.831***	0.835***	0.494***	0.500***
	(0.069)	(0.069)	(0.077)	(0.077)
EDUC	0.220***	0.209***	0.090***	0.092***
	(0.017)	(0.018)	(0.022)	(0.023)
log(LPOP-DENSE)		1.852	-1.249	-1.313
		(1.216)	(1.183)	(1.186)
log(PERCAPI)			4.094***	4.114***
			(0.509)	(0.510)
ACTSUB				-0.013
				(0.016)
Observations	408	408	408	408
R-squared	0.904	0.905	0.920	0.920
Adj. R-squared	0.889	0.890	0.907	0.907
F-statistic	832.0	668.5	668.7	572.8

Note: All models use state and year fixed effects. Standard errors in parentheses.
$^{\cdot}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

The regression results mirror the previous regression analysis, with the addition of land population density in Model (3) stripping clean energy production of statistical significance at the 99% confidence interval. The independent variables possess coefficients within 0.2 of the previous regression, with the largest change present in the clean energy coefficient, though the variable lacks a presence of statistical significance. There is no notable difference of replacing the electrical generation method in the regressions; however, due to the absence of significance for the clean energy ratio, no definite correlation can be drawn from the new analysis. Looking at the R-squared values for Model (3) in both regressions, the R-squared remained the same in the clean energy model as the renewable energy model, highlighting no decrease in efficiency by replacing the primary independent variable. Following the previous renewable energy regression, the high significance of income per capita can not be ignored, meaning the ratio of clean energy in a state's electrical production possesses no statistically significant effect on EV ownership.

4.3 Additional Regressions

Further regressions with both renewable and clean energy generation are performed, with the omission of the nonsignificant variables of land population density and active subsidies. The statistical significance of the electrical generation ratios remained unchanged as shown in Table 7. All additional independent variables maintained their statistical significance levels from the previous regressions, with the dependent variable remaining as EV-DENSE for both regressions.

Table 7: Significance Tests

Variables	**Renewable**	**Clean**
STATE-RENEW	$0.696^{\cdot}$	
	(0.408)	
STATE-CLEAN		$0.740^{\cdot}$
		(0.440)
log(GASPRICE)	0.524^{***}	0.514^{***}
	(0.128)	(0.128)
log(CHARGE-DENSE)	0.515^{***}	0.511^{***}
	(0.075)	(0.075)
EDUC	0.096^{***}	0.089^{***}
	(0.023)	(0.022)
log(PERCAPI)	3.827^{***}	3.919^{***}
	(0.492)	(0.481)
Observations	408	408
R-squared	0.919	0.919
Adj. R-squared	0.907	0.907
F-statistic	802.2	802.0

All models use state and year fixed effects. Standard errors in parentheses.

$^{\cdot}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

To test any other potential relationship between the variables of interest, two additional regressions were analyzed: the original model with the addition of electricity prices and a new model using gross EV registrations per state instead of the EV density of each state, in addition to taking the real value of each independent variable instead of the logarithm. The results are shown in Table 8 for the electricity price model and for the raw model. The dependent variable in Model (A) remains as EV-DENSE while Model (B) utilizes total registrations through the dependent variable EV-RAW. Both models use state and year fixed effects.

Table 8: Additional Fixed Effects Regression Results

(A) FE Price of Electricity

Variables	Renewable	Clean
STATE-RENEW	$0.676^{\cdot}$	
	(0.409)	
STATE-CLEAN		$0.732^{\cdot}$
		(0.441)
log(GASPRICE)	0.554^{***}	0.549^{***}
	(0.136)	(0.136)
log(CHARGE-DENSE)	0.514^{***}	0.510^{***}
	(0.075)	(0.075)
EDUC	0.098^{***}	0.091^{***}
	(0.023)	(0.023)
log(PERCAPI)	3.824^{***}	3.910^{***}
	(0.492)	(0.482)
ELECPRICE	-0.010	-0.011
	(0.015)	(0.015)
Observations	408	408
Adj. R^2	0.907	0.907
F-statistic	667.5	667.5

Standard errors in parentheses. State and time effects are fixed.

$^{\cdot}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

(B) FE Gross Registrations

Variables	EV-RAW
STATE-RENEW	11079.69
	(69804.89)
GASPRICE	3828.36
	(7621.59)
CHARGE-DENSE	4628.19^{***}
	(911.07)
PERCAPI	1.34
	(1.33)
EDUC	$-7284.70^{\cdot}$
	(3813.88)
Observations	408
Adj. R^2	0.095
F-statistic	19.50

Standard errors in parentheses. State and time effects are fixed.

$^{\cdot}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

While the variable electricity price lacked statistical significance in the renewable and clean models, the price of electricity possesses a negative coefficient which is empirically supported as an increase in substitute fueling prices should decrease EV ownership rates, though the results show the variable as not statistically viable for the purposes of this study. To test the economic significance, further testing is performed and expressed in the robustness check section of this study. Looking at the gross registration data, the omission of logarithms conducted exists to assess the results without the safeguard of homoskedasticity protections. With the previous models, logarithms were included to limit homoskedasticity as performed in previous empirical studies; however, the primary economic analysis relating to this study utilized a cross-country analysis, meaning homoskedasticity could be a larger issue for cross-country studies than research within the United States (Li et al., 2017). Even so, the model produces no tangible or statistical proof for the targeted relationship of this study, especially with the variable education lacking the expected positive coefficient with previous literature and models within this study providing clear statistical evidence of the correlation between the targeted variables and education. An adjusted R-squared value of 0.095 further highlights that using gross data in a US based EV study is highly suggested to be inaccurate.

4.4 Robustness Testing

As the FE regressions fail to produce a causal relationship between the target variables, multiple robustness checks are performed for the data to correct for any potential endogeneity. Using the Arellano and Bond (AB) method for endogeneity testing, EV density is lagged to predict coefficients for the renewable energy ratio and charging density, as shown in Table 9.

Table 9: Robustness Tests: EV Density

Variable	Arellano and Bond Method		Instrumental Variable Method	
	Estimated Coefficient	**p-value**	**Estimated Coefficient**	**p-value**
STATE-RENEW	-0.201	0.64568	-0.216	0.855
log(CHARGE-DENSE)	-0.184	0.06012	Control	
Other Variables	Control		Control	
First Stage Result			-0.0182	3.255e-08
Entity Fixed Effect	Yes		Yes	
Time Fixed Effect	Yes		Yes	
Observations	306		408	

Using the AB method as shown in Table 9, the transformation of the dependent variable fails to prove a significant relationship between renewable energy and EV density, indicating that controlling for dynamic structure lacks a meaningful relationship linking the variables. Interestingly, the AB method indicates that EV charging density possesses a marginally significant p-value though the variable expresses a negatively correlated coefficient when regressed on EV density, meaning that with the lagged variables there may be some reverse causality present. This result does have economic backing, as EV adoption rates could impact the charging density, though this result is not expressed in other literature or the earlier models of this study. With the AB method, an incorrect assumption of the FE regression coefficients results in the real value of the state renewable coefficient lying between the initial FE regression and the AB estimation, meaning that both variable coefficients included in the AB estimation would fall between -0.201-0.698 and -0.184-0.495 for renewable energy and charging density respectively. Based on previous Hausman tests and through the robustness check, the FE model appears to be correctly specified, with the AB estimation providing a lower potential limit for the effect of the primary independent variable. Based on the tabulated p-value, the lack of a significant p-value shows that the estimated coefficient of -0.201 is not statistically different than zero.

To further test data robustness, an instrumental variable (IV) estimator is included to control for endogeneity. Coal consumption is introduced as an instrument for renewable energy, following the process from previous literature (Li et al., 2017). Figure 5 illustrates coal consumption per capita in the United States for 2023.

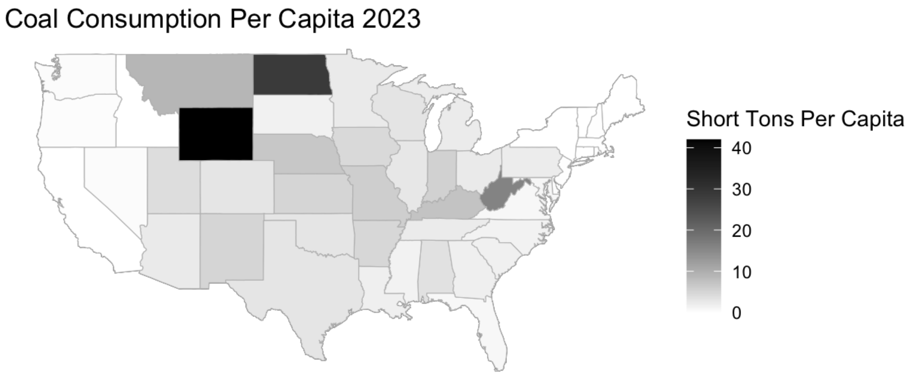

Figure 5: US Coal Consumption Per Capita (2023)

In theory, coal consumption should express opposite effects to renewable energy, as large coal consumption limits willingness to expand into renewable energy sectors or develop renewable energy infrastructure. Using the IV estimation in Table 9, the inclusion of coal consumption is not statistically significant, implying that correcting for endogeneity shows no presence of a strong relationship between renewable energy access and EV density. The complete results for the first and second-stage IV estimation are shown in Table 14 in the Appendix. By isolating the variation in the renewable energy variable using coal consumption per capita, states that use less coal for energy production may possess larger EV density, though this relationship is not shown when controlling for state and year effects. As coal consumption alone has no noted economic or behavioral impact on EV sales, this result provides that increases in renewable energy may not impact EV density in a statistically significant way when controlling for variation. The low p-value of the first-stage regression shows that the coal consumption IV is statistically significant with an expected negative coefficient value, making the instrument statistically valid to use for a second-stage estimation. With a p-value of 0.855 and an estimated coefficient of -0.216 through the second-stage estimation, the presence of a link between renewable energy and EV density is not shown when isolating the variation in renewable energy generation using coal consumption. Though this relationship may not be statistically significant, in terms of renewable energy, states that move away from coal may switch to natural gas, nuclear, or other non-renewable sources. As coal consumption decreases in certain states, EV adoption may not be directly causated with a higher renewable energy share.

4.5 Additional Robustness Check

A final robustness check is performed to assess potential endogeneity within the models. While the price of gasoline, a fueling method for a substitute of EVs (ICEVs), is consistently statistically significant in the primary models, the price of electricity may require restructuring within the model to ascertain significance. An IV estimation is used to simulate the price of electricity to avoid endogeneity as the prices of gasoline and electricity may be economically intertwined: as EV adoption rates rise, the demand for gasoline may decrease while electricity demand increases. To address this issue, the IV estimator is represented as the lagged cost of the fossil fuels of natural gas and coal for electricity generation by region, weighted by individual share of electricity produced by each electricity generation method. In practice, a state or region that uses a higher share of natural gas or coal for electricity production will be more sensitive to a change in the price of gasoline while including the weighted share of each provides an analysis for full fossil fuel usage over the examined time period.

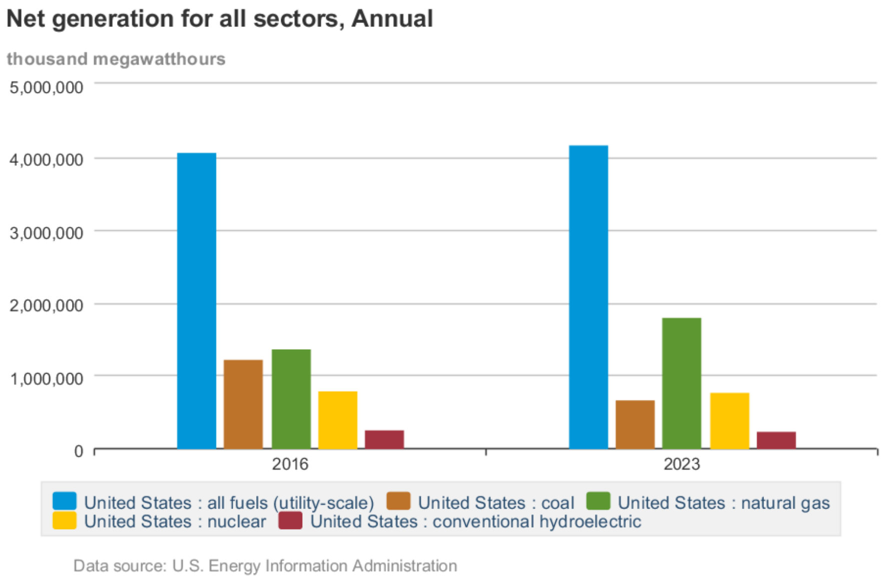

Figure 6: US Net Electricity Generation by Fuel Type (U.S. Energy Information Administration, 2024)

As shown in Figure 6, coal and natural gas constitute a large percentage of energy production in the United States. Though the share of renewable energy is not included in this figure, the fossil fuel generation methods outweigh other large scale generation methods, such as nuclear power. Using the generation methods excluded from the renewable energy share calculations, an IV estimate may provide additional insight into possible endogeneity within the model.

In consideration of this regression, the data structure needs to be addressed. Due to proprietary protections of major electrical companies, a small share of the data available for the cost of fossil fuels consumed for electricity generation is withheld. As a portion of the data is missing, data smoothing is needed to predict median values (ie. a missing value for 2017 can be extrapolated by using the values present for 2016 and 2018). The predictions were made in line with linear growth between two years, following the overall growth trend within the United States. For longer gaps, a linear trend between years is applied to simulate consistent growth over the time period.

Further complicating the data, the cost of natural gas and coal are only available as regional data, leading to some adjustment of the regression analysis. Instead of using state level fixed effects, regions are controlled for in this regression, making the IV estimation economically diverse from the previous regressions in this study. The amount of coal consumed and the amount of natural gas consumed for electrical production both provide a balanced panel after data smoothing, though including the price of natural gas and coal for electrical production requires removing the state-level fixed effects for the analysis in favor of regional fixed effects, while year-level fixed effects remain in place. Regions are divided by geographic area of the United States as follows: East South Central, Middle Atlantic, Mountain, New England, Pacific Contiguous, Pacific Noncontiguous, South Atlantic, West North Central, West South Central. The complete list of US states and their corresponding region are listed in Table 15 in the Appendix. As the data is based on region instead of individual state, including state-level fixed effects would provide colinearity when examining states within the same region, leading to limited and biased effects. As the data are cross-sectional, there is minimal variation between years, providing efficient time FE. The economic implications remain sound with the inclusion of the control variables to account for state-level differences while assessing regional FE.

For this IV estimation, commercial energy prices are used in favor of all-sector energy prices. As the all-sector energy price accounts for greater variation in prices by state or region, the inclusion of residential and industrial energy prices may not address public use charging. As shown in previous modeling, charging density remains highly significant throughout the study and using commercial energy prices directly accounts for public charging and the price of charging an EV on public infrastructure (Bae & Tyagi, 2022). Additionally, commercial energy prices may account for some grid strength, with prices fluctuating in higher demand environments. For the regression, commercial energy prices are shown though the variable ELECPRICE.

Looking at the analysis of the IV estimation, the following equations represent the tested models in the proposed IV estimation. Equation (2) represents the first-stage estimation of the IV regression while Equation (3) represents the second-stage estimation.

$$\begin{aligned}\ln(ELECPRICE_{it}) = \pi_1(FuelMix\_Lag_{it}) + \pi_2 \ln(GASPRICE_{it}) + \pi_3 \ln(CHARGE\text{-}DENSE_{it}) \\ + \pi_4(EDUC_{it}) + \pi_5 \ln(PERCAPI_{it}) + \pi_6(STATE\text{-}RENEW_{it}) + \gamma_i + \mu_t + u_{it}\end{aligned} \tag{2}$$

$$\begin{aligned}\ln(EV\text{-}DENSE_{it}) = \beta_1(\ln(\widehat{ELECPRICE})_{it}) + \beta_2 \ln(GASPRICE_{it}) + \beta_3 \ln(CHARGE\text{-}DENSE_{it}) \\ + \beta_4(EDUC_{it}) + \beta_5 \ln(PERCAPI_{it}) + \beta_6(STATE\text{-}RENEW_{it}) + \gamma_i + \mu_t + \varepsilon_{it}\end{aligned} \tag{3}$$

As the price of commercial electricity, $ELECPRICE_{it}$, may be endogenous or potentially correlated with unobserved factors that also influence EV demand, Equation (2) serves as the first-stage regression of the IV estimation. A visual of the variation in state-level electricity prices are shown in Figure 9 in the Appendix. The instrument $FuelMix\_Lag_{it}$ is constructed using lagged region-level fossil fuel costs weighted by their electricity generation shares, capturing exogenous variation in electricity price driven by input fuel markets. This approach isolates the causal impact of electricity price on EV adoption while controlling for common year-specific effects and mitigating simultaneity bias.

For each variable in the first equation, there is a regression π coefficient to be determined. The fixed effect for each region is represented by γ_i, the fixed effect for year is represented by μ_t, and the random disturbance term is u_{it}. To reduce the level of heteroskedasticity, several independent variables, including EV-DENSE, GASPRICE, CHARGE-DENSE, and PERCAPI, are expressed in natural logarithmic form.

The second-stage equation, Equation (3), measures the effect of commercial electricity prices, gasoline costs, income per capita, education, and renewable energy generation ratios on EV adoption across regions of the United States and stated years of study. For each variable in the second equation, there is a regression coefficient β to be determined in order to estimate *EV-DENSE*. The second-stage equation follows the same processes as the first-stage equation for fixed effects and variables, with the disturbance term for the second-stage represented by ε_{it}.

Multiple variations of the IV estimation are performed, with the following regression the most statistically grounded to estimate an IV for the price of electricity. A comparison between the primary model, an IV with combined lagged fossil fuel mix, and the lagged mixes of coal and natural gas are shown in the Appendix through Table 16. The primary IV model is the estimation of the price of electricity using a region's lagged fossil fuel cost for producing electricity, weighted by share of fossil fuel production inputs. Time based fixed effects are controlled for within the regression, with specific regional fixed effects included in the results. An additional robustness check is performed using residential energy prices to account for home charging, with the results shown in Appendix Table 17.

Table 10: OLS vs. IV using Commercial Energy Prices

Variables	**OLS**	**First Stage**	**Second Stage (IV)**
Dependent Variable:	log(EV-DENSE)	log(ELECPRICE)	log(EV-DENSE)
log(ELECPRICE)	0.1532		-3.9584
	(0.2822)		(2.8454)
log(GASPRICE)	0.4929***	0.1798***	1.3342*
	(0.1407)	(0.0262)	(0.6045)
log(CHARGE-DENSE)	0.5158***	-0.0076	0.4837***
	(0.0750)	(0.0141)	(0.0975)
EDUC	0.0943***	0.0114**	0.1359***
	(0.0231)	(0.0043)	(0.0409)
log(PERCAPI)	3.8200***	0.0845	4.0095***
	(0.4924)	(0.0938)	(0.6372)
STATE-RENEW	0.7073	-0.0142	0.4055
	(0.4086)	(0.0805)	(0.5575)
FuelMix_Lag		0.0037*	
		(0.0015)	
Observations	408	408	408
Adjusted R^2	0.907	0.470	0.853
Residual SS	32.80	1.155	52.64
Diagnostic Tests			
First-Stage Partial F-stat (Wald)			5.629*
Hausman Test (χ^2)			2.1088
Hausman Test (p-value)			0.9094
Overall Model Chisq			2496.41***

Note: All models include time and region fixed effects. Standard errors in parentheses.
Significance: * p < 0.05, ** p < 0.01, *** p < 0.001

Analyzing the validity of the instrument first in Table 10, a weak instrument F-statistic (Wald Test) of 5.629 provides high statistical validity for the inclusion of the instrument, with the IV estimator considered strong for predicting in the second-stage of the regression. Surprisingly, the Hausman test statistic of 2.1088 suggests that the inclusion of regional effects in the ordinary least squares (OLS) model's estimates are not statistically different than the estimates of the IV regression; however, as the OLS estimate results in lower standard error value, the OLS results are statistically preferable to the IV estimation of the price of electricity using a lagged fossil fuel mix.

Examining Table 10, the OLS, the first-stage IV, and second-stage IV estimates are tabulated. The primary coefficient of consideration, the natural logarithm of the price of electricity, shows a non statistically significant coefficient of 0.1532 in the OLS estimate while the IV estimation shows a coefficient of -3.9584 with no significance. Though the Hausman test indicated that OLS is no more efficient than the IV estimate, emphasis is placed on the OLS estimate due to the standard errors; however, the IV estimation shows the affected negative coefficient value for the variable compared to a positive value for the OLS estimation. Though the result is insignificant in the OLS model, the economic meaning is counterintuitive, with a 1% increase in the price of electricity resulting in a 0.1532% increase in EV density. Economic reasoning would argue that the increase of a fuel or input discourages demand for the product, which is supported by the previously modeled effects of the price of gasoline; however, the low magnitude of the coefficient shows an inelastic yet significant positive relationship between the two when controlling for regional effects. The IV estimation provides an economically sound relationship between the variables with a coefficient of -3.9584, though the lack of statistical significance limits a defined relationship.

Additionally, though the model controls for personal income and charging infrastructure through additional regressed variables, some structural trends such as state/region environmental policies remain omitted in this study, potentially influencing the effect of the price of electricity on EV adoption on the regional scale. The majority of the control variables follow similar patterns as previous regressions, with charging density and education maintaining predicted positive coefficients with high significance values.

The variable of interest for this research, the effect of renewable energy on EV density, follows the same pattern and results of previous testing. A lack of statistical significance at a minimum of the 90% confidence interval shows that the availability of renewable energy within a region does not possess a causal effect on EV density. Though the economic interpretation of a 1% increase in the state's average renewable energy generation share would result in a 0.283% decrease in the state's EV density contradicts this study's expected effect, no viable relationship can be drawn from the results of this regression on the effects of renewable energy on EV adoptions.

Broadly examining this robustness check, some interesting observations can be analyzed. By controlling for variation in the price of electricity through regional FE and the weighted share of fossil fuel generation methods, a strong instrument can be extrapolated through the first-stage regression of the IV estimate. Though the second-stage regression provided similar results compared to OLS, weighted fossil fuel shares are shown to have large significance as an instrument for the price of electricity, potentially creating a relationship that can be further explored through a similar study in the research of environmental economics.

Returning to the estimations, the effect of income shows a strong relationship between EV adoption and personal income, with electric vehicles in the United States tending to possess larger price tags and are generally seen as a luxury product, reinforcing the claim that an increase of income theoretically increases EV adoption. The effect of income per capita in the OLS estimate possesses a strong positive coefficient, with a 1% increase in the income per capita resulting in a increase in EV density of 3.82% at the 99.9% confidence interval.

Through the use of this IV estimation, there is no defined link between access to renewable energy and EV adoption when using commercial energy prices. Energy prices themselves do not appear to have a direct correlation to EV adoption either, potentially revealing that American consumers might not weigh costs for the different fueling methods equally. Controlling for energy price effects in the estimations highlights that education, charging density, the price of gasoline, and personal income are extremely significant within the confines of an EV focused study within the United States.

5 Conclusion

This analysis of the United States from 2016-2023 studies the effect of renewable energy access and EV demand using state-level panel data. Of the initial seven independent variables tested, six are deemed appropriate to include in the final fixed effects model, with the omission of active subsidies most likely due to overgeneralization in the data. The following four variables showed significance for the study in the primary FE model: gasoline prices, EV charger density, education, and income per capita. Of the remainder, population density lacked significance while the variable of primary interest, renewable energy generation, failed to produce effective results.

Exclusions added in later models and an Arellano and Bond test reinforced the initial FE model projections, while the various IV estimations of coal consumption and the fossil fuel generation of electricity weighted by input cost as instruments for renewable energy and the price of electricity provided little evidence supporting strong significance of renewable energy impacting EV adoption in the United States during the time horizon of this study. With the results reinforced by an OLS FE model utilizing regional controls instead of state-level controls, all models showed limited effects on the targeted relationship of this study.

Though this study can not determine a direct significant relationship between the target variables as provided in other environmental economic literature, the operation of the United States' renewable energy infrastructure development and behavioral patterns of American residents compared to other countries requires consideration, particularly in consumer energy and behavioral trends.

As this research is focused on interstate trends in the United States, previous economic literature assessing the United States as an individual unit within a cross-country study may fail to account for major differences between the United States and other nations. Examining energy production, specifically fossil fuels, the United States primarily utilizes coal for energy production during the observed time frame of this study, with 2022 estimates showing 594 million short tons of coal produced within the borders of the country. Compared to the European Union in the same year, EU coal production was less than half of the United States production value at 257 million short tons (U.S. Energy Information Administration, 2024). While studies account for some of the observed production, consumption, and price of coal in the United States during the time period of interest, differences in business trends in the electrical generation sector require examination when trying to establish common EV adoption trends between EU countries and the United States in future studies. Compared to the EU, American power producers lack similar financial pressure to switch their grids to renewable or clean sources due to overarching environmental policies influencing fines and regulations.

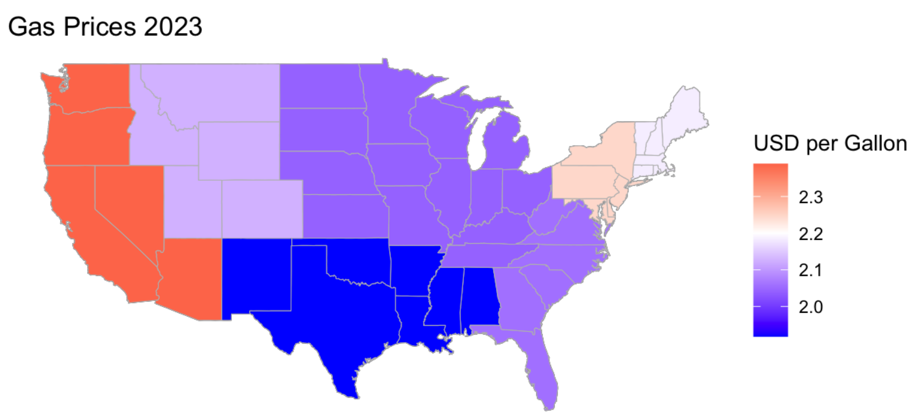

Figure 7: US Regional Gas Prices (2023)

On the consumer side, American residents face little incentive to transition as quickly to EV technology as compared to countries in the EU, as gasoline prices remain comparatively low in the United States. As shown in

Figure 7, the maximum price of gasoline in this study is 4.595 USD per gallon while the June 2025 price of gasoline in Germany is 6.274 USD per gallon or 1.651 USD per liter (Cargopedia, 2025). The literature shows that socioeconomic factors heavily impact EV and renewable energy adoption, yet previous literature maintains a focus on the countries paving the way for EV adoption, countries that lack the abundance of natural resources the United States currently enjoys.

Figure 8 helps visualize the disparity of natural resource abundance between the United States and the EU, focusing specifically on proved natural gas reserves. Reserves for natural gas are defined as commercial reserves that are proved or probable for future extraction. Figure 10 highlights the geography of American natural gas prospect basins for the year 2023. Figure 11 shows the shares of proved natural gas reserves in Europe for 2022. Both figures are included in the Appendix.

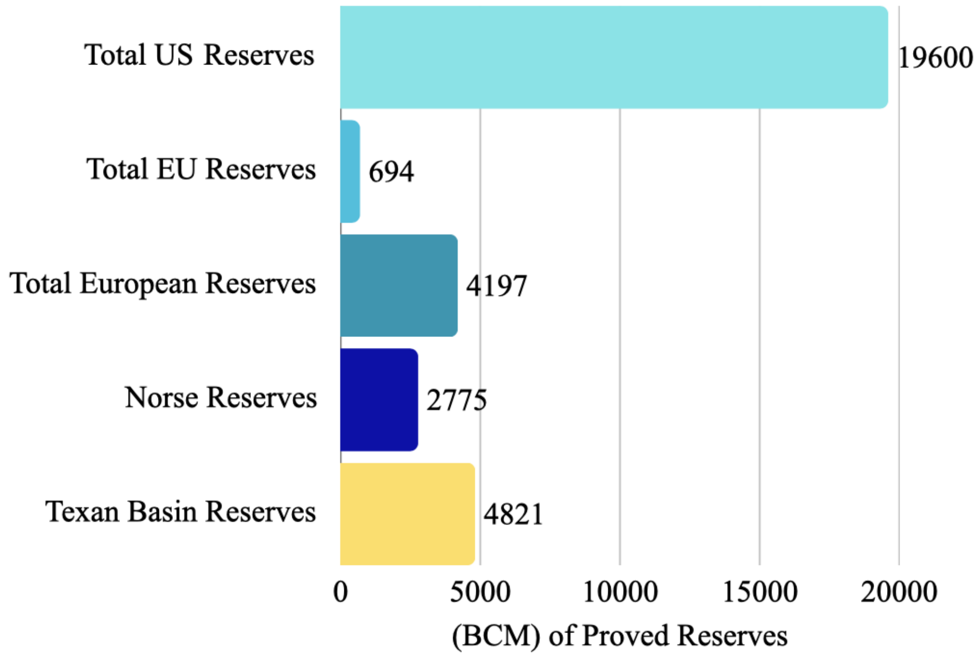

Figure 8: Proved Natural Gas Reserves 2022 (EIA 2023 and IOGP 2022)

Using 2022 as the comparison year, the United States possessed 19,600 BCM (billion cubic meters) of proved natural gas reserves while the EU prospected 694 BCM, with total production of all European nations peaking at 4,197 BCM in that year (International Association of Oil and Gas Producers, 2022). The inclusion of Norway, the lead natural gas producer in Europe for 2022 at 2,775 BCM, tightens the resource gap yet the United States prospected approximately 4.5 times the amount of proved reserves than recorded levels in Europe (U.S. Energy Information Administration, 2023). Examining the maps, the visualized Texan basins alone accounted for 4,821.2 BCM in 2023, approximately 25% of total American proved natural gas reserves and larger than total European natural gas prospects in the previous year (U.S. Energy Information Administration, 2025). The abundance of fuel minerals in the United States creates a differing view on energy compared to European nations, countries where the majority of previous studies concentrate their research. Using this examination of natural gas as a proxy for American fuel mineral resource abundance, the United States possesses a steep advantage in creating large quantities of supply for the energy and fossil fuel sectors, creating a system of limited regulation to encourage fuel extraction. The proven reserves of natural gas indicate that in the absence of a supply shock in American gas reserves, there is little incentive to move away from fossil fuels towards renewable energy sources, especially from a federal regulation standpoint.

As the costs of fueling ICEVs remain low within the United States across the time period of this study, the effect of changes in the price of electricity is deemed insignificant in this study for determining consumer EV demand; however, differences in fueling practices for both vehicles requires attention. In addition to the low cost of fuel, the time efficiency effect of fueling ICEVs appears to be significant both in the literature and in this research. EV charging density maintains a significant effect on EV adoption within this study; however, certain considerations are required to examine this statistic accurately.

This study uses public charging stations to determine charging access while a substantial amount of EV drivers possess private home chargers to fuel their vehicles, usually on the regional grid of their city/county. Though more limited, households utilizing home-installed solar panels can use clean energy production to charge their vehicles. Ignoring the upfront cost of installation, household energy production can affect the relationship between the elasticity of the price of electricity and EV demand due to bidirectional meters lowering long-term energy costs at specific “self sustaining” homes. This observation provides potential insight to the effect of charging an EV, as EV owners can charge at leisure in their home, with most leaving their houses with a full battery charged on household produced electricity, potentially negating public data due to private EV maintenance behavior patterns. The public data also requires some speculation as states that have shorter average commute distances may not see much use in public charging infrastructure and therefore may not experience aggressive growth in charging density if private charging remains the easiest method of charging.

Looking at states with longer commute distances, an EV may not be able to make a round trip on a single charge depending on the model of the vehicle, whereas an ICEV possesses a substantial fueling advantage, allowing for a rapid refueling while an EV can take much longer and face limited charging options along a given route utilizing public charging infrastructure. The uncertainty of EV public charging speed along major commuting routes may drive more Americans to keep their ICEV, removing the uncertain nature of charging and providing security in the event of emergencies. While literature has addressed the charging availability component, a micro-based study would be needed to show at what charging speed Americans would be willing to give up the convenience of gasoline station refueling, especially as fast chargers and V2G grids become increasingly popular.

Examining this topic through a political lens, this study could go further and investigate the cross-country differences in consumer behavioral reactions to environmental legislation between the United States and countries within the EU; however, the large differential in environmental policy regulations of the United States compared to the EU expressly highlights the legislative differences and how Americans view EV purchases in the political sphere.

During the time period of this study, low transportation costs allowed American consumers to buy vehicles based on their personal preferences instead of as a cost-saving measure or due to legislative mandates. In terms of restricting ICEVs, the United States primarily uses incentive and subsidy systems to promote the shift towards accelerated EV adoption instead of limiting current gasoline infrastructure or vehicles, with the notable exception of California, though a case study analysis of California is outside the scope of this research. Within this research, an attempt to quantify incentive and subsidy programs is performed; however, the wide variation across the various states of the US in incentive programs and their durations, from direct cash injections or future tax credits to public and private entities alike, is difficult to measure in regard to this study. Additional microeconomic research into a quantifying measure for incentives specifically targeting EV adoption would be extremely beneficial for a similar study in the future.

Within this analysis, the personal preferences throughout the time period appear to be quality of life focused, with fuel costs and ease of access to charging networks driving EV adoption, overshadowing the environmental impacts of EVs and electricity generation. Though this analysis does not include complete gasoline fueling station densities, as charging stations approach parity with gasoline stations a behavioral shift may occur with EV purchases; however, as of the current moment, the technology that would allow EVs to charge at a similar speed to fueling an ICEV does not exist, further limiting the ease of access EVs can achieve compared to gasoline vehicles.

Though this study is constrained by the time period 2016-2023, there is a noticeable sustained upward trend in EV development and green technology in both the United States and the global vehicle market. Shown in the data, the United States is making a gradual progression towards EV input cost parity with ICEV inputs which could lead to different results of a similar study using more modern data. As time goes on, opportunities for further research into this topic will expand and the behavioral consumerism of Americans may adapt to the progressive nature of EV adoption.

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7 Appendix

7.1 Tables

Table 11: Hausman Test for Model Consistency

Test Statistic	Degrees of Freedom	p-value
$\chi^2 = 113.79$	5	$< 2.2 \times 10^{-16}$

Note: The Hausman test compares the fixed and random effects estimators. A significant test statistic indicates that the random effects model is inconsistent, and the fixed effects model should be preferred.

Table 12: First Stage ADF on Select Lagged Variables

Variable	**Statistic**	**P-value**	**Variable**	**Statistic**	**P-value**
log(EV-DENSE)	-3.013	0.1493	d_log(EV-DENSE)	-8.999	0.0100
STATE-RENEW	-8.039	0.0100	log(GASPRICE)	-3.366	0.0599
d_log(GASPRICE)	-7.059	0.0100	log(CHARGE-DENSE)	-3.490	0.0436
d_log(CHARGE-DENSE)	-7.373	0.0100	EDUC	-5.324	0.0100
log(LPOP-DENSE)	-5.803	0.0100	d_log(LPOP-DENSE)	-11.995	0.0100
log(PERCAPI)	-3.745	0.0219	d_log(PERCAPI)	-7.292	0.0100
ACTSUB	-5.360	0.0100			

Table 13: Engle-Granger Test Results

Test Statistic (Dickey-Fuller)	Lag Order	p-value
-4.6949	7	0.01

Note: The ADF test was applied to the residuals from the cointegration regression. A p-value of 0.01 indicates rejection of the null hypothesis of a unit root, supporting stationarity.

Table 14: Robustness IV Regression Results

Variables:	**First Stage**	**Second Stage**
Dependent Variable:	Renewable Energy	EV Density
log(GASPRICE)	-0.2947*	-2.1426*
	(0.1187)	(0.8883)
log(CHARGE-DENSE)	0.0100	0.2614***
	(0.0102)	(0.0686)
EDUC	-0.0093**	-0.0044
	(0.0033)	(0.0265)
log(PERCAPI)	0.3293**	-0.6185
	(0.1157)	(0.9060)
ELECPRICE	0.0005	-0.0422**
	(0.0021)	(0.0137)
Coal Consumption Per Capita	-0.0182***	
	(0.0032)	
STATE-RENEW		-0.2157
		(1.1780)
Observations	408	408
Adjusted R^2	0.032	-0.061
Residual SS	0.475	21.105
F-statistic / Chi-square	12.746	40.924

Note: All models include time and state fixed effects. Standard errors in parentheses.

$^{\cdot}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 15: States and Regions (U.S. Census Bureau Definitions)

State	**Region**	**State**	**Region**
Alabama	East South Central	Nebraska	West North Central
Alaska	Pacific Noncontiguous	Nevada	Mountain
Arizona	Mountain	New Hampshire	New England
Arkansas	West South Central	New Jersey	Middle Atlantic
California	Pacific Contiguous	New Mexico	Mountain
Colorado	Mountain	New York	Middle Atlantic
Connecticut	New England	North Carolina	South Atlantic
Delaware	South Atlantic	North Dakota	West North Central
District of Columbia (DC)	South Atlantic	Ohio	East North Central
Florida	South Atlantic	Oklahoma	West South Central
Georgia	South Atlantic	Oregon	Pacific Contiguous
Hawaii	Pacific Noncontiguous	Pennsylvania	Middle Atlantic
Idaho	Mountain	Rhode Island	New England
Iowa	West North Central	South Carolina	South Atlantic
Kansas	West North Central	South Dakota	West North Central
Kentucky	East South Central	Tennessee	East South Central
Louisiana	West South Central	Texas	West South Central
Maine	New England	Utah	Mountain
Maryland	South Atlantic	Vermont	New England
Massachusetts	New England	Virginia	South Atlantic
Michigan	East North Central	Washington	Pacific Contiguous
Minnesota	West North Central	West Virginia	South Atlantic
Mississippi	East South Central	Wisconsin	East North Central
Missouri	West North Central	Wyoming	Mountain
Montana	Mountain		

Table 16: Second Stage IV Regression Results
Using Alternative Fuel Mix Instruments

Variables:	**Coal and Nat Gas Mix**	**Coal Mix**	**Nat Mix**
Dependent Variable:	EV-DENSE	EV-DENSE	EV-DENSE
log(ELECPRICE)	-3.958421	-2.746154	19.078515
	(2.845387)	(2.461417)	(36.055875)
log(GASPRICE)	1.334215*	1.086175*	-3.379331
	(0.604465)	(0.524466)	(7.392732)
log(CHARGE-DENSE)	0.483705***	0.493174***	0.663646
	(0.097484)	(0.087589)	(0.396061)
EDUC	0.135925***	0.123664***	-0.097068
	(0.040858)	(0.036077)	(0.374460)
log(PERCAPI)	4.009496***	3.953614***	2.947551
	(0.637197)	(0.572732)	(2.471703)
STATE-RENEW	0.405483	0.494482	2.096758
	(0.557506)	(0.499208)	(3.050694)
Year Fixed Effects	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes
Observations	408	408	408

Note: All models include time and region fixed effects. Standard errors in parentheses.

$^{\cdot}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 17: OLS vs. IV using Residential Energy Prices

Variables Dependent Variable:	**OLS** log(EV-DENSE)	**First Stage** log(RES-ELEC)	**Second Stage (IV)** log(EV-DENSE)
log(RES-ELEC)	0.3615		-3.7686
	(0.2806)		(2.7142)
log(GASPRICE)	0.4651***	0.1377***	1.1412*
	(0.1361)	(0.0263)	(0.4732)
log(CHARGE-DENSE)	0.5104***	0.0119	0.5586***
	(0.0749)	(0.0141)	(0.1002)
EDUC	0.0924***	0.0109*	0.1319***
	(0.0230)	(0.0043)	(0.0390)
log(PERCAPI)	3.7902***	0.1423	4.2110***
	(0.4921)	(0.0941)	(0.6372)
STATE-RENEW	0.7378	-0.0532	0.2613
	(0.4085)	(0.0808)	(0.6052)
FuelMix-Lag		0.0038*	
		(0.0015)	
Observations	408	408	408
Adjusted R^2	0.907	0.516	0.852
Residual SS	32.67	1.162	52.84
Diagnostic Tests			
First-Stage Partial F-stat (Wald)			6.174*
Hausman Test (χ^2)			2.3406
Hausman Test (p-value)			0.8859
Overall Model Chisq			2486.85***

Note: All models include time and region fixed effects. Standard errors in parentheses.
Significance: * p < 0.05, ** p < 0.01, *** p < 0.001

7.2 Figures

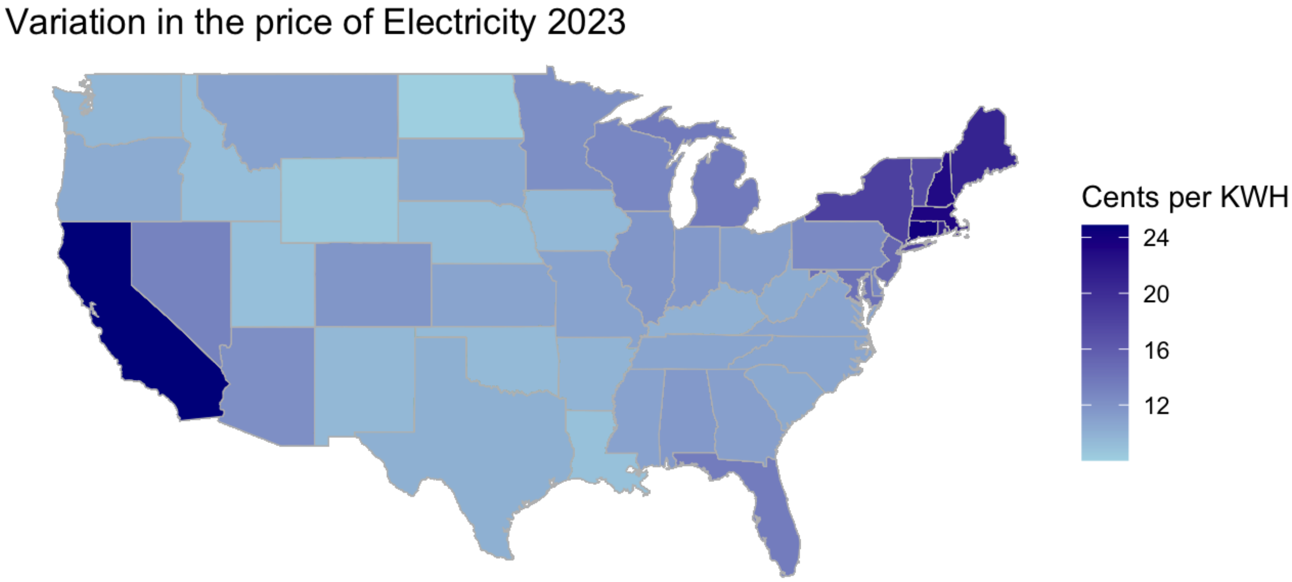

Figure 9: US Price of Electricity 2023

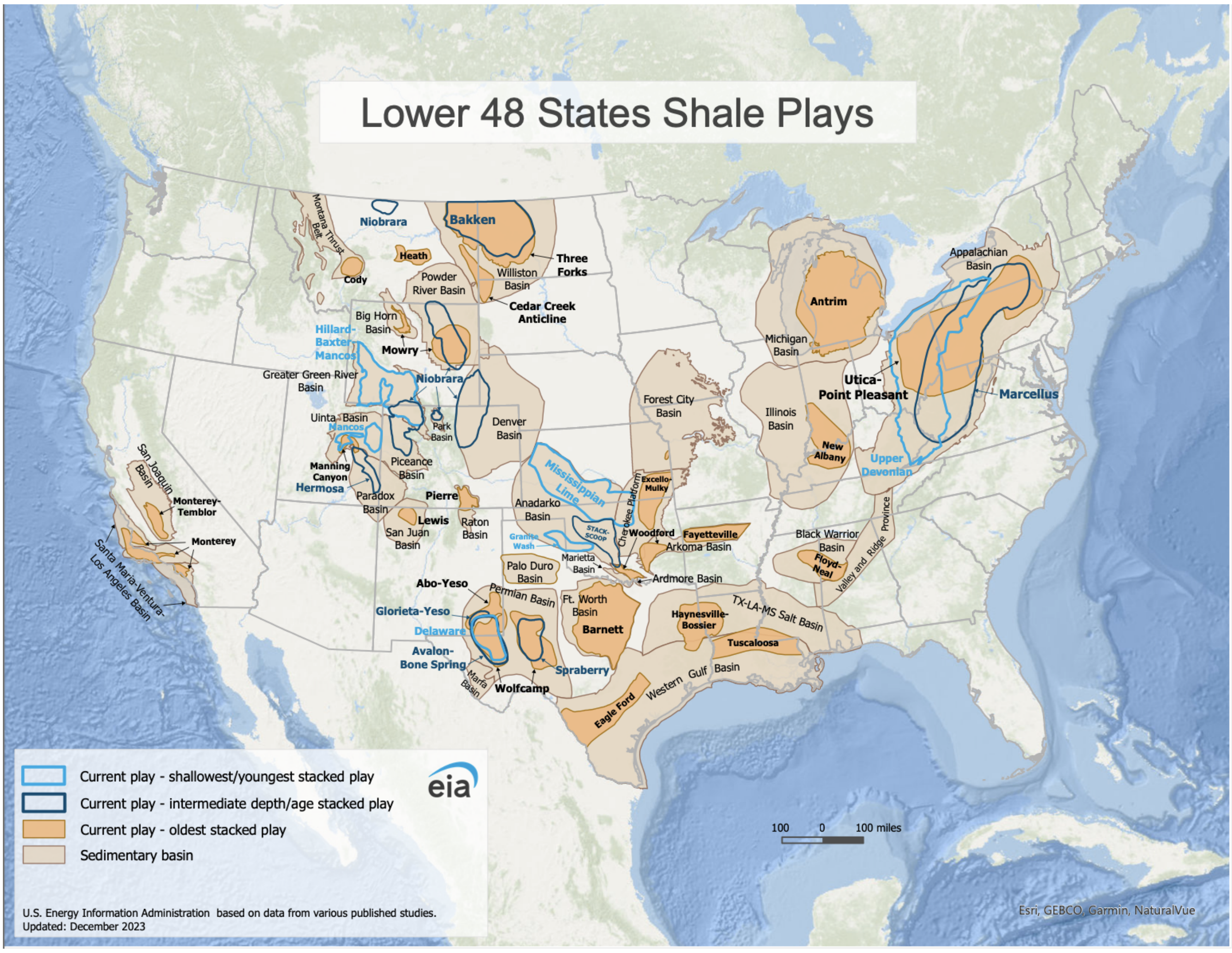

Figure 10: American Natural Gas Prospecting (2023)

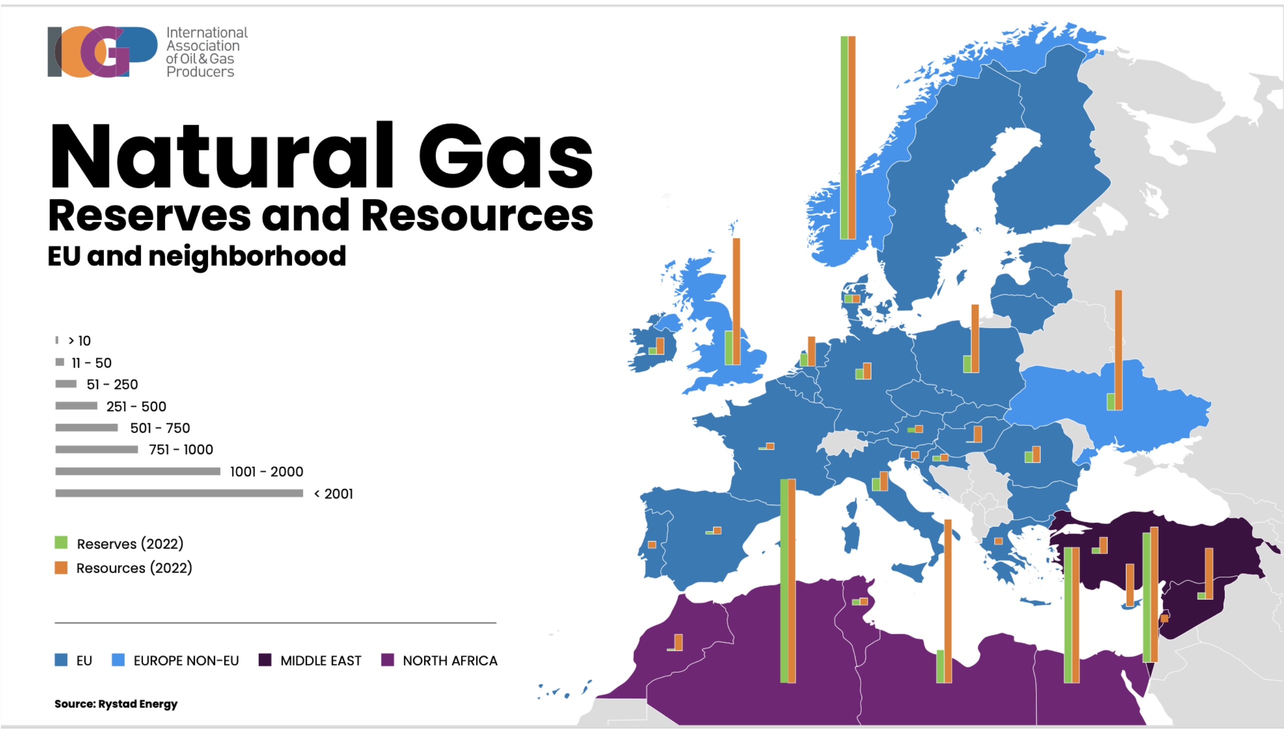

Figure 11: European Proved Reserves (2022)