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Impact of Charging Infrastructure on Electric Vehicle Sales: An Analysis from Counties in 13 US States

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Adoption of battery electric vehicles (BEVs), and plug-in hybrid electric vehicles (PHEVs), has become a priority for the government because of the constant threat of climate change. Over the years, government monetary incentives like tax credits, tax rebates, and other monetary subsidies are the leading way to increase electric vehicle sales in the United States. While these incentives are necessary to combat the high costs of electric vehicles (EVs), there hasn't been too much attention given to combat range anxiety. Since EVs are run on lithium-ion batteries, there is a limited range for different EVs, with the maximum being around 400 miles on a full charge. Charging Infrastructure is a way to reduce range anxiety and further incentivize EVs in the United States. Many states have different incentives for private gas station owners to build charging stations to increase EVs in a state. I use an Ordinary Least Squares (OLS) model to see the impact of charging infrastructure on EV registration from the year 2018- 2022 on a county level in 13 states. In order to see the true effect of charging infrastructure, I control for monetary incentives using state * year interaction fixed effects, total vehicle registration in each of the counties, income, and population. I find that Charging Infrastructure has a positive significant relationship with EV registrations.

Keywords

battery EV, plug-in hybrid EV, electric vehicles, charging infrastructure, charging station, incentives

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An analysis from Counties in 13 US States

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Honors Thesis

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Adoption of battery electric vehicles (BEVs), and plug-in hybrid electric vehicles (PHEVs), has become a priority for the government because of the constant threat of climate change. Over the years, government monetary incentives like tax credits, tax rebates, and other monetary subsidies are the leading way to increase electric vehicle sales in the United States. While these incentives are necessary to combat the high costs of electric vehicles (EVs), there hasn't been too much attention given to combat range anxiety. Since EVs are run on lithium-ion batteries, there is a limited range for different EVs, with the maximum being around 400 miles on a full charge. Charging Infrastructure is a way to reduce range anxiety and further incentivize EVs in the United States. Many states have different incentives for private gas station owners to build charging stations to increase EVs in a state. I use an Ordinary Least Squares (OLS) model to see the impact of charging infrastructure on EV registration from the year 2018- 2022 on a county level in 13 states. In order to see the true effect of charging infrastructure, I control for monetary incentives using state * year interaction fixed effects, total vehicle registration in each of the counties, income, and population. I find that Charging Infrastructure has a positive significant relationship with EV registrations.

Keywords: Battery EV (BEVs), Plug in Hybrid EV (PHEVs), EV (EVs), Charging Infrastructure, Charging Station, Incentives.

Introduction

Electric Vehicles (EVs) have grown in popularity after the need to decrease carbon emissions. In 2016, Tesla produced approximately 75,000 cars and in 2021, the same company produced approximately 700,000 cars: a nearly 800% increase in 7 years (Carlier, 2023). This is a similar trend with other EV manufacturers showing that EVs are growing in popularity. EVs are run on lithium-ion batteries that need to be charged via a public charging station or charging ports installed in the house. In return, there is fewer greenhouse gas emission by EVs as it is operated via a battery in contrast to internal combustion vehicles that emit CO2 in the atmosphere. The EPA predicts that a typical gas-powered vehicle passenger emits 4.6 metric tons of carbon dioxide per year (2022). According to the IEA, energy security is a "lifeblood" of the modern economy, and with the growing security issues, reliance on imports of fossil fuels hinders a nation's energy efficiency. Therefore, adoption of EVs are a crucial way to have energy security while also limiting effects of climate change.

There are two main roadblocks to adopting EVs: the increased cost and range anxiety. While EV owners spend less money on fuel prices, due to lack of technology, the prices for EVs are still significantly higher than gas-powered vehicles, about $10,000 price difference (Lindwall, 2022). To promote EVs, the federal government provides a $7500 tax credit for purchase of a new EV (IRS 2023). Nevertheless, according to J.D. Powers, a private research company, consumers are hesitant to buy EVs due to range anxiety (Wardlaw, 2020). Range anxiety is the worry consumers have that the EV they drive will run out of battery before reaching a suitable battery station or their destination. This is a critical concern for most buyers as many states in the US don't have good infrastructure for EV charging stations (Kampshoff, Kumar, Peloquin, Sahdev, 2022). The FAST act authorizes the installation, operation, and maintenance of electric vehicle supply equipment (EVSE) for the purpose of recharging privately owned vehicles under the custody or control of the General Services Administration or the Federal agency (2015). This act extends to having workplaces provide charging stations for their employees and it contains a roadmap for agency workplace charging programs and defines roles and responsibilities.

On February 15, 2023, the Biden- Harris administration extended their efforts to build a national network of electric vehicle chargers by building 500,000 chargers along the national highways (The White House: Fact Sheet, 2023). Since this infrastructure law is fairly new, there hasn't been too much research about the impacts of charging infrastructure on EV sales in the US. Prior research shows that charging infrastructure has a positive relationship with EV sales when looking at state level data. Since this is a fairly new topic, EV market data for plug-in hybrid vehicles is used along with EVs for the year 2011- 2015 on a state level.

In my research, I analyze the effect of charging infrastructure on EV sales on a county level in 13 states in the United States. I use county level data because county-level associations can better account for regional trends not captured by state data. I use an Ordinary Least Squared (OLS) model with fixed effects to control for the changes within a county, within a year and within a state and year the county is based in. I find that charging stations have a significant positive relationship with EV sales when controlling for federal incentives, state-level incentives, income, total population, education, unemployment, and total vehicle share. I use Gas Stations as my instrumental variable to solve the reverse causality while also exploring other instrumental variables like Alternative Fuel Stations and Business Establishments. My second stage results show that an increase in one charging station per person would increase EVs by 52.

Background (Literature Review)

The significance of EVs have been identified by multiple authors to combat the ongoing issues with climate change while also creating energy security within a country. Countries in Europe and China are increasing their efforts to promote EV and lower their carbon footprint in the world (IEA, *fast publicly available chargers*, 2021). The most decisive way to make this change is by promoting technological advancements and increasing incentives that promote electric vehicle sales. EVs are also linked with population density, education, GDP per capita, and income per capita (Vergis et Chen, 2015). Prior literature mentioned below summarizes the research that has been conducted by economists in different parts of the world. These articles provide a blueprint for my research as I intend to build upon the knowledge that is already published by using different control variables and conducting my research through a smaller unit of observation.

Federally, the most popular incentive provided by the government is the $7,500 tax credits for electric vehicle purchase (IRS, 2023). While this is a substantial amount, tax credits aren't promised to every household and at the same time, the amount varies from household to household. Some other incentives provided by the government are in the form of rebates, toll credits, access to HOV lanes and other monetary incentives (Department of Energy: Alternative Fuels Data Center (AFDC), 2023). I am going to focus my research on charging infrastructure while also considering the effects of other incentives provided by the state and federal governments.

Hardman et al. (2017) evaluate the effectiveness of financial purchase incentives for battery EV in the United States. This article is a thorough review of prior research in a similar area. Their findings show that incentives that are provided before the purchase of an electric vehicle are significantly more beneficial than incentives that are provided after. They also conclude that incentives show significant results when they are applied to BEVs rather than PHEVS. One of the key components of this paper was the effectiveness of tax exemptions on electric vehicle purchase rather than subsidies for private sectors.

While incentives are slowly going out of favor, prior research shows that incentives have a significant impact on electric vehicle sales in the United States. In an article by Jenn et al. (2018), they measure the effect of monetary and non-monetary incentives on the adoption of EV. Their results show that every $1000 offered as a rebate or tax credit increases average sales of EV by 2.6%. This includes monetary incentives provided by both the state and the federal government. Similarly, they find that HOV lane access is a significant contributor to EV, with an effect of a 4.7% increase corresponding to density of HOV lanes (every 100 vehicles per hour). These results match the results found in a paper published by the Massachusetts Institute of Technology Energy Initiative, where two researchers study the impact of financial incentives on battery electric vehicle adoption (Clinton & Steinberg, 2019). They use national level data and account for state level incentives in their regression analysis and accounting for variation in years from 2011- 2015. Their results show that incentives offered as direct purchase rebates generate increased levels of new BEV registrations at a rate of approximately 8 percent per thousand dollars of incentive offered. Vehicle rebate incentives are associated with an increase in overall BEV registrations of approximately 11 percent.

In a more global view, many countries in Europe have begun the pursuit of cleaner vehicles earlier than the United States. Similar to the US, European countries have also implemented EV purchase incentives in monetary and non-monetary form. Münzel et al. (2019)

look at the impact of incentives in 32 European countries from 2010 to 2017. In their regression analysis they control income, fuel prices and other economic factors that might increase EV adoption. They use year fixed effects and account for the change in incentives for different countries in that time period. Results showed that incentives have a positive relationship with EV adoption in European countries with an effect of 5-7% increase in EV sales for an additional €1000 in incentive subsidies. He et al. (2018) also looks at how incentives provided by the government affect EV sales. They find that the termination of HOV lanes leads to a decrease in EV sales. This negative effect is also greater in counties where the work commutes are longer and household income is higher. This shows that incentives have an effect on EVs and thus should be used to promote EVs. In another article, Gu et al. (2017) discuss the effects of government subsidies and battery recycling programs on EV manufacturers' production strategy. They hypothesize that an increase in both these sectors would lead to an increase in production. The main issue they tackle in this paper is the battery recycling rate; since many households are changing to EVs, the near future looks to have an abundance of used batteries. In order to efficiently use EVs and have the least impact on the environment, manufacturers and government subsidies should incentivize the battery recycling rate. The authors use a profit function and utility maximization function to back their theories.

Hardman et al. (2017) discuss the incentives people have to buy an EV compared to an internal combustion engine vehicle. They suggest that the incentives provided by the government (around \$2500- \$20000) are not enough for consumers to purchase an expensive commodity like an EV. This article looks at past literature on purchase incentives and how that has motivated consumers to buy EVs. Simultaneously, it also looks at how sales have not increased even with the implementation of policies that should have produced more sales. One of the key findings from their data suggests that consumers held high importance on incentives and played a big role in their willingness to buy an EV. Thus, it was important to look at other types of incentives or policies that may increase EV sales. Nadine, et al. (2015) write about range anxiety among people considering purchasing EVs. In this paper, they compare experienced BEV drivers and inexperienced BEV drivers to look at the difference between range anxiety for these two groups. They find that more experienced drivers tend to have less range anxiety and thus conclude that it is important to have experience driving BEVs. Additionally, it is important to educate consumers on how to use BEVs to reduce the wrong notion about range anxiety. While this paper talks about the issues with EV promotion and Range anxiety, it doesn't give a statistical analysis of incentives or policies as a way to improve EV sales.

Insights from prior research suggest that incentives have the ability to influence EV sales in the United States of America however growing interest in charging station incentives and concerns regarding range anxiety show that charging stations are a vital aspect of EV sales. My research could help policy makers make informed decisions about how to incentivize customers to buy EVs without having a financial burden. Policymakers can then make thorough decisions about the allocation of funds towards incentives. My research also pertains to county level observations in 15 states that range from large population states like California, New York, and Texas to small population states like Montana and Vermont. This provides a comprehensive population for my analysis as different states promote EVs via different incentives.

Theoretical Framework

Charging infrastructure is vital for long range commutes as EVs have a limit on how far they can travel on one charge. The maximum miles traveled on EVs is about 400 miles on a full charge, although many existing automobile companies are trying to increase the mileage (Dungs, 2022). A new startup, Lightyear, is trying to create a solar EV that would have a mileage of 500 miles; this is still a work in progress and thus doesn't solve the issue of range anxiety (Doll, 2023).

EVs are very new to the market compared to regular gas-powered vehicles since they were only widely introduced in the late 2000's when Tesla came out with their first EV model. Although there were EVs and hybrid vehicles before Tesla's first model, they were not widely popular because they were mainly designed to be used locally for short distances. Since the 2016 Paris COP summit, there was an agreement, which was agreed upon by the United States, to keep the global temperature below 2 degrees Celsius and to pursue efforts to limit the temperature increase even further to 1.5 degrees Celsius (Paris Agreement, 2016). There has been a more advanced effort to create net-zero economies on a state and country level. One of the main contributors to greenhouse gases is gas powered vehicles, so the government is incentivizing automobile companies to make electric vehicles.

One of the ways to incentivize the public to change their behavior towards EV purchases is to incentivize using monetary and other benefits. In the past, EV purchases came with benefits such as tax credits and rebates from the federal government up to $7500 (IRS, 2023). Different states have used other mechanisms like HOV lane access, toll discounts, additional credits, and tax benefits. Some states like California and New York, have been successful in implementing incentives that benefit the public and thus promote EVs. In recent years, EV incentives have become unpopular and households that have range anxiety are hesitant to purchase EVs. In this case charging infrastructure will prove to incentivize households that worry about range anxiety.

I argue that Charging infrastructure will increase EV sales as consumers will not worry about the running out of battery before they reach a suitable charging station or their destination.

To see the relationship between electrical vehicle incentives, particularly charging infrastructure, and electrical vehicle registration, I use a function that predicts that an increase in electric vehicle incentives will lead to an increase in electric vehicle registration:

$$\text{Electrical Vehicle Registration} = f\,(\text{Charging Infrastructure})$$

Where my independent variable and dependent variable have a linear relationship due to the measure of impact incentives can have on electric vehicle sales.

My model shows that electric vehicle incentives, particularly Charging Station count per capita in each county will increase electric vehicle registration per capita in that county. Using this theoretical model, I theorize that there will be an upward-sloping, positive relationship, linear model for the relationship between charging stations and electric vehicle registration.

Model

I estimate the relationship between charging infrastructure and electric vehicles using a linear reduced- form model. The main challenge to estimate the relationship between my dependent and independent variable are extraneous variables that factor into the regression. Many of these variables can be accounted for with information in data collected by the American Community Survey, the Census Bureau and the Department of Transportation such as population, net income, education, commuting patterns and unemployment. Unobserved factors such as monetary incentives, HOV lane access, percent population that works in another county or state are more problematic to control for as data is not available for these variables on a county level. For example, individuals who spend more time traveling will benefit from charging infrastructure than individuals who do not travel. Similarly, counties that have more people owning EVs will have a higher demand for charging stations.

To address the question regarding the relationship between charging infrastructure and electric vehicles, we model using two different equations.

$$(1)\quad Y_i = \beta_0 + \beta_i X_i + \beta_h X_h + \varepsilon_i$$

Where Y_i electric vehicle share and X_i is charging infrastructure in the form of charging station count. X_h are control variables for charging infrastructure and electric vehicles.

When running my regressions with other variables such as population, total vehicle in counties, and income distribution; I model this equation as a control on charging infrastructure.

$$(2)\quad Y_i = \beta_0 + \beta_i X_i + X_h \beta_h + \varepsilon_i$$

Where β_h shows the coefficient of , which are all my control variables including all the nonlinearities, the natural log of adjusted net income. In doing so, I can analyze the relationship between charging infrastructure and electric vehicles controlling income distribution in different counties. Similarly, I do the same thing with total vehicle share to improve my variance of the regression. I also include interaction variables that tell me the effect of a variable given my independent variable.

I use a fixed effects model to eliminate variables that are constant over time such as region, climate change, federal and state incentives, etc. In my research I use year fixed effect and county fixed effect to eliminate these biases. In doing so, I create a model that predicts changes for one particular county and changes in one particular year.

$$(3)\ \ Y_{it} = \beta_0 + \beta_1 X_{it} + X_{it}\,\beta_h + \alpha_i + \lambda_t + \varepsilon_i$$

Here, α_i is my fixed effects for the county and λ_t is the fixed effect for time, measured by county. This particularly allows me to get rid of effects such as pandemics, recessions and other variables that have occurred throughout the world.

To control changes at a state level, I use a State * Time fixed effects that will capture the changes made at a state level for the counties residing in those states. This will allow me to control the change in state incentives as they apply to all the counties in that particular state.

$$(4)\ \ Y_{it} = \beta_0 + \beta_1 X_{it} + X_{it}\,\beta_h + \alpha_i + \lambda_t + \delta_{st} + \varepsilon_i$$

Here, delta (δ_{st}) is the state * time interaction fixed effect to control for the changes made in a state on a yearly basis. In doing so, I control state laws like monetary incentives, infrastructure laws, education standards, etc.

I also use a model with an instrumental variable in order to control for instrumental variables.

$$(5)\ \ X_{it} = \pi 0 + \pi\ 1\ Z_{it} + \pi\ h\ X_{it} + \alpha_i + \lambda_t + \delta_{st} + \varepsilon_i$$

$$(6)\ \ Y_{it} = \beta_0 + \beta_1 X_{it} + \beta_h X_{it} + \alpha_i + \lambda_t + \delta_{st} + \varepsilon_i$$

Z_{it} represents a gas station count variable that charging infrastructure without directly affecting Electric Vehicles. This is my first stage OLS model regressing charging infrastructure, dependent variable, on gas station count, instrumental and independent variable (5). In my second stage model, I use Y_{it} to represent electric vehicle share and X_{it} to represent the change in charging infrastructure (6). Similarly, I use Alternative Fuels Stations as another instrumental variable that allows me to use all 13 states from my vehicle registration data. As mentioned above, I use the equation (4) for my first stage regression and equation (5) for my second stage regression.

The results for my regressions will be presented by showing a unit change in my dependent variables, based on the change in my independent variable. These results change when I add more control variables to my regression, making my analysis more sound and compelling. The instrument variable affects my independent variable without any relationship to my dependent variable. This will estimate the true causal effect that my independent variable has on my dependent variable.

Data

I will be using data from the Department of Energy for Charging stations in each state and zipcode, this is measured using other charging station data sources like Blink, ChargePoint, Electrify America, EVgo, FLO, Greenlots, SemaConnect, OpConnect, and Webasto, via each network's application programming interface. The data provides information from 2007 to 2022. The raw data comes on a zip code level that needs to be aggregated to county level data. Some of the other variables included in the dataset are EVSEs, City, State, address, charging station type, Private/Public, and open date. I use Geocodio, a geocoding website, to match the zip code, City, State and Address to correspond to the county that it belongs in. After further exploration of the data, one of the issues with cleaning the data for an OLS regression model was the duplicates in county names. For example, since there are many counties across different states with the same name, I instead use county GEOID as a unit of measurement. GEOIDs are numeric codes that uniquely identify all administrative/legal and statistical geographic areas for which the Census Bureau tabulates data (United States Census Bureau). This is a 5-digit unique number that identifies the state and county, the first two digits uniquely identify the state, and the last three digits identify the county.

I use EV registration data from EV Hub that collects their data through affiliation with state governments that are willing to participate in this initiative. The source provides data for 13 states in the United States with the unit of observation being zip code. The States included in the data are California, Colorado, Connecticut, New Jersey, New York, Oregon, Minnesota, Montana, Texas, Washington, Wisconsin, Virginia, and Vermont. I have EV registration data for the years 2018- 2021 because that is the time frame I had data for all the 13 states mentioned above. Other variables for each observation include registration date, VIN model, VIN number, state, vehicle type, vehicle model, and vehicle make. I intend to use vehicle models and vehicle make in my regression to analyze the relationship of just tesla vehicles and tesla charging stations. The vehicle registration data was a little more tedious to work with as the dataset came only on a zip code level. I could not use Geocodio to convert the zip code to county GEOID as the address and city name was not available.

I use a master file that has a list of all GEOID codes corresponding to zip code, county name, county code, state code. I could not use the merge tool through Stata to correspond the zip codes in my vehicle registration file and charging station file to the county names associated with it because there are multiple zip codes in the United States that correspond to two or more counting. There are more than 9000 zip codes in the United States that associate with two or more counties. In this case, I had to manually assign zip codes with equal weights to different counties. To do so, I use the 2021 population data for each county GEOID using the American Consumer Survey. I correspond the population of each county GEOID to my master file of all GEOID to zip code using the merge code in Stata. I then merge my master GEOID and population file with the vehicle registration file. This gives me vehicle registration data that corresponds to county statistics depending on the population of the county.

For my control variables, I use county transportation profiles from the US Department of Transportation that provide variables like population that commutes. I also use the American Community Survey to extract county demographics data like total population, education attainment (population over the age of 25 that have a high school degree), population of white/Caucasian, population that is unemployed and income. The American Consumer Survey reports estimates based on consumer survey data that is recorded each year. They report a one-year estimate and a five-year estimate for each year. The one-year estimate is recorded using survey data from just one year, whereas the five-year estimate data uses the surveys from the previous 5 years to report the data. The five-year estimate is more accurate, however, the American Consumer Survey does not have a five-year estimate for 2020 due to the pandemic and thus I use the one-year estimates for all the years to keep my data consistent. The data also differs in the total counties that are measured; for example, some datasets only record data for half the total number of counties. Therefore, it's tricky to find data that corresponds to the counties that have an EV registration and Charging Station data.

Based on prior research, I estimate that income per capita will have positive relationship with EV registration because EV's cost significantly more than Gas-powered vehicles (NRDC). Therefore, including income in my analysis will account for the changes in EV registration based on county demographics and wealth. Similarly, I use white population per capita as a control for the income distribution in the United States. Predominantly, white Americans have more wealth than other races in the US, hence I hypothesize that counties with more white population per capita will have higher number of EVs per capita because of the wealth distribution. Population that is unemployed also makes an impact on EV share because higher share of unemployed people in a county will lead to a fewer people purchasing a more expensive vehicle. Therefore, I hypothesize that the increase in unemployed people per capita will decrease the EV share per capita in a county.

I also include the population that commutes to work as a control variable; this is the population either commutes to different counties or the same county for work. The data also comprises of population that either commutes to work with another person or alone. Thus, based on the HOV incentive, I hypothesize that increase in population that commutes would increase the EV share per capita in that county.

I also include the population that has high school degree over the age of 25 as a control variable. As EVs were widely introduced in 2010, there may not be enough education regarding the benefits of EVs to people who don’t have a high school degree. Simultaneously, the US made a pledge to have net-zero carbon emissions by 2050 which may not be widely known to people who are not educated about climate change. One of the ways to increase EV registration is education and thus I theorize the Education attainment has a positive relationship with EV registration.

I also include total population and total vehicle registration as a control variable because I hypothesize that an increase in both these factors increase EV registration in a county. I use a weighted method to find the total vehicle registration for each county for the states I include. I collect the total vehicle registration data from the U.S. Department of Transportation, Federal Highway Administration for the 13 states. I then use the estimate of total population for each year and county to find the percentage of population in that county for that particular year. I then multiply the percentages of county population with the total vehicle registration in the state to find a weighted vehicle registration based on total population. I understand that population as vehicle registration may not have a positive correlation with vehicle registration. However, since there are more manufacturers promoting EVs, there might be a correlation between total vehicle registration and EV registration in a county. Therefore, it is important to include this as a control variable and thus account for the change in total vehicle registrations.

The descriptive statistics for my independent variables, my dependent variables, and my control variables (including the instrumental variable) are presented in Table 1 of the appendix. It is worth reiterating that my total vehicle registration data is generated through a weighted method using vehicle registration data for the state. California is the only state that reports total vehicle registration data at a county level that is publicly accessible and thus does not use the weighted method in the analysis. For my model with instrumental variables, I only have data for California and thus may not be able to explain the endogeneity issues for all the 13 states. The gas station data comes from the California Energy Commission with zip code and county location. I also use Alternative Fuels Station as another instrumental variable that affects charging stations but not EV registration. I find my data for Alternative Fuels Station from the AFDC for all the counties in the United States. Similar to the charging station data, I use GEOCODIO to decode my zip code and street address data to county level specifics.

Results

I run two preliminary regressions, with my dependent variable being EV registration and my independent variable being, first, Charging Stations and, second, Electric Vehicle Supply Equipment (EVSE) port using equation (1). The regression results for charging station as independent variable show that an increase in 1 charging station would increase EV registration by 376 vehicles in a county for the 15 states, significant at 95% confidence. Similarly, my regression results for EVSE port count as an independent variable shows that an increase in 1 EVSE port would increase EV registration by 158 vehicles, significant at the 99% confidence. There is a small variability in both regressions, therefore in order to increase my *R-squared* and the variability in my regression, I add control variables and other OLS tools to strengthen my results. I also end up not using EVSE ports because I wanted to look at the charging stations per person.

I then compare my regression results for individual states to see how charging infrastructure affects different states. Here I find that observations for three states are significantly lower than the rest of the ten states. This could be due to no EV registration in those counties, the lack of American Consumer Survey data or no charging stations in those counties. Nevertheless, I include all the 13 states in my regression analysis to have a larger set of observations and increase the variability. For my regression with fixed effects, equation (4), like I mentioned earlier, I use a county fixed effect, time fixed effects and an interaction of State * Time fixed effects. I use EV count per capita by dividing the EV counts and population of the county to capture how EV per person increases with changes in Charging Infrastructure per capita. Here, I find that an increase in one Charging Infrastructure per capita at a county level results in an increase in EV count per capita by 83 vehicles per person (Table 2). Other control variables like mean income per capita, white population per capita, total population, education attainment per capita and population that commutes per capita are controlled for. Mean income per capita shows a significant positive relationship with EV count per capita which can be justified due to the higher cost for purchasing EV according to NRDC (2021). Increase in income by $100,000 results in an increase in EV registration by 0.03 per person. Similarly white population per capita also shows significant positive relationships. An increase in white population per capita will increase EV registrations per capita by 0.04 vehicles. Commuter population per capita and unemployment per capita have a negative relationship with EV registration per capita, showing that when unemployment per capita increases there is a decrease in EV registration per capita, and when commuters per capita increase , there is a decrease in EV registration per capita, however these are not statically significant (Table 2). While I hypothesize that unemployment per capita has a negative relationship with EV registration, the results for population that commutes per capita does go against my hypothesis. I suspect that since this dataset consists of people who carpool and commute to work as well, if there is an increase in people who carpool, there will be a decrease in EV registrations as people may not be motivated to purchase a vehicle that is costlier than internal combustion gas vehicles.

Furthermore, I include an instrumental variable to strengthen the validity of my argument. Instrumental variables are variables that are exogenous in nature, meaning that it does not affect my dependent variable, EV registration, unless it is through my independent variable, Charging Stations. I choose gas stations as my instrumental variable because the number of gas stations in a county does not have a direct effect on EV registrations. This variable, therefore, allows me to account for unexpected behavior between my dependent variable, independent variable, and other control variables. Since gas-station count per capita has an f-test score of less than 10, I cannot use this variable as my instrumental variable. However, theoretically, this variable should work as an instrument and may not have a high F-test score due to low number of observations for the state of California. When I add Gas Stations per capita as my instrumental variable, I run a first stage OLS regression for Charging Stations per capita as my dependent variable and Gas Stations as my independent variable along with other control variables from before. Results show an increase in Gas Stations per capita leads to an increase in Charging Stations per capita, statistically significant at 95% level. Population that is white has a negative significant relationship with charging station; showing that increase in 1 white person per capita, there is a decrease in charging station by 0.0004. Total vehicle share per capita also has a negative significant relationship with charging stations per capita showing that increase in vehicles per person, there is a decrease in charging stations. I suspect that this is because if there is an increase in gas powered vehicles there will lesser use of charging stations. However, after running an F-test for my instrumental variable, I find that the score is less than 10 showing that it may not be the best instrument to use. I also argue that due to the limited observations for California, I may not receive a significant F-test score (Table 3).

I then use the change in charging stations as an independent variable in my second stage regression where the dependent variable is EV registrations per capita. I find that an increase in 1 charging station per capita leads to an increase in 52 EV registration per capita. However, this is not statistically significant and therefore may not be used to make sound arguments for policy implications. The result with my instrumental variable drops the significance for all my variables other than income. Income per capita has a positive relationship with EV registration per capita; increase in $100000 leads to an increase in 0.01 EV per capita. The results of my first stage OLS regression are presented in Column 1 of Table 3 and the second stage is presented in Column 2 of Table 3. Although the f-test score for gas stations per capita as my instrument does not show explanatory power, it may show some insight to future research with data for each state in the United States.

To test another instrumental variable to solve for the reverse causality issue, I use alternative fuel stations (other than charging stations). I theorize that an increase in alternative fuel stations will lead to an increase in charging stations. In doing so, I gain the advantage of having data for all the 13 states in the US while also being able to see the effect of alternative fuel stations per capita on charging infrastructure. In my first stage regression, using charging stations per capita as my dependent variable and alternative fuel stations as my independent variable, I find that Alternative Fuel stations per capita have a positive relationship with Charging stations per capita, however not statistically significant. My f-test score for alternative fuel stations is 1.33 thus being lower than the threshold of 10. Simultaneously, my second stage regression shows that an increase in charging stations per capita leads to a 42 EV registration per capita not statistically significant. Income is the only variable that remains statistically significant showing that an increase in $100000 would lead to an increase in 0.3 EVs per capita. Although I have data for all the counties, I cannot use this variable as there are low number of Alternative Fuel Stations (n = 256).

Similarly, I use a third instrumental variable where I look at the real estate establishments; more specifically, number of establishments that are parking lots, convenient stores, retail stores, etc. I hypothesize that an increase in real estate establishments will increase charging stations because charging stations are being implemented in more parking lots, malls, etc. I find that there is a positive significant relationship with Charging Stations and real estate establishments in my first stage results, aligning with my hypothesis. Similarly, in my second stage results, I also find a positive significant relationship with charging stations and EV registration. However, it is important to note that my standard error is 129 which is statistically very high. The result for this regression is in Table 5 of the appendix.

I also use general business establishments as an instrument and hypothesize the same relationship with charging station as above. In my first stage regression analysis, total establishments have a positive significant relationship with charging stations 100000 establishments would lead to an increase in 0.2 charging stations per person. Here too my f-test score is lower than the 10 threshold and thus cannot be used to make conclusions. However I do also find a positive relationship between EV registration and charging stations. The p-value is not less than 95% hence it is not significant and the standard errors are very high (92). The results are listed in Table 6 of the appendix.

Conclusion

Electric Vehicles are a great way to combat climate change while also keeping the same lifestyle as humans already do. With more technological advancements, the cost of EVs have lowered in the last 5 years and thus the monetary incentives provided by the government may not be the right way to promote EVs in the United States. Similarly, the concern of range anxiety brings up a different challenge to EV promotion and the single way to combat this is improving Charging Infrastructure in the US. Compared to China and the EU, the US has done a poor job at implementing charging stations for public use. Therefore, I argue that Charging Infrastructure will increase EV sales in the US.

My results for 13 states in the US show that charging infrastructure has a positive relationship with EV sales when holding vehicle registration, income and other variables constant. However, there is an endogeneity issue where one may argue that EV sales may affect the number of charging stations in the US. To solve this reverse causality, I use gas stations as my instrumental variable because gas stations have an effect on EV sales only if it is through charging stations. Here gas stations have a positive relationship with charging stations, however it does not show statistical power due to the low number of observations. I also try using alternative fuel stations as an instrumental variable; although I have data for all the states in the US, I only have 250 observations that merge with my county level registration data. This is due to the low amount of Alternative Fuel Stations in the US. Thus, the F- test for this instrument is low as well.

Despite the limitations with my data, I do believe that gas stations are a good instrumental variable that will allow future researchers to solve the endogeneity issue. COVID-19 also affected the data that was reported by the ACS as they did not have the 5-year estimates for the year 2020. Hence, that might affect the data a little bit. Along with that the ACS also does not report statistics for counties with population less than 5000, thus limiting the true population size and effect of the variables. Researchers can focus on refining the data to get more precise statistics on the variables found from the ACS and the vehicle registration data on a county level.

In the future I would also like to see the effects of household preferences on EV sales as consumers may be motivated to purchase EVs due to their concern of climate change. This brings up a different issue that goes beyond the variable I find from ACS and thus may require experimental or survey level data to see the change in preferences based on worry of Climate Change. I also think including electricity prices and gas prices on a county level may help increase validity and limit causal biases. Vehicle prices for different EVs may also help determine the quantity demanded by the consumers based on the price of the vehicle.

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Appendix

Table 1. Descriptive Statistics for Independent Variable, Dependent Variable, Control Variables and Instrumental Variables.

Variables	*N*	Mean	St. Dev.
Electric Vehicle Registration	2555	4041	17726
Charging Station Count	2555	6	22
Charging Ports (EVSE)	2555	17	56
Income	1287	176361	301385
Total Population	1287	490366	892625
White/Caucasian Population	1061	292612	446557
Education Attainment	1287	73842	128640
Unemployment	1059	12707	25849
Commuter Population	1059	223868	404720
Total Vehicle Registration	1287	144971	301993
Gas Station (California Only)	314	185.27	305.89
Alternative Fuel Stations	954	1.55	5.04

Table 2. Results with aggregated control variables and county, year and state * year interaction fixed effects.

Variables Dependent: Electric Vehicle per capita	Preliminary Results	Control Variables
Independent: Charging Station per capita	101.44***	83.75**
	(43.153)	(38.321)
Total Population * 100000		-0.004
		(0.018)
Income per capita * 100000		0.03**
		(0.001)
Education Attainment per capita		-0.014
		(0.043)
Unemployment per capita		0.1
		(0.109)
Commuter Population per capita		-0.019
		(0.036)
White/ Caucasian Population per capita		0.042**
		(0.019)
Vehicle Registration		0.004
		(0.007)
Constant	0.03	-0.08
	(0.003)	(0.045)
Observations	1287	1,058
R-squared	0.842	0.317
Number of GEOID	433	430
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

Table 3. Results for first and second stage regressions with instrumental variable of Gas Station.

Variables	Column 1	Column 2
Dependent: Electric Vehicle per capita	First Stage	Second Stage
Independent: Charging Station per capita		52.957
		(33.538)
Instrument: Gas Stations per capita	0.492**	
	(0.192)	
Income per capita * 100000	0.0000115	0.002**
	(9.22e-10)	(8.93e-06)
Total Population *100000	-0.0000017	-0.0003
	(2.79e-10)	(2.44e-6)
White/Caucasian Population per capita	-0.00042***	-0.021
	(0.00015)	(0.019)
Education Attainment per capita	-0.0006	0.001
	(0.00046)	(0.045)
Unemployment per capita	0.002*	-0.064
	(0.001)	(0.097)
Commuter Population per capita	0.0006	0.047
	(0.0005)	(0.040)
Total Vehicle Share	-5.42e-10***	1.70e-8
	(1.62e-10)	(2.26e-8)
Constant	-0.00003	-0.044
	(0.0005)	(0.043)
Observations	151	151
R-squared	0.0133	0.063
Number of GEOID	50	50
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

Table 4. Results for first and second stage regressions with instrumental variable of Alternative Fuel Station.

Variables	Column 1	Column 2
Dependent: Electric Vehicle per capita	First Stage	Second Stage
Independent: Charging Station per capita		43.038
		(509.001)
Instrument: Alternative Fuel Stations	0.261	
	(0.227)	
Income per capita	3.58e-10**	3.47e-07*
	(1.70e-10)	(2.11e-07)
Total Population	1.73e-11	7.56e-08
	(4.17e-10)	(2.44e-07)
White/Caucasian Population per capita	-0.00003	-0.047
	(0.00004)	(0.031)
Education Attainment per capita	-0.00002	-0.106
	(0.0002)	(0.145)
Unemployment per capita	0.001**	0.663
	(0.0005)	(0.736)
Commuter Population per capita	0.0001	0.123
	(0.0002)	(0.152)
Total Vehicle Share	-8.10e-10	1.39e-07
	(1.36e-09)	(8.96e-07)
Constant	-0.00006	-0.044
	(0.0002)	(0.043)
Observations	256	256
R-squared	0.0003	0.040
Number of GEOID	153	153
Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$		

Table 5. Results for first and second stage regressions with instrumental variable of real estate establishments.

Variables	Column 1	Column 2
Dependent: Electric Vehicle per capita	First Stage	Second Stage
Independent: Charging Station per capita		114.583
		(129.741)
Instrument: Real Estate	0.008	
	(0.005)	
Income per capita	8.15e-10	3.74e-07
	(1.25e-09)	(2.77e-07)
Total Population	1.67e-09	-2.56e-07
	(3.14e-10)	(6.76e-07)
White/Caucasian Population per capita	-0.0003	-0.052
	(0.0003)	(0.050)
Education Attainment per capita	-0.00007	-0.167*
	(0.0004)	(0.080)
Unemployment per capita	0.0004	0.051
	(0.0009)	(0.204)
Commuter Population per capita	-0.0003	0.034
	(0.0004)	(0.091)
Total Vehicle Share	-3.89e-09	8.76e-07
	(8.96e-09)	(1.89e-06)
Constant	-0.008	-0.043
	(0.005)	(0.116)
Observations	153	153
R-squared	0.6773	0.040
Number of GEOID	60	60
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

Table 6. Results for first and second stage regressions with instrumental variable of total establishments.

Variables	Column 1	Column 2
Dependent: Electric Vehicle per capita	First Stage	Second Stage
Independent: Charging Station per capita		123.448
		(92.219)
Instrument: Total Establishments	2.14e-08**	
	(9.55e-09)	
Income per capita	7.62e-10	3.66e-07
	(1.123e-09)	(2.66e-07)
Total Population	-3.00e-09	-2.40e-07
	(3.15e-09)	(6.60e-07)
White/Caucasian Population per capita	-0.00009	-0.050
	(0.0004)	(0.046)
Education Attainment per capita	-0.0001	-0.165**
	(0.0004)	(0.076)
Unemployment per capita	0.0006	0.046
	(0.0009)	(0.197)
Commuter Population per capita	-0.0003	0.037
	(0.0004)	(0.086)
Total Vehicle Share	-8.18e-08	8.39e-07
	(9.01e-09)	(1.86e-06)
Constant	-0.0001	-0.047
	(0.0005)	(0.109)
Observations	153	153
R-squared	0.0020	0.015
Number of GEOID	60	60
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		