# Team 41 Final Report

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## OBJECTIVE/PROBLEM

### Project Title: The Impact of Electric Vehicle Incentives on Adoption

**Background Information and Problem Statement:**
Light cars and trucks are responsible for roughly 20% of CO2 emissions from the U.S. Transitioning to Electric Vehicles (EV) is a key method to reduce CO2 emissions and our dependence on fossil fuels. Many factors influence EV growth and encourage adoption, including government and car manufacturer incentives, economic factors, local infrastructure, and supply and demand.

There is lots of evidence supporting the need for EV adoption for environmental purposes. "In 2021, PEVs used 6.1 terawatt-hours of electricity to drive 19.1 billion miles, offsetting 700 million gallons of gasoline. We find that this fuel switching reduced consumer fuel costs by $1.3 billion in 2021. Since 2010, 65% of PEVs sold in the United States have been assembled domestically." (Gohlke)

EV Sales account for about 5% of all US car sales (IEA). California is responsible for approximately 40% of those, and about 19% of all car sales in California are EVs. Government and business resources are limited, so governments and manufacturers must invest efficiently to maximize EV adoption by consumers and commercial vehicle fleets. We aim to identify factors that influence EV sales positively.

**Primary Research Question (RQ):**
What environment facilitates the highest EV Sales?

**Supporting Research Questions:**
- Do government incentives have a significant impact on EV sales?
- How significantly do different types of government incentives affect EV sales?
- How much do local conditions such as population, commute length, charging infrastructure, and personal income affect EV vehicle adoption?

We chose to test this by creating models to predict EV Sales based on these and other related incentive and geographic independent variables. Through variable selection, we can identify which may be related and impactful.

**Business Justification:**
Once we identify the environment and variables that facilitate the highest EV sales, car manufacturers and governments can use this information to maximize incentive spend and determine the best place to build EV infrastructure to encourage EV adoption. Businesses can improve sales and profits while the government can continue to encourage EV adoption to reduce CO2 emissions.

**Literature Review:**
The International Energy Agency identifies fiscal incentives such as purchase subsidies as a leading policy driver of EV adoption. They also emphasize tightening fuel economy and emissions standards and the availability of convenient and affordable chargers (IEA). The Bureau of Labor Statistics similarly identified financial incentives as a significant factor driving demand for electric vehicles. Additionally, they cite consumers' desire to protect the environment, wider vehicle choice, and improved electric vehicle range as factors expected to drive consumer demand (BLS).

## DATA CLEANING

**Summary of the Sources of Data:**

| Name and Link | Description |
|---|---|
| **CA County Level ZEV Sales** | Yearly sales for zero emissions vehicles in CA by County |
| **Vehicle Registrations by State** | Yearly State Level Vehicle Registrations by Type (2016-2021). Shows CA is about 39% of EV Registrations |
| **Monthly US Auto Sales** | US level auto sales by month, not seasonally adjusted. |
| **Alternative Fueling Station Counts** | 2008-2022 state level fuel stations by type - includes EV and breakouts of types of EV charges |
| **Laws and Incentives** | Federal and State Level Laws and incentives summary table. A download of all the laws and incentives at a state or federal level is available. Data Info |
| **United States Personal income** | Per capita income by county for 2016-2021 |
| **United States Population** | US population by county in 2021, 2020 and earlier years (2nd link) |
| **United States Commute Data** | National survey data of travel patterns |
| **Gas Prices** | Weekly gas price data by state / region of the US. Source |

We first took time to understand the data sets and the variables contained in each. We needed to determine primary keys that we could establish within each table and use to join the data sets. For the data sets above, we transformed each into a format where we can join them at the State level. For data sets containing data for the state of California, we decided to further break it out into County-level. California represents almost 40% of all US EV sales, so we decided breaking it out by county would be worthwhile for our modeling purposes. The datasets have different levels of detail, so these transformations were unique for each. We hypothesized that changes in EV sales take time, so we may see different results for the different time intervals. Thus, we decided to start by exploring our data at weekly, monthly, and quarterly time intervals.

**Detailed Cleaning and Transformation Process:**
For EV sales, there are two primary sources of data: CA County Sales and US State Car Registrations. Both the CA County and US State sales sources are annual. Because the registration data is cumulative, we must take the yearly differences as a proxy for sales for states other than California. We ran into several issues here where previous months' registration was higher than the current. In these cases, we removed those data points. While these datasets are yearly, some of our other data is more granular, such as weekly gas prices. In order to transform this data to different levels of detail, we chose to use the monthly US Auto Sales data. Doing so will capture the seasonality of car sales, such as high sales around the holidays. To accomplish this, we take the percentage of total yearly auto sales that occur each week, month or quarter and multiply them by the yearly sales for that row. While this may not be perfect, we believe this will be more accurate than dividing yearly sales by 52, 12 or 4 to evenly distribute yearly sales.

The U.S. Department of Energy provided the state and federal laws and incentives data. We filtered the initial data set to include only laws and incentives that affected individuals, or personal vehicle owners, to align with our other data sources and the scope of our project. The excluded laws and incentives were those that affect manufacturing, public transit, or mass transit. We also filtered the data to focus on electric vehicles, removing vehicle types such as propane, natural gas, or biodiesel.

After completing the preliminary filtering, we focused on identifying key dates for each law or incentive. We identified the main dates for each record manually. The raw data contained five date fields: Enacted Date, Amended Date, Significant Update Date, Expired Date, and Archive Date. We worked to narrow this down to an Active Date and an Expired Date for each field. Most records did not have an entry for all five date fields; most only had one or two, so identifying the Active Date and Expired Date required working through the data set line-by-line.

After identifying the key dates, we divided the data geographically. We divided the data into three groups: all states except for California, California, and federal data. We cleaned all the data in the three groups to match our determined format. We then separated the state data into incentives and fees. The California data set required additional manual work as each law or incentive needed to be matched to a county to join our other data sets. After all the alterations, we ended with four data sets: federal incentives, state incentives, state fees, and California incentives.

Personal Income data was provided by the Bureau of Economic Analysis, which publishes an annual report of personal income by County and State. Data cleaning for this data required manually combining the separate annual reports, resulting in a dataset of personal income for each state by year, and a dataset of personal income for each county in California by year.

Population data was provided by Census.gov in the form of annual estimates for each county and state. Data cleaning was similar to the manual process required for Personal Income data.

The Alternative Fueling Station Counts source was also provided by the U.S. Department of Energy. The data includes several years of EV charging station counts. As time went on, the government split the counts between plugs and stations, and later split again into the counts of different types of plugs at each station. We decided to use the station count, since that was the most constant number in the set. Similar to the incentives data set, we only used charging stations for electric vehicles, and removed stations for other alternative fuel types. We used a long form of data table, having a column for state, year, and station count.

The US Commute data is from 2011-2015 survey data provided by the Census bureau. We only have a single data point, so it will be constant for every week in our models. We don't think this is a significant problem because people don't change their commute often. Commute distances and flow, number of respondents, are recorded by Census track. We had to map Census tracks to the State and County and then summarize the mean by State and County in California. Some commutes are thousands of kilometers long, which is not a practical route for an EV, but we decided to include them in the model because these could affect EV sales.

The gas price data comes from the US EIA. The main challenge using this source is that the EIA provides gas prices according to varying geographies. Some prices are given by region, some by state (including California, Washington, and Texas), and some by area within a state. For the state-level data, we built a lookup table to use the state-level data when available and the region-level data when it was not. We also had to format the State and County names in all caps and then change the start of the week to Sunday instead of Monday to join the data with the other tables. In California, we used the San Francisco data for the Bay Area counties, Los Angeles data for the LA area, and the state-level data for all other counties.

# METHODOLOGY

**Approach:**
After aggregating and cleaning our separate data sets, we joined them together. The data was combined and aggregated into weekly, monthly, quarterly, and yearly versions of our data. We suspected there may not be any meaningful movement at the weekly level, so we also incorporated the three higher-level time intervals.

**Exploratory Data Analysis:**
Prior to building any models, we visualized our data in Tableau. We used Tableau to explore the data and do some sanity-checks. We also created several visualizations to better understand the trends of EV Sales over time shown in Appendix A: US EV Sales Dashboard. Our combined data allowed us to visualize our different dependent and independent variables.

We created an interactive view to analyze the correlation between variables at the yearly level, see Appendix B: Variable Correlation Dashboard. This view helped confirm our suspicions that some variables were strongly correlated, so we focused on variable selection for our modeling purposes. Many correlated variables aligned with common sense, like the higher the population, the more charging stations there are.

Additionally, we explored and visualized the data in R. We generated the following correlation matrix to observe the data further, see Appendix C: State Variable Correlation Matrix.

**Key Variables for Modeling:**
Our dependent variable is the number of EV Sales per quarter.

Independent variables (and their names in our data):

1. Commute distance (*AvgCommuteKM*)
2. Number of commuters (*Flow*)
3. Population (*Population*)
4. Personal Income (*Personal.Income*)
5. Government Incentives and Fees, both State and Federal (*incentives*, *fees*, fed_*incentives*)
6. Number of charging stations/charging station density, State Level Only (*Density.stations.per.sqmi*)
7. Gas Prices (*Gas_Price*)

**Modeling Preparation:**
Once we had our combined datasets (state and CA county), additional preparation was needed before creating models. First, we inspected the data for outliers. We used common approaches to identify potential outliers in the data. To begin, we checked the variables' minimum, maximum, and interquartile values. Using this data, we further inspected the variables that could potentially contain outliers. We did this by graphing the data using boxplots and histograms. We found that some variables contained data points statistically qualify as outliers but were valid so they should still be included in the analysis. The variables that contained significantly higher values correlated to California data, where sales and availability to EV resources are significantly higher than in other states. Thus, we concluded that our data had no outliers that should be removed from the data sets.

**STATE-LEVEL MODELING**
**Linear-Linear Modeling:**
We began with linear regression on our quarterly state level data. Using Lasso with cross-validation, we selected the best predictors and created a linear model with only the selected predictors. We chose Lasso as our variable selection because of its global variable selection, considering all variables when selecting, instead of a greedy variable selection method such as Stepwise, which only looks at one variable at a time. Since we have more data points than predictors, the limits of Lasso should be minimized. The following predictors were selected by Lasso for this linear-linear model: *AvgCommuteKM, Gas_Price, Population, Density.stations.per.sqmi, incentives*. We achieved a decent Adjusted R-squared of 0.67 for this model and the p-values show the features are highly likely to be significant. The features selected by this model and the coefficients all make logical sense. Longer commutes, higher gas prices and incentives make EVs more affordable vs gas powered cars. Higher charging station densities make it easier to own an EV. While a higher population means there are more people to buy an EV.

Unfortunately, some of our plots to test underlying model assumptions indicated that model assumptions do not hold. The Q-Q plot (Figure 1: Q-Q Plot of Quarterly State level EV Sales) and residuals vs fitted plot (Figure 2: Residuals vs Fitted Values for State level Linear-Linear Model) show that the quarterly sales are strongly heteroskedastic, which can degrade the fit of the model.

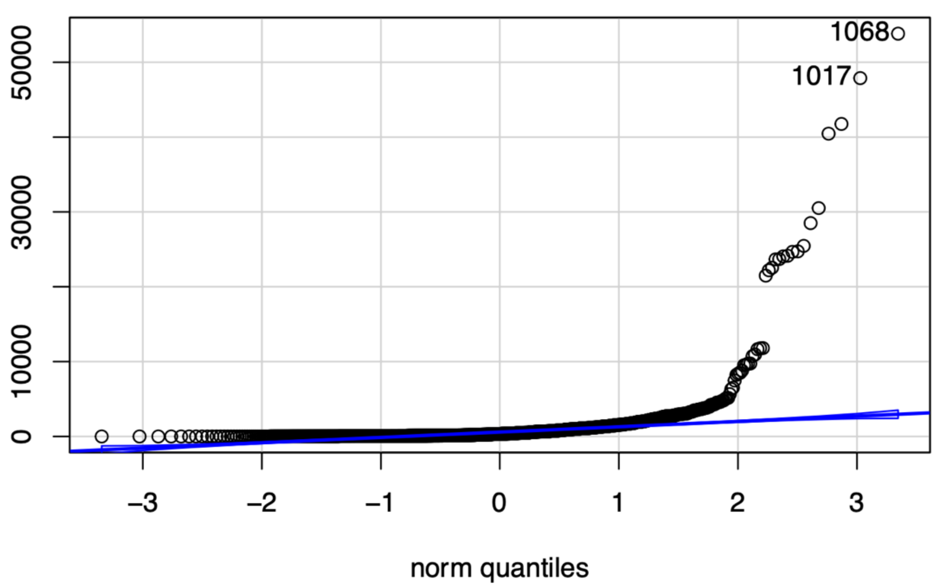


*Figure 1: Q-Q Plot of Quarterly State level EV Sales*

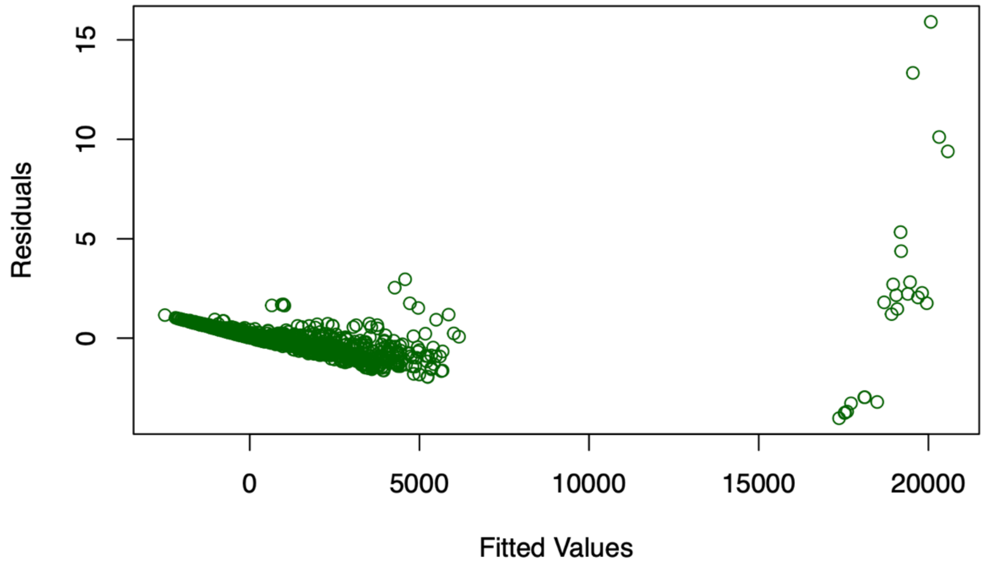


*Figure 2: Residuals vs Fitted Values for State level Linear-Linear Model*

**Log-Linear Modeling:**
From here, we decided that it would be best to try a log-linear model. We transformed our EV Sales into the log of EV Sales plus 1 since there were zeros in the data then re-ran Lasso. Lasso selected the following predictors: *AvgCommuteKM, Flow, Gas_Price, Personal.Income, incentives*, *fees*. It's interesting to note that *Flow*, *Personal.Income* and *fees* were selected instead of *Population* and *Density.stations.per.sqmi* here, while *AvgCommuteKM, Gas_Price,* and *incentives* were selected for both models.

This time, we achieved a lower adjusted R-squared value, 0.57, but had a more normal distribution in the Q-Q plot (Figure 3: Q-Q Plot of log transformed Quarterly State level EV Sales) and residuals (Figure 4: Residuals vs Fitted Values for State level Log-Linear Model) were much smaller for large fitted values. The features selected with this model are all significant and their coefficients also generally make sense. This model also selected *AvgCommuteKM*, *Gas Prices* and *incentives* all with positive coefficients as expected. It selected *Flow* instead of *Population*, which is likely just an artifact of Lasso randomly selecting one over the other since *Flow* and population strongly correlate with R-squared of 0.99. Where is differs from the linear-linear model is in selecting *Personal.Income* and *fees*. Higher personal income causing higher sales makes sense but it's hard to explain how more fees would increase sales.

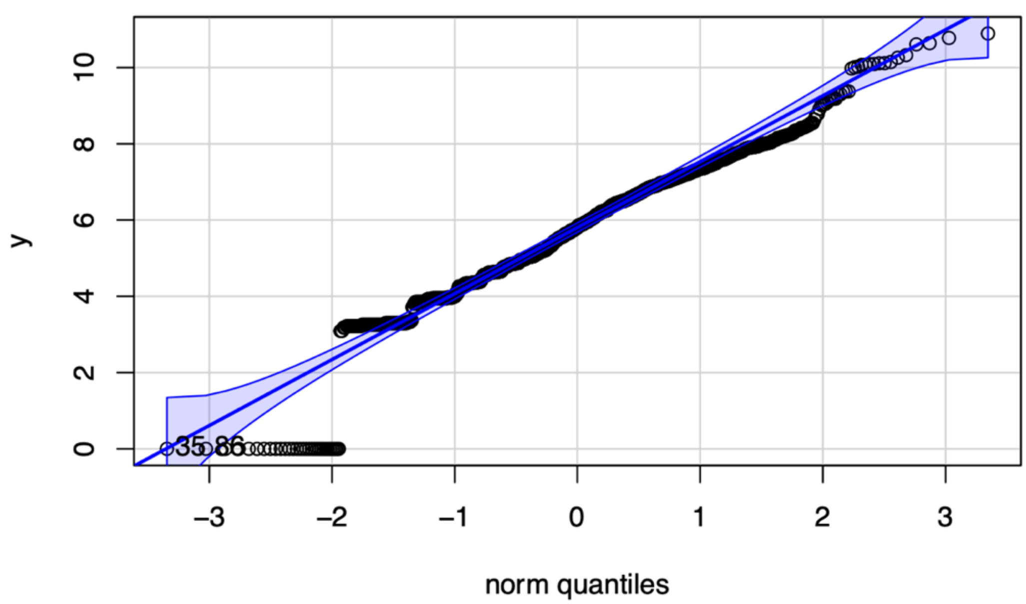


*Figure 3: Q-Q Plot of log transformed Quarterly State level EV Sales*

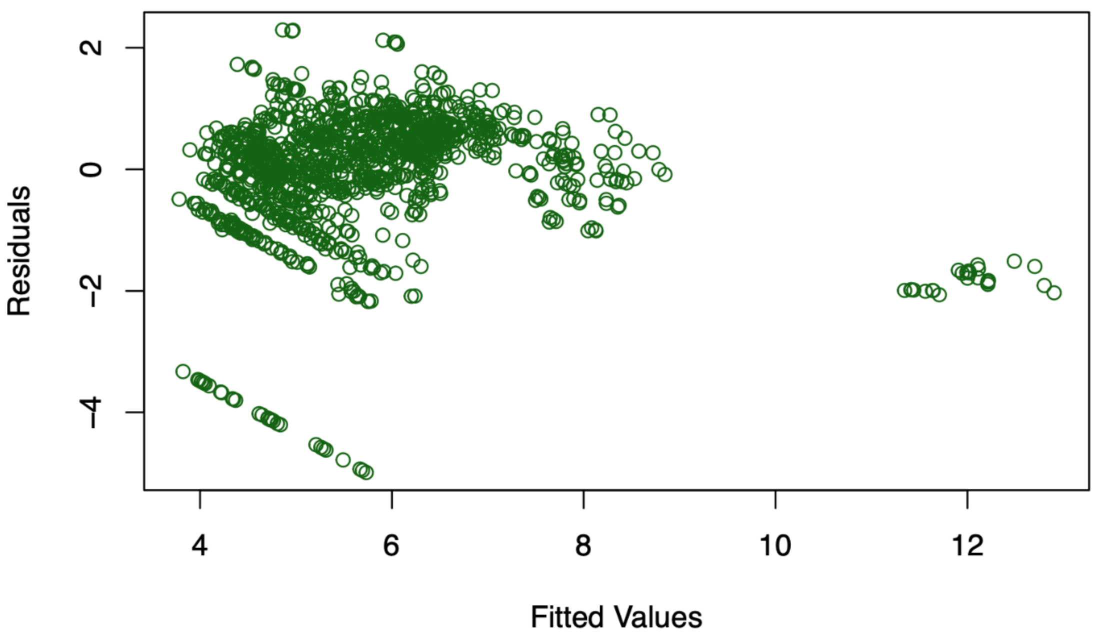


*Figure 4: Residuals vs Fitted Values for State level Log-Linear Model*

**Sqrt-Linear Modeling:**
For good measure, we also tested a square root transformation on EV Sales. The Q-Q plot (Figure 5: Q-Q Plot of Sqrt transformed Quarterly State level EV Sales) of Sqrt transformed EV Sales shows a more normal distribution than with no transform but it's not as normal as with a Log transfer. For this model, Lasso selected *AvgCommuteKM, Gas_Price, Personal.Income, Population, incentives* and *fees*. However, on the final linear fit the p-value for *fees* was >5%, so we eliminated it from the model. The Sqrt-Linear model improved on the Log-Linear and Linear-Linear model's adjusted R-squared, achieving 0.85 and extremely low p-values for every feature. Like the Q-Q plot, the residuals vs fitted plot (Figure 6: Residuals vs Fitted Values for State level Sqrt-Linear Model) less heteroskedasticity than the linear-linear model but more than the log-linear model. We were hesitant to declare this a win and select it as our model, as we think there's some risk in the normality of the model.

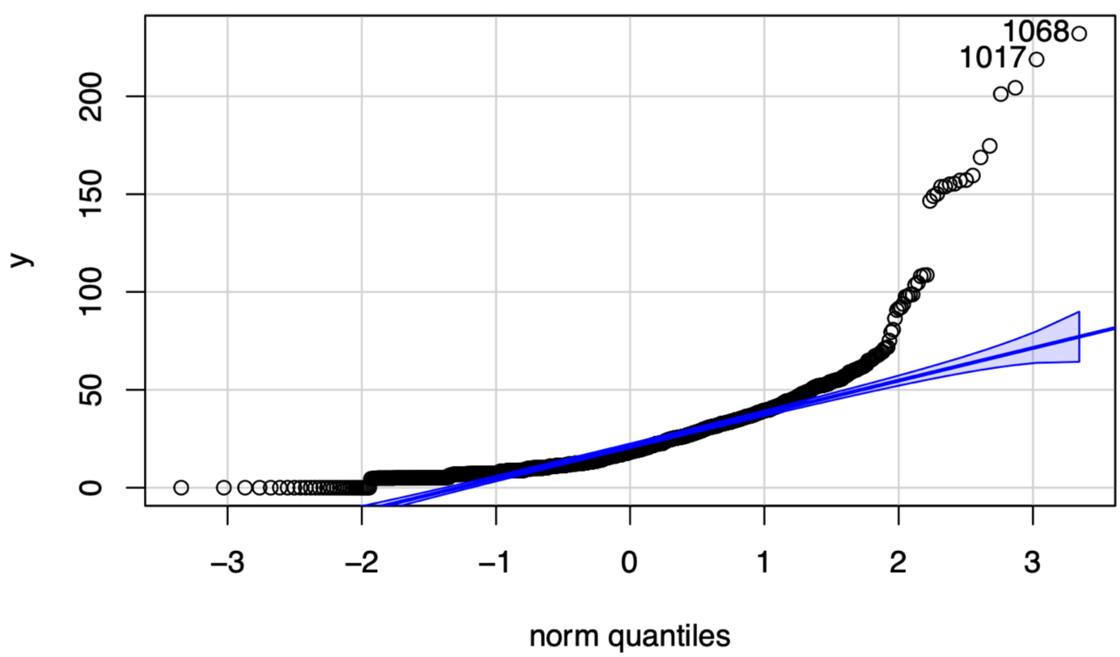


*Figure 5: Q-Q Plot of Sqrt transformed Quarterly State level EV Sales*

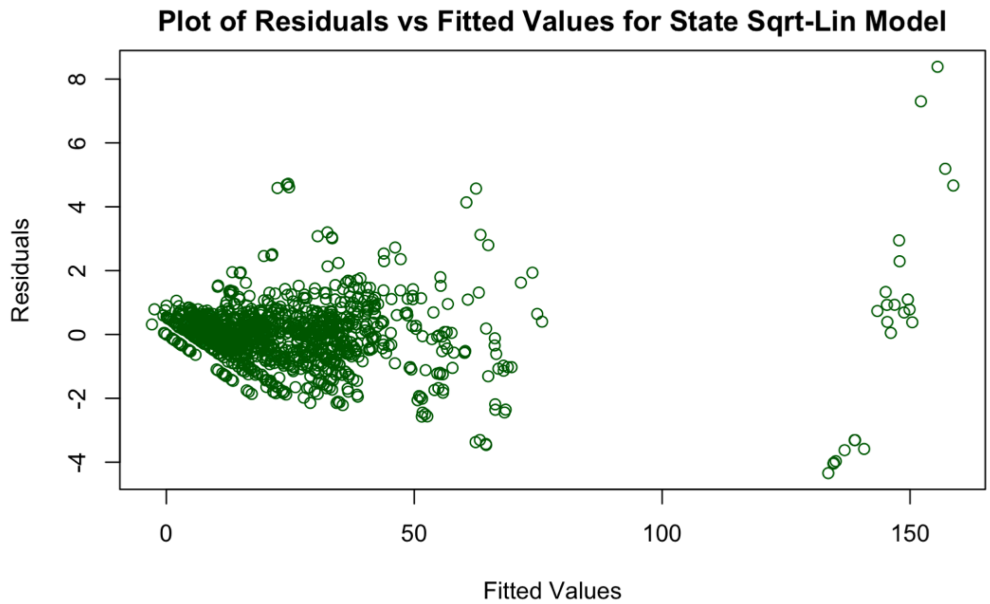


*Figure 6: Residuals vs Fitted Values for State level Sqrt-Linear Model*

**Summary of the State-Level Models:**
Full model results for each of the three models is shown in the report from Stargazer, Table 1 - Comparison of models for State level EV Sales (Quarterly).

We selected Square Root transformation offers a much greater degree of significance in our selected variables and explained the most variation in EV sales with an R-squared of 0.85. However, we do have some reservations with this model since the Q-Q and residuals vs fitted plot show the distribution is not normal and there is significant heteroskedasticity. Given more time we'd evaluate additional transforms to try to normalize the distribution and reduce heteroskedasticity.

*Table 1 - Comparison of models for State level EV Sales (Quarterly)*

**State Results**

| | *Dependent variable:* | | |
|---|---|---|---|
| | Quarterly Sales | | |
| | Linear | Log | Sqrt |
| | (1) | (2) | (3) |
| AvgCommuteKM | 36.982** | 0.067*** | 0.628*** |
| | (16.224) | (0.009) | (0.072) |
| Flow | | 0.00000*** | |
| | | (0.00000) | |
| Gas_Price | 1,018.875*** | 0.410*** | 6.460*** |
| | (150.403) | (0.085) | (0.687) |
| Population | 0.0002*** | | 0.00000*** |
| | (0.00001) | | (0.00000) |
| Density.stations.per.sqmi | 637.526*** | | |
| | (165.313) | | |
| Personal.Income | | 0.00004*** | 0.0004*** |
| | | (0.00000) | (0.00003) |
| incentives | 255.384*** | 0.020*** | 1.127*** |
| | (11.738) | (0.007) | (0.051) |
| fees | | 0.431*** | 1.040* |
| | | (0.071) | (0.567) |
| Constant | -5,328.083*** | -0.137 | -48.700*** |
| | (483.109) | (0.333) | (2.677) |
| Observations | 1,216 | 1,216 | 1,216 |
| $R^2$ | 0.672 | 0.572 | 0.855 |
| Adjusted $R^2$ | 0.671 | 0.569 | 0.855 |
| Residual Std. Error | 2,158.756 (df = 1210) | 1.152 (df = 1209) | 9.264 (df = 1209) |
| F Statistic | 496.123*** (df = 5; 1210) | 268.772*** (df = 6; 1209) | 1,192.321*** (df = 6; 1209) |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

**CALIFORNIA COUNTY-LEVEL MODELING**

As mentioned previously, we chose to separate California into its counties for our modeling purposes. California represents nearly 40% of yearly US EV sales and has more detailed sales information. We performed the same steps on the California counties data that we performed on the State data. The California county data showed many similarities to the State level data. Quarterly sales also had outliers but in this case the outliers are due to the two counties with the highest population (Los Angeles and Orange). The correlation matrix (Appendix D: CA County variable correlation matrix) also showed strong correlation between Quarterly sales, Flow and Population.

Similar to the state level analysis, the square root transformation performed best when looking at adjusted R-squared. The Q-Q plot of Sqrt transformed sales (Figure 7: Q-Q Plot of Sqrt transformed Quarterly CA County EV Sales) and residuals vs fitted values (Figure 8: Residuals vs Fitted Values for CA County Sqrt-Linear Model) also look very similar to the state level model. The summary of all three models is shown in the Stargazer report (Table 2 - Comparison of models for California County EV Sales (Quarterly)). It's interesting to note that for California counties, Lasso on both the log and square root transformation selected the same variables: *Gas_Price, Personal.Income, Population,* and *incentives*. The coefficient for both *Personal.Income* and *Population* is extremely small because the values themselves are large.

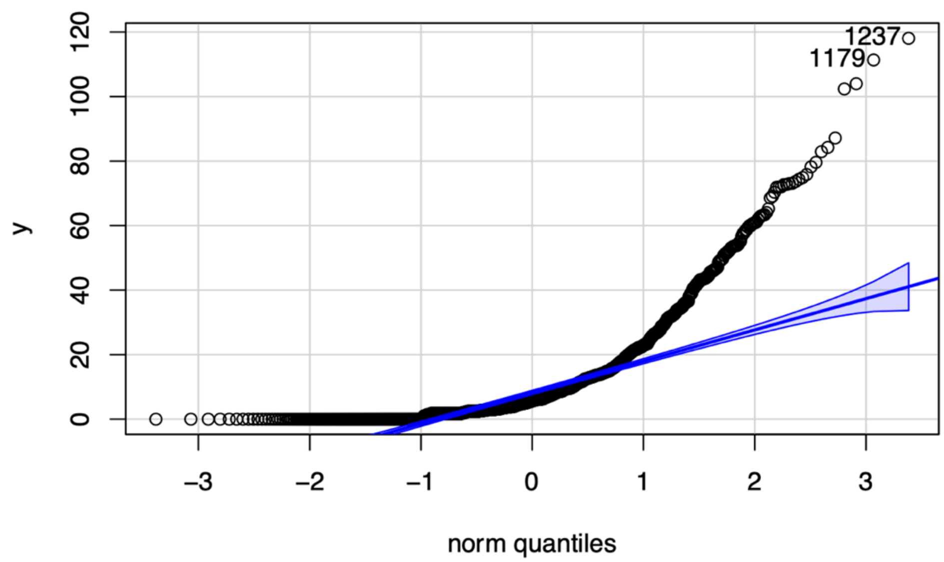


*Figure 7: Q-Q Plot of Sqrt transformed Quarterly CA County EV Sales*

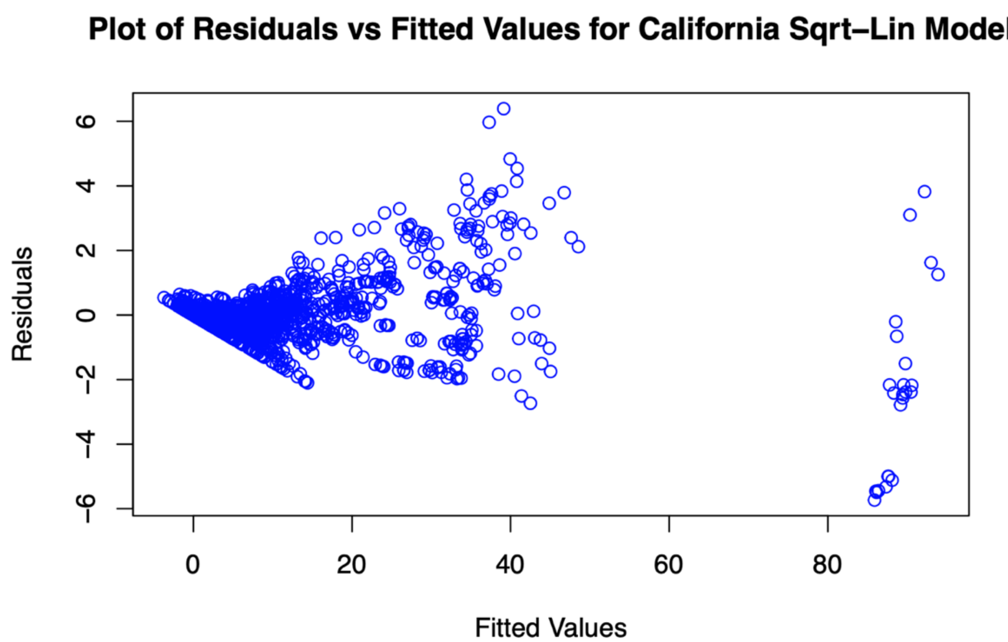


*Figure 8: Residuals vs Fitted Values for CA County Sqrt-Linear Model*

*Table 2 - Comparison of models for California County EV Sales (Quarterly)*

**CA County Results**

| | Dependent variable: | | |
|---|---|---|---|
| | Quarterly Sales | | |
| | Linear | Log | Sqrt |
| | (1) | (2) | (3) |
| AvgCommuteKM | 0.757 | | |
| | (1.651) | | |
| Flow | 0.001*** | | |
| | (0.00003) | | |
| Gas_Price | 249.515*** | 0.580*** | 3.638*** |
| | (33.240) | (0.087) | (0.390) |
| Personal.Income | 0.010*** | 0.00004*** | 0.0003*** |
| | (0.001) | (0.00000) | (0.00001) |
| Population | | 0.00000*** | 0.00001*** |
| | | (0.00000) | (0.00000) |
| incentives | 0.630 | 0.257*** | 0.567*** |
| | (9.763) | (0.025) | (0.114) |
| Constant | -1,401.543*** | -2.269*** | -22.841*** |
| | (129.458) | (0.297) | (1.339) |
| Observations | 1,392 | 1,392 | 1,392 |
| $R^2$ | 0.717 | 0.618 | 0.818 |
| Adjusted $R^2$ | 0.716 | 0.617 | 0.817 |
| Residual Std. Error | 586.192 (df = 1386) | 1.527 (df = 1387) | 6.874 (df = 1387) |
| F Statistic | 701.993*** (df = 5; 1386) | 560.420*** (df = 4; 1387) | 1,554.154*** (df = 4; 1387) |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

**Anticipated Conclusions/Hypothesis:**
We predicted that states or locales with higher government and car manufacturer incentives would also have higher EV sales rates. However, some local factors may interact with incentives, altering the number of EV sales.

**Unfinished Business:**
Given more time, we think joining weather data to the sales data tables may impact the results. EV batteries perform better in warmer climates on distance per charge, charging times, and overall length of life. We found that long commutes in affluent areas are an excellent recipe for EV sales, but we do not know if areas with high incomes in the snow would see the same purchasing drive as the warmer Southern California beach counties.

We also think converting EV sales into a percentage of total auto sales would offer more information about their popularity for geographic locations. Even though California represents the largest single state EV sales in the country, we may see that those sales only account for 5% of all California auto sales, while a smaller state's EV sales account for 15% of its total auto sales. We can't see that ratio from this analysis, only that California overtakes all other states in raw EV sales. Unfortunately, we had difficulty getting total auto sales by state and county, as most of the publishing and government focus is solely on EVs.

For further future work, the normality (Q-Q Plots) could be improved through a Box-Cox transformation of the EV sales data. We began testing and found that it may improve our normality, but it also makes our model more complex and challenging to explain, which is a primary criticism of the Box-Cox method. Even after applying the additional transformation, there was no notable increase in fit. Primarily due to a lack of exposure to the method, we were unsure how to apply the transformation appropriately.

While we considered income data as a variable impacting EV sales, our study looked at income as a static value at different time periods. It would be interesting to look at income growth rate as a factor and use that to recommend specific areas around the US to target for marketing investment.

**Conclusions and Final Thoughts:**

We were surprised that we could build a model with a high R-squared value and by the significance of each predictor in the final sqrt-linear model. Our model indicates that the most effective way for states and local governments to increase EV sales is to increase taxes on gas, thereby increasing gas prices, and using the revenue to fund incentives. That is unsurprising and would be unpopular with most voters, but it would be effective.

The other features in the model are significant but governments cannot readily control personal income or population. Similarly, governments cannot easily increase commute distances, and it would be counterproductive to the overall goal of reducing energy use.

Given the positive correlation between our predictors and EV sales, we recommend that EV retailers and manufacturers invest marketing budgets in high income and population areas, particularly ones that are poised for income and population growth (tech hubs, improving infrastructure, affordable housing). We also recommend lobbying for greater EV incentives at various levels of government to boost sales in the aforementioned areas, as well as offset population losses, or gas price decreases.

Based on the current trends, we predict that EV sales will continue to increase in California in places where gas prices, federal and state incentives, and income increase. For all other states, in addition to those increases, we predict that EV sales will see increases in areas where people are moving farther from their workplaces, and commute distances are increasing. Because of that prediction, we think manufacturers and EV retailers should focus on US cities and states where incomes appear to be growing, as well as places where people commute *from*, for example, the suburbs around a major city where people would commute to work.

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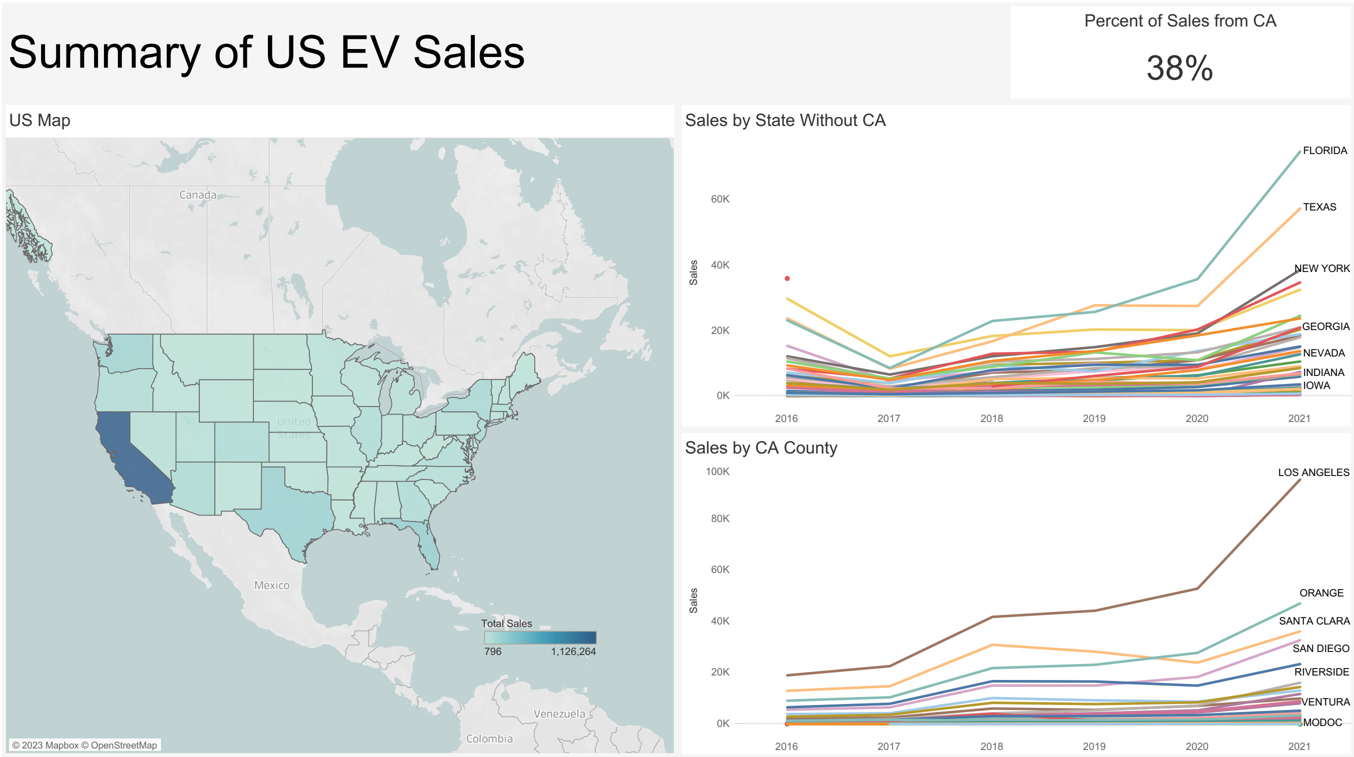
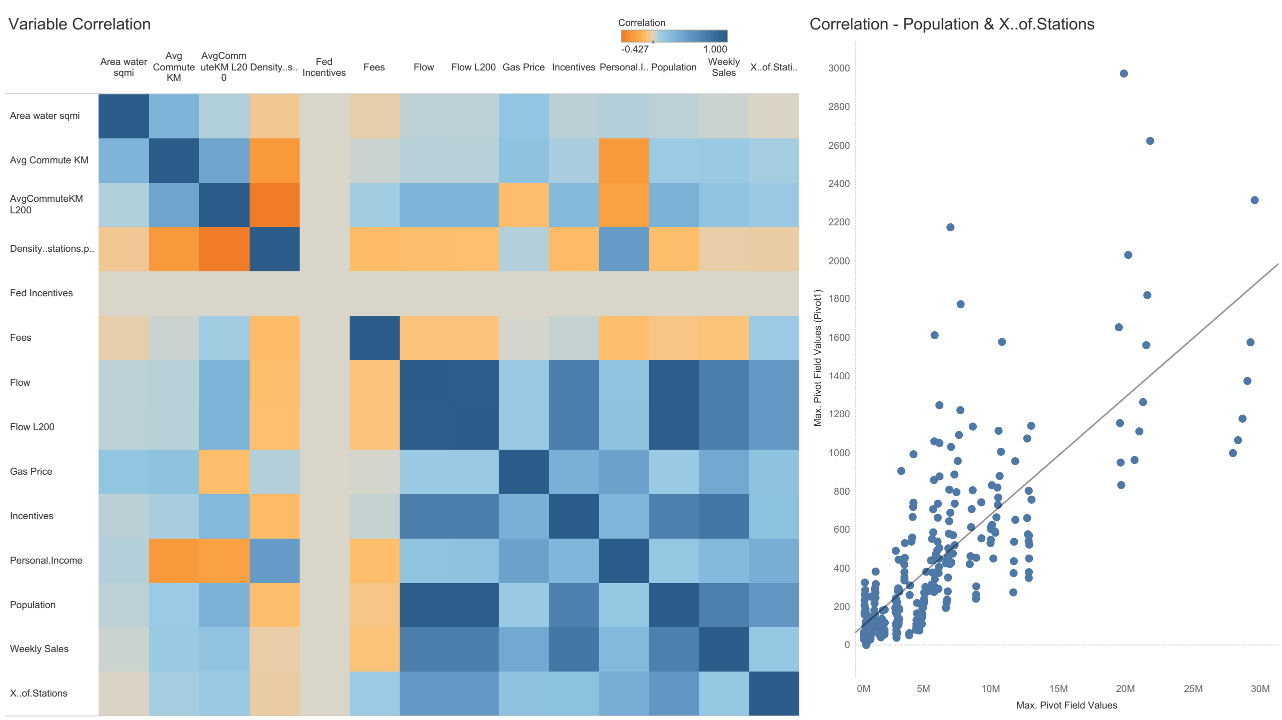
**Appendix:**

Appendix A: US EV Sales Dashboard

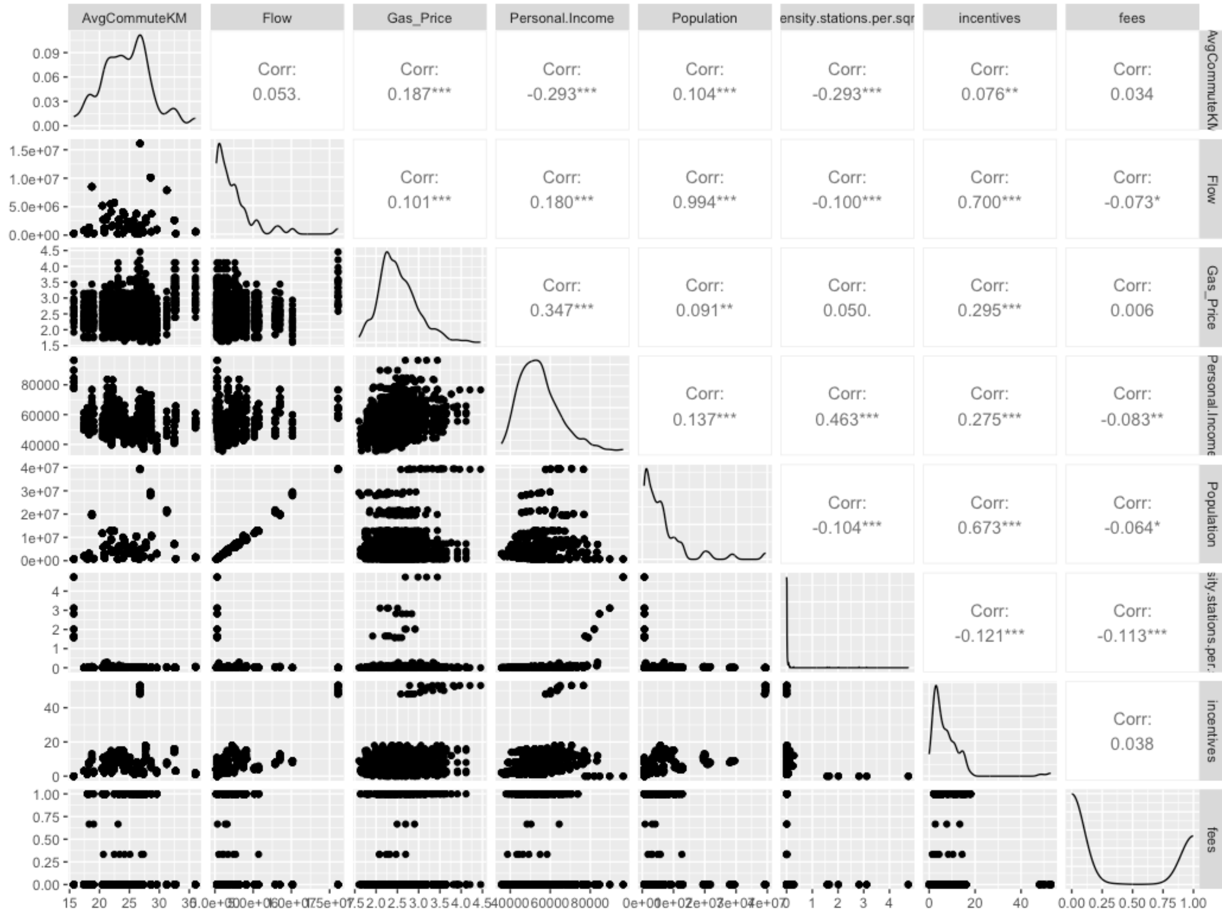



Appendix B: Variable Correlation Dashboard

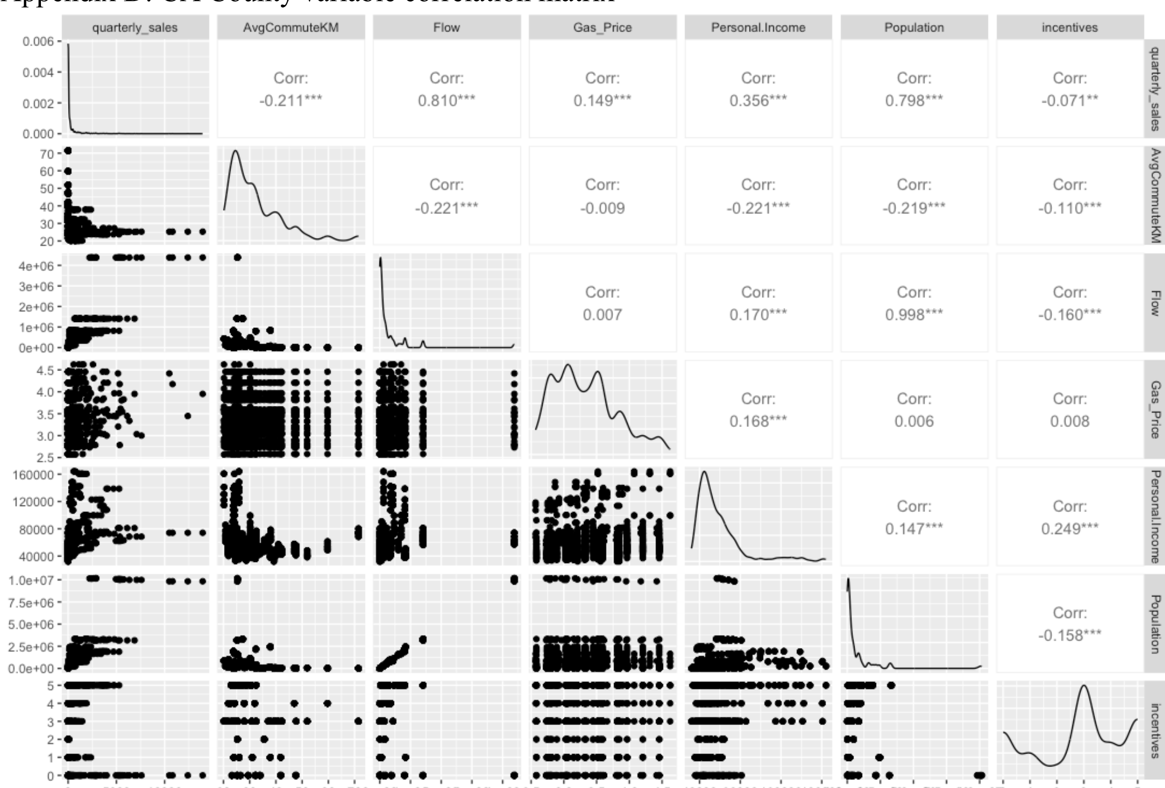



Appendix C: State Variable Correlation Matrix

State Level Correlation Matrix




Appendix D: CA County variable correlation matrix



## CA County Level ZEV Sales

| Data Ye | County | FUEL_TYPE | MAKE | MODEL | Number of Vehicles |
|---|---|---|---|---|---|
| 1998 | Los Angeles | Electric | Ford | Ranger | 1 |
| 1998 | Orange | Electric | Ford | Ranger | 1 |
| 1998 | San Bernardino | Electric | Ford | Ranger | 2 |
| 1998 | San Mateo | Electric | Ford | Ranger | 1 |
| 1999 | Santa Barbara | Electric | Ford | Ranger | 1 |

## Vehicle Registrations by State

**2021 Light-Duty Vehicle Registration Counts by State and Fuel Type**

| State | Electric (EV) | Plug-In Hybrid Electric (PHEV) | Hybrid Electric (HEV) | Biodiesel | Ethanol/Flex (E85) | Compressed Natural Gas (CNG) | Propane | Hydrogen | Methanol | Gasoline | Diesel |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Alabama | 4,700 | 3,300 | 42,500 | 40,500 | 449,500 | 500 | 100 | 0 | 0 | 4,051,000 | 123,500 |
| Alaska | 1,300 | 500 | 7,300 | 7,600 | 50,100 | 100 | 0 | 0 | 0 | 464,200 | 31,700 |
| Arizona | 40,700 | 15,500 | 132,200 | 51,000 | 460,400 | 900 | 900 | 0 | 0 | 5,395,300 | 191,800 |
| Arkansas | 2,400 | 1,800 | 26,100 | 28,700 | 290,200 | 300 | 0 | 0 | 0 | 2,241,600 | 88,800 |
| California | 563,100 | 315,300 | 1,355,900 | 163,600 | 1,343,200 | 12,600 | 1,500 | 11,800 | 0 | 30,512,600 | 710,500 |

## Alternative Fueling Station Counts

**Station Counts by State and Fuel Type**

| State | Biodiesel | CNG | E85 | Electric[a] (station locations \| EVSE ports Level 1 \| Level 2 \| DC Fast) | Hydrogen[b] (retail \| non-retail \| total) | LNG | Propane[c] (primary \| secondary \| total) | Renewable Diesel | Total[d] |
|---|---|---|---|---|---|---|---|---|---|
| Alabama | 2 | 5 | 20 | 256 \| 690<br>0 \| 454 \| 236 | 0 \| 0 \| 0 | 2 | 29 \| 30 \| 59 | 0 | 778 |
| Alaska | 0 | 1 | 0 | 59 \| 110<br>0 \| 79 \| 31 | 0 \| 0 \| 0 | 0 | 1 \| 1 \| 2 | 0 | 113 |
| Arizona | 2 | 9 | 15 | 953 \| 2,629<br>0 \| 1,972 \| 657 | 0 \| 0 \| 0 | 1 | 43 \| 27 \| 70 | 0 | 2,726 |
| Arkansas | 16 | 9 | 73 | 227 \| 608<br>0 \| 519 \| 89 | 0 \| 0 \| 0 | 0 | 16 \| 19 \| 35 | 0 | 741 |
| California | 34 | 157 | 303 | 14,092 \| 38,101<br>178 \| 29,244 \| 8,657 | 54 \| 1 \| 55 | 15 | 132 \| 88 \| 220 | 573 | 39,458 |

## Laws and Incentives by State

Technology/Fuel | Incentives | Regulations | User Type

| Jurisdiction | Grants | Tax Incentives | Loans and Leases | Rebates | Exemptions | Time-of-Use Rate | Other |
|---|---|---|---|---|---|---|---|
| Totals | 231 | 111 | 38 | 263 | 130 | 52 | 150 |
| Federal | 41 | 13 | 5 | 1 | 3 | 0 | 10 |
| Alabama | 3 | 1 | 1 | 2 | 1 | 2 | 1 |
| Alaska | 1 | 0 | 0 | 3 | 1 | 1 | 0 |
| Arizona | 1 | 2 | 0 | 7 | 5 | 3 | 3 |
| Arkansas | 3 | 0 | 1 | 0 | 0 | 0 | 1 |
| California | 23 | 4 | 3 | 57 | 5 | 3 | 20 |

## United States Personal income by County, State

| | Per capita personal income[1] | | | | Percent change from preceding period | | |
|---|---|---|---|---|---|---|---|
| | Dollars | | | Rank in state | Percent change | | Rank in state |
| | 2019 | 2020 | 2021 | 2021 | 2020 | 2021 | 2021 |
| **United States** | **56,250** | **59,765** | **64,143** | **--** | **6.2** | **7.3** | **--** |
| **Alabama** | **43,288** | **46,179** | **49,769** | **--** | **6.7** | **7.8** | **--** |
| Autauga | 42,846 | 45,248 | 48,347 | 11 | 5.6 | 6.8 | 60 |
| Baldwin | 48,380 | 51,348 | 54,659 | 4 | 6.1 | 6.4 | 63 |
| Barbour | 34,870 | 37,120 | 40,428 | 54 | 6.5 | 8.9 | 33 |
| Bibb | 31,800 | 34,598 | 36,892 | 66 | 8.8 | 6.6 | 62 |
| Blount | 36,542 | 38,351 | 42,634 | 39 | 5.0 | 11.2 | 10 |
| Bullock | 27,192 | 30,429 | 33,267 | 67 | 11.9 | 9.3 | 27 |

## United States Population by County, State

| Geographic Area | April 1, 2020 Estimates Base | Population Estimate (as of July 1) | |
|---|---|---|---|
| | | 2020 | 2021 |
| **United States** | **331,449,281** | **331,501,080** | **331,893,745** |
| Autauga County, Alabama | 58,805 | 58,877 | 59,095 |
| Baldwin County, Alabama | 231,767 | 233,140 | 239,294 |
| Barbour County, Alabama | 25,223 | 25,180 | 24,964 |
| Bibb County, Alabama | 22,293 | 22,223 | 22,477 |
| Blount County, Alabama | 59,134 | 59,081 | 59,041 |

## United States Commute Data (2 tables must be joined on GEOID and OFIPS)

| USPS | GEOID | POP10 | HU10 | ALAND | AWATER | ALAND_SQM | AWATER_SC | INTPTLAT | INTPTLONG |
|---|---|---|---|---|---|---|---|---|---|
| AL | 1001020100 | 1912 | 752 | 9809944 | 36312 | 3.788 | 0.014 | 32.4771112 | -86.490303 |
| AL | 1001020200 | 2170 | 822 | 3340505 | 5846 | 1.29 | 0.002 | 32.475758 | -86.472468 |
| AL | 1001020300 | 3373 | 1326 | 5349274 | 9054 | 2.065 | 0.003 | 32.4740243 | -86.459703 |
| AL | 1001020400 | 4386 | 1823 | 6382705 | 16244 | 2.464 | 0.006 | 32.4710782 | -86.444681 |

| OFIPS | DFIPS | OSTFIPS | OCTFIPS | OTRFIPS | DSTFIPS | DCTFIPS | DTRFIPS | FLOW | MOE | LENKM | ESTDIVMOE |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 6073018700 | 6073018700 | 6 | 73 | 18700 | 6 | 73 | 18700 | 20950 | 2359 | 0 | 8.88 |
| 5.171E+10 | 5.171E+10 | 51 | 710 | 902 | 51 | 710 | 902 | 10155 | 2516 | 0 | 4.04 |
| 4.5079E+10 | 4.5079E+10 | 45 | 79 | 11501 | 45 | 79 | 11501 | 8735 | 875 | 0 | 9.98 |
| 1.3215E+10 | 1.3215E+10 | 13 | 215 | 10802 | 13 | 215 | 10802 | 7720 | 1144 | 0 | 6.75 |
| 6071010402 | 6071010402 | 6 | 71 | 10402 | 6 | 71 | 10402 | 7040 | 848 | 0 | 8.3 |

# US EV Registration Details

| State | ZIP Code | Registration | Vehicle Mak | Vehicle Mod | Vehicle Mod | Drivetrain Ty | Vehicle GVW | Vehicle Cate | Vehicle Coun | DMV Snapsh | DMV Snapsh | Latest DMV Snapshot Flag |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| TX | 77014 | 10/1/21 | TESLA | Model 3 | 2020 | BEV | 1 | Light-Duty (C | 1 | DMV Snapsh | 9 | FALSE |
| TX | 77630 | 10/1/21 | TESLA | Model 3 | 2020 | BEV | 1 | Light-Duty (C | 1 | DMV Snapsh | 9 | FALSE |
| TX | 78526 | 10/1/21 | TESLA | Model 3 | 2020 | BEV | 1 | Light-Duty (C | 1 | DMV Snapsh | 9 | FALSE |
| TX | 78045 | 10/1/21 | TESLA | Model 3 | 2020 | BEV | 1 | Light-Duty (C | 1 | DMV Snapsh | 9 | FALSE |

# US gas prices by region and week

| Back to Contents | Data 2: Regions | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Sourcekey | EMM_EPM0_PTE_R10_DPG | EMM_EPM0_PTE_R1X_DPG | EMM_EPM0_PTE_R1Y_DPG | EMM_EPM0_PTE_R1Z_DPG | EMM_EPM0_PTE_R20_DPG | EMM_EPM0_PTE_R30_DPG | EMM_EPM0_PTE_R40_DPG | EMM_EPM0_PTE_R50_DPG | EMM_EPM0_PTE_R5XCA_DPG |
| Date | Weekly East Coast All Grades All Formulations Retail Gasoline Prices (Dollars per Gallon) | Weekly New England (PADD 1A) All Grades All Formulations Retail Gasoline Prices (Dollars per Gallon) | Weekly Central Atlantic (PADD 1B) All Grades All Formulations Retail Gasoline Prices (Dollars per Gallon) | Weekly Lower Atlantic (PADD 1C) All Grades All Formulations Retail Gasoline Prices (Dollars per Gallon) | Weekly Midwest All Grades All Formulations Retail Gasoline Prices (Dollars per Gallon) | Weekly Gulf Coast All Grades All Formulations Retail Gasoline Prices (Dollars per Gallon) | Weekly Rocky Mountain All Grades All Formulations Retail Gasoline Prices (Dollars per Gallon) | Weekly West Coast All Grades All Formulations Retail Gasoline Prices (Dollars per Gallon) | Weekly West Coast (PADD 5) Except California All Grades All Formulations Retail Gasoline Prices (Dollars per Gallon) |
| Apr 06, 2015 | 2.466 | 2.443 | 2.522 | 2.43 | 2.375 | 2.271 | 2.389 | 3.017 | 2.677 |
| Apr 13, 2015 | 2.47 | 2.435 | 2.528 | 2.436 | 2.367 | 2.275 | 2.421 | 2.983 | 2.666 |
| Apr 20, 2015 | 2.553 | 2.566 | 2.633 | 2.489 | 2.463 | 2.328 | 2.498 | 3.028 | 2.695 |
| Apr 27, 2015 | 2.627 | 2.644 | 2.706 | 2.563 | 2.506 | 2.391 | 2.55 | 3.244 | 2.802 |

# US state by size for fueling station density

| fips | state | densityMi | pop2023 | pop2022 | pop2020 | pop2019 | pop2010 | growthRate | growth | growthSince2010 | TotalArea | LandArea | WaterArea |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | Alaska | 1.29738 | 740339 | 738023 | 733391 | 731075 | 710231 | 0.00314 | 2316 | 0.04239 | 665384 | 570641 | 94743 |
| 48 | Texas | 116.16298 | 3E+07 | 3E+07 | 2.9E+07 | 2.9E+07 | 2.5E+07 | 0.01336 | 4E+05 | 0.20679 | 268596 | 261232 | 7365 |
| 6 | California | 258.20877 | 4E+07 | 4E+07 | 4E+07 | 3.9E+07 | 3.7E+07 | 0.00571 | 2E+05 | 0.07971 | 163696 | 155779 | 7916 |
| 30 | Montana | 7.64479 | 1112668 | 1103187 | 1084225 | 1074744 | 989415 | 0.00859 | 9481 | 0.12457 | 147040 | 145546 | 1494 |