CAPSTONE

A Quantitative Analysis of Policy Levers for driving Electric Vehicle Adoption in Washington State

Submitted by

Graham Jacob Michael Marmion

School of Interdisciplinary Arts & Sciences

In partial fulfillment of the requirements

For the Degree of Master of Arts in Policy Studies

University of Washington Bothell

Summer 2018

Advisor: Tate Twinam

Co-Advisor: Bruce Kochis

Abstract

This paper identifies key drivers of Electric Vehicle adoption to determine policy levers that promote Electric Vehicle purchase and to evaluate the ethical implications of current and future Electric Vehicle policy. The paper's conclusions are drawn from a regression analysis performed at the ZIP code level, which concludes that the most significant drivers are a population's commute time, median income, educational attainment, rental stock, and median age. These characteristics are valuable for determining where EV policy would be most effective, but only commute time and median income are identified as viable policy levers.

1.0 – Introduction

1.1 - Problem Statement

Electric Vehicles comprise a very small portion of the light duty transportation sector in Washington State, but recent policies aim to change that. As of 2017, there were roughly 25,000[1] Electric Vehicles (EVs) on the road – including both Hybrid Electric Vehicles (HBEVs) and Battery Electric Vehicles (BEV). These EVs represent less than one percent[2] of the total number of vehicles on the road with the bulk of the Light Duty Vehicle population consisting of Internal Combustion Engine Vehicles (ICEs). This low density of EVs poses a key obstacle to efforts to prevent or mitigate climate change damage. The EPA has identified that the transportation sector in Washington State is - by far the largest source of carbon emissions responsible for over 45% of the State's total[3].

---

[1] G3: 1.1.c Electric Vehicles

[2] There are 2,599,791 Automobiles in Washington State as of 2010. 25,000 EVs ÷ 2,599,791 x 100 = 0.962%. Office of Highway Policy Information

[3] Total 2011 emissions: 91.7. Transportation 2011 emissions: 41.9. 41.9 ÷ 91.7 x 100 = 45.692% (Washington State Greenhouse Gas Emissions Inventory: 2010 – 2011, Page 4.

According to the Washington Utilities and Transportation Commission, one of the key causes of low adoption rates in the Seattle Metro Area is that the infrastructure has been built to support Internal Combustion Engine vehicles (ICE), not EVs[4] . The most prominent evidence of this infrastructural preference is that within King County there are over one thousand publicly accessible gasoline pumps[5] and only 449 public EV Charging connections [6]. With such little available infrastructure, there's little wonder why EVs have a low adoption rate; it's been made difficult to use an EV.

This seems a bleak situation. With such low density of light duty EVs despite their critical role in combating climate change and the way the system appears stacked against EV adoption, the situation is ripe for policy intervention. In fact, Washington Governor Jay Inslee's "Results Washington" plan aims to put 50,000 EVs on the road in Washington by 2020. The goals of this action plan are being advanced by policies brought to bear by organizations across the state, including energy utilities, Electric Vehicle charging providers, cities, counties, the state legislature, and the state executive branch. As future policy solutions are developed to solve the problem of low EV density, it is important that the policy is developed intelligently and ethically. Within this paper, I analyze the 2015 *Electric Vehicles-Infrastructure Build-out*[7], which strives to promote EV adoption through the expansion of Electric Vehicle infrastructure. I then leverage available Electric Vehicle registration data to identify the characteristics of populations by ZIP codes to indicate which areas would be best suited to benefit from infrastructure build out, to identify the levers that are most important to EV adoption, and to discuss the question of equity involved in policy promoting EV adoption.

[4] Electric Vehicle Supply Equipment, Page 29

[5] Gas Stations: Area 410, Page 3

[6] Washington State Electric Vehicle Action Plan, Page 26

[7] Results Washington (2017)

1.2 - Literature Review

The key motivators Electric Vehicle adoption have been a focus of studies for many years. This study relied on several pieces of this research, which are discussed below. One such paper relied upon was Soltani-Sob, Heaslip, Stevanovic, Bosworth, and Radivojevic's *Analysis of the Electric Vehicles Adoption over the United States*. With the pretext of acknowledging that Electric Vehicles are being considered as a solution to Climate Change, their paper sought to assess the impact of government incentives and subsidies on EV market share as well as assess the impact of various socioeconomic factors. Their study was performed at the national level and found electricity price affects Electric Vehicle price most significantly and that Electric Vehicle adoption is increasing at an increasing rate as the technology diffuses into more communities.

Bilotkach and Mills' *Simple Economics of Electric Vehicle Adoption* (2012) served as a primer to become familiarized with Electric Vehicle adoption models. In their paper, these researchers developed an EV adoption forecast model and discovered that many customers are likely to purchase a gasoline-powered car as their primary vehicle and an Electric Vehicle as their second vehicle. This suggests that an increase in Electric Vehicle adoption does not actually mean a reduction in carbon emissions. Instead, a metric that would be beneficial is the number of Electric Vehicles as a percentage of total cars on the road.

In 2017, Li, Chen, and Wang's paper *Impacts of Renewables and Socioeconomic Factors on Electric Vehicle Demands – Panel Data studies across 14 coun*tries assessed the impact of renewable energy and socioeconomic factors on Electric Vehicle adoption. The factors they accounted for were the percentage of renewable energies in electricity generation, number of charging stations, education level, population density, gasoline price, GDP per capita and urbanization. They discovered that the first four of these factors were significant drivers of EV adoption but the last two were not. They found that renewable percentage is the most significant factor in driving adoption and made policy recommendations based on this. However, they concluded that because a high percentage of renewables is often associated with low cost energy, that energy cost and public sentiment are likely the key reasons for this adoption.

Harrison and Thiel's *An exploratory policy analysis of Electric Vehicle sales competition and sensitivity to infrastructure in Europe* (2017) provided a view into the causal characteristics of Electric Vehicle adoption outside of US specific features. Their research specifically focused on policy interventions as a means of encouraging Electric Vehicle adoption. They discovered that for policy promoting infrastructure as a means of encouraging Electric Vehicle adoption, the most significant impact of the policy was actually on favoring one type of drive train technology over another and had less effect on promoting Electric Vehicle adoption.

Finally, Yong and Park's *A Qualitative Comparative Analysis on Factors Affecting the Deployment of Electric Vehicles* (2017) assessed the driving factors of EV adoption as a means of meeting new carbon regulations throughout the world. They employed a qualitative comparative analysis methodology to compare region specific factors to identify the drivers of EV adoption and from those discoveries make policy conclusions. They determined that there is no clear policy solution that works but that policy targeting specific characteristics – as this paper begins to do – is needed.

2.0 - Policy Review

2.1 - Electric Vehicles-Infrastructure Build-out 2015

On June 14, 2017, the Washington Utilities and Transportation Commission issued its Policy and Interpretive Statement Concerning Commission Regulation of Electric Vehicle Charging Services. This Policy Statement was the product of almost a year of regulatory proceeding and – as this paper aims to show – over a century of policy decisions before that. Key stakeholders in the EVSE industry participated in the proceeding that produced this policy statement, including investor-owned utilities (IOUs), environmental advocacy groups, Electric Vehicle charging equipment businesses, automobile manufacturing advocacy groups, low income advocates, industrial advocates, and more[8].

In the final Policy Statement, the Washington Utilities and Transportation Commission took a policy position that endorsed electrical companies offering EV charging as a regulated service, subject to commission approval and regulation. In doing so, the WUTC Policy Statement provided guidelines as to how IOU EVSE programs would be regulated by the WUTC. These regulations can be grouped into four main components: (1) it provided guidance on what is required of IOUs to recover investment into EVSE through rates, (2) provided the framework of what an IOU operated EV Program would look like, (3) instructed electric companies to take certain steps in planning EV programs, and (4) specified the conditions under which the electric company can receive the incentive rate of return on EVSE investment authorized by RCW 80.28.360.

IOU Recovery of Investment into EVSE through Rates

This policy statement enabled IOUs to recover investment into Electric Vehicle Charging Infrastructure through rates. One of the primary forms of regulating that the WUTC does of IOUs is regulating the IOU's revenue recovery. Revenue recovery is the amount of revenue that the IOU is allowed to recover from its customers in a given year. In a simplified form, the allowable revenue recovery (or Revenue Requirement) is equal to the Utilities annual Operating Expenses plus a rate of return on the total Depreciated value of capital investments made by the IOU.

Operating Expenses + (Depreciated Value of Capital x Rate of Return) = Revenue Requirement.

[8] Electric Vehicle Supply Equipment, Main Page

The WUTC Policy Statement allowed IOUs to count investment into Electric Vehicle Charging equipment and other EVSE as Capital Investment under certain conditions, which in turn would let the utility earn a profit on that investment. For the capital investment to be eligible, the IOU first would have to demonstrate that the investment is used and useful through a business case. Second, the IOU would have to demonstrate prudence of investment using similar regulatory methodologies. Finally, the IOU would need to demonstrate that the rates used to recover the revenue are Just, Fair and Reasonable by providing data on equipment utilization, demand, load shapes, and the amount of overall fixed and variable costs recovered through user payments[9].

Framework of an IOU EV Program

The WUTC Policy Statement also provides the framework that IOUs are expected to use for programs they offer to support EVSE. Another major regulatory responsibility of the WUTC regarding IOUs is to regulate not just how much revenue the IOU recovers, but also *how* the IOU recovers it. This means regulating the prices the IOU sets and regulating the types of programs offered. Therefore, the WUTC Policy Statement's expectations for EVSE supporting Program design effectively dictate the program design. The Policy Statement explicitly requires the utilities provide dynamic program options such as portfolio of services that let the customer choose the type of relationship the IOU has with their EVSE[10].

It further requires the IOU to include cost effectiveness components such as designing program portfolios that maximize monetized benefits (specifically identified in the policy statement)[11] and designing the programs such that the Electric Vehicles do not raise the system level costs of providing electricity. For instance, to avoid increases to capacity costs, which are brought on by more energy

[9] Electric Vehicle Supply Equipment, 10 - 13
[10] Electric Vehicle Supply Equipment, 33
[11] Electric Vehicle Supply Equipment, 4

usage at peak usage times, the program can include a load shifting component to encourage customers to charge their EVs at times other than peak[12].

The Policy Statement outlined key expectations for equal access, consumer protection, and reporting. To ensure equal access, the EV Charging programs had to be offered equally to all similarly-situated customers[13], it had to include an education and outreach component[14], and a portion of the program cost must be dedicated to directly benefiting low-income customer access to the benefits of EVSE[15]. To protect consumers, the policy statement makes specific instructions for how EVSE is to be handled at the end of its depreciable life[16] and requires IOUs to adopt and ensure certain service quality standards[17]. Finally, for reporting requirements the policy statement instructs IOUs to include a comprehensive plan for regular reporting of certain identifiers regarding the EVSE[18] and also report calculations of quantifiable non-monetized benefits accrued for customers[19].

Required Steps for IOUs planning EV programs

In the Policy Statement, the WUTC instructed IOUs to take specific steps in planning and proposing EV programs. IOUs were required to take a proactive approach to planning for EV Charging Load while ensuring that infrastructure remains adequate and efficient[20]. IOUs were expected to collaborate with WSDOT to identify priority corridors for EV Charging[21] and with industry leaders to identify the capacity for transformation of the EV market[22]. The WUTC further instructed IOUs to include

[12] Electric Vehicle Supply Equipment, 35
[13] Electric Vehicle Supply Equipment, 17
[14] Electric Vehicle Supply Equipment, 41
[15] Electric Vehicle Supply Equipment, 37
[16] Electric Vehicle Supply Equipment, 17
[17] Electric Vehicle Supply Equipment, 37
[18] Electric Vehicle Supply Equipment, 40
[19] Electric Vehicle Supply Equipment, 41
[20] Electric Vehicle Supply Equipment, 21
[21] Electric Vehicle Supply Equipment, 31
[22] Electric Vehicle Supply Equipment, 26-31

an interoperability analysis in proposing EV charging services (which would assess the ability of electric vehicle owners to use different charging stations regardless of the company that owns them)[23] and mandated that the IOUs form a stakeholder group to keep informed on all program developments[24].

Conditions for IOUs to Receive the Incentive Rate of Return

The final component of the WUTC Policy Statement was that it established the condition under which the IOUs would be able to receive the incentive rate of return legally enabled by RCW 80.28.360, which would enable IOUs to collect additional profit beyond what is normally legal on Capital Investment into EVSE. In order to qualify for this incentive rate of return, the Policy Statement insists that the IOU must assess the rate impacts on a net basis to ensure it does increase the company revenue recovery by more than 0.25%. It also requires that the EVSE investment must be in an area that a PEV or PHEV is expected to be parked at for intervals of at least two hours[25].

3.0 - Methodology

3.1 - Variable Overview

General Data Source

The ZIP code level customer characteristics data used in this study is drawn primarily from the Census Bureau's pooled 5-year 2012 – 2016 American Community Survey, obtained from NHGIS**.** The Electric Vehicle registration data is extracted from a file provided by the WA DOL. The data referenced within this study is specific to ZIP codes within the State of Washington. Any ZIP code that had missing

[23] Electric Vehicle Supply Equipment, 38
[24] Electric Vehicle Supply Equipment, 40
[25] Electric Vehicle Supply Equipment, 22

or invalid data for any of the variables within this study was excluded from the analysis. Consequently, there are 555 observations within this study.

Electric Vehicles

The variable Electric Vehicles represents the sum of registered Battery Electric Vehicles (BEVs) and Plug-In Hybrid Electric Vehicles (PHEVs) within a given ZIP code during each year. The data is drawn from the Washington State Department of Licensing, which twice annually reports - by ZIP code - the number of Registered Electric Vehicles (EVs) in Washington in June and December. The reading for the number of Electric Vehicles for 2016 is representative of December 2016. Across the 555 observations, the mean number of registered EVs is 29.47027(SD = 57.02622). However, as population varies significantly across ZIP codes, the EV count is dealt with in terms of EV per capita. The mean number of per capita EVs is 0.0017 (SD = 0.00268). Figure 1 is a histogram, which depicts the frequency of observations within each EV per capita bin.

Figure 1 - Electric Vehicles Per Capita by Zip Code

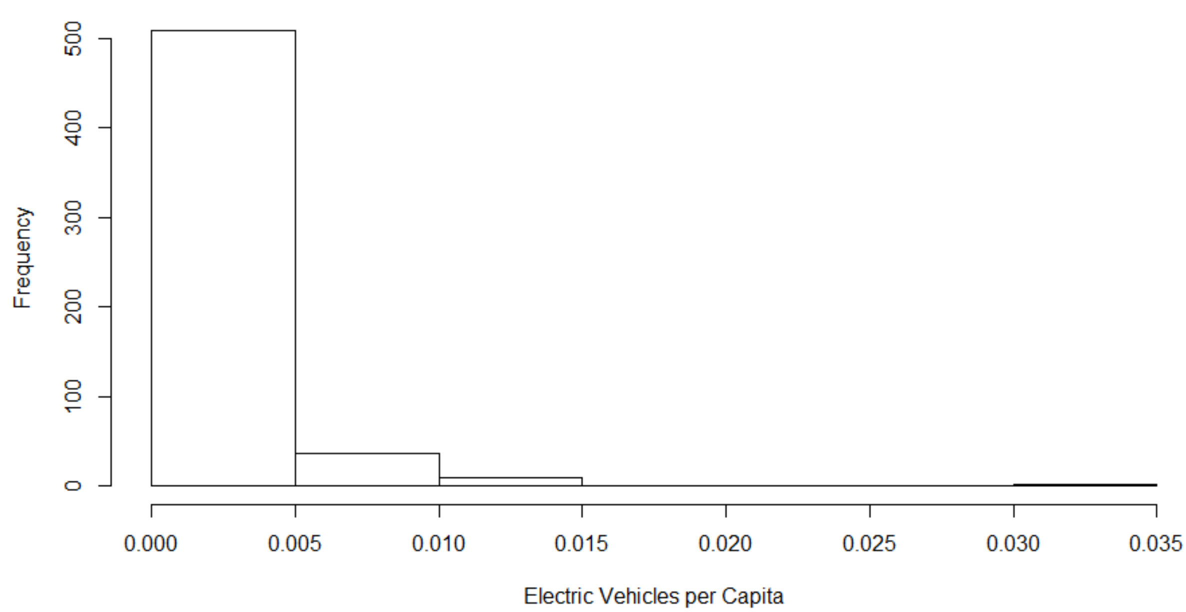


Figure 1 clearly shows that the Electric Vehicle per capita counts are right-skewed. The Median number of EVs per capita is 0.00088.

Population Density

Each ZIP is associated with a population density, which represents the number of people per square mile. The Total Population counts by ZIP code were drawn from the 2016 5-Year ACS. The Area of each ZIP was drawn from the 2016 ACS. The mean population density is 1356.046 (SD = 3017.843). Due to the large variability of this factor, the population density was standardized by taking the log of the population density. The mean of the log of the population density is 2.09983 (SD = 1.152217). Figure 2 is a histogram presenting the frequency of ZIP codes in each bin of the log of population density.

Figure 2 - Population per Sq Mi. by ZIP Code

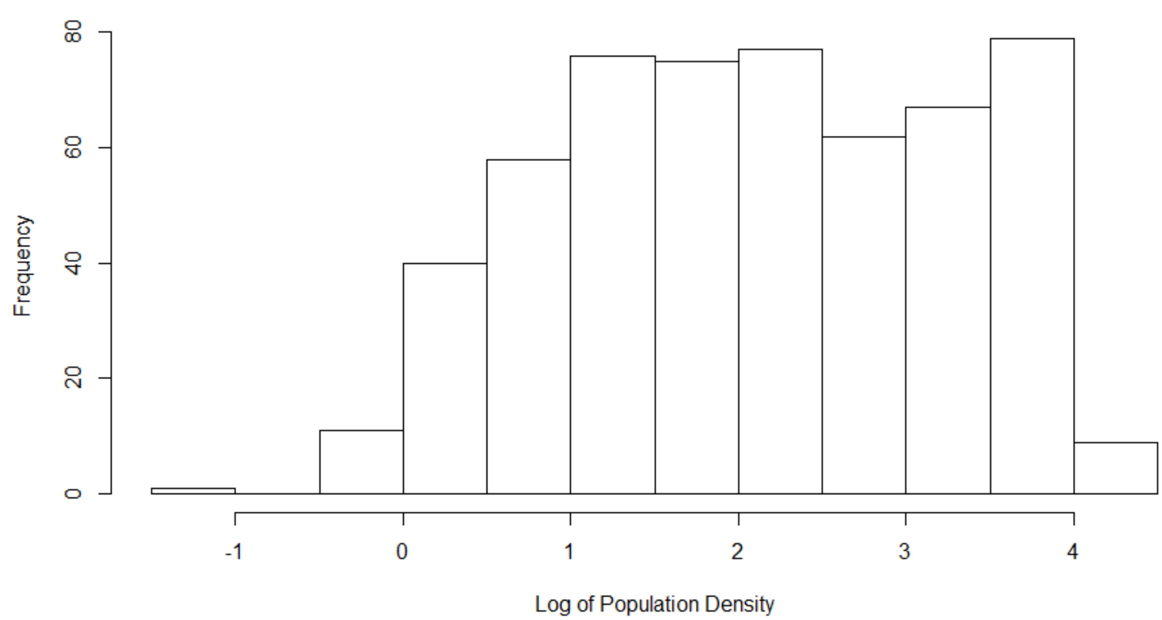


Figure 2 portrays that there is a wide range of population densities throughout the State of Washington. It further illustrates that Washington has many sparsely populated ZIP codes. A Pearson's R test to determine the correlation between population density of a ZIP code and the EVs per capita in that ZIP code revealed a significant positive correlation (0.3621546, p < 2.2x10^-16, df = 553). Figure 3 presents the relationship between a ZIP codes population density and the number of EVs per capita with a linear trend line applied.

Figure 3 - Electric Vehicles Per Capita by Population Density

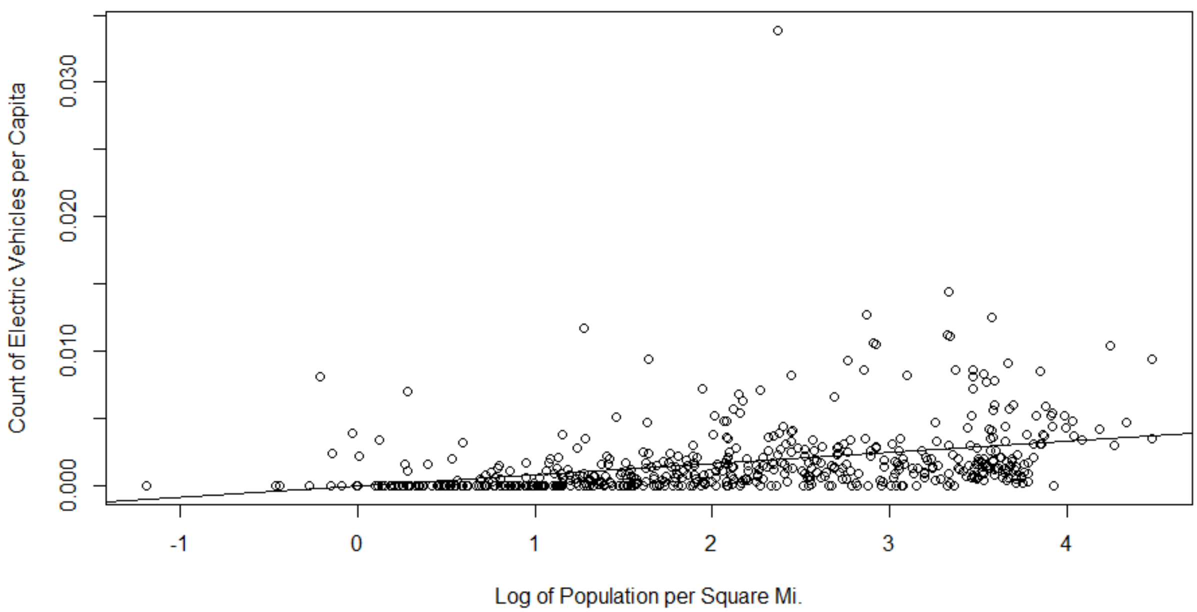


Figure 3 a positive relationship between a zip codes population density and the number of EVs per capita in that ZIP Code. The high frequency of low population density ZIP codes is visible within Figure 2 as well as there is a dense concentration of ZIP codes between 0 and 2.

Median Age

Each Year ZIP is associated with a median age of its population. The median age data is drawn directly from the 2016 5-Year ACS. The mean of the median ages across the ZIP codes is 42.4773 (SD = 9.397716) with a median of the median ages of 41.3. This variable was standardized for consistency with other variables. The standardization was done by subtracting from each value the mean (42.4773) and then dividing by the standard deviation (9.397716). When standardized, the resulting mean is 0.02084 (SD = 1.022778). Figure 4 is a histogram that displays the frequency of observation in each bin of standardized age.

Figure 4 - Median Age by Zip Code

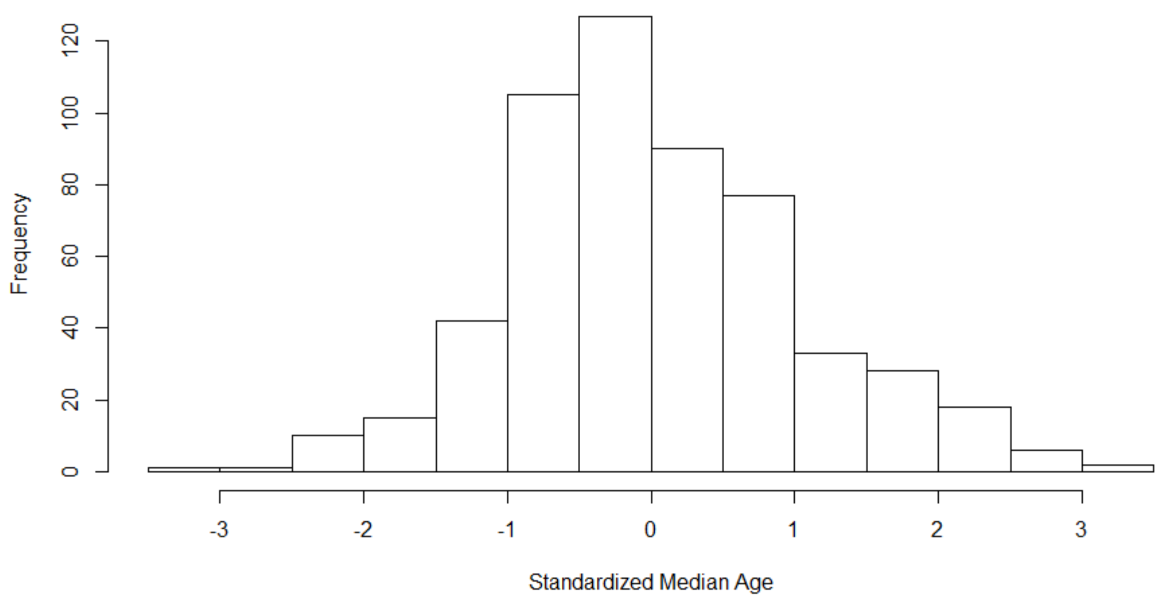


Figure 4 demonstrated that the Median age in Washington ZIP codes is much less skewed than has been seen with other variables in this study but it is still slightly right skewed. A Pearson's test for correlation with the standardized median age revealed an insignificant and weak positive correlation between the Median age of a ZIP code and the EV per capita within it (0.07859, p = 0.0643, df = 553). Figure 5 displays the relationship between the standardized Median age within each ZIP and the corresponding EV per capita with an added linear trend line.

Figure 5 - Electric Vehicles Per Capita by Median Age

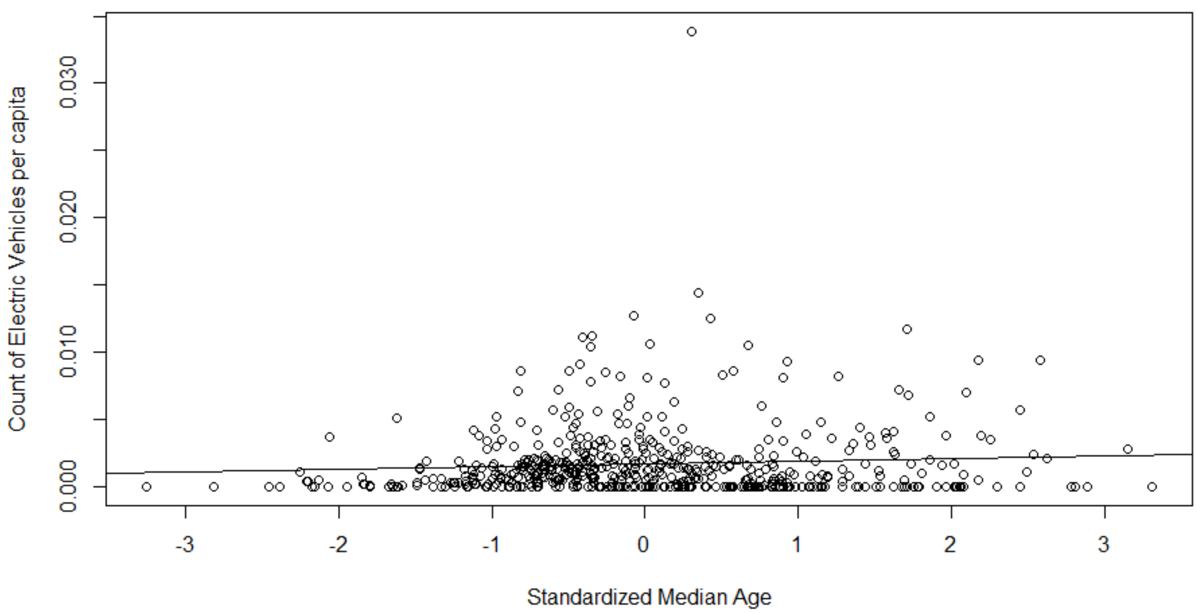
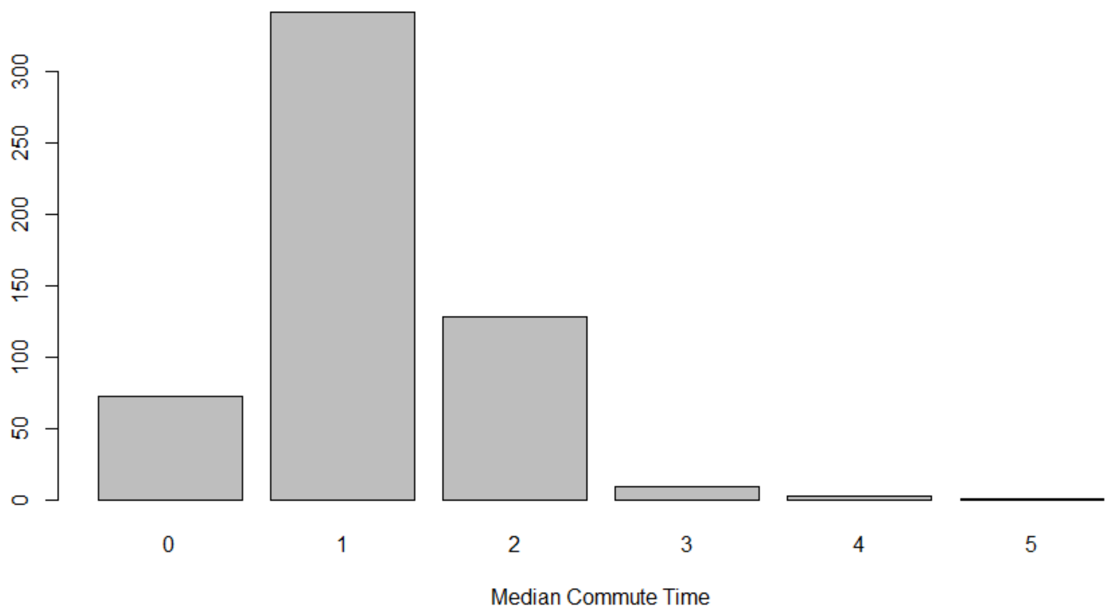


Figure 5 suggests that the EV per capita in a given ZIP code by Median Age follows the same pattern as number of ZIP codes with each Median Age. This pattern mirroring the shape of median age and the weak correlation suggests that the relationship shown in Figure 5 is likely the product of their being more ZIP codes with a median age around 40 rather than the product of EV counts being correlated with Median Age.

Commute Time

Each observation is associated with a median travel time for people living within that ZIP code. The Travel time data is drawn from the 2016 5-Year ACS but the bins are expanded to enable easier data manipulation. Travel Time (referred to as “Commute”) is an ordinal variable with the following levels: Commute of Less than 15 minutes, 15 to 29 minutes, 30 to 44 minutes, 45 to 59 minutes, 60 to 89 minutes, and 90+ minutes. Within the regression model, these levels are treated as separate variables each indicating the percentage of the ZIP code’s population at each level. The category “Less than 15 minutes" was excluded from the regression model to avoid overfitting. Across all observation, the median commute time was level 1 (15 to 29 minutes). Figure 6 is a bar chart that presents the number of observations in each level of the commute variable.

Figure 6 - Median Commute Time by Zip Code



Evidently, most ZIP codes had a median commute time of 15 to 29 minutes (61.44%), followed by a commute time of 30 to 44 minutes (23.06%), followed by a commute time of Less than 15 minutes (13.15%). Very few observations (2.35%) have a median commute time in a level above 30 to 44 minutes. A spearman's r test for correlation revealed a significant positive relationship between median commute time and number of Electric Vehicles per capita (0.1973559, p = 2.799x10^-6). Figure 7 presents the relationship between Electric Vehicles per capita and the median commute time for a ZIP code with a linear trendline applied.

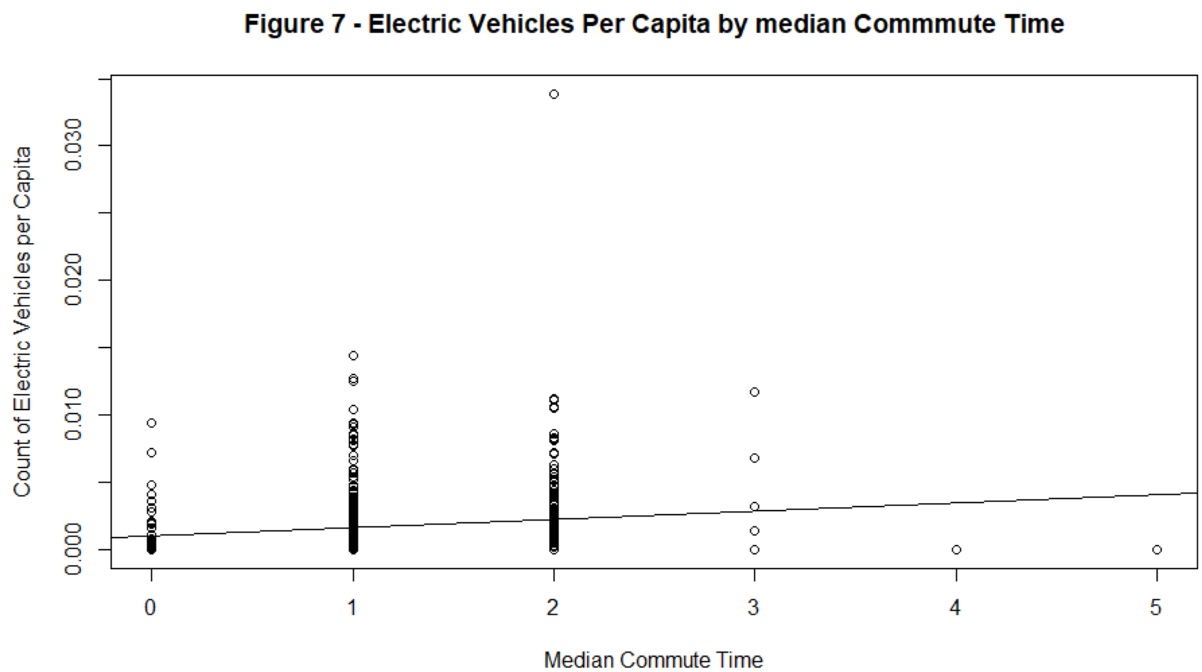


Figure 7 displays the positive correlation between the median commute time and EV per capita. However, the dense concentration of commute times in levels 1 and 2 are clearly the more dominant factor in determining where EVs are located.

Educational attainment

Educational Attainment represents the median highest level of education attained by people within each ZIP and respective year. The Educational attainment level was calculated 2016 5-year ACS data, but was reduced to wider buckets to facilitate easier computations. Educational attainment is an ordinal variable with the following levels: Less than high school, High school degree or equivalent, Less than bachelor's degree, Bachelor degree, and Advanced degree. Within the regression model, each level is treated as a separate variable indicating the percentage of the ZIP codes population with that level of educational attainment. The lowest level – less than high school – was excluded from the regression model. Across observations, the median of the median educational attainment was at level 2 – Less than a bachelor's Degree. Figure 8 presents a bar plot that indicates the frequency of observation in each level of the ordinal variable.

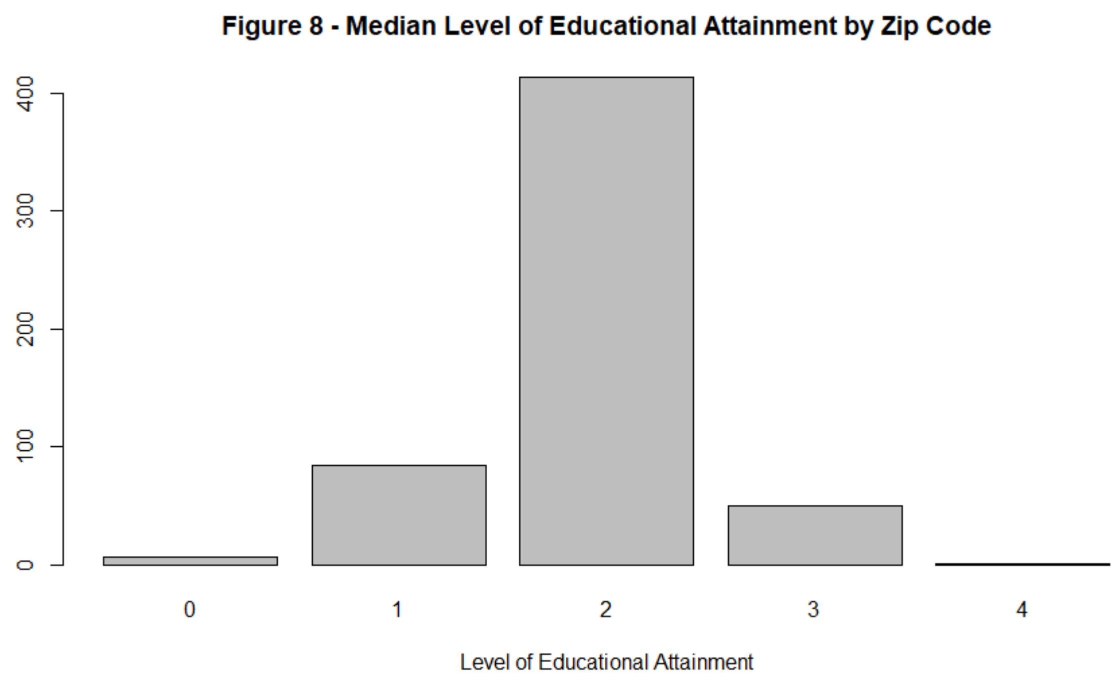


Figure 8 clearly illustrates that the Median level of educational attainment is neither left nor right skewed. Instead, the medians for each observation are well clustered around achieving an educational attainment level of less than a bachelor's degree. The vast majority of observations have a median level of attainment of less than a bachelor's degree (74.41%), followed by high school or equivalent, (15.14%), followed by Bachelor's degree (9.01%), less than high school (1.26%), and an Advanced Degree (0.18%). A Spearman's R test for correlation revealed a significant strong positive correlation between the median educational attainment level of a ZIP and the number of EVs per capita within that ZIP (0.48389, p < 2.2x10^-16). This relationship is presented in Figure 9 with a linear trend line added.

Figure 9 - Electric Vehicles Per Capita by Median Educational Attainment

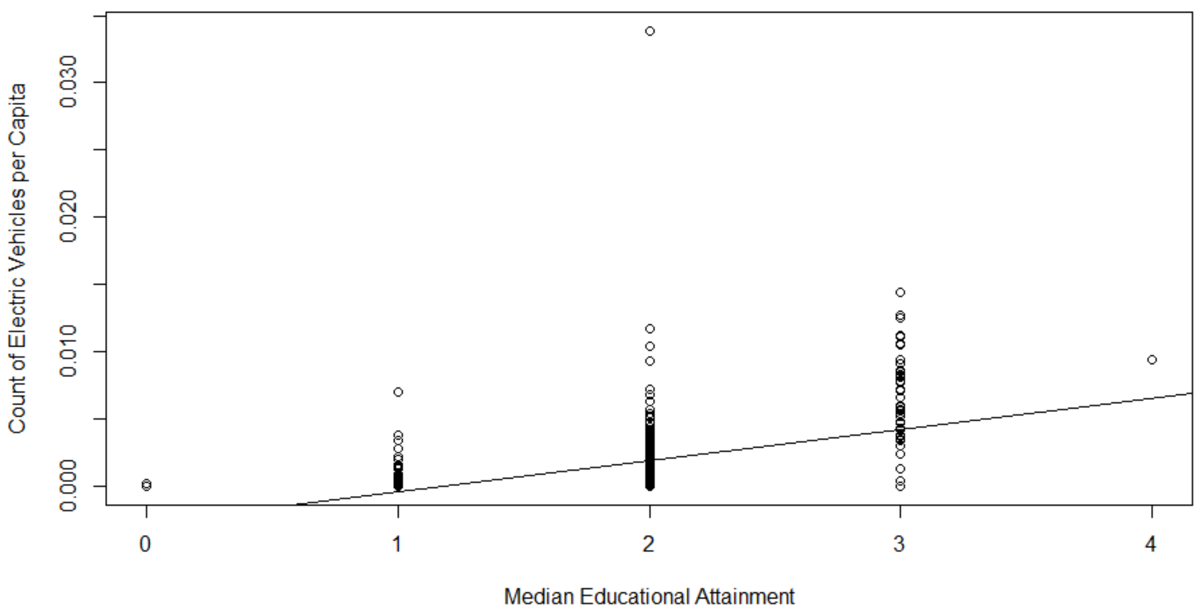


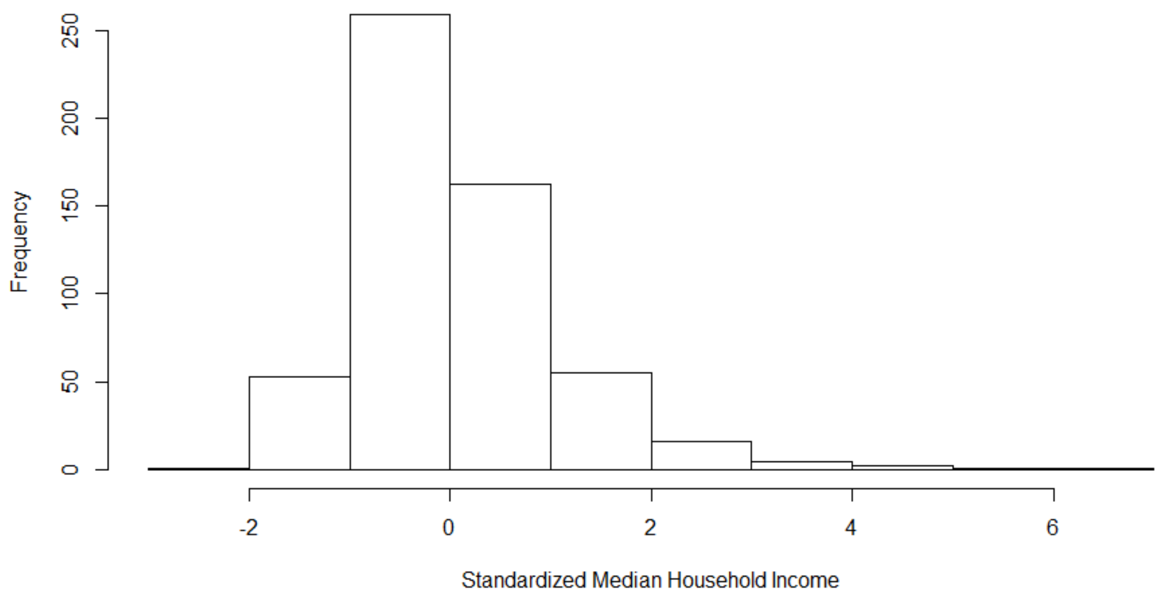
Figure 9 makes clear the positive relationship between educational level and the count of Electric Vehicles. It also displays that this positive relationship exists outside of simply the concentration of ZIP codes at the 2nd level of educational attainment, which supports the strong positive correlation discovered.

Median income

The Median Income for each ZIP represents the median Household Income for that ZIP during that year. The Median income was extracted from the 2016 5-Year ACS. Across all observations, the mean Median Income is $58,387.94 (SD = $20,711.06). The median of the median income is $54,707. This data was normalized using the same method as median age (subtracting the mean and dividing by the standard deviation). The mean of the standardized median income was 0.04951 (SD = 1.02711).

Figure 10 is a histogram presenting the frequency of observations in each Median Household income bucket.

Figure 10 - Median Household Income by Zip Code



The median household income is slightly skewed to the right, but evidently the largest share of the household income falls around the $50,000 mark. Considering that Electric Vehicles typically are typically on the expensive side, it is likely that this low median income mark is a key inhibitor of Electric Vehicle adoption. A Pearson's test for correlation revealed a significant strong positive relationship between median household income and EVs per capita (0.5774895, $p < 2.2x10^{-16}$, df = 553). Figure 11 displays the relationship between standardized Median income of ZIP codes and the corresponding number EV per capita in that ZIP.

Figure 11 - Electric Vehicles Per Capita by Median Income

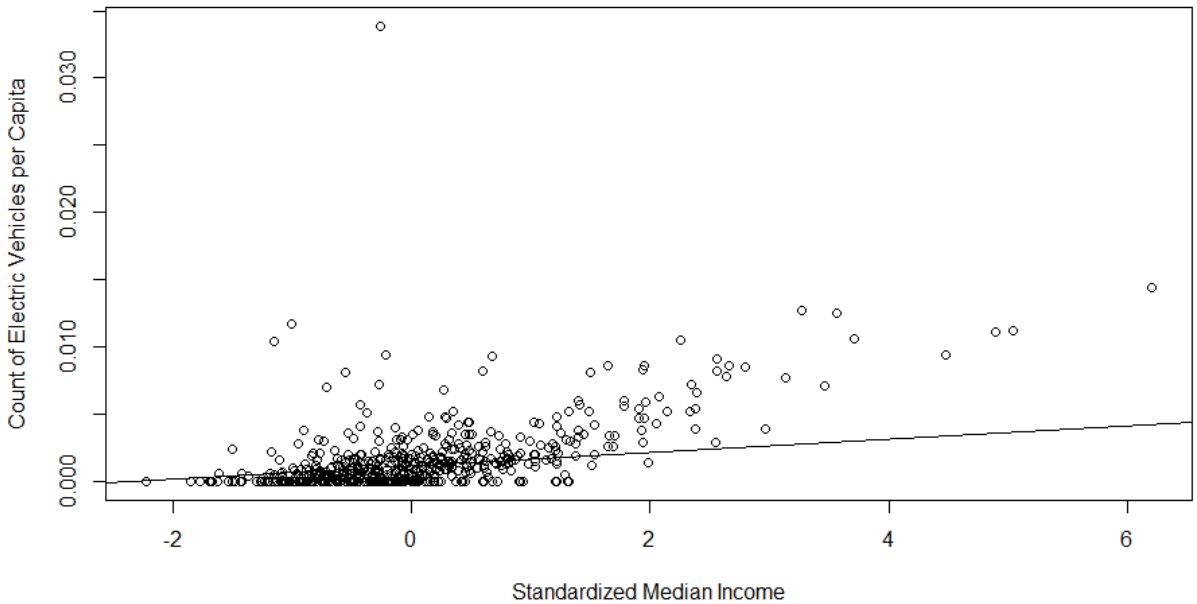


Figure 11 illustrates the positive correlation between Median Income and EVs per capita clearly. In fact, it appears that the relationship increases at an exponential rate suggesting a polynomial is in order for the regression.

Rental Percentage of Households

Rental percentage of households represents the percentage of households in each ZIP for each year that are occupied by renters instead of owners or other. The mean of rental percentages across observations is 31.88% (SD = 16.02%). Figure 12 is a histogram presenting the frequency of observations by rental percentage level.

Figure 12 - Rental Households as a Percentage of total Households by Zip Code

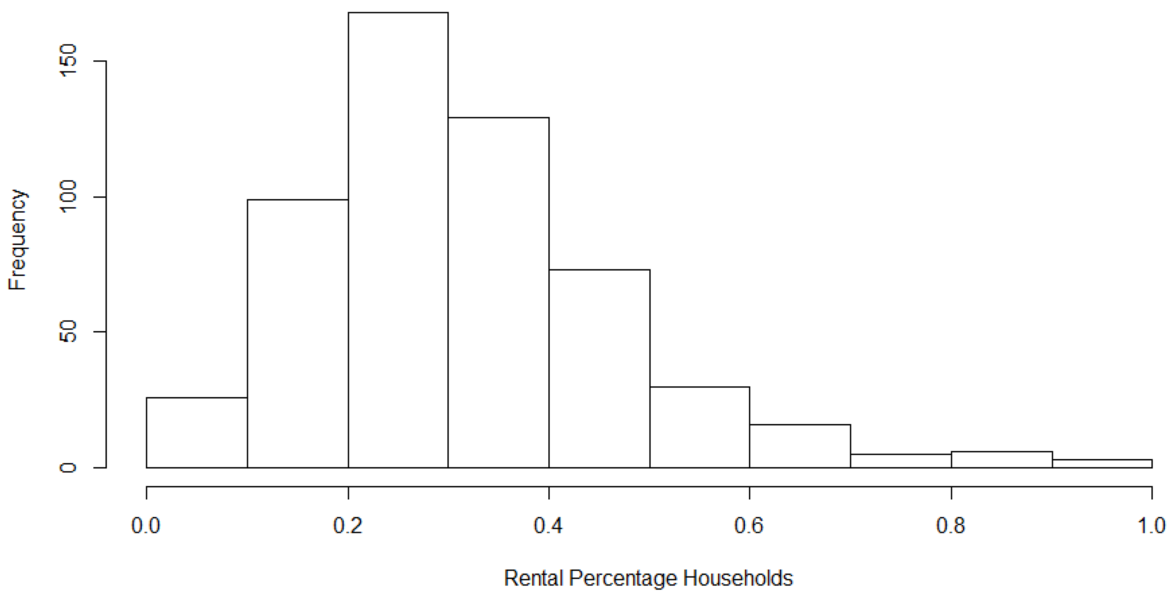


Figure 12 illustrates that most observations have a relatively low percentage of rental households of the total households within that zip. A Pearson's test for correlation reveals an insignificant weak negative correlation between the percentage of rental households and EV per capita within a given ZIP (- 0.0062833, p = 0.8826, df = 553). Figure 13 presents this relationship with a trendline.

Figure 13 - Electric Vehicles Per Capita by ZIP Code Rental Percentage

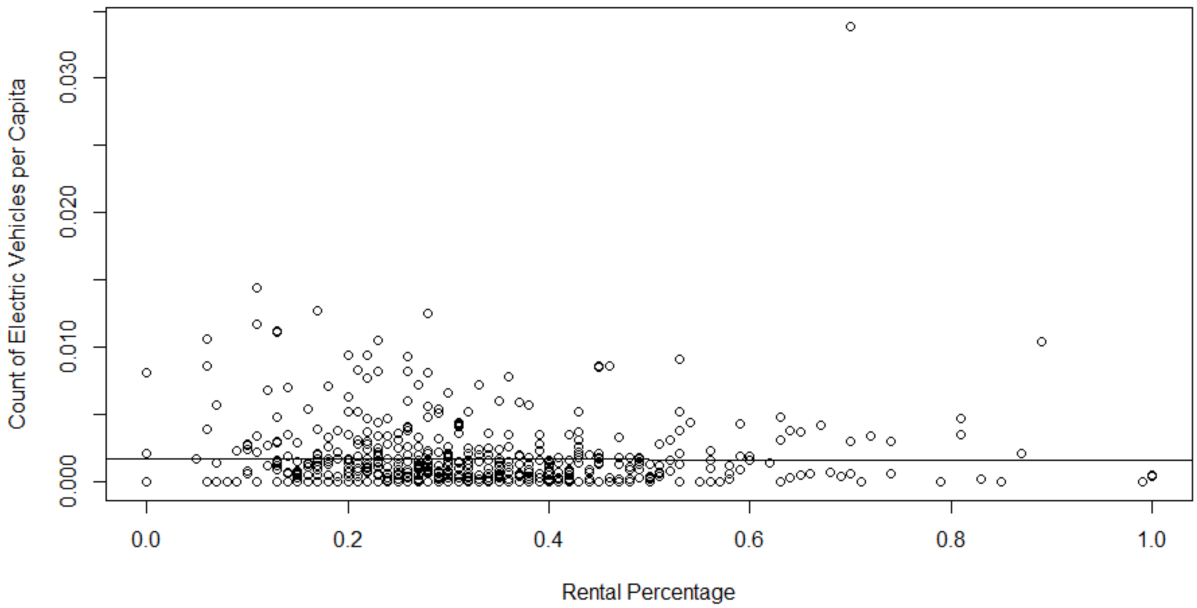
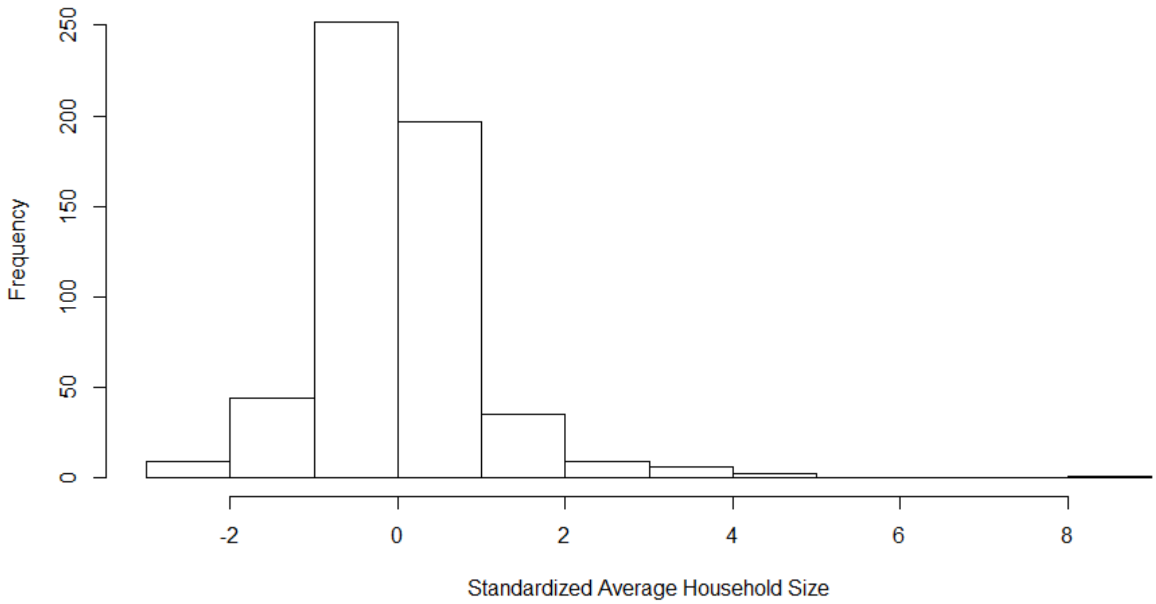


Figure 13 suggests that the count of Electric Vehicles is spread relatively evenly across the rental percentage. With a denser concentration between 20% and 40%, which is similar to the distribution of ZIP codes by rental percentage affirming that correlation between the two is insignificant.

Average household size

The Average household size represents the average household size within ZIP for each Year. The data is extracted from the 2016 5-year ACS. The mean Average household size across all observations is 2.57528 (SD = 0.52377). The average household size was standardized by subtracting the mean and dividing the resulting value by the standard deviation. This presented a mean of $-9.009008 \times 10^{-12}$ (SD = 1.000902). Figure 14 is a histogram presenting the distribution of observations by average household size.

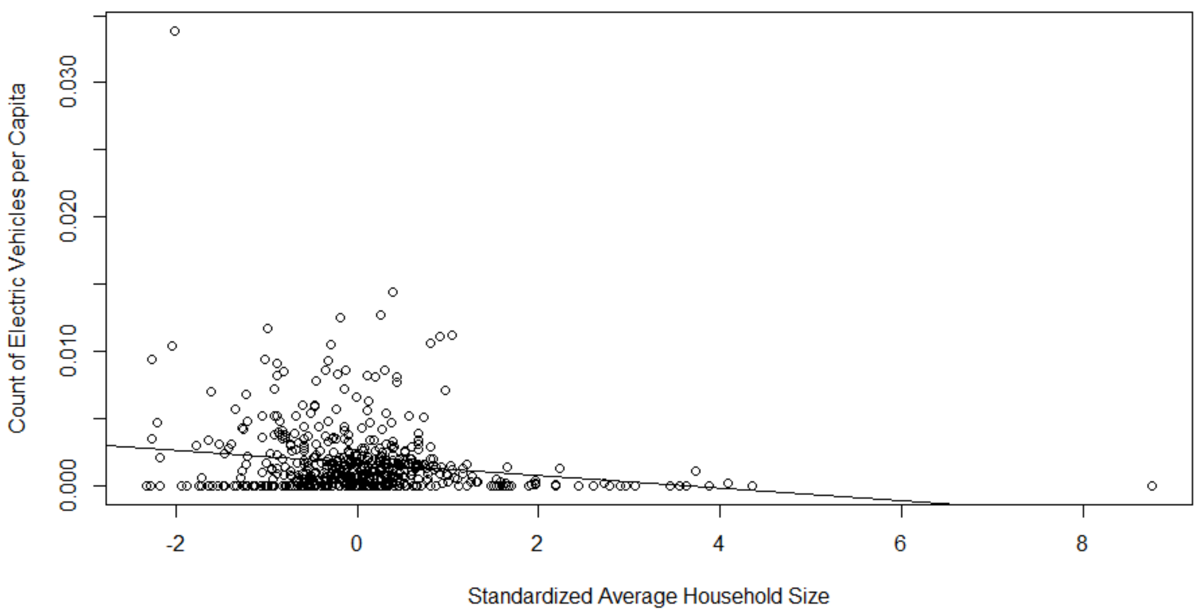
Figure 14 - Average Household size by Zip Code



Most observations have an average household size near the mean (of roughly 2.5 people) with little variance (as indicated by the relatively small standard deviation). A Pearson's test for correlation reveals a significant negative correlation between Average household size and total count of EVs (.1746908, p = 3.503×10^{-3}, df = 553). Figure 15 presents the relationship between standardized Average

Household Size and EV per capita within a ZIP code

Figure 15 - Electric Vehicles Per Capita by Average Household Size



The distribution of Electric Vehicle counts by Average Household size closely mirrors the distribution of ZIP codes by Average Household Size seen in figure 14, but there is still a clear negative relationship between average household size and EVs per capita.

Percent of population living in urban area of the zip code

This variable represents the Percent of population living in an urban area within each ZIP code for each year. Across all observations, the mean is 47.64% (SD = 44.23%). Figure 16 is a histogram presenting the frequency spread of observations by urban percentage.

Figure 16 - Urban Population as a Total ZIP Level Population by Zip Code

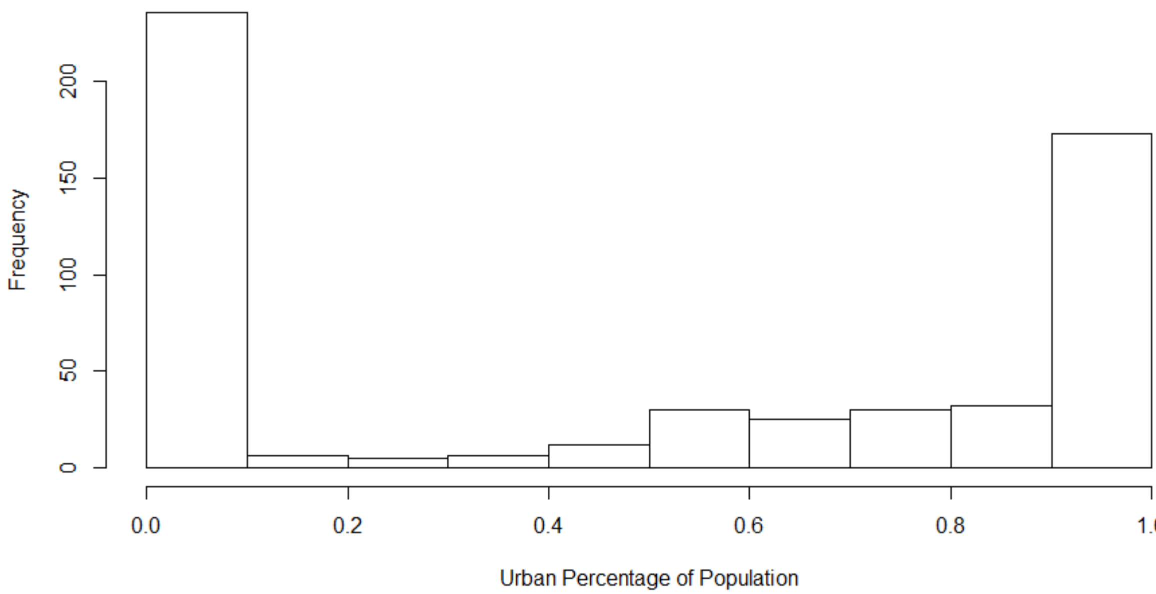


Figure 16 reveals that the Urban population percentage clearly does not follow a normal distribution. This is to be expected as a ZIP code is typically a small enough area such that it doesn't contain both rural and urban areas. The largest share of observations are 0% Urban (42.16%) followed by 100% Urban (23.78%) and the remaining are mixed (34.06%). A Pearson's test for correlation reveals a significant positive relationship between the percentage of each ZIPs population living in an urban area and the total number of EVs in that ZIP (0.2999454, p = 5.309x10^-13, df = 553). Figure 17 presents the relationship between the percentage living in an Urban area and the total number of EVs.

Figure 17 - Electric Vehicles Per Capita by ZIP Code Urban Percentage

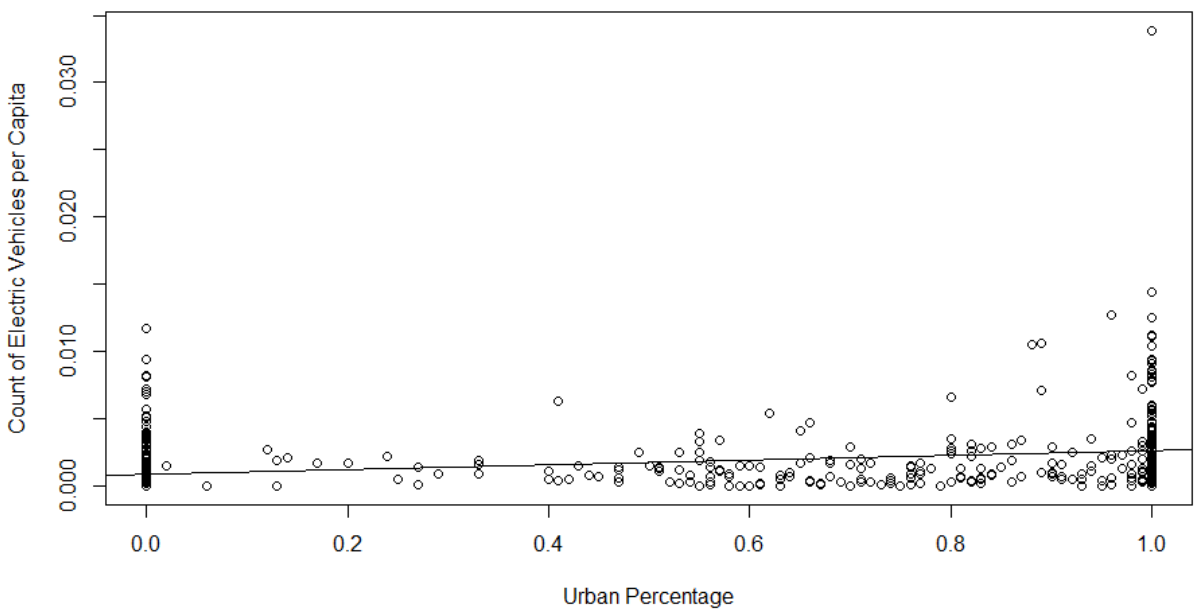


Figure 17 makes clear the that the EVs per capita within a ZIP are positively correlated with the percentage of that ZIP code's population living in an urban setting. This relationship does *not* mirror the distribution of ZIP codes by urban percentage seen in figure 16, suggesting this correlation is more likely to be a causal relationship. This is not shocking as an urban setting conveys shorter driving distances and more access to Electric Vehicle chargers, making it easier to own an electrical vehicle. However, there could be cross correlation with income or rental percentage within this correlation.

3.2 - Analysis Method

To determine the drivers of Electric Vehicle adoption and the key indicators of the presence of EVs, I developed a multilinear regression. This process began by truncating the data set into a training data set and a test data set and then built a multilinear regression model that would indicate which of the variables covered in Section 3.1 – Variable Overview - were significant influencers.

Cleaning and Preparing the Data

Before building a model or truncating the data, it had to be cleaned and prepared. Section 3.1 indicates the source of each data variable as well as any calculations done to create the data. However, there were missing values within the originally sourced data. Any observation (each ZIP) that had at least one missing value for a variable used in the model was removed from the data set. For the ordinal variables Commute Time and Educational Attainment, the various levels were treated as separate variables as described. The data set was then imported into the R programming environment under the name “ev” and is referred to as such throughout the figures displaying the R code used in the Appendix 1.

Building the Training and Test Data Sets

The training and test data sets were created to ensure that the model does not overfit the data and so verify if the identified levers are actually the drivers of adoption. I truncated the data by first randomly sorting the data and then identifying the first 80% of observations. For this data set, that represented the 444th observation. These first 80% of the randomly sorted data set were deemed the “Training” data set and the remaining 20% were deemed the “Testing” data set. For this analysis, the training data set included 111 observations. This process was performed using R and the code for it can be found in Appendix 1.

Building the Regression Model

With the training and test data sets prepared, I proceeded to build a multilinear regression model that would regress the number Electric Vehicles per capita onto Population Density, Median Age, Commute time, Educational Attainment, Median Household Income, Rental Percentage, Average Household Size, and Urban Percentage. Median Household Income was thought to have a polynomial relationship with EVs per Capita and so a squared version of those two variables was included in the regression model as well. The Regression model was built using exclusively the Training Data set. This analysis was also performed using the R programming language.

The results of the regression model can be found in Tables 1 and 2. Table 1 provides the coefficients and their significances while table 2 presents the summary statistics on the fit of the model.

Table 1 - Regression Coefficients

Variable	Description	Estimate	Std. Error	t value	Pr(>|t|)	Sign.
(Intercept)		0.0006626	0.001338	0.495	0.62082	
pop_dense_log	Log of Population Density	0.0001124	0.0001601	0.702	0.48325	
med_age_std	Standardized Median Age	0.0005476	0.0001911	2.866	0.00436	**
pct_rental	Rental Percentage	0.002438	0.0009768	2.495	0.01296	*
avg_household_std	Standardized Average Household Size	-0.0001182	0.0001745	-0.677	0.49857	
pct_urban	Urban Percentage	0.0003112	0.000401	0.776	0.43813	
	Percentage of Population with Commute length of...					
com_15_to_29	...15 to 29 min	0.001485	0.0008464	1.754	0.08007	.
com_30_to_44	...30 to 44 min	0.001563	0.00102	1.533	0.12602	
com_45_to_59	...45 to 59 min	0.003393	0.001149	2.954	0.00331	**
com_60_to_89	...60 to 89 min	0.003521	0.001538	2.289	0.02259	*
com_90	...90+ min	0.003182	0.00217	1.467	0.14325	
	Percentage of Population with Educational Attainment level of...					
educ_highschool	...Highschool diploma or Equivalent	-0.005523	0.001773	-3.115	0.00196	**
educ_lt_bachelor	...Less than Bachelor's Degree	-0.003091	0.001535	-2.013	0.04476	*
educ_bachelor	...Bachelor's Degree	0.003078	0.001768	1.741	0.0824	.
educ_advanced	...Advanced Degree	0.00227	0.002205	1.029	0.30388	
med_income_std	Standardized Median Income	0.0004593	0.000185	2.482	0.01345	*
I(med_income_std^2)	Standardized Median Income Squared	0.0002131	0.00004384	4.86	0.00000165	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 2 - Regression Summary Statistics

Statistics	Result
Residual Standard Error	0.001991 on 427 degrees of freedom
Multiple R-Squared	0.53
Adjusted R-Squared	0.5124
F-Statistics	30.09 on 16 and 427 DF
P-Value	< 2.2e-16

According to Table 1, the variables that are significant drivers of the number of Electric Vehicles per capita in a ZIP code are the standardized median age, the rental percentage, several levels of commute length, several levels of educational attainment, median level of Educational Attainment, and the median income. The remaining variables - population density, average household size, urban percentage, and certain levels of educational attainment and commute are insignificant drivers.

Of peculiar note that warrants further investigation are the reasons behind Median Age as a driver and Rental Percentage as a driver. The correlation tests revealed insignificant relationships between these variables and the number of EVs per capita, yet the regression identified them as significantly influential.

The Standardized Median Age is deemed a significant driver with an increase in 1 of the standardized median age being associated with a .00005476 increase in per capita EVs. This suggests that as the population gets older, the number of EVs per capita increase. This could be due to a correlation between age and income and educational attainment and further research should be done to determine if these variables are too heavily connected.

The rental percentage is also a significant driver of the presence of EVs with each one percentage point increase in rental stock being associated with a 0.002438 increase in EVs per Capita. This would suggest that if a ZIP was 100% rental, there would be 0.2438 EVs per Capita or – in other words one EV for everyone four people. This is a significant lever and so the causal relationship between Rental Percentage and EVs per capita warrants more investigation.

The other significantly influential levers – commute length, educational attainment, and median income – are more easily explainable. Most intuitive is the significant positive coefficient around income. EVs cost more relative to non-EV cars and so ZIPs with a higher median income are like to have more.

Each level of commute length has a positive coefficient with the most significantly influential level being the third level (45 to 59 minutes). An increase of 1% percentage point of a ZIPs population having a commute of this length is associated with a 0.003393 increase in per Capita EVs. If 100% of a population had a commute of this length, there would be 0.3393 EVs per capita, or 1 EV for every 3 people. The reason for this commute length being the most significant is likely that it is short enough to be a manageable distance for most EV batteries while being long enough to justify a more cost-effective form of transportation compared to an internal combustion engine. The relationship between EVs per Capita and Commute length warrants more investigation.

Educational attainment has the potential to increase the number of EVs per capita or reduce them. The lower levels of educational attainment (High school and less than a bachelor's degree) both hold significant negative coefficients, meaning that the larger portion of the population in those levels, the less EVs per capita a ZIP code will have. On the other hand, that higher levels of educational attainment (specifically Bachelor's degree) have positive coefficients means that if a larger portion of the population is more educated, then the ZIP will have a higher EV per capita. This influence could be the product of income differences between educational attainment levels, transportation needs, awareness, and more.

The variables that were *not* revealed to be significant influencers warrant more investigation. Most significant of which are population density and urban percentage as both had significant positive correlations with EVs per capita. It makes intuitive sense that these factors would be associated with more EVs per capita as more urbanization and density provide more opportunity for Electric Vehicle Servicing Equipment. It could be that an increase in urban percentage and an increase in population density are both associated with an increase in population, whereas EV per capita is negatively associated with an increase in population. Meaning that as the population increases, the ev per capita decreases. More research ought to be performed into the relationship between EV per capita and population density, total population, land area, and other factors relevant to urbanization.

Testing Model Fit on Training Data

The fit of the Regression Model was tested using Adjusted R-Squared as well as the Root Mean Square Error (RMSE). The Adjusted R-Squared of the Model was 0.6043, indicating that it is a good fit.

The RMSE is calculated by squaring the residuals, finding the average of the squared residuals, and then taking the square root of the result. It can be written with the following notation, where Z_{fi} represents the predicted value that the function produces and Z_{oi} represents the *actual* value in the data set.

$$\text{RMSE}_{fo} = [\sum_{i=1}^{N} (z_{f_i} - z_{o_i})^2 / N]^{1/2}$$

In effect, the RMSE provides an indicator for how accurately a model fits the test data set relative to the training data set. When calculated for the regression model built in this paper, the $\text{RMSE}_{\text{Train}}$ equaled 0.00195. To determine how significant this error is, the Mean Absolute Error (MAE) is calculated.

Testing Model Fit on Testing Data

By calculating the RMSE for the Model when applied to on the Training Data set from which it was built, we are able to determine how well the model fits that training data set. However, another important factor to consider is how well the model fits data that was not part of the training data set. Theoretically, a model could be designed to perfectly mirror a training data set and so reduce the RMSE to 0. However, this model would likely suffer from being over fitted to the training data set and so be useless for purposes outside of that training data set. To test if this model is overfitted, the RMSE is calculated for the model when applied to the Testing data ($\text{RMSE}_{\text{Test}}$), and the result is compared to the RMSE of the model when applied to the Training data ($\text{RMSE}_{\text{Train}}$). When calculated, the $\text{RMSE}_{\text{Test}}$ was

0.00126. Remarkably, this is *lower* than the $RMSE_{Train}$ of 0.00195, which indicates that the model fits the test data set *better* than it fits the training data set.

Testing Model Fit compared to Average

To evaluate whether the model is better than simply taking the average (and so worth using), the Mean Absolute Error is calculated first for the training data set and then for an intercept only model.

The MAE is simply the mean of the absolute value of the error between the data set and the model's predictions. For the training data set, the MAE was 0.00095, meaning that any prediction of EV per Capita is off – on average - by 0.00095. Considering the mean for EV per capita is 0.0017 (SD = 0.00268), this error is not *too* extreme. For the test data, the MAE continues to indicate that the model is a superior fit for the test data than it is for the training data as the MAE for the test data set is computed at 0.00084.

To calculate the MAE for an intercept only model, first a regression is built regression EV per capita on to a constant (in this case 1). When the resulting intercept only model is applied to the training data set, the MAE is calculated at 0.00172, which is nearly double the MAE for the model built within this paper. This indicates that even if the model is not a *perfect* fit, it's better than taking the average.

4.0 Discussion

4.1 - Policy Levers

For future policy intended to promote the adoption of Light Duty EVs in certain areas (or across the state as whole), the policy ought to be designed to manipulate the characteristics that are most influential on the number of Electric Vehicles per capita. These manipulatable characteristics should be thought of as "policy levers" - that is, levers that the policy can pull to accomplish certain objectives. For promoting EV adoption in a given area, these levers are the influential characteristics identified in

Section 3.0 - Methodology. The most significant levers include the commute time to work, level of educational attainment, and Median Income.

A very real lever that EV promoting policy could aim to pull is the lever of commute time. The regression model suggested that policy would be most effective by promoting commutes that are 45 to 59 minutes. To this end, policy designed to shorten commutes that are typically greater than an hour (such as highway expansion or other road construction) would be effective at increasing EVs per Capita. Such policy would also likely get public support.

According to the regression model herein, to pull the lever of educational attainment, EV policy ought to be designed to promote a higher median educational attainment in the area where the policy wants to increase EV adoption. Policy would be best aimed at raising education levels from less than a bachelor's degree to a Bachelor's degree. However, this is likely an inefficient policy lever for two reasons. First, as discussed before, the link between educational attainment and EV per capita is likely an indirect link and so policy that manipulates educational attainment will only partially effect EVs per capita. Instead, more research should be done into explaining the link between educational attainment and number of EVs per capita before policy is designed to pull this lever. The second reason educational attainment makes for an inefficient policy lever is that getting a bachelor's degree requires a large amount of time, effort, and money – altogether making it hard to design policy to effectively encourage this.

One of the most prominent levers EV policy should be designed to pull is the Income Lever. The regression analysis revealed that an increase in the median income of an area leads to an increase in the adoption of EVs. Realistically, the causal relationship between higher income and higher EV population is likely due to the higher income making it easier to afford an EV, although this ought to be explored in more research. If true, then EV policy should pull this lever by making EVs more affordable through subsidies or tax exemptions. The effectiveness of these affordability measures will be ripe for research within the next few years as more data becomes available after the 2009 Washington State Alternative Fuels and Hybrid Vehicle sales tax exemption expired in May of 2018.

4.2 - Equity

EVs are currently being adopted primarily in ZIP codes where - at the median - the population is highly advantaged. Two of the strongest influencing factors of EV adoption are educational attainment and median income. Lower educational attainment and lower income levels lead to lower rates of EV per capita across Washington ZIP codes, which results in EVs being concentrated in more highly advantaged populations within the state.

This concentration raises a question of equity: is it fair for the state to design policy and provide support to improve EV adoption and the EV experience even if the disadvantaged to do not get to experience the benefits? On the one hand, it could be argued that in the battle of climate change it doesn't matter *who* reduces their carbon emissions as the world as a whole will avoid the associated costs of climate change. This argument would suggest that it *is* ok to provide policy supporting EVs regardless of who benefits directly from the policy. However, it cannot be ignored that access to an EV provides significant benefits to a driver (not least among which is the lower costs of transportation and maintenance). Consequently, the policy is certainly providing more benefit to one group over another. In the interest of designing fair and equitable policy, EV policy should be designed to benefit those with lower income or less education, which the EV Infrastructure Build-Out policy specifically attempts to do.

Appendix 1 – R Code

"Setting Data set"

```
ev <- EV_Analysis_Only_2016
```

"Creating Train and Test Data Sets"

```
set.seed(123)

rows <- sample(nrow(ev))

ev <- ev[rows, ]

split <- round(nrow(ev) * .80)

ev.train <- ev[1:split, ]

ev.test <- ev[(split + 1):nrow(ev), ]
```

"Creating training regression"

```
lm.evtrain <- lm(ev_per_capita ~ pop_dense_log + med_age_std + com_15_to_29 +
com_30_to_44 + com_45_to_59 + com_60_to_89 + com_90 + educ_highschool +
educ_lt_bachelor + educ_bachelor + educ_advanced + med_income_std +
I(med_income_std^2) + pct_rental + avg_household_std + pct_urban, data = ev.train)

summary(lm.evtrain)
```

"RMSE: Training Set"

```
p.evtrain <- predict(lm.evtrain, ev.train)

error.evtrain <- p.evtrain - ev.train[["ev_per_capita"]]

sqrt(mean(error.evtrain^2))
```

"RMSE: Test Set"

```
p.evtest <- predict(lm.evtrain, ev.test)

error.evtest <- p.evtest - ev.test[["ev_per_capita"]]

sqrt(mean(error.evtest^2))
```

"MAE: Training Set"

```
mean(abs(error.evtrain))
```

"MAE: Test Set"

```
mean(abs(error.evtest))
```

"MAE: Test against average"

```
lm.average <- lm(ev_per_capita ~ 1, data = ev.train)

summary(lm.average)


p.evaverage <- predict(lm.average, ev.train)

error.average <- p.evaverage - ev.train[["ev_per_capita"]]

mean(abs(error.average))
```

"Histograms of Variables - descriptives"

```
hist(ev$ev_per_capita, main="Figure 1 - Electric Vehicles Per Capita by Zip Code", xlab = "Electric Vehicles per Capita")

hist(ev$pop_dense_log, main="Figure 2 - Population per Sq Mi. by ZIP Code", xlab = "Log of Population Density")

hist(ev$med_age_std, main="Figure 4 - Median Age by Zip Code", xlab = "Standardized Median Age")

hist(ev$med_income_std, main="Figure 10 - Median Household Income by Zip Code", xlab = "Standardized Median Household Income")

hist(ev$pct_rental, main="Figure 12 - Rental Households as a Percentage of total Households by Zip Code", xlab = "Rental Percentage Households")

hist(ev$avg_household_std, main="Figure 14 - Average Household size by Zip Code", xlab = "Standardized Average Household Size")

hist(ev$pct_urban, main="Figure 16 - Urban Population as a Total ZIP Level Population by Zip Code", xlab = "Urban Percentage of Population")
```

"Bar Plots - descriptives"

```
counts.com <- table(ev$med_commute_lvl)

counts.educ <- table(ev$med_educ_lvl)

barplot(counts.com, main="Figure 6 - Median Commute Time by Zip Code", xlab = "Median Commute Time")

barplot(counts.educ, main="Figure 8 - Median Level of Educational Attainment by Zip Code", xlab = "Level of Educational Attainment")
```

"Correlations with EV_per_capita"

```
cor.test(x = ev$pop_dense_log, y = ev$ev_per_capita, method = "pearson")

cor.test(x = ev$med_age_std, y = ev$ev_per_capita, method = "pearson")

cor.test(x = ev$med_commute_lvl, y = ev$ev_per_capita, method = "spearman")

cor.test(x = ev$med_educ_lvl, y = ev$ev_per_capita, method = "spearman")

cor.test(x = ev$med_income_std, y = ev$ev_per_capita, method = "pearson")

cor.test(x = ev$pct_rental, y = ev$ev_per_capita, method = "pearson")

cor.test(x = ev$avg_household_std, y = ev$ev_per_capita, method = "pearson")

cor.test(x = ev$pct_urban, y = ev$ev_per_capita, method = "pearson")
```

"Visual Relationship with EV_per_capita"

```
plot(ev$pop_dense_log,ev$ev_per_capita, main = "Figure 3 - Electric Vehicles Per Capita by Population Density", xlab = "Log of Population per Square Mi.", ylab = "Count of Electric Vehicles per Capita")

abline(lm(ev$ev_per_capita ~ ev$pop_dense_log))


plot(ev$med_age_std,ev$ev_per_capita, main = "Figure 5 - Electric Vehicles Per Capita by Median Age", xlab = "Standardized Median Age", ylab = "Count of Electric Vehicles per capita")

abline(lm(ev$ev_per_capita ~ ev$med_age_std))
```

```
plot(ev$med_commute_lvl,ev$ev_per_capita, main = "Figure 7 - Electric Vehicles Per Capita by median Commmute Time", xlab = "Median Commute Time", ylab = "Count of Electric Vehicles per Capita")

abline(lm(ev$ev_per_capita ~ ev$med_commute_lvl))


plot(ev$med_educ_lvl,ev$ev_per_capita, main = "Figure 9 - Electric Vehicles Per Capita by Median Educational Attainment", xlab = "Median Educational Attainment", ylab = "Count of Electric Vehicles per Capita")

abline(lm(ev$ev_per_capita ~ ev$med_educ_lvl))


plot(ev$med_income_std,ev$ev_per_capita, main = "Figure 11 - Electric Vehicles Per Capita by Median Income", xlab = "Standardized Median Income", ylab = "Count of Electric Vehicles per Capita")

abline(lm(ev$ev_per_capita ~ I(ev$med_income_std^2)))


plot(ev$pct_rental,ev$ev_per_capita, main = "Figure 13 - Electric Vehicles Per Capita by ZIP Code Rental Percentage", xlab = "Rental Percentage", ylab = "Count of Electric Vehicles per Capita")

abline(lm(ev$ev_per_capita ~ ev$pct_rental))


plot(ev$avg_household_std,ev$ev_per_capita, main = "Figure 15 - Electric Vehicles Per Capita by Average Household Size", xlab = "Standardized Average Household Size", ylab = "Count of Electric Vehicles per Capita")

abline(lm(ev$ev_per_capita ~ ev$avg_household_std))


plot(ev$pct_urban,ev$ev_per_capita, main = "Figure 17 - Electric Vehicles Per Capita by ZIP Code Urban Percentage", xlab = "Urban Percentage", ylab = "Count of Electric Vehicles per Capita")

abline(lm(ev$ev_per_capita ~ ev$pct_urban))
```

"Descriptive Statistics"

```
"EV"
        mean(ev$ev_total)
        sd(ev$ev_total)
        mean(ev$ev_per_capita)
        sd(ev$ev_per_capita)
        median(ev$ev_per_capita)
"Pop Dense"
        mean(ev$pop_dense)
        sd(ev$pop_dense)
        mean(ev$pop_dense_log)
        sd(ev$pop_dense_log)
        median(ev$pop_dense_log)
"Age"
        mean(ev$med_age)
        sd(ev$med_age)
        median(ev$med_age)
        mean(ev$med_age_std)
        sd(ev$med_age_std)
        median(ev$med_age_std)
"Commute"
        median(ev$med_commute_lvl)
"Education"
        median(ev$med_educ_lvl)
"Income"
        mean(ev$med_income)
        sd(ev$med_income)
        median(ev$med_income)
```

mean(ev$med_income_std)

sd(ev$med_income_std)

median(ev$med_income_std)

"Rental"

mean(ev$pct_rental)

sd(ev$pct_rental)

median(ev$pct_rental)

"Household"

mean(ev$avg_household)

sd(ev$avg_household)

median(ev$avg_household)

mean(ev$avg_household_std)

sd(ev$avg_household_std)

median(ev$avg_household_std)

"Urban"

mean(ev$pct_urban)

sd(ev$pct_urban)

median(ev$pct_urban)

Works Cited

Fhwa.dot.gov. (2017). *Office of Highway Policy Information - Policy | Federal Highway Administration*. [online] Available at: https://www.fhwa.dot.gov/policyinformation/statistics/2010/mv1.cfm [Accessed 11 Dec. 2017].

Fortress.wa.gov. (2017). *Washington State Greenhouse Gas Emissions Inventory: 2010 - 2011*. [online] Available at: https://fortress.wa.gov/ecy/publications/SummaryPages/1402024.html [Accessed 11 Dec. 2017].

Utc.wa.gov. (2017). *Electric Vehicle Supply Equipment, Docket UE-160799*. [online] Available at: https://www.utc.wa.gov/docs/Pages/ElectricVehicleSupplyEquipment,DocketUT-160799.aspx [Accessed 11 Dec. 2017].

(2017). *Kingcounty.gov. Gas Stations Area 410*. Retrieved 11 December 2017, from http://www.kingcounty.gov/depts/assessor/Reports/area-reports/2016/~/media/depts/Assessor/documents/AreaReports/2016/Commercial/410.ashx

(2017). Wsdot.wa.gov. *Washington State Electric Vehicle Action Plan*. Retrieved 11 December 2017, from http://www.wsdot.wa.gov/NR/rdonlyres/28559EF4-CD9D-4CFA-9886-105A30FD58C4/0/WAEVActionPlanFebruary2015Print.pdf

WSDOT - *Results Washington* . (2017). Wsdot.wa.gov. Retrieved 11 December 2017, from https://www.wsdot.wa.gov/Accountability/PerformanceReporting/ResultsWashington.htm

Soltani-Sobh, Ali, et al. “Analysis of the Electric Vehicles Adoption over the United States.” Transportation Research Procedia, vol. 22, 2017, pp. 203–212., doi:10.1016/j.trpro.2017.03.027.

Li, Xiaomin, et al. “Impacts of Renewables and Socioeconomic Factors on Electric Vehicle Demands – Panel Data Studies across 14 Countries.” Energy Policy, vol. 109, 2017, pp. 473–478., doi:10.1016/j.enpol.2017.07.021.

Yong, Taeseok, and Chankook Park. “A Qualitative Comparative Analysis on Factors Affecting the Deployment of Electric Vehicles.” Energy Procedia, vol. 128, 2017, pp. 497–503., doi:10.1016/j.egypro.2017.09.066.

Harrison, Gillian, and Christian Thiel. “An Exploratory Policy Analysis of Electric Vehicle Sales Competition and Sensitivity to Infrastructure in Europe.” Technological Forecasting and Social Change, vol. 114, 2017, pp. 165–178., doi:10.1016/j.techfore.2016.08.007.

Bilotkach, Volodymyr, and Mike Mills. “Simple Economics of Electric Vehicle Adoption.” Procedia - Social and Behavioral Sciences, vol. 54, 2012, pp. 979–988., doi:10.1016/j.sbspro.2012.09.813.