The Distribution of Electric Vehicles and Subsidies by Income

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Abstract

Increasing the market share of electric vehicles could be an effective method of decreasing harmful CO_2 emissions into the environment. However, the price of EVs is a barrier to purchase for low-income individuals. Federal and state governments have implemented several types of subsidies to incentivize the purchase of EVs. This paper looks at the distribution of these subsidies across incomes in Washington state. Using data from the US Census and car registration data from Washington, we create models showing the effect of different variables on the amount of subsidies a household receives and the share of EVs in a census tract. We also find that over half of the subsidies are going to individuals in the top 20% of the income distribution.

I. Introduction

In recent years, much of the developed world has grown increasingly conscious of climate change and overdependence on fossil fuels. Electric vehicles (EVs) are proposed as a potential solution to part of these issues and EV use has increased in recent years, partly because of large government incentives for purchasers. However, as EVs become increasingly widespread and the incentives increasingly more expensive for society, a question of equity arises: will EVs be primarily used by the rich, and to the extent they are, do the subsidies represent an inequitable transfer from taxpayers to the wealthy?

The United States federal government and many state governments have implemented a series of tax credits and rebate opportunities to subsidize the EV market. The goal of such subsidization is to increase EV market share to reduce dependence on fossil fuels, decreasing our overall carbon footprint. Because EVs are relatively newer technology they are also more expensive, making it harder for low-income people to purchase them, even with subsidies. On the one hand, a given amount of subsidies are likely to have more impact on EV takeup if they go to the rich. On the other hand, this will exacerbate existing income inequality. While we are unable to determine the effect of subsidies on takeup, much less separate this effect out by income, we are able to show that the bulk of current subsidies go to those living in the wealthiest census tracts.

We will look at two subsidies. The first is the EV and Fuel Cell Electric Vehicle (FCEV) Federal Tax Credit. This credit is directed towards middle and low-income households buying an EV and was enacted on October 3rd, 2008. Eligible households must have a modified adjusted gross income (AGI) that can not exceed $300,000 for married couples filing jointly, $225,000 for heads of households, and $150,000 for all other filers. In addition, the EVs being bought must have an MSRP of less than $80,000 for vans, sport utility vehicles, and pickup trucks, and less than $55,000 for all other vehicles. This program was modified on August 16th, 2022, so that for vehicles placed in service from January 1 to April 17, 2023 the tax credit is a base amount of $2,500, plus $417 for a vehicle with at least 7 kilowatt hours of battery capacity, plus $417 for each kilowatt hour of battery capacity beyond 5 kilowatt hours. The tax credit can be up to $7,500. Vehicles placed in service on April 18, 2023 and after must first meet all previous criteria. The tax credit is then $3,750 if the vehicle meets the critical minerals requirement only, $3,750 if the vehicle meets the battery components requirement only, and $7,500 if the vehicle meets both. For new EVs purchased in 2022 or earlier, the credit is $2,917 for a vehicle with a battery capacity of at least 5 kilowatt hours, plus $417 for each kilowatt hour over 5.

The second subsidy we will examine is Washington's Alternative Fuel Vehicle Tax Exemption, enacted on May 6th, 2005. We look at Washington specifically because we can obtain excellent data on Washington car registrations. For vehicles sold on or after August 1st, 2019 the buyer does not have to pay sales tax on the vehicle if the transaction does not exceed $45,000 in purchase price or lease payments for new vehicles, or $30,000 in fair market value or lease payments for used vehicles. Because Washington has a relatively high sales tax, this exemption can lead to substantial savings for consumers purchasing alternative fuel vehicles.

We propose a study to answer these income related questions: Who is receiving these EV subsidies? Are they effectively serving lower-income people, allowing them to increase the uptake of EVs? Or are the majority of the subsidies instead going to higher-income people who are inframarginal, meaning the subsidy does not affect their decision to purchase an EV or not? This could mean that the current subsidies are not the most effective way to incentivize low-income people to purchase EVs

II. Literature Review

Examining prior research on EV subsidies is crucial for contributing new insights. By looking into previous studies, we aim to identify and formulate research questions that have not previously been answered. Additionally, analyzing past research methodologies enables us to refine our approach and select appropriate data sources to investigate the complex relationships between EV subsidies and income. This review serves as a foundation for our study, guiding our exploration of the evolving landscape of EV adoption and the role of governmental incentives in shaping sustainable transportation initiatives.

Yaoming et al. (2018) analyze the effect of subsidies on the Chinese EV market. China implemented a "dual credit" policy, the combination of a New Energy Vehicle (NEV) Credit Program and Corporate Average Fuel Consumption regulation. This system awards credits to manufacturers for each NEV produced based on the characteristics of the vehicle, such as range and battery size. Quotas are then set, with companies being required to earn a certain number of credits. These credits are exchangeable and purchasable, so companies that do not produce enough NEVs will be required to purchase enough credits to meet the quotas. This is intended to take the financial burden off of the Chinese government, creating a more market-driven approach to NEV production.

To determine whether this dual credit program is effective in increasing the number of NEVs in the Chinese market, the authors implement a game theory-based simulation model. The model separates companies into four different categories based on their size, history, location, and various other factors. Then, the profit to each firm is modeled based on the number of each type of vehicle they produce, and the resulting credits awarded. Additionally, purchased and traded credits are considered in this profit model. Profits are then calculated for a number of given scenarios to determine which scenarios are most likely to occur.

The paper found that the dual credit system is a measurable improvement over the previous green-car subsidy, with the potential to double the total number of NEVs in the Chinese market. This would correspond with an increase in market share of 3.9%.

While this paper is effective in demonstrating the success of subsidization in increasing the EV market share in China, it does not assist in answering our research question.

Ankney (2022) explores what the author refers to as the "energy efficiency gap." The gap can be roughly summarized as follows. While EVs and fuel-efficient vehicles are often more expensive than their gas-burning competitors in terms of up-front cost, they are cheaper to the consumer in the long run, as the cost of fuel is far lower. Therefore, low-income consumers should purchase EVs through loans or other means, as they will save money in the long run. However, what we observe in the market is that low-income consumers do not buy as many EVs as theory suggests they should. This gap between the number of EVs expected to be purchased by low-income consumers and the actual number observed is the energy efficiency gap.

The explanation for this gap which this paper attempts to show empirically is that low-income consumers do not have sufficient access to credit to allow them to purchase EVs. Therefore, the hypothesis being tested is that "credit constraints inhibit investment in fuel efficiency." The paper uses data from auto loan APRs and self-reported consumer credit histories to analyze the relationship between credit availability and new vehicle consumer income. This cross-sectional survey data is sourced from Resources for the Future.

The paper found that there is a relationship between credit constraints and fuel efficiency demand, and that this relationship can be shown empirically. Notably, the paper also found that this relationship does not exhaustively explain the energy efficiency gap. In other words, while this relationship exists, there are other reasons for low-income people to avoid purchasing energy-efficient vehicles. We assume this is likely due to high discount rates for low-income people.

This paper is useful as it begins to explore the income distribution of EV owners, which is directly applicable to our proposed research. Additionally, this paper gives some insight into the causes of the current income distribution of EV owners, which can help us understand what the real effect of these subsidies may be.

As mentioned previously, the high initial costs of EVs make it difficult for low-income people to purchase them, and reap the benefits of lower fuel costs. Bauer et al. (2021) attempts to answer the question: When will EVs reach the price equivalent of gasoline cars? To do this, the authors use data from the National Household Travel Survey and the Consumer Expenditure Survey. They use this data to estimate vehicle ownership cost at the household level to see how much consumers at different income levels pay for their vehicles. They then compare this with estimated resale values and cost projections they make by using data on vehicle purchase price, depreciation, fueling, charging, maintenance, and insurance.

They find that used EVs will reach cost parity with equivalent gas-powered cars later than new ones. They predict that new EVs will reach parity with corresponding gas cars in 2026, and model year 2020 EVs will reach parity with corresponding gas cars sometime in 2028. They also state that when used vehicles are 10 years old in the year 2030, they will cost around $10,000 no matter the fuel type. The likely reasoning for this is that because EV technology is relatively new it will improve quickly, so once a new EV comes out with better technology, it will cause the EVs that came out right before, which are still considered new, to depreciate quicker.

This paper gives useful insight into how the price of EVs will likely change in the future. It also shows how the change in prices of new and used EVs over time will affect people across the income distribution. One important limitation is that the analysis does not take into account the fact that EV subsidies would affect the purchase price of EVs, specifically for low-income consumers. The paper acknowledges this by stating in the conclusion that low-income consumers are the most likely people to benefit from EVs and that purchasing incentives targeted at them would be effective.

Borenstein & Davis (2016) examine the effectiveness of these kinds of incentives. The authors use tax return data from the IRS to examine the socioeconomic characteristics of taxpayers who receive US federal income tax credits. Of the four clean energy tax credits they look at, the one most applicable to our study is the qualified plug-in electric drive motor vehicle credit (PEDVC). This is the FCEV described earlier that we will be looking at.

After analyzing the data, Borenstein and Davis found that for all the clean energy, the higher someone's adjusted gross income (AGI), the more clean energy credits they receive. They split AGI into five categories in thousands of dollars: less than 10, 10-20, 20-40, 75-200, and greater than 200. Specifically for the PEDVC, people with an AGI of $200,000 or more receive over three times the average amount received by filers in all other categories. The authors also find that the PEDVC is the most concentrated out of all other clean energy tax credits. Only about 10% of these credits go to the bottom 80% of filers, and the bottom 90% of filers receive about 40%. This means that 60% of these tax credits go to the top 10% of the income distribution. The most likely reasoning for this that the authors provide is that it’s because even with the tax credits, because EVs are relatively new they are still more expensive than equivalently sized gasoline cars. Another possible reason is that EVs are an indicator of status, so higher-income people are more likely to buy them.

Overall, this paper shows how clean energy tax credits are used across the income distribution, and it is specifically useful because it includes EVs. The findings of this paper foreshadow the outcomes of our study, showing that high-income people receive nearly all subsidies for green energy initiatives.

Looking at the economic characteristics of EVs, Rapson & Muehlegger (2021) attempt to do three main things: explain why consumers would want to substitute gasoline-powered cars for EVs, why policymakers are using subsidies to increase the adoption of EVs, and to evaluate the current policies in place compared to what the optimal policy would be. The authors begin by saying that EVs are projected to reach cost parity with ICEs later this decade, similar to what Bauer et al. predict. However, EVs have better torque and acceleration while being quieter and driving smoother because of the absence of gear changes. EVs also have lower operational costs than ICEs, but these costs vary greatly due to differences in electricity and gasoline costs depending on location. EVs also have lower operational costs because fewer moving parts lead to lower maintenance costs. But this saving on maintenance costs is found to only be about $200 per year.

Next, the authors discuss the positive and negative externalities created by EVs, and how these externalities are used as justification for intervention by the government. The externalities are split into two categories, usage-based (intensive margin), and stock-based (extensive margin). The usage-based externalities include carbon emissions, local emissions of EVs and charging stations, accident fatality rate due to vehicle weight, and the effect of the increased use of EVs in the U.S. on things like gasoline prices, imports, and exports. The stock-based externalities include learning by doing and network effects in charging infrastructure.

Lastly, the authors discuss the current policies in place, and what would be economically efficient. They find that while subsidies are associated with an increase in EV market share, it is not enough to reach the ambitious goals set by states and the government. The authors claim that the market share of EVs in 2035 is more closely associated with non-monetary factors of demand such as battery range and charging station density. This is important information to understand, because it may show that increasing funding to subsidy programs is not the most optimal way to increase EV purchases.

Similar to Rapson & Muehleggher (2021), Jenn et al. (2018) look at the effectiveness of monetary and non-monetary incentives aimed at increasing the adoption of EVs. To find these effects, the authors use vehicle registration data from two business data providers, R.L. Polk and IHS Automotive. Their data has new vehicle registrations from across the US by month, model, and state from January 2010 to November 2015.

Using this data, the authors produce three regression models. The first one is a generalized model, used to show the average effect of incentives across the country. The second model is a knowledge model which includes consumer knowledge and awareness of the incentives. The authors use this to measure the heterogeneity of incentive efficacy across different states. The final model is a lagged-dependent model used to address endogeneity issues in the econometric models.

What the authors find is that monetary incentives are statistically significant and positive across all regression models. One important effect found is that for every $1000 increase in tax credit, there is about a 2.6% increase in the average sales of EVs. Another important non-monetary incentive relationship the authors find is that for every increase of 100 in vehicle density in HOV lanes per hour, there is a 4.7% increase in average sales of EVs. This paper is useful, as it provides us with information on the effectiveness of EV incentives across the US.

III. Data

For information on income, education, age, marital status, commute time, and household size, we use census tract-level data from various subsets of the 2022 American Community Survey (ACS). From this survey, we obtained the median income, proportion of individuals with a bachelor's degree, average age, proportion of households with married couples, average commute time, average household size, and proportion of single-family homes for each census tract in the state of Washington.

For information on electric vehicles, we turn to the Washington Department of Licensing. We use information on all registered electric vehicles in the state of Washington, as well as all vehicles (electric or otherwise) registered or re-registered since 2020. The inclusion of registration renewals in this data set allows us to effectively observe all vehicles in Washington, including those produced before 2020. From this, we obtain the year, make, and model of each electric vehicle, as well as each vehicle's census tract. We also calculate the proportion of electric vehicles to total vehicles in each census tract.

Finally, to determine the dollar amount by which each vehicle was subsidized, we turn to the Internal Revenue Service (IRS). The IRS has a comprehensive data table indicating the subsidy eligibility of each make, model, and year of electric vehicle. Additionally, the table indicates when each vehicle's subsidization period ended phased out, allowing us to determine the specific subsidy for each vehicle in our data set. We also were able to aggregate this to determine the total and average subsidy for each census tract.

IV. Methodology

All of our analysis is conducted on data within the state of Washington at the census tract level. Our first goal is to find how the amount of subsidies a census tract receives varies by income, while controlling for the variables shown below. We regress our data using Ordinary Least Squares (OLS) according to the following equation:

$$SubsidiesPerHousehold = \beta_0 medianIncome + \beta_1 avgComTime + \beta_2 married\_couples\_prop + \beta_3 avg\_household\_size + \beta_4 bachelors\_prop + \beta_5 avg\_age + \beta_6 single\_prop$$

Where *SubsidiesPerHousehold* is the sum of the subsidies awarded to each vehicle in a census tract divided by the total number of households within the tract, *medianIncome* is the median income in the census tract, *avgComTime* is the average time it takes a person in the tract to commute from home to work, *married_couples_prop* is the proportion of households in the tract inhabited by a married couple, *avg_household_size* is the number of people living in an average household in the tract, *bachelors_prop* is the proportion of people in the tract with a bachelor's degree, *avg_age* is the age of the average person in the tract, and *single_prop* is the proportion of residential buildings in the tract that are single-family homes (no more than 1-unit).

We also investigate which census tracts buy more electric vehicles as a proportion of total vehicles. We again run OLS on the following regression:

$$EV\_percent = \beta_0 median\_income\_thousands + \beta_1 avgComTime + \beta_2 married\_couples\_prop + \beta_3 avg\_household\_size + \beta_4 bachelors\_prop + \beta_5 avg\_age + \beta_6 avg\_age^2 + \beta_7 single\_prop$$

Where *EV_percent* is the proportion of total vehicles in the census tract which are EVs expressed as a percentage, and *median_income_thousands* is equal to *medianIncome / 1000*. Additionally, a quadratic term for average age is included, as we suspect the effect of this variable may be parabolic. The logic behind this is that very young or very old people may not be able to afford EVs or be aware of them as much when compared to middle-aged people.

For our third and fourth regressions, we experiment with various additional interaction terms. We first add a quadratic term for median income, and then we add an interaction between income and average commute time. The goal is to see if income has a more dynamic effect, or if there is an “income sweet spot” where people are most likely to purchase an EV.

V. Results

Looking at how the subsidies are distributed by income, we find that people in the top income quintile received $550 million in EV subsidies, or about 50.1% of the total EV subsidy amount of $1.098 billion in Washington. This is more than those in the bottom 4 quintiles of income receive combined, which is $548 million (about 49.9% of the total EV subsidy amount in Washington).

The results yielded by the regressions explained in the previous section are shown in Tables 1-4. We found that holding all other variables constant, income has a significant positive relationship with subsidies per household. This means that more subsidies are being directed to higher-income people. As shown in Table 1, an additional $1000 in median income correlates to an additional $8 in subsidies per household within a given census tract. The second table shows that this is in alignment with our finding that higher-income people are more likely to purchase an EV rather than an ICE vehicle.

Inspection of the coefficients on the control variables also yields some additional interesting findings. For example, longer commute times are associated with lower takeup of EVs. This may be due to more frequent refueling requirements, which can be much more time-consuming for electric vehicles. It may also be due to longer commute times being more likely in rural areas with less developed infrastructure for EVs. We also find that married couples are less likely to have EVs over ICE vehicles. Areas with more single-family homes are similarly unlikely to have EVs. The logical reasoning behind these is not necessarily clear. Interestingly, we do see a slight parabolic relationship between age and EVs, but not in the expected direction. Rather, the coefficient on the quadratic term is positive while the linear term is negative. This indicates that very old and very young people may be more likely to own an EV than middle-aged people.

Turning to our third and fourth regressions, there appears to be a significant quadratic effect of income on EV adoption. However, when an interaction term is introduced between income and commute time, this effect is no longer significant. The interaction term is significant, however, with a value of -0.001, indicating that the effect of commute time decreases as income increases. The quadratic effect is shown in Figure 6. Here, we can see that EV adoption rises with income, but at a decreasing rate.

We also construct a correlation matrix from the regression variables (shown in Table 5) from which we make some additional interesting observations. The variables that are shown to have a negative correlation with the percent of EVs in a census tract are commute time, household size, age, and proportion of single-family homes. This is quite different from the effects shown in the first regression, which is reasonable, as many of these variables are correlated with one another as well. One surprising observation is that income is positively correlated with commute time, indicating that higher-income people have longer commute times.

VI. Conclusions

Our results are consistent with our expectations and the prior literature, in that higher-income people receive more subsidies for EVs. Our finding that the top income quintile is receiving more subsidies than the other quintiles combined is comparable to Borenstein & Davis' (2016) results. As previously mentioned, they found that individuals with an AGI of $200,000 or more received more than three times the number of clean energy credits as people in other income categories. Specifically, we find that every additional thousand dollars of median income is associated with an $8 increase in the value of subsidies per household in a given census tract. This effect decreases slightly as average commute times increase, as the effect of income on the likelihood of owning an EV decreases as commute time increases. While this dollar effect might seem small, this is because EV ownership is still small.

When considering the implications of these findings, it is important to first consider the motivations that guide subsidies to begin with. In this case, there are two purposes to EV subsidies: to make the cost less prohibitive for low-income people (this is the equity motivation), and to speed up the general process of EV adoption to phase out polluting ICE vehicles (this is the efficiency motivation). While it seems that the subsidies have been largely ineffective at achieving equity-related goals, the marginal effects are not necessarily clear. A person who's not willing to buy an EV in the absence of a subsidy may be persuaded to buy an EV because of the subsidy. A very rich person when given a subsidy is unlikely to change their behavior, as the subsidy amount is less consequential for them. When this rich person buys a subsidized EV, they may enjoy the benefits of the subsidy, but it is not a likely motivator for their purchase. A lower-income person who wants an EV but cannot afford it is more likely to be motivated by the subsidy, which enables them to buy an EV that they otherwise could not. However, this effect is difficult to measure without comparing samples with data on EV adoption in both the absence and presence of a subsidy. This is similarly true for understanding the success of the subsidies from an efficiency standpoint. While it is clear who is buying EVs, it is unclear how much more they are buying because of the subsidy. This again could be better understood by comparing it with a sample in which subsidies are absent.

If equity is a real motivation behind these subsidies, perhaps it is time to consider a different strategy. Over half of the subsidies being allocated to the top quintile of earners is not a very equitable distribution. One potential solution is to allocate greater subsidies to lower-income buyers. Taking away some of the money that would go to those who could afford an EV anyways would allow more money to go to those who could not, which could have an even greater marginal effect on EV adoption among low- to middle-income people. Another option could be to shift focus to used EVs, which are more likely to be more accessible to lower-income people. Though this may decrease the efficiency of the subsidy, as the focus shifts away from increased EV adoption to instead favor equitable distribution, it may also encourage EV adoption, as new EV buyers could be assured that their EV will sell on the second-hand market.

The clear path for future research is to investigate the effects of these subsidies, rather than their allocation. A comparison between regions or time periods that differ in subsidy presence may reveal the marginal effects. How many more low-income people buy an EV because of the subsidy? How many more high-income people? Understanding the answers to these questions is critical for understanding the success of the equity-related goals of these subsidies, as well as the efficiency goals.

Table 1:

	Dependent variable:
	subsidiesPerHousehold
medianIncome	0.008***
	(0.00003)
avgComTime	−7.258***
	(0.114)
married_couples_prop	−316.652***
	(9.284)
avg_household_size	315.020***
	(3.595)
bachelors_prop	463.014***
	(5.760)
avg_age	22.212***
	(0.209)
single_prop	−504.104***
	(5.268)
Constant	−1,376.049***
	(13.227)
Observations	830,279
R^2	0.281
Adjusted R^2	0.281
Residual Std. Error	622.903 (df = 830271)
F Statistic	46,388.410*** (df = 7; 830271)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2:

	Dependent variable:
	EV_percent
median_income_thousands	0.054***
	(0.0001)
avgComTime	−0.022***
	(0.0004)
married_couples_prop	−4.585***
	(0.033)
avg_household_size	−0.474***
	(0.013)
bachelors_prop	6.347***
	(0.020)
avg_age	−0.373***
	(0.005)
I(avg_age^2)	0.005***
	(0.0001)
single_prop	−2.367***
	(0.019)
Constant	11.733***
	(0.103)
Observations	806,261
R^2	0.659
Adjusted R^2	0.659
Residual Std. Error	2.154 (df = 806252)
F Statistic	194,449.400*** (df = 8; 806252)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 3:

	Dependent variable:
	EV_percent
median_income_thousands	0.062***
	(0.0003)
I(median_income_thousands^2)	−0.00003***
	(0.00000)
avgComTime	−0.024***
	(0.0004)
married_couples_prop	−4.671***
	(0.033)
avg_household_size	−0.434***
	(0.013)
bachelors_prop	6.228***
	(0.021)
avg_age	−0.395***
	(0.005)
I(avg_age^2)	0.006***
	(0.0001)
single_prop	−2.398***
	(0.019)
Constant	11.681***
	(0.103)
Observations	806,261
R^2	0.659
Adjusted R^2	0.659
Residual Std. Error	2.153 (df = 806251)
F Statistic	173,065.000*** (df = 9; 806251)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4:

	Dependent variable:
	EV_percent
median_income_thousands	0.074***
	(0.0004)
I(median_income_thousands^2)	−0.00000
	(0.00000)
avgComTime	0.054***
	(0.001)
married_couples_prop	−4.385***
	(0.033)
avg_household_size	−0.507***
	(0.013)
bachelors_prop	6.451***
	(0.021)
avg_age	−0.450***
	(0.005)
I(avg_age^2)	0.006***
	(0.0001)
single_prop	−2.277***
	(0.019)
median_income_thousands:avgComTime	−0.001***
	(0.00001)
Constant	10.976***
	(0.103)
Observations	806,261
R^2	0.661
Adjusted R^2	0.661
Residual Std. Error	2.146 (df = 806250)
F Statistic	157,260.900*** (df = 10; 806250)
Note:	*p<0.1; **p<0.05; ***p<0.01

	subsidiesPerHousehold	medianIncome	avgComTime	married_couples_prop	avg_household_size	bachelors_prop	avg_age	EV_percent	single_prop
subsidiesPerHousehold	1.00	0.52	0.04	0.24	0.10	0.45	-0.03	0.55	0.11
medianIncome	0.52	1.00	0.20	0.57	0.29	0.77	-0.14	0.68	0.37
avgComTime	0.04	0.20	1.00	0.33	0.32	0.09	-0.01	-0.02	0.33
married_couples_prop	0.24	0.57	0.33	1.00	0.73	0.37	0.01	0.11	0.79
avg_household_size	0.10	0.29	0.32	0.73	1.00	0.08	-0.37	-0.14	0.68
bachelors_prop	0.45	0.77	0.09	0.37	0.08	1.00	-0.04	0.70	0.21
avg_age	-0.03	-0.14	-0.01	0.01	-0.37	-0.04	1.00	-0.02	0.16
EV_percent	0.55	0.68	-0.02	0.11	-0.14	0.70	-0.02	1.00	-0.05
single_prop	0.11	0.37	0.33	0.79	0.68	0.21	0.16	-0.05	1.00

Table 5: Correlation Matrix

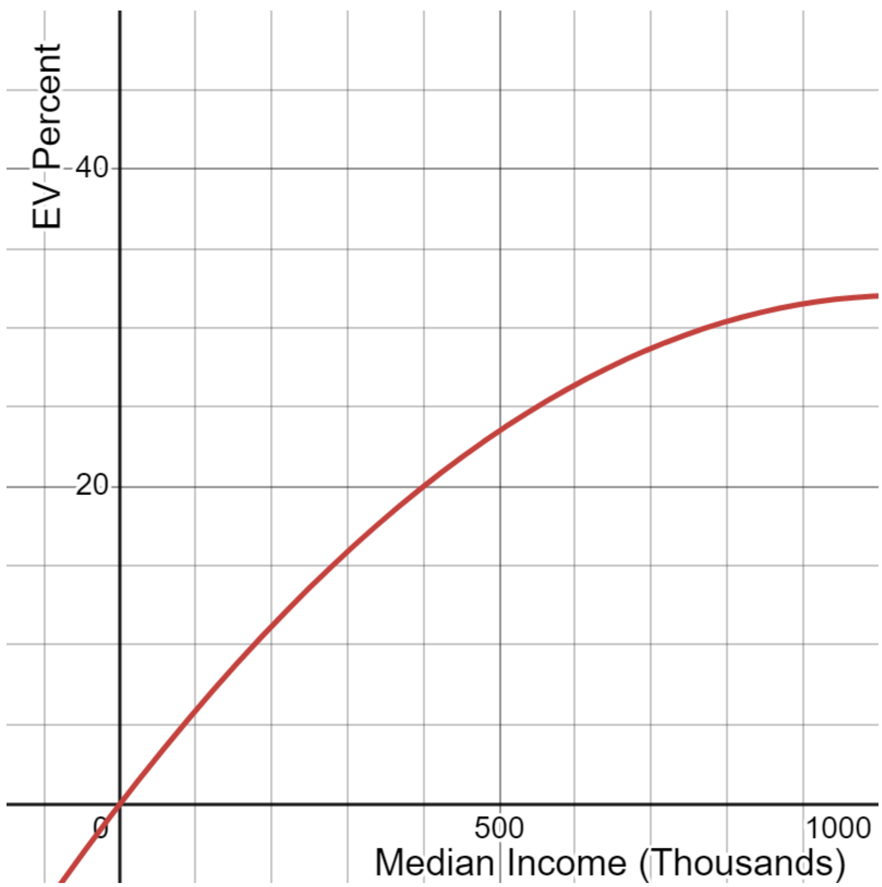

Figure 6: Income vs EV Percent (Max at 1033)

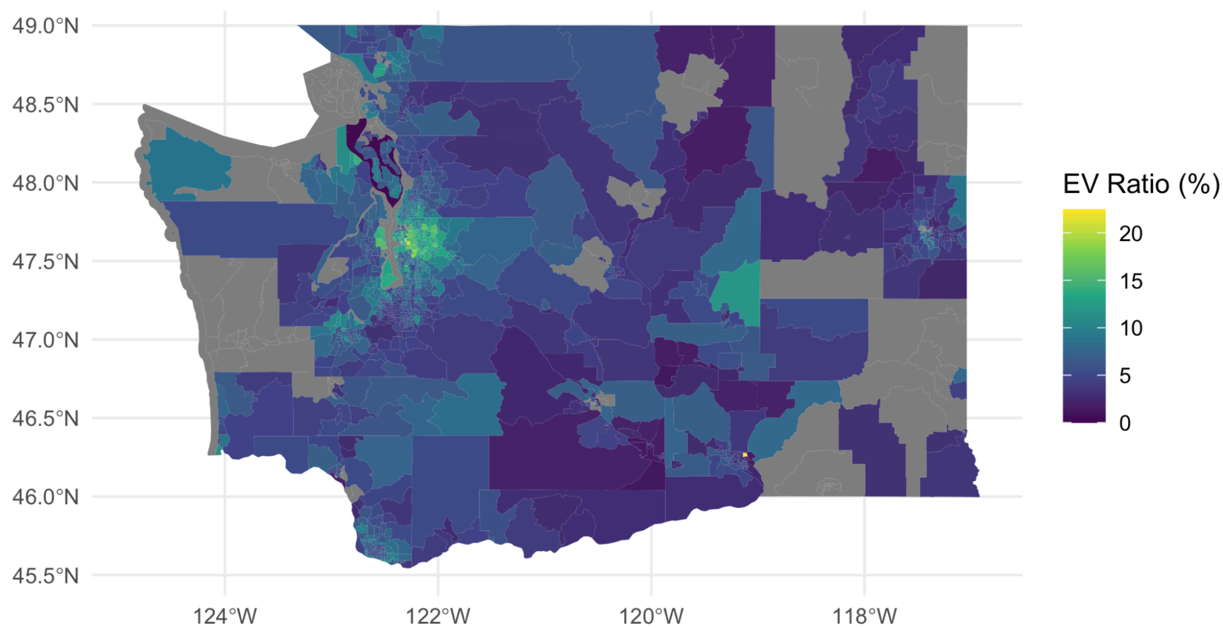

Figure 7: Ratio of EVs per census tract

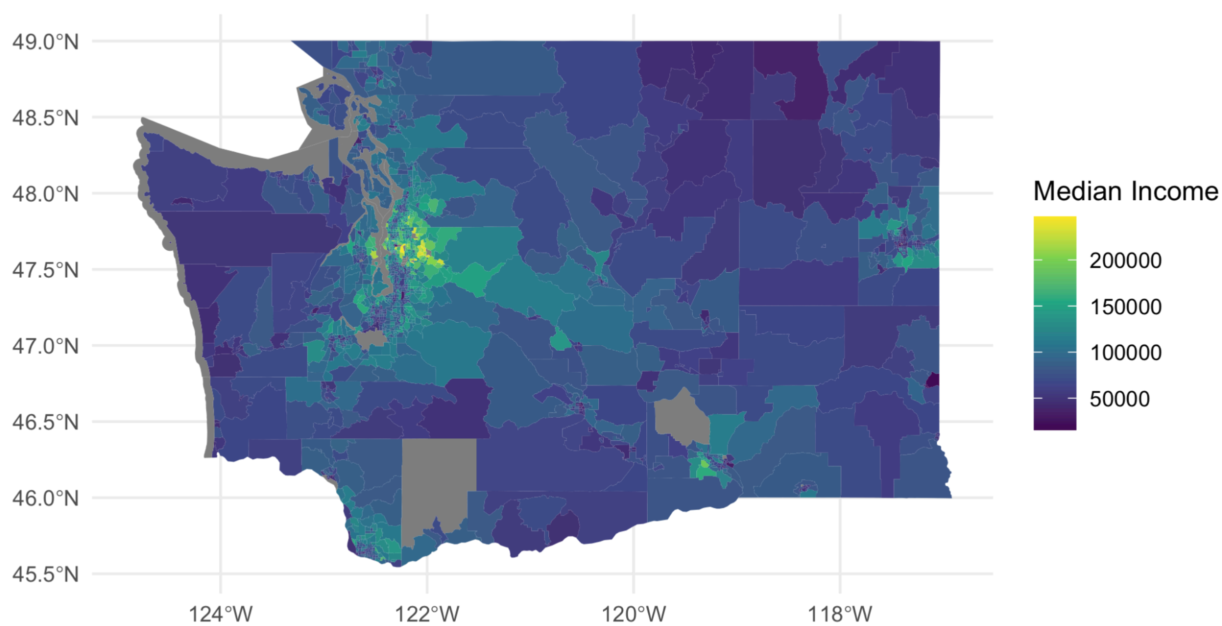

Figure 8: Median income by census tract

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