

DISPARITIES IN PUBLIC CHARGING INFRASTRUCTURE DEPLOYMENT
AND INEQUITABLE ELECTRIC VEHICLE OWNERSHIP COST BASED ON
INCOME AND RACE

By

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ABSTRACT

DISPARITIES IN PUBLIC CHARGING INFRASTRUCTURE DEPLOYMENT AND INEQUITABLE ELECTRIC VEHICLE OWNERSHIP COST BASED ON INCOME AND RACE

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Widespread electric vehicle (EV) adoption will be crucial for achieving decarbonization goals in California. The inclusion of marginalized populations in this process is important and involves challenges related to their physical access to charging infrastructure and economic access to EVs. Public access electric vehicle chargers (PAEVCs) and upfront financial incentives for EVs may help reduce the barriers affecting these populations. In this thesis, a spatial analysis at the census block group level shows that, in California, PAEVC access is lower in areas with below median household incomes and areas with a black and Hispanic majority. The PAEVC access disparities are even more pronounced in areas with higher rates of renter-occupied housing and multi-unit housing. An economic cost model analysis shows that a used or new battery EV has a comparable, and sometimes lower, ownership cost than an internal combustion engine vehicle. Current incentives in place to encourage the purchase of new EVs can also lead to the cost of ownership of new EVs being lower than used EVs. For populations unable to access home chargers, however, the savings advantage of owning an EV is effectively negated due to the higher operational cost of relying on PAEVCs relative to home chargers. My results suggest that while greater access to PAEVCs may

help address a critical barrier to EV uptake in marginalized communities, additional measures that address high operating costs, such as increasing access to the lower cost residential curbside charging, may be needed to make EVs competitive in these communities.

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LIST OF ACRONYMS

API – Application Program Interface
BEV – Battery Electric Vehicle
CBG – Census Block Group
CVRP – Clean Vehicle Rebate Project
DC – Direct Current
EV – Electric Vehicle (including battery and plug-in hybrid electric vehicle)
GAM – Generalized Additive Model
GIS – Geospatial Information System
GGRF – Greenhouse Gas Reduction Fund
H100 – 100% home charging scenario
H20P80 – 20% home charging and 80% public charging scenario
H50P50 – 50% home charging and 50% public charging scenario
H80P20 – 80% home charging and 20% public charging scenario
HPS – High Pressure Sodium
ICE – Internal Combustion Engine
LADWP – Los Angeles Department of Water and Power
LED – Light-emitting diodes
LOWESS – Locally Weighted Scatterplot Smoothing
MSRP – Manufacturer Suggested Retail Price
MUD – Multi-unit Dwelling
MUDNP – Multi-unit Dwelling with No Off-street Parking
RMEL – Restricted Maximum Likelihood Approach
P100 – 100% public charging scenario
PAEVCS – Public Access Electric Vehicle Charging Station
PHEV – Plug-in Hybrid Electric Vehicle
PG&E – Pacific Gas and Electric Company
POI – Point of Interest

TCO – Total Cost of Ownership

ZEV – Zero-Emissions Vehicle

CHAPTER 1: INTRODUCTION AND BACKGROUND

Battery electric vehicle (BEV) technology is still in the early stages of development but is growing rapidly. Current estimates project that in the U.S. by 2030, 18.7 million electric vehicles (EV), including both plug-in hybrid electric vehicles (PHEV) and BEVs, will be on the road, accounting for 20% of total annual vehicles sales (Figure 1-1) (Cooper & Schefter, 2018). BEVs and PHEVs together accounted for 3.87% of the California auto market share and 1.66% of the national market share in 2018 (Alliance of Automobile Manufacturers, 2019). Consistent with the exponential upward trend in the national EV sale forecast (Figure 1-1), California's EV market penetration is estimated to reach 36% by 2030 (Figure 1-2) with the state's five million zero-emission vehicle mandate.

Barriers to EV adoption are shrinking overall, but at a slower rate for the lower-income populations that primarily buy used vehicles and are more likely to live in rented homes or multiunit dwellings (MUDs). This thesis examines whether the current public access electric vehicle charger (PAEVC) infrastructure is disproportionately unavailable to specific income, race, and ethnicity groups making BEV ownerships less economic and convenient for the groups leading to persisting barriers for BEV adoptions. It also examines the cost of ownership for used and new BEVs and explores whether the financial incentives for new BEVs makes BEV ownership cost regressive for used vehicle buyers. Together, the findings shed light on the BEV adoption barriers for lower-income populations statewide. Lastly, I propose an alternative charging infrastructure for

high MUD locations and the policies needed to address adoption barriers for low-income groups.

1.1. Electric Vehicle Adoption and Barriers

EVs are not adopted by everyone universally at this early stage. EV early adopters tend to be highly educated, environmentally friendly, and people who have previously owned hybrid vehicles (Carley, Krause, Lane, & Graham, 2013). Symbolic attributes of EVs also positively influence early adopters' decisions, as early adopters often perceive adoption to positively impact their social status (Noppers, Keizer, Bockarjova, & Steg, 2015). In California, the majority of current EV owners that received the state financial incentive are in the demographic groups with higher education (86% with a bachelor's degree or higher), annual household income of \$100,000 and higher (79%), living in detached houses (83%), and owning their houses (87%) (California Clean Vehicle Rebate Project, 2015).

Upfront cost, battery range, charging ("fueling") speed, and public charging infrastructure are among the top barriers in adopting BEVs (Biresselioglu, Demirbag Kaplan, & Yilmaz, 2018; Egbue & Long, 2012). BEVs often have a higher purchase cost, longer refueling time, and fewer public fueling locations compared to conventional vehicles.

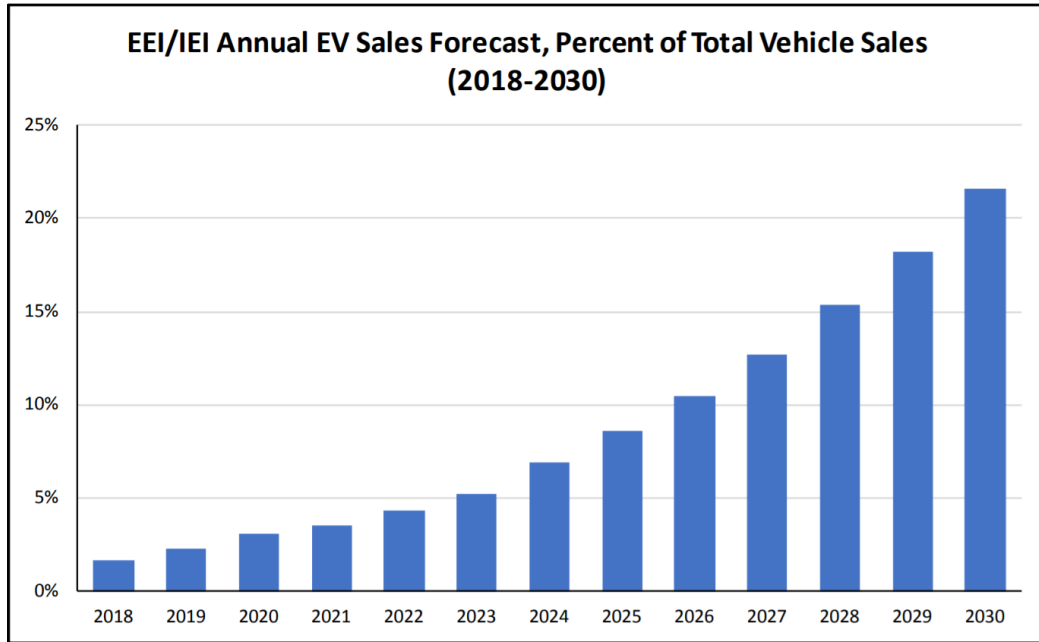


Figure 1-1 Battery and plug-in hybrid battery electric vehicle market penetration in the United States adapted from Cooper & Schefter (2018). The forecast was developed by compiling five independent forecasts: Bloomberg New Energy Finance, Boston Consulting Group, Energy Innovation, U.S. Energy Information Administration, and Wood Mackenzie.

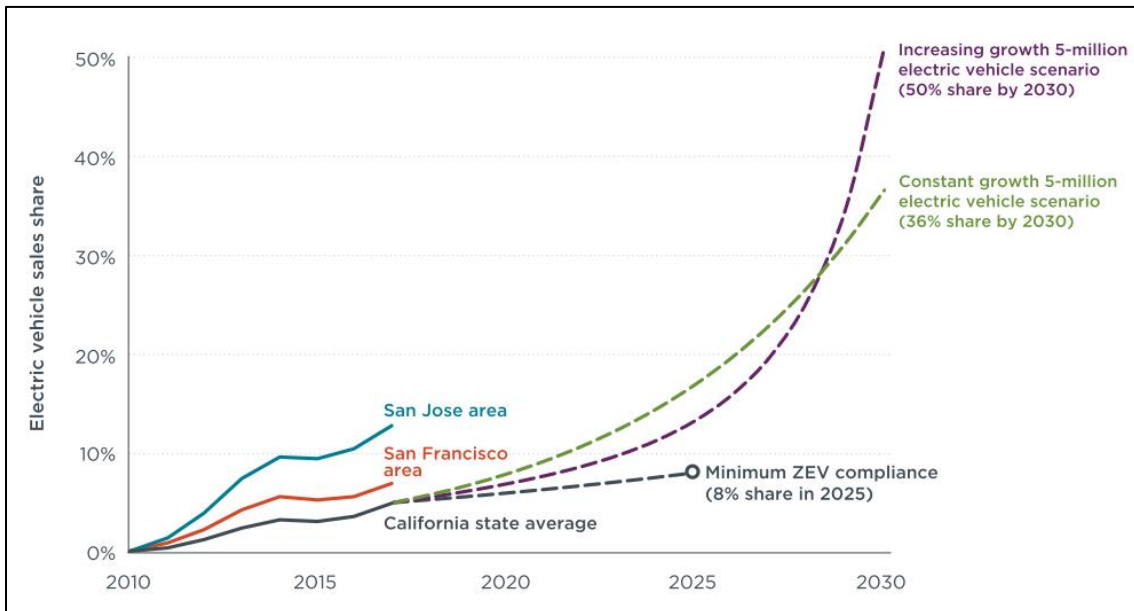


Figure 1-2 Zero-emissions vehicle market penetration in California adapted from Lutsey (2018).

The average purchase cost of BEVs is currently higher than most non-luxury internal combustion engine (ICE) vehicles. According to a National Renewable Energy Laboratory consumer survey, 47% of the survey respondents would pay extra, ranging from \$1 to more than \$9,000, for a EV that could reduce their fuel cost by one-third (Singer, 2017). Only 32% of the respondents are willing to pay more than \$3,000 additional cost for an EV, which is a very conservative price premium compared to ICE vehicles. The same study shows the respondent group aware of the EV tax credit is most likely to purchase EVs, followed by the group that is aware of EV charging stations and the group that can plug in the EVs at home.

Although the ideal range of a BEV on a single charge is still unclear, as it will vary with advancements in onboard charging technology, charging infrastructure, and battery technology, consumer surveys have shown generally that a BEV range exceeding 200 miles is acceptable to most consumers (AutoList.com, n.d.; Cox Automotive, 2017; Miwa, Sato, & Morikawa, 2017). The National Renewable Energy Laboratory, in its 2017 study, found that although half of the survey respondents would consider a BEV if the range exceeds 300 miles on a single charge, only 16% were aware of the charging stations along their commute routes (Singer, 2017). Before BEV technology achieves the average range of 300 miles and more, increasing the numbers and visibility of PAEVC could potentially further increase consumers' willingness to adopt BEVs by reducing the perceived minimum acceptable range and mediating range anxiety.

1.2 Equity of Electric Vehicle Adoption

Some of the BEV adoption barriers discussed above are breaking down for the general public. The cost of new BEVs is projected to become competitive with ICE vehicles by 2024 (Bloomberg New Energy Finance, 2018). The range of BEVs has also increased, in some cases doubled, since the first commercial BEV model was introduced, and many 2019 BEV models provide ranges of 200 miles or more. Moreover, the state of California has been aggressively building out PAEVC infrastructure. California currently has an estimated 37,400 Level 2 chargers and 2,900 DC fast chargers, and funding is secured for additional 124,600 Level 2 chargers and 3,500 DC fast chargers (California Energy Commission, 2019).

However, looking at this progress through an equity lens, some of the above barriers still hold for disadvantaged communities, such as those with lower income. Charging, specifically over-night charging, could still be a barrier for the population without off-street parking and the ability to charge at home.

Lower-income families spend a larger portion of their income on transportation expenses (The PEW Charitable Trusts, 2016), and BEV adoption could help reduce their transportation expenditure. However, if the planning of PAEVC infrastructure is not evaluated with consideration of equity, it could be developed around the higher income early adopters and become locked-in (Wells, 2012) to prevent lower-income communities from adopting BEVs. For example, if the charging infrastructure is developed based on the demand of current and future EV drivers, lower-income communities—having fewer

EV drivers—would likely attract less infrastructure investment. Wells further explained that adoption policies lacking coherent focus on social equity could lead to the unequal distribution of the new technology and would likely cause harm to the excluded population.

Current EV owners living in multi-unit dwellings (MUDs) are more likely to only utilize PAEVCs compared to the EV owners living in detached houses. Residents living in MUDs, often with lower incomes, usually do not have access to private garages and off-street parking and are thus unable to charge EVs at home or overnight. A survey study shows 81% of the lower-range BEV owners (i.e., those with driving ranges below 150 miles) that live in MUDs charge exclusively at public chargers, compared to only 16% for lower-range BEV owners living in detached houses (Tal, Lee, & Nicholas, 2018). The disproportionate reliance on public charging infrastructure for EV owners living in MUDs implies that operating an EV becomes more expensive as charging using public infrastructure is more costly than at-home charging. Thus, more EV charging infrastructure needs to be available to EV drivers living in MUDs without off-street parking.

For the MUDs with off-street parking, California Assembly Bill 1796 (CAL. CIV. PROC. CODE § 1947.6) grants tenants the right to install EV chargers at MUDs at the tenant's expense, but residents in MUDs still face more barriers such as higher installation costs associated with detached parking layouts, lower investment motivation, and difficult negotiations between the building management and the residents (Turek &

Deshazo, 2016). The higher EV charger installation cost borne by the tenants in MUD compared to single home residents creates an additional barrier in adopting EVs.

Used EVs could be one way for lower-income families to adopt EVs. The primary method of vehicle acquisitions for the majority of Americans is by purchasing used vehicles (Paszkievicz, 2003), which demonstrates the importance of the used EV market for a widespread EV adoption. The secondary EV market will see increases in options and affordability as the new EV market matures and reaches price parity with ICE vehicles, which should allow a broader consumer base to adopt EVs. However, even the current used EV buyers still have a higher income than the general car-owning population (Turrentine, Tal, & Rapson, 2018). Lower-income buyers will face a higher relative cost barrier, and adequate incentives and assistance programs need to be in place to stimulate EV adoption. Prime examples include incentive programs like a) California's Clean Vehicle Assistance Program that provides grant and low-interest finance for qualified households to purchase new and used EVs and b) the Assembly Bill 193 Zero-Emissions Assurance Project (CAL. HSC.CODE § 1947.6) that mandates the provision of incentives for battery replacements for used EVs.

New BEV owners in California can qualify up to \$2,500, or \$4,500 for lower-income consumers, in rebates (California Air Resources Board, n.d.) and up to \$7,500 in federal tax credits (26 U.S.C. § 30D). A lower income consumer will not likely be able to receive the full \$12,000, or even \$10,000, in combined incentives. With the California rebate structure, an annual income of \$35,640 is the maximum a person could earn to qualify as a single person lower-income household (California Air Resources Board,

n.d.). This level of income, without other tax credits, would only have approximately \$4,100 in federal tax liability and subsequently maximum \$4,100 federal tax credit for purchasing an BEV.¹ For this person, the combined incentives would be \$8,600 rather than the \$10,000 a higher income individual could potentially receive. Lastly, incentives are not permanent and may not be available in the future years when BEV adoption may become more mainstream.

Most of the currently available used BEV models, such as Nissan Leafs from model years 2010 to 2017, come with limited range and could be impractical to commute with for many drivers. Drivers with the need to travel more than 30 miles for a one-way commute without charging stations at their destinations may find it challenging to use early model BEVs. For example in Humboldt County, early model BEVs technically would be able to travel throughout the county with the existing PAEVCs (Hsu, 2019), but without adequate DC fast charging infrastructure and fast charging compatible BEVs, traveling across the county in the early model used BEVs would be impractical and undesirable. Late-model (model years 2017 to 2019) and the new-model (model years 2019 and beyond) BEVs will include more options compared to the first-generation BEVs and have significantly longer driving ranges.

¹ Calculated with the 2019 federal single filer tax bracket

1.3. Humboldt County Electric Vehicle Adoption

This section introduces the status of the EV adoption locally in Humboldt County, California.

1.3.1. Electric Vehicle and Infrastructure Adoption and Projection

As of January 1, 2019, out of 32 million registered vehicles, California has 262,568 (0.87%) zero-emissions vehicles (ZEVs) (California Department of Motor Vehicles, 2019). The state has set the goal to reach five million ZEVs by 2030, an extension of the previous goal of one million ZEVs by 2020. To reach the 2030 goal—19 times the current number of ZEVs—the ZEV fleet would need to grow at a 31% annual growth rate. Humboldt County had 423 BEVs as of January 1, 2019 (California Department of Motor Vehicles, 2019). If the state has a uniform adoption rate across counties, the number of ZEVs in Humboldt County could be 8,072 by 2030, which is approximately 5% of the projected total number of vehicles registered in the county in 2030.²

To achieve the state-wide goal of 250,000 PAEVC stations and 10,000 DC fast-charging stations by 2025, Humboldt would see 868 Level 2 chargers and 35 DC fast chargers installed, assuming the chargers are distributed evenly across the state on a per capita basis. Currently, there is a plan in place to install three DC fast chargers along the major highway corridors in the county, primarily to facilitate long-distance travel (e.g.,

² Assuming the Humboldt County vehicle growth rate is constant and continues at the growth rate from 2018 to 2019.

from Humboldt to San Francisco). With DC fast chargers, not only will long-distance travel in BEVs become more convenient, but it could also encourage the adoption of used BEVs that are DC fast charging compatible, as the diminished short range of used BEVs could be partially compensated by the ability to recharge with DC fast chargers quickly.

1.3.2. Charging Infrastructure Adequacy

Studies have shown public charging infrastructure, although not the sole factor, is critical in promoting EV adoption (Slowik & Lutsey, 2017; Sierzchula, Bakker, Maat, & Van Wee, 2014). The EV-to-charging plug ratio can inform the progress toward the charging infrastructure target. Based on different methods, the recommended public EV-to-plug ratio ranges from 7:1 to 24:1 for the U.S; in California, considering local factors with the more detailed EVI-Pro tool, the recommended EV-to-plug ratio is 27:1 (Hall & Lutsey, 2017). Due to the nascence of the EV market and infrastructure, the ideal public EV-to-plug ratio could shift as both the market and the technology further develop. Furthermore, local context (e.g., most Humboldt County residents live in rural areas) would also influence the optimal EV-to-plug ratio.

Nevertheless, these ratios could be used as interim benchmarks. Currently, Humboldt County has 33 PAEVC stations, of which nine are exclusively for Tesla BEVs (U.S. Department of Energy, 2019). Excluding the Tesla chargers, these 24 stations have a total of 41 Level Two charging plugs and six DC fast charging plugs. The Humboldt County EV-to-plugs ratio is 27 vehicles to one charger (including both Level Two and DC fast chargers). The county's EV-to-charger ratio meets the aforementioned recommended ratio of 27:1 and is similar to the state ratio of 24:1 (Table 1-1). Based on

the EV-to-charger ratio, Humboldt County is on par with the rest of the state with respect to PAEVC infrastructure.

Table 1-1 Electric Vehicles (EVs) to charger ratio for Humboldt County and California. Data sources: vehicle registration data from the California Department of Motor Vehicles; charger data from the U.S. Department of Energy; renter population data from the U.S. Census Bureau

	EV: Level Two and Fast Charger	EV: Level Two Charger	EV: DC Fast Charger	Renter Population Percentage
Humboldt County	25:1	29:1	194:1	44.5%
California	24:1	26:1	298:1	46.5%
Literature Recommendation	7:1 – 24:1	n/a	n/a	n/a

1.3.3. Charging Infrastructure Location

As EV adoption transitions out of the early phases, EV charging infrastructure will need to serve beyond the early adopters. In general, the optimal locations for PAEVCs are determined by the following factors: parking, transit access, power supply, business locations, local and regional traffic impact, cost, and vehicle range (Hall & Lutsey, 2017). Based on the local context, it determines which of the abovementioned key factors are to be considered for the optimal locations for PAEVCs.

Although the current Humboldt County PAEVC infrastructure is serving the majority of buildings and population geographically, as 76% of buildings are within five miles of a PAEVC station (Hsu, 2019), future infrastructure may need to extend to areas currently not covered by the current PAEVC infrastructure. Most PAEVC stations in Humboldt County are located along the coast between Trinidad and Rio Dell. This leaves

the areas including the Yurok Indian Reservation, Orick, the Hoopa Indian Reservation, Orleans, and the majority of Southern Humboldt County without public chargers within a short driving distance.

1.3.4. Previous Local Charger Siting Study

Previously, the macro-siting of PAEVC has been done for Humboldt County with agent-based simulation modeling (Zoellick, Carter, Sheppard, & Carman, 2011). The study investigated the number and locations for the PAEVC needed for 0.5%, 1%, and 2% plug-in EV penetration rates. The plug-in EV adoption pattern was projected using data from Humboldt County's hybrid vehicle adoption pattern. The study result was generated for a ten-year time horizon, which is only two years away at the time this thesis is written. The plug-in EV market penetration rate in Humboldt county was 0.91% as of October 2018, and the county had 24 PAEVC stations with 41 plugs which is between the plug estimations for 1% (31 plugs) and 2% (45 plugs) penetration rates. With the state's five million ZEV goal, the BEV penetration rate alone could reach as high as 5% by 2030 in the county, as shown in Section 1.3.1, indicating a need to install more chargers to both support and increase the equity of PAEVC access. The study modeling results show chargers tend to be sited in and around population centers and major corridors. It did not investigate the access equity issues for areas with a low projected EV adoption pattern nor address the charger access issue for residents without off-street parking.

1.4. Structure of Analyses

The analyses in the thesis are separated into three chapters with the goals of examining the infrastructure and financial barriers to EV adoption with the main focus on BEVs. The first analysis in Chapter Two investigates the equity of the current PAEVC distribution based on 1) sociodemographic factors and 2) the availability and accessibility of PAEVCS surrounding specific points-of-interest. This analysis magnifies the potential disparity of PAEVC availability and access based on income, race and ethnicity, and housing status. The second analysis in Chapter Three compares the total cost of ownership of both new and used BEVs based on different BEV depreciation and operation scenarios. The chapter also examines the economics of used and new BEVs to assess whether the inability to afford the upfront cost of the new BEVs could penalize the owner financially. And finally, Chapter Four introduces the idea of installing residential curbside PAEVCS on light or utility poles and creates an inventory of these poles next to MUDs without off-street parking for Eureka, California. This alternative PAEVC infrastructure could benefit MUD residents that do not currently have a viable charging method to adopt BEVs. Lastly, Chapter Five draws conclusions from the results of the three separate analyses and provides policy recommendations to improve the equity of EV adoption in California.

CHAPTER 2: DISTRIBUTION EQUITY OF PUBLIC ELECTRIC VEHICLE SUPPLY EQUIPMENT INFRASTRUCTURE

Chapter Two aims to investigate the equity of California statewide charging infrastructure distribution (Figure 2-1). Specifically, the investigations include the 1) public access electric vehicle charger (PAEVC) access based on sociodemographic factors and 2) the PAEVC access surrounding different grocery store and fitness club/studio locations. The first analysis provides insight into whether the PAEVCs are distributed disproportionately depending on sociodemographic factors such as household income, home-owning status, and race. The second analysis uses points-of-interest (POIs) (i.e., the grocery store and gym/studio locations) to examine PAEVC availability among stores with different customer bases and among different types of census block groups (CBGs.) Both analyses examine the convenience and visibility of the current PAEVC infrastructure for different race, ethnicity, and income groups.

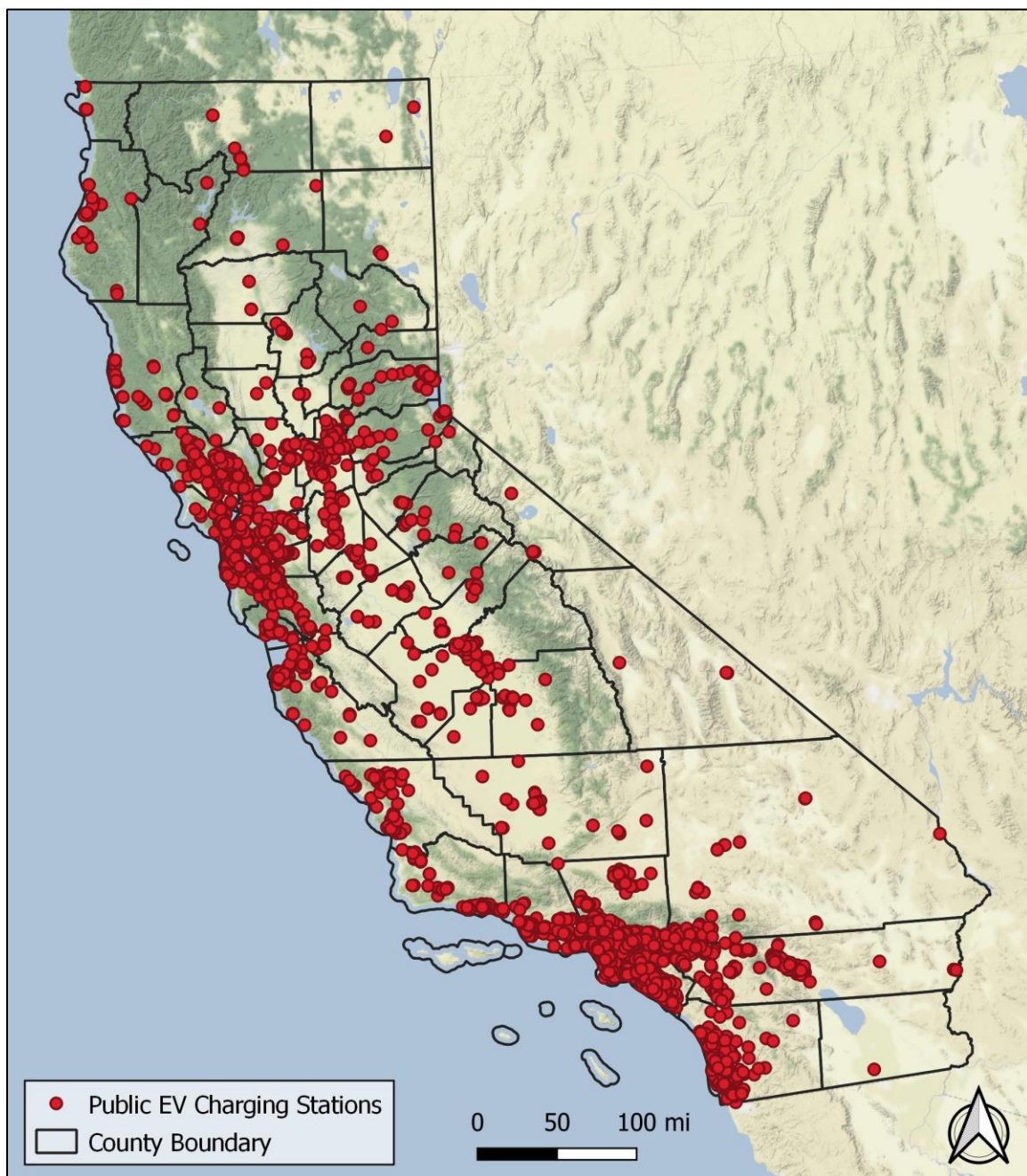


Figure 2-1 Public electric vehicle charging stations in California. Data source: U.S. Department of Energy Alternative Fuels Data Center.

2.1. Sociodemographic Charger Distribution Equity Analysis Method

Level Two and DC fast charge PAEVC locations and census sociodemographic data were used to analyze the relationship between the distribution of the PAEVC infrastructure and different sociodemographic factors. First, I compared the count of PAEVC stations in each of the California counties to the corresponding population size. I further compared the PAEVC station counts within a mile of the center of each CBG to income, race, housing type, and home-owning status. The sociodemographic data from the 2016 American Community Survey were obtained from the U.S. Census Bureau (U.S. Census Bureau, 2016) and PAEVC location data were obtained from the U.S. Department of Energy (U.S. Department of Energy, 2019).

Tabular PAEVC location data were converted to a shapefile and processed with following different methods for the county level and the CBG level. At the county level, PAEVC stations located within the borders of each county were counted. For the CBG level, the presence and absence binary variable indicating access to PAEVCs were generated. Finally, the PAEVC station count data were merged with the census sociodemographic data.

2.1.1. County Level

To investigate the distribution of PAEVC infrastructure at the county level, a simple linear regression was used to predict the PAEVC station count based on the county population size. The simple linear regression result was then used to identify the top ten counties with the largest positive residual values of the predicted PAEVC station

count and another ten with the largest negative residual values. The purpose of this was to identify counties with more or with less PAEVC stations than predicted if PAEVCs were equally distributed across California's population.

2.1.2. Census Block Group Level

The CBGs included for the analysis are all CBGs located completely within or overlapped with either Urban Areas or Urban Clusters as defined by the U.S. Census Bureau, which accounts for 95% of the state's population (see Appendix A for the Urban Area Map of California). The non-urban CBGs were excluded due to larger block group geographic areas. A PAEVC located within one side of a large CBG would hardly be accessible to residents on the opposing side. For example, in Figure 2-2, a single non-urban CBG in Buttonwillow has the similar area as all the Bakersfield Urban Area CBGs combined. Even though there are two PAEVC stations in Buttonwillow, it is unreasonable to assume the residents living at the fringe of the CBG would have the same level of access to the PAEVC as the residents living in the smaller urban CBGs with a PAEVC in Bakersfield.

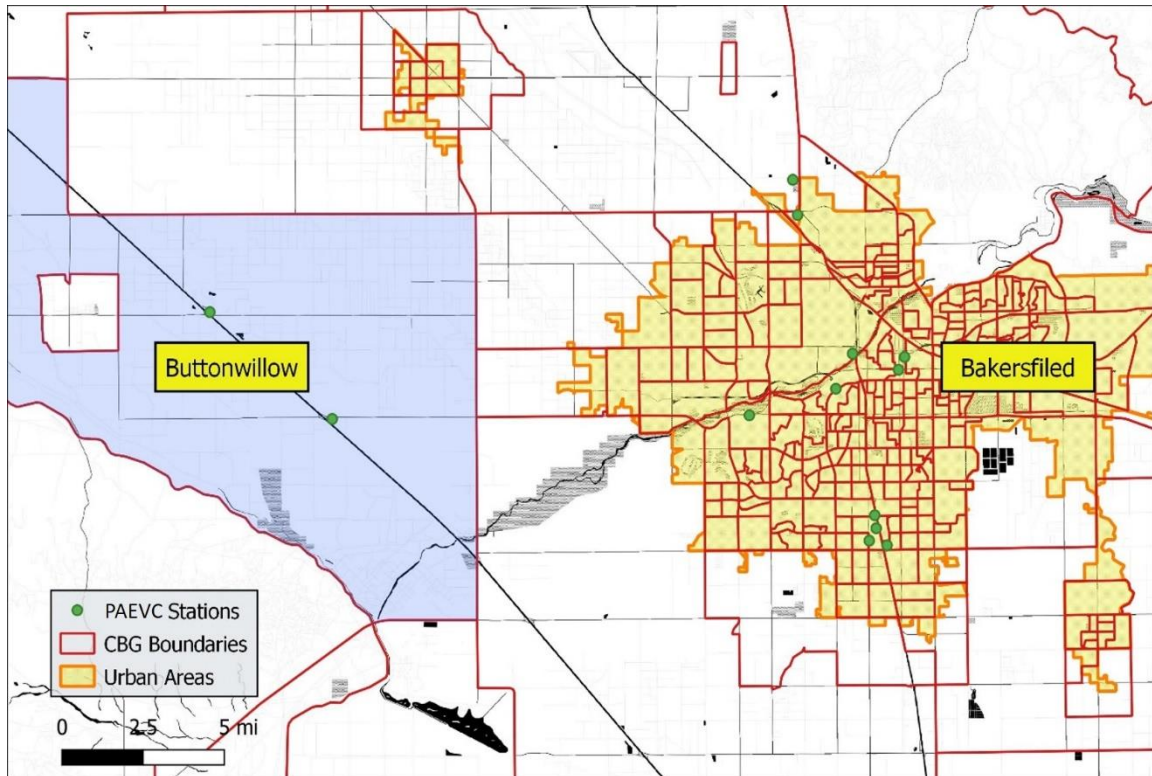


Figure 2-2 Example comparison between the public access electric vehicle charger (PAEVC) stations located in urban and non-urban census block groups.

For the CBG-level analysis, the combined PAEVC station count and CBG sociodemographic data were grouped with two different variables separately. To investigate the potential PAEVC distribution disparity based on income, the data were grouped by the quartiles of the CBG median household incomes. To investigate the potential racial disparity in PAEVC distribution, the data were grouped by the majority race and ethnicity (i.e., greater than 50% of the population in the CBG) in each CBG. The races and ethnicities considered were Non-Hispanic Asian, Non-Hispanic black, Hispanics, and Non-Hispanic white. CBGs without a race and ethnicity majority were labeled “no majority”.

Population-weighted PAEVC stations in each CBG were used to compare state-wide PAEVC share to the population proportion by race and ethnicity. The population-weighted PAEVC stations in the CBG were calculated as the PAEVC stations available in the CBG multiplied by the percentage of the population of a specific race.

To compare the PAEVC access across income and race groups, I used generalized additive model (GAM) with “mgcv” package in R to fit thin-plate spline curves with a binomial distribution for the binary PAEVC access data. The fitted curves minimized the expected squared error using the restricted maximum likelihood approach (RMEL). Smoothing curves with RMEL in GAM, akin to the locally-weighted scatter plot smoothing (LOWESS) method used by Sunter et al. with census data to detect disparities in rooftop photovoltaic solar deployment (Sunter, Castellanos, & Kammen, 2019), does not need a global function to describe the whole data sample. But in addition, GAM with a “mgcv” package can fit local polynomial relationships, as opposed to local linear relationships in LOWESS, and has built-in likelihood-based selection method (i.e., RMEL) that selects the optimal smoothing parameter by balancing between goodness-of-fit and model smoothness.

Various covariates were tested in the attempt to generate the PAEVC access GAM models. The final covariates used to generate the GAM models include distances to the nearest highway, renter-occupied housing unit rates of the CBGs, and MUD housing unit rates of the CBGs. Distances to the nearest highway were chosen as the main covariate for modeling PAEVC access because PAEVCs are usually sited along the major corridors. The values were calculated by finding the shortest distance between the

centroids of the CBGs to the nearest primary and secondary roads—highways and freeways—in the shapefile obtained from the U.S. Census Bureau (U.S. Census Bureau, 2018). Population density, one of the potential covariates tested, was not included due to the following reason. The original intent of using population density was to control for the urbanity of the CBGs. However, this was alternatively achieved by using only CBGs located in Urban Areas and Urban Clusters as defined by the U.S. Census Bureau. The filtered CBG data were still meaningful as these urban CBGs account for almost 95% of California’s population. Lastly, renter-occupied housing unit rates and MUD housing unit rates were only used as covariates for data of the CBGs located within one mile from the nearest highway in the attempt to investigate PAEVC access differences between income and racial groups when all groups are located near the freeways.

2.2. Charger Distribution Equity Based on the point of Interest Method

In addition to the availability of and access to PAEVC based on residential locations (i.e., CBGs), I was also interested in the availability and access differences of PAEVCs at driving destinations (i.e., points of interest [POIs]) based on different stores and their different clienteles and neighborhoods. Grocery store and fitness club/studio locations—POIs typically with longer stop duration—were included in the analysis. Workplaces were not included in the study since incomes of the people associated with a

workplace, compared to shops, are more heterogeneous and workplace EV chargers may not allow general public access.

The grocery stores included in this analysis were ALDI, all individual Co-ops, Costco, Grocery Outlet, Safeway, Sprouts Farmers Market, Target, Trader Joe's, Vons, Walmart, WinCo, and Whole Foods. The fitness clubs/studios included in this analysis were 24 Hour Fitness, all yoga studios, Crunch Fitness, Equinox, LA Fitness, Planet Fitness, Soul Cycle, and YMCA.

The store locations were obtained from the Open Street Map application program interface (API) using R. The store location data were overlaid in QGIS with the PAEVC location data obtained from the U.S. Department of Energy (U.S. Department of Energy, 2019). The numbers of the PAEVC stations within 0.1 miles of each individual POI were counted and aggregated to determine the mean and standard deviation of each individual chain of grocery stores and fitness clubs/studios. The baselines, one for grocery stores and one for fitness clubs/studios, were calculated using the same method mentioned earlier for all locations under the categories of grocery store and fitness club/studio as categorized by Open Street Map API. For example, the grocery store baseline was collected using the "osmdata" in R and filtered to all POIs that are considered to be a grocery store. The distance of 0.1 miles was chosen to attempt to only include the PAEVCS in the immediate parking lots next to the grocery or fitness club/studio locations.

To capture the neighborhood characteristics, the sociodemographic information from census data such as income, race, and ethnicity were merged with the POI data. To

categorize and estimate the income level of the clientele at each location, internet search results based on consumer reports and membership fees from fitness clubs/studios were used. For grocery stores, average grocery price index data were obtained from Bay Area Consumers' Checkbook (Brasler, 2018c, 2018a, 2018b).³ The fitness club and studio membership or class fees were obtained from the official company websites when available. When different tiers of membership exist, the most basic or the cheapest option of the membership was selected. For fitness studios that charge on a per-class basis, the five-class package was selected or the cost of five classes was calculated. Note it is possible that the same gym or studio brand may have different membership fees or class fees at different chain locations. The generally published prices were used since capturing the price variations was outside the scope of this analysis.

To further compare the access and availability difference between income, race, and ethnicity groups, I used the same GAM model approach outlined in 2.1.2. GAM models with binomial distributions were used to analyze the PAEVC access at different POIs.

³ The price index data was surveyed in the San Francisco Bay Area which may not accurately represent state-wide grocery price index. Price index data for ALDI was obtained from the Chicago Area Consumers' Checkbook website since it was not included in the San Francisco Bay Area data.

2.3. Sociodemographic Charger Distribution Equity Analysis Result and Discussion

PAEVC access disparities based on the household income were found at the county level, and PAEVC access disparities based on the household income, race, and ethnicity were identified at the block group level.

2.3.1. County Level

At the county level, the simple linear regression (r -squared = 0.9312) suggests a significant positive correlation between the counts of PAEVC stations and the county populations. The positive and significant correlation between population and the PAEVC station count is expected, as PAEVCs, like other public services and infrastructure, are most cost-effective if utilized more often by more people. The model residual could be used as an indicator in detecting the counties with more or with less PAEVC stations given the county population. Santa Clara has the highest positive residual and San Bernardino has the most negative residual. Furthermore, Santa Clara and San Mateo, the top two counties with the most positive residuals of the predicted PAEVC station count based on the population sizes, have just received an additional \$33 million in state funding to install more PAEVCs (Silicon Valley Clean Energy, 2019) which would further solidify their positions on the PAEVC infrastructure leader board. Humboldt County lies close to the best-fit line on the simple linear regression plot (Figure 2-3) and is ranked 15th out of 58 counties in California with 11 more PAEVC stations compared to the predicted value based on its population size. The full regression result can be found in Appendix B.

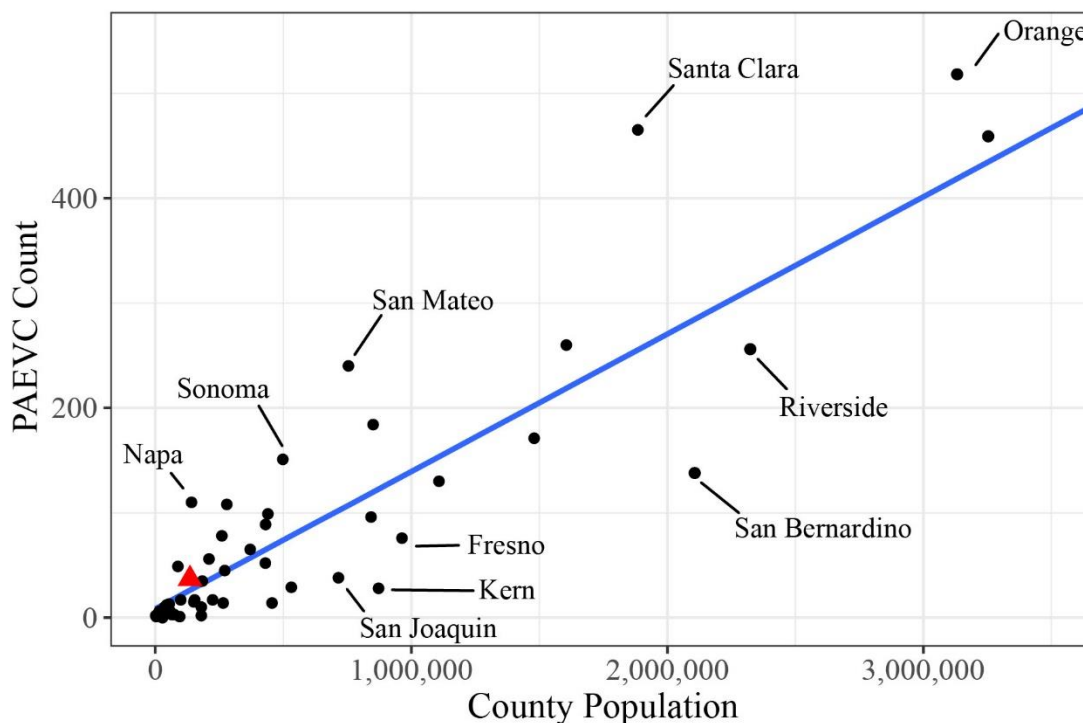


Figure 2-3. The relationship between county populations and public access electric vehicle charger (PAEVC) stations. The blue line represents the best-fit line of the simple linear regression model for PAEVC stations as a function of the county population. The top and bottom five counties with largest predicted value residuals were labeled. The red triangle is Humboldt County. Note Los Angeles County, which lies closely below the best-fit line, is not shown on the graph as it was the only county with a population (i.e., 10 million people) more than 3.5 million people.

When the income levels of the counties are considered, counties with higher average incomes seem to fair off better in terms of having more PAEVCs as predicted by the regression best fit line as discussed above. When the residue of the PAEVC count and population regression (refer to as “PAEVC bias index” in Figure 2-4 for clarity purpose) are compared to the mean household income of each county, a positive trend emerges. As the mean household income increases, the PAEVC residual—or PAEVC bias index — tend to become more positive (Figure 2-4) suggesting a bias in PAEVC distribution

toward richer counties and against poorer counties. Even though the analysis at the county level provides a quick and clear glance into how counties are doing in terms of PAEVC build-out, the study resolution, in terms of sociodemographic factors and geographic area, is too low to be used to more definitively detect the income, race, and ethnicity disparity. The next section discusses such matter at the CBG level.

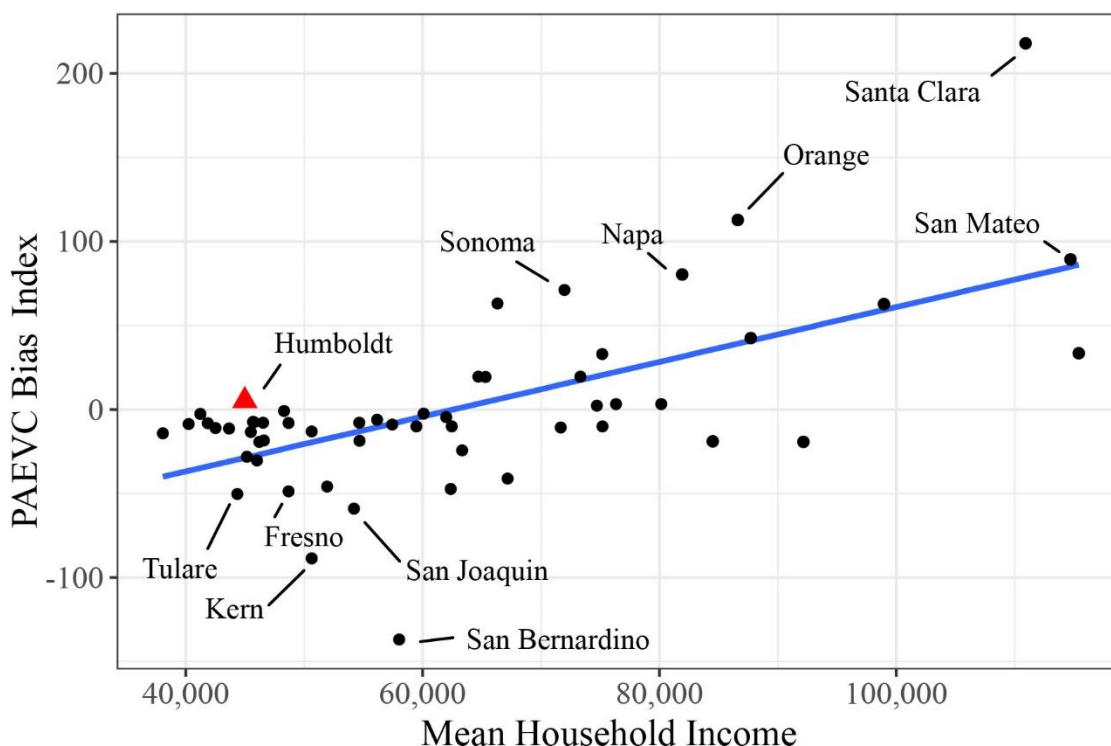


Figure 2-4 The relationship between the mean household incomes and the public access electric vehicle charger (PAEVC) bias index. The blue line represents the best-fit line of the simple linear regression model (R-square of 0.39) for PAEVC bias index as a function of the mean median household income. The top and bottom five counties with most positive and most negative PAEVC bias index are labeled. The red triangle is Humboldt County.

2.3.2. Block Group Level

Asian population and white population are the two groups that share higher percentages of PAEVCs than their percentages of state population than other race and

ethnicity groups (Table 2-1). The Asian population accounts for 13.7% of the state population but disproportionately shares 16.2% of all PAEVCs and 18.2% of the PAEVCs available within a one-mile radius of their CBGs. The white population accounts for 38.4% of the state population but shares 47.5%, nearly 10% more than its population proportion, of all PAEVCs. On the other hand, the Hispanic population, with approximately the same percentage of the state population as the white population, shares only 26.9% of all PAEVCs.

Table 2-1 Population weighted share of public access electric vehicle charger (PAEVC) stations and PAEVC stations available within one mile of the center of census block groups (CBGs) for California.

Race & Ethnicity	PAEVC Share Station Count	Percentage of State Population
Asian	900 (16.6%)	13.7%
Black	264 (4.9%)	5.6%
Hispanic	1,457 (26.9%)	38.6%
Native	21 (0.4%)	0.4%
Other	186 (3.4%)	3.1%
Pacific Islander	17 (0.3%)	0.4%
White	2,575 (47.5%)	38.4%

Originally, I divided CBGs based the majority race and ethnicities into five groups: Asian, black, Hispanic, white, and no majority groups. However, the final results combined black and Hispanics into a single category as there were relatively fewer black majority CBGs compared to other groups (Table 2-2). The small sample size of the black majority CBGs resulted in models with large uncertainty bands. However, the black

majority CBG group had a more similar trend line to the Hispanic majority CBG group compared to all other groups. Thus, for robustness and clarity of the final results in the chapter, the new category—black and Hispanic majority CBGs—replaced the black majority CBG group and Hispanic majority CBG group.

Table 2-2 Census block group groupings based on race and ethnic majority.

Original Groupings	Count & Proportion	Final Groupings	Count & Proportion
Asian	1,121 (4.8%)	Asian	1,121 (4.8%)
Black	247 (1.1%)	Black and Hispanic	8,557 (37.0%)
Hispanic	6,988 (30.2%)	White	9,547 (41.2%)
White	9,547 (41.2%)	No Majority	3,926 (17.0%)
No Majority	5,248 (22.7%)		

The proximity to highways has a positive effect on the possibility of CBGs having access to at least one PAEVC station within its boundaries (Figure 2-5). The possibility of access to PAEVC stations is at the highest (i.e., approximately 18%) right next to the freeways and flattens out starting about one mile (i.e., ~1,600 meters) away from the highway. With the proximity to freeways controlled, we can now investigate the PAEVC access difference between income and race groups.

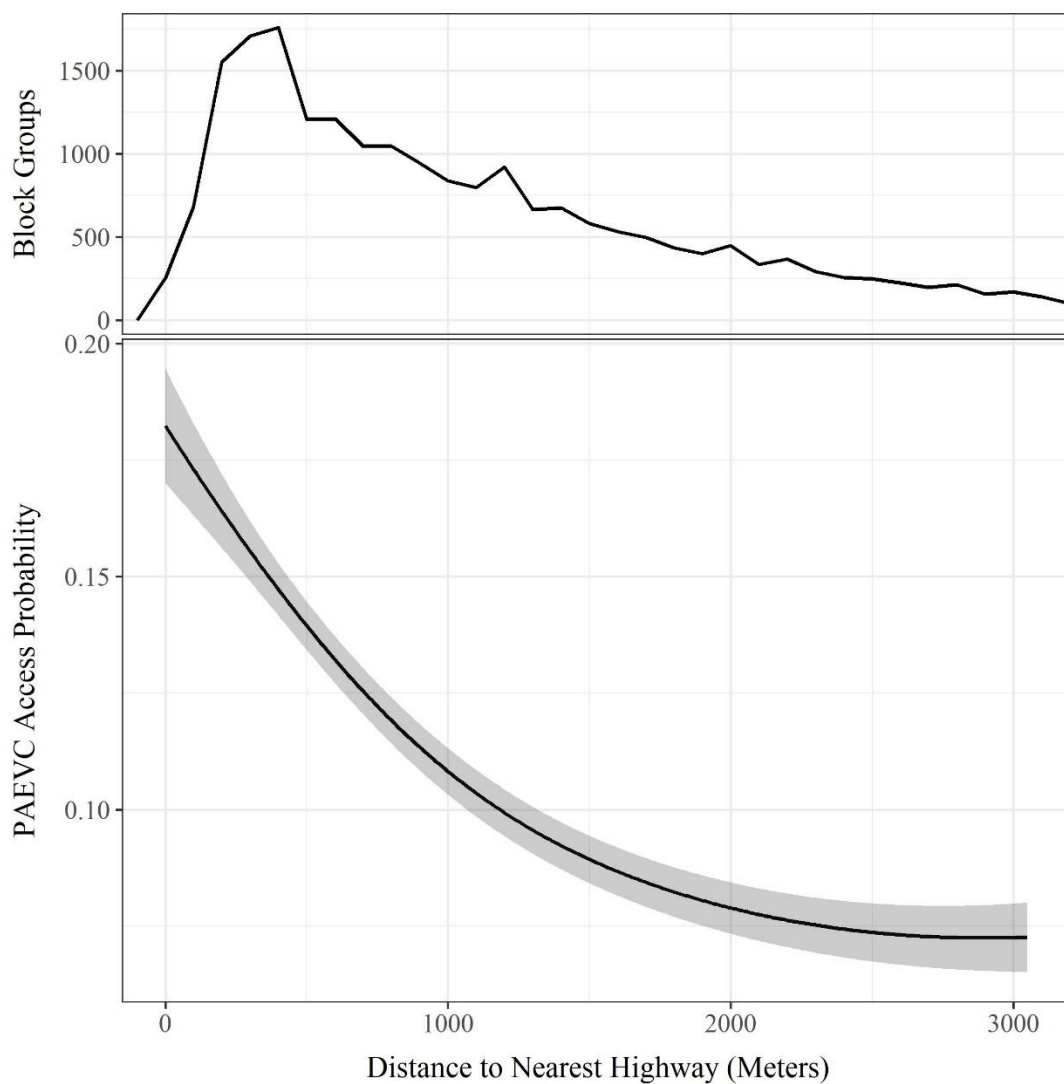


Figure 2-5 Relationship between public access electric vehicle charger (PAEVC) access probability and the distance to the nearest highway for census block groups. **Top)** Frequency plot of census block groups. **Bottom)** PAEVC access probability as the function of the distances to the nearest highway.

When the distance to the nearest highway is controlled for, all income groups exhibit the decreasing trend in the possibility of having access to at least one PAEVC station as the distance to the nearest highway increases. However, the lowest household income CBG group (i.e., lower than first quartile, \$44,000 per year, of the median

household income of all CBGs) has lower PAEVC access compared to all other income CBG groups when the distance to the nearest highway is half a mile (i.e., 800 meters) or less (Figure 2-6).

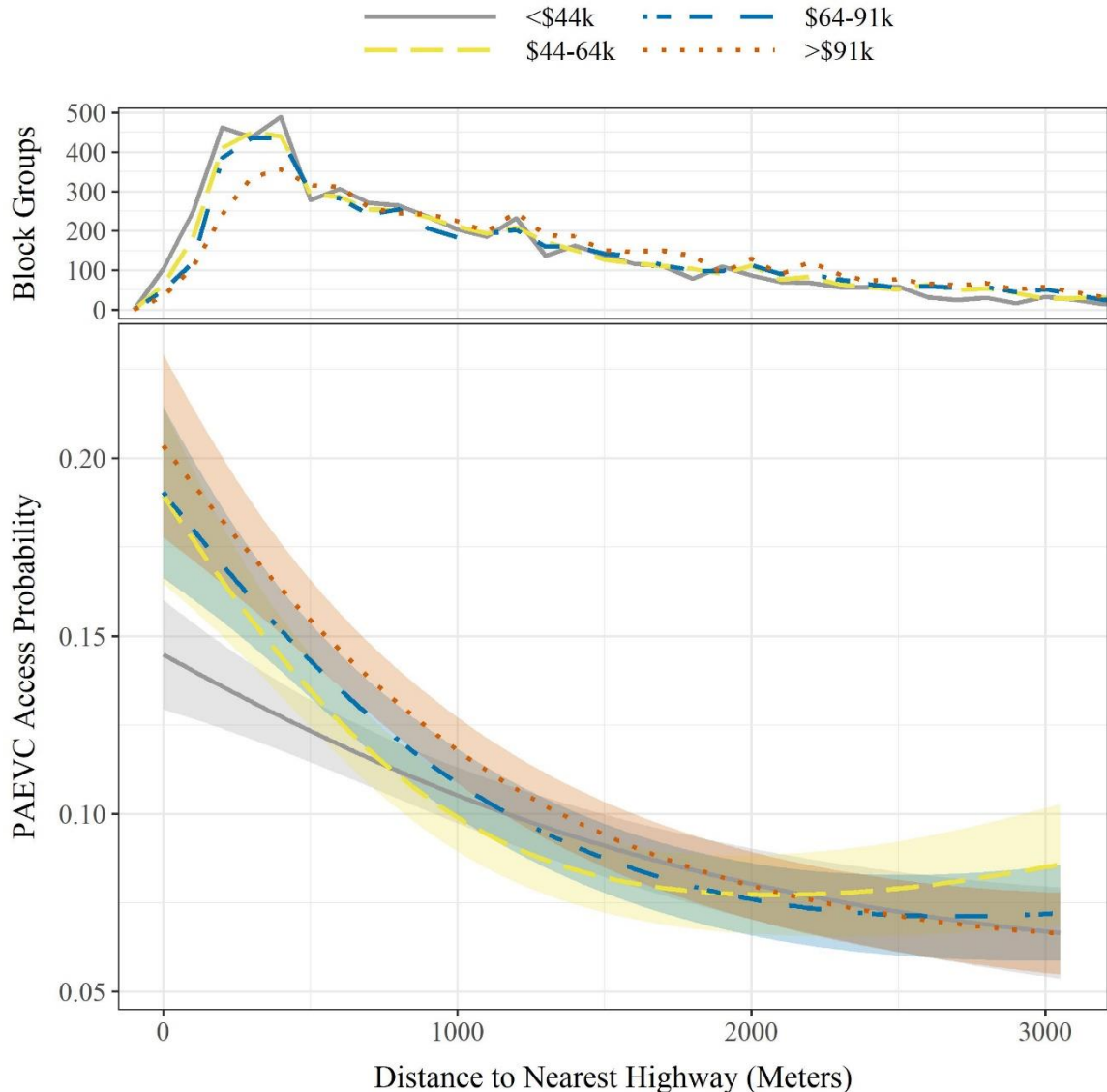


Figure 2-6 Comparison of public access electric vehicle charger (PAEVC) access between census block groups (CBGs) grouped by medium household income controlling across population density. **Top**) Frequency plot of the CBGs. **Bottom**) Probability of having access to at least one PAEVC station in the CBGs as a function of distance to the nearest highway by different income groups. The semi-transparent bands represent the 90% confidence interval.

In terms of race and ethnicity, when comparing at the same distance to the nearest highway, black and Hispanic majority CBGs have lower possibility to have access to at

least one PAEVC station compared to other CBG groups (Figure 2-7). For example, the result suggests at 0 to 60 meters away from the nearest freeway, white-majority CBGs have 13% or higher likelihood to have access to PAEVCs compared to black and Hispanic majority CBGs—the largest gap between any two trend lines.

Within a single race majority CBG group, annual household incomes do not seem to impact a CBG's probability to have access to PAEVCs as much as the distance to the nearest highway. With the exception of Asian majority CBGs with the smallest sample size, most groups have a flatter trend line between annual household income and PAEVC access possibility (Figure 2-8) compared to the trend lines when compared across different distances to the nearest freeway (Figure 2-7). The slight decrease in the PAEVC access probability with the increasing household income is likely due to the fact that more affluent households tend to live in less mixed used zones, or in other words more residential zones, thus having fewer potential spaces to install PAEVCs to begin with. However, black and Hispanic majority CBGs have the lowest possibility of PAEVC access across the income spectrum. This suggests that when all CBGs are considered, the majority race and ethnicity of the CBG is likely a better predictor of PAEVC access disparities compared to median annual household income.

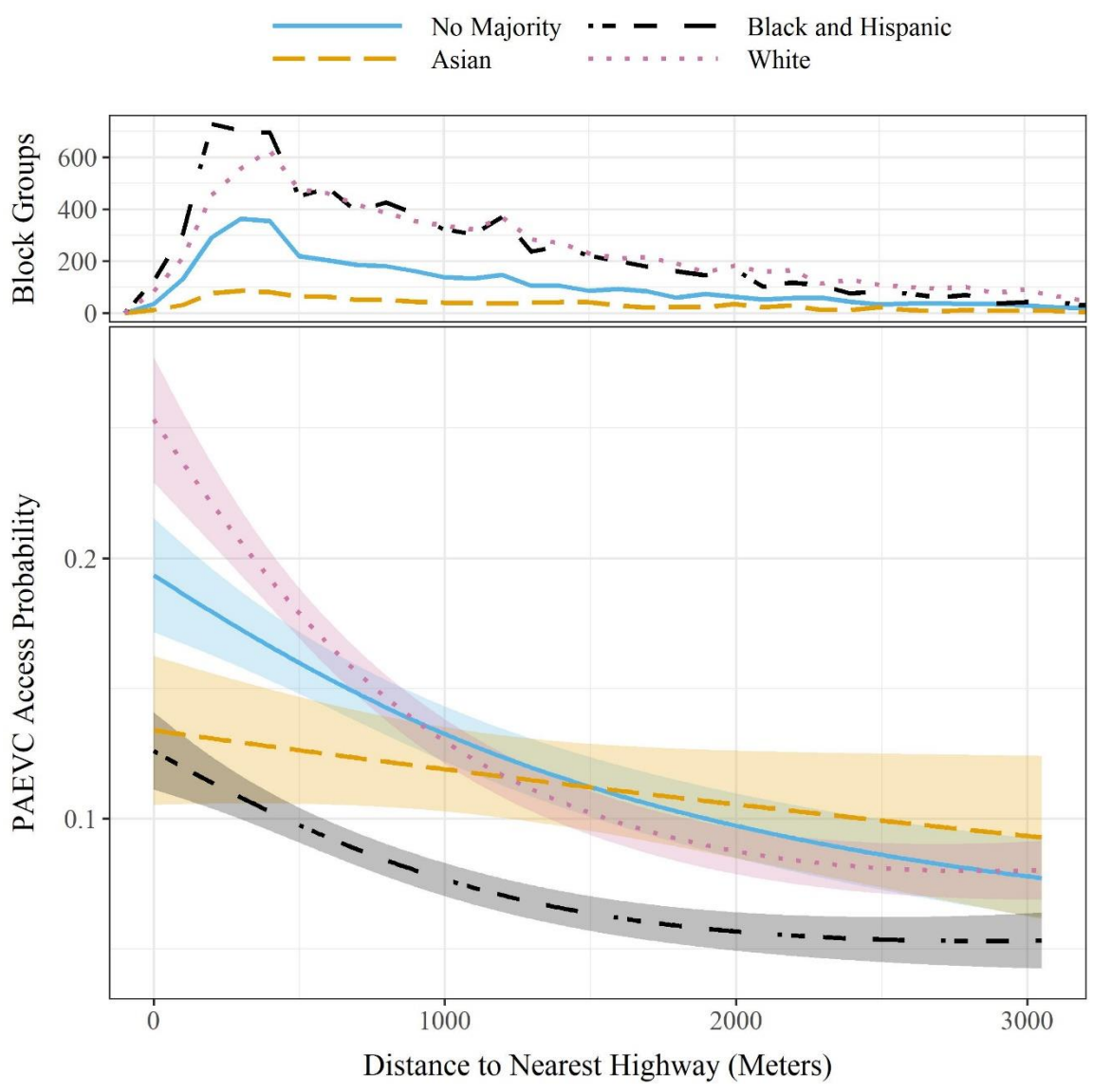


Figure 2-7 Comparison of public access electric vehicle charger (PAEVC) access between census block groups (CBGs) grouped by different race and ethnic majority controlling across population density. **Top**) Frequency plot of the CBGs. **Bottom**) Probability of having access to at least one PAEVC station in the CBGs as a function of distance to the nearest highway by different majority race and ethnicity groups. The semi-transparent bands represent the 90% confidence interval.

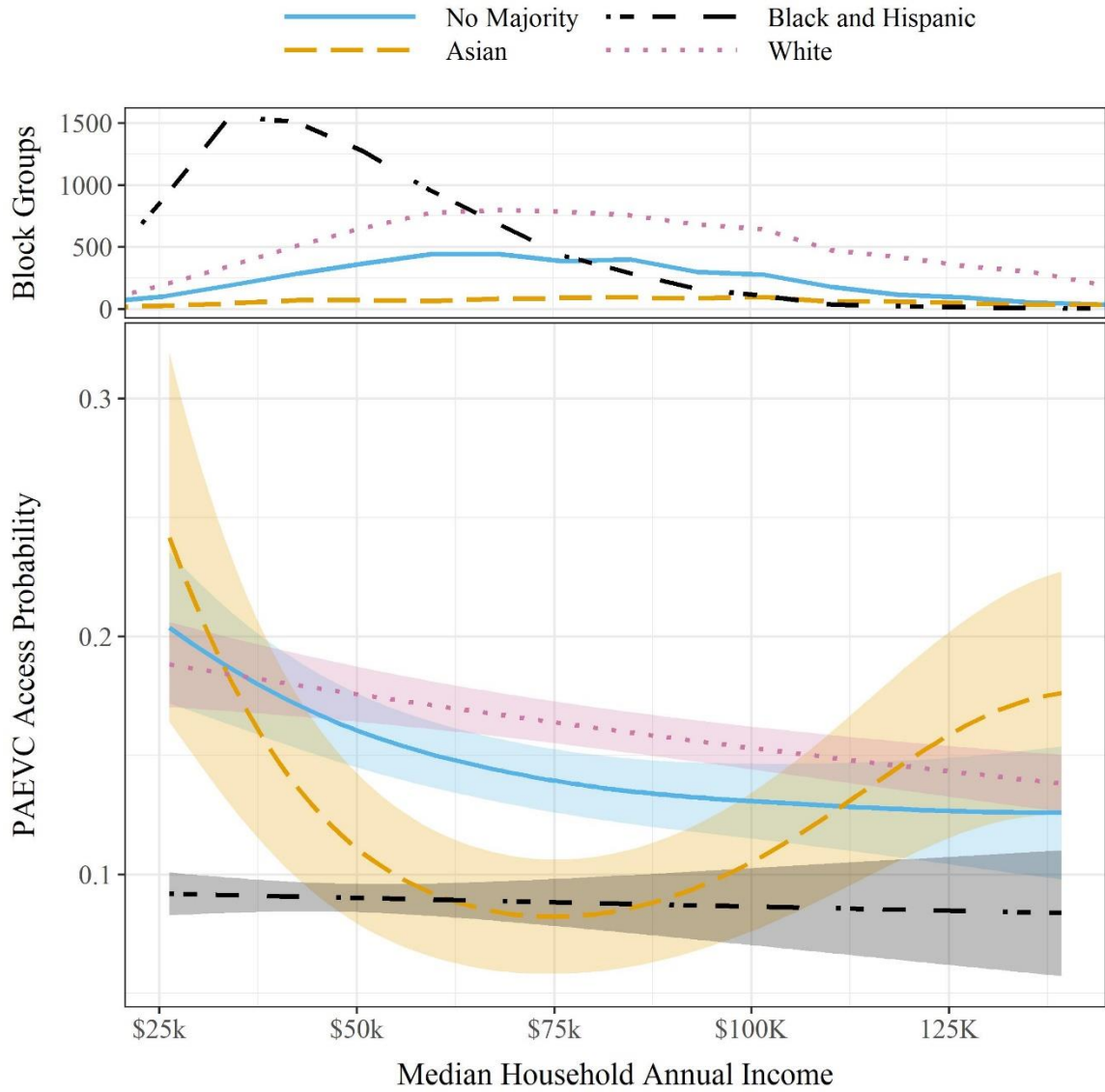


Figure 2-8 Relationship between median household annual income of the census block groups (CBG) renters and the probability to public access electric vehicle charger (PAEVC) access by CBG with different race and ethnic majorities. **Top)** Frequency plot of CBGs. **Bottom)** Probability of having access to at least one PAEVC in the CBGs as a function of median household income. The semi-transparent bands represent the 90% confidence interval.

Disparities across housing characteristics. The next set of results in the section investigates whether PAEVC access disparities persist across different housing

characteristics. The CBG sample pool is now isolated to CBGs located within one mile of the nearest freeway to only compare CBGs that are expected to have higher PAEVC access and reduce the confounding effect of proximity to the nearest highway.

When isolated to only the CBGs located within one mile of the nearest freeway, in general, as the percentage of renter-occupied housing unit increases, the probability of PAEVC access also increases (Figure 2-9 & Figure 2-10). One possible explanation for this pattern could be that more CBGs with higher renter-occupied housing unit rate have mixed-use development zones. Mixed-use zones blend commercial use and residential uses together which would be more likely to have commercial locations with PAEVCs than residential zones. Mixed-used zones are more often located near urban centers. People are more likely to rent, not buy, the housing units at these higher rent locations which agrees with the income disparities seen in Figure 2-9. The highest income groups, likely associated with the high rents of the mixed-use urban central locations, have the highest PAEVC access.

Across the renter-occupied housing unit rate, the probability seems to increase at a lower rate for CBGs with the lowest medium household incomes. Between the highest and lowest income CBGs, the difference in PAEVC access possibility is as large as 26%. Interestingly, the PAEVC access possibility trend line for the CBGs with lower than \$44,000 annual household income stayed flat between the 30% to 75% renter-occupied housing unit rate when the trend lines for all other groups continue to rise (Figure 2-9). Similarly, when grouped by majority race and ethnicity, the PAEVC access probability remained flat for black and Hispanic majority CBGs from approximately 0% to 60%

renter-occupied housing unit rate (Figure 2-10). Unlike the results grouped by different median household incomes, where there are clear PAEVC access differences between each income group (Figure 2-9), only black and Hispanic majority CBGs are left behind when all other CBGs seem to have similar PAEVC access across different renter-occupied housing unit rates (Figure 2-10). Lastly, white majority CBGs have higher PAEVC access than CBGs with no race and ethnic majority across all renter-occupied housing unit rates—by as much as 19% compared to black and Hispanic majority CBGs.

PAEVC access disparity analysis based on the percentage of total housing units that are MUDs (MUD housing unit rate) shows similar disparity patterns as the analysis based on renter-occupied housing unit rate. Although there is the general trend of increasing possibility of PAEVC access as MUD housing unit rate increases, lower median household income CBGs and black and Hispanic majority CBGs still have lower likelihood of PAEVC access compared to the higher income and other race and ethnic majority CBGs (Figure 2-11 & Figure 2-12).

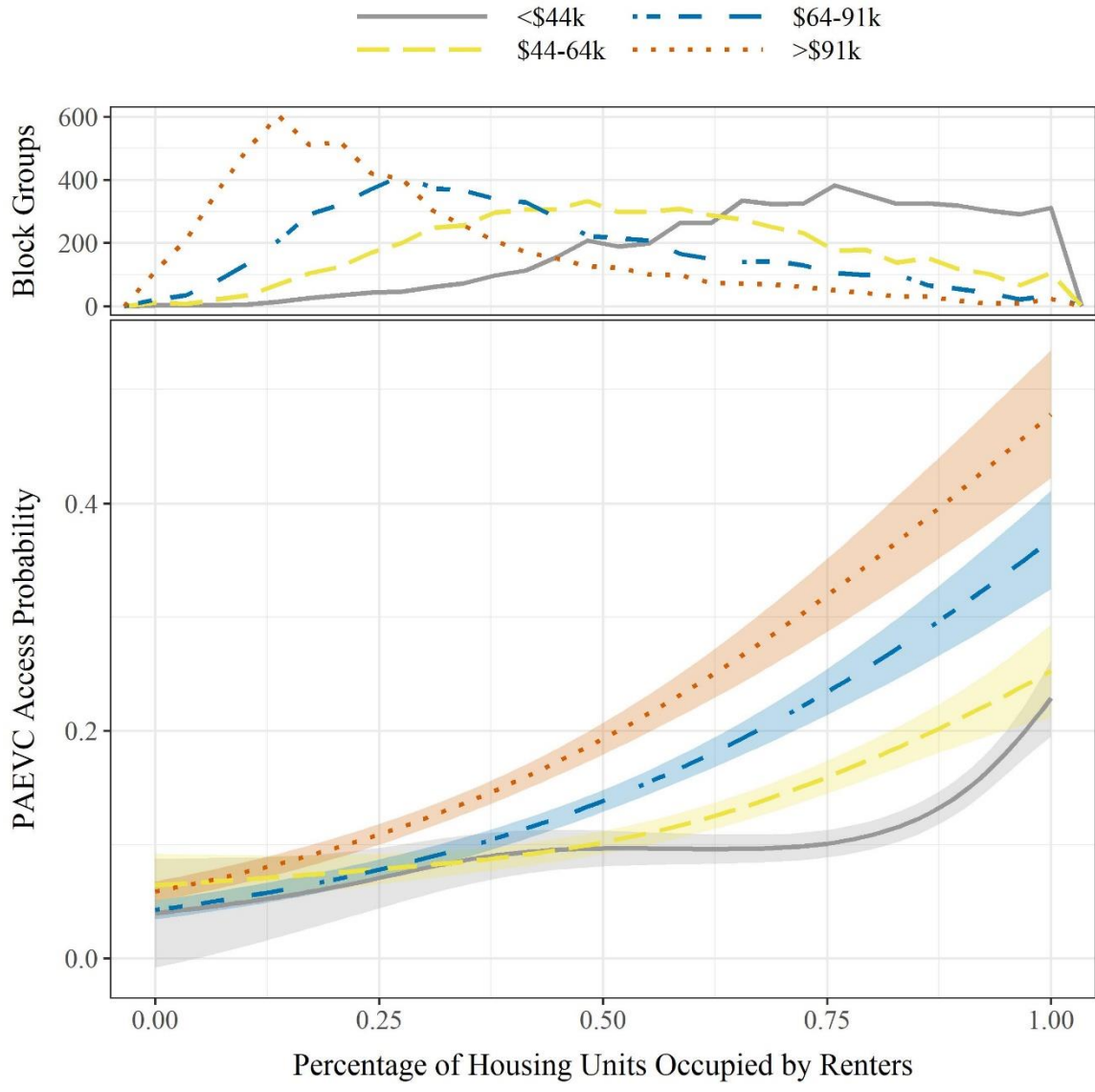


Figure 2-9 Relationship between the percentage of housing units occupied by renters and the probability to public access electric vehicle charger (PAEVC) access by census block groups (CBG) with different median household incomes. **Top**) Frequency plot of CBGs. **Bottom**) Probability of having access to at least one PAEVC in the CBGs as a function of renter-occupied housing unit rate. The semi-transparent bands represent the 90% confidence interval.

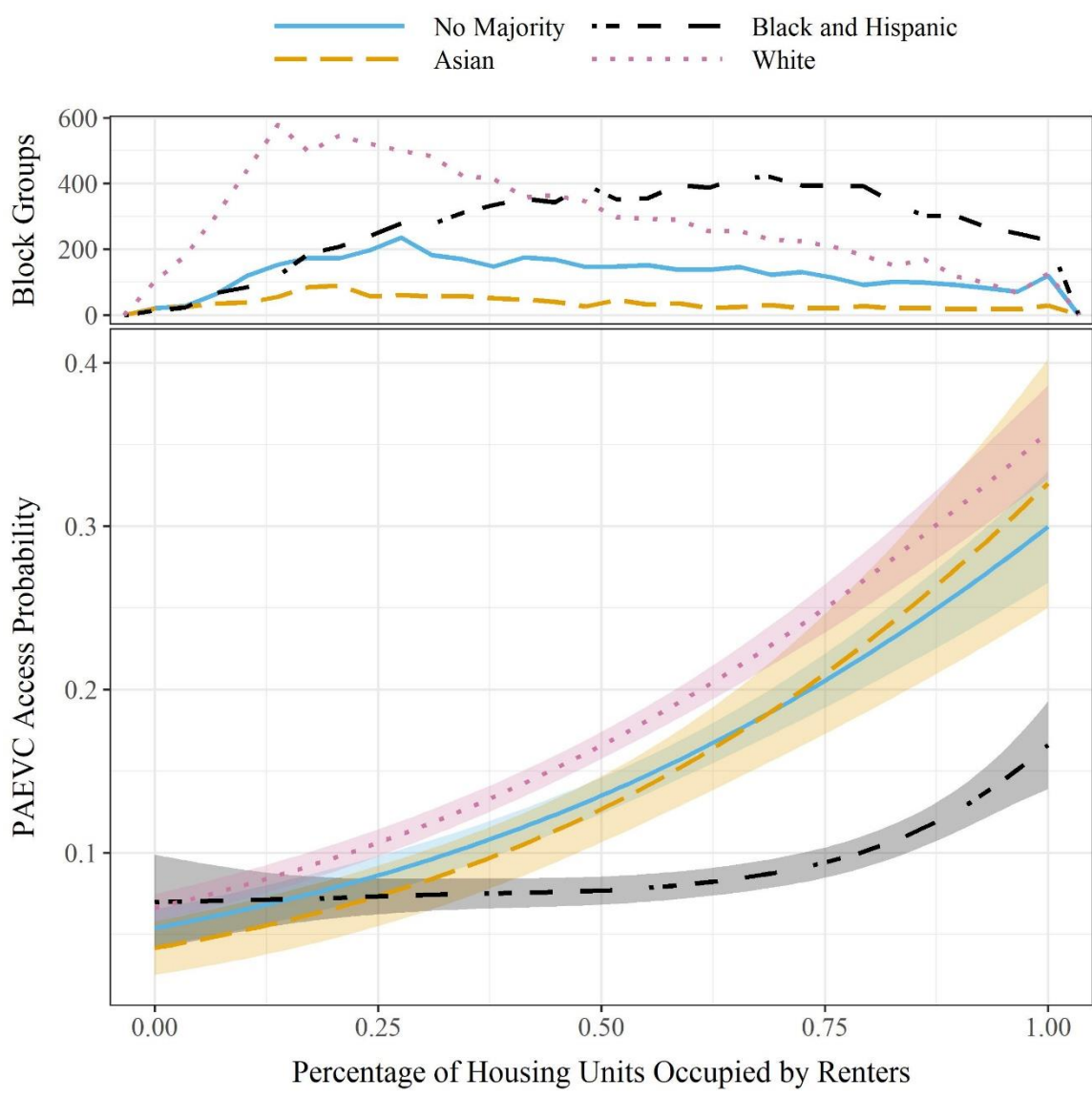


Figure 2-10 Relationship between the percentage of housing units occupied by renters and the probability to public access electric vehicle (PAEVC) access by census block groups (CBG) with different race and ethnic majorities. **Top**) Frequency plot of CBGs. **Bottom**) Probability of having access to at least one PAEVC in the CBGs as a function of renter-occupied housing unit rate. The semi-transparent bands represent the 90% confidence interval.

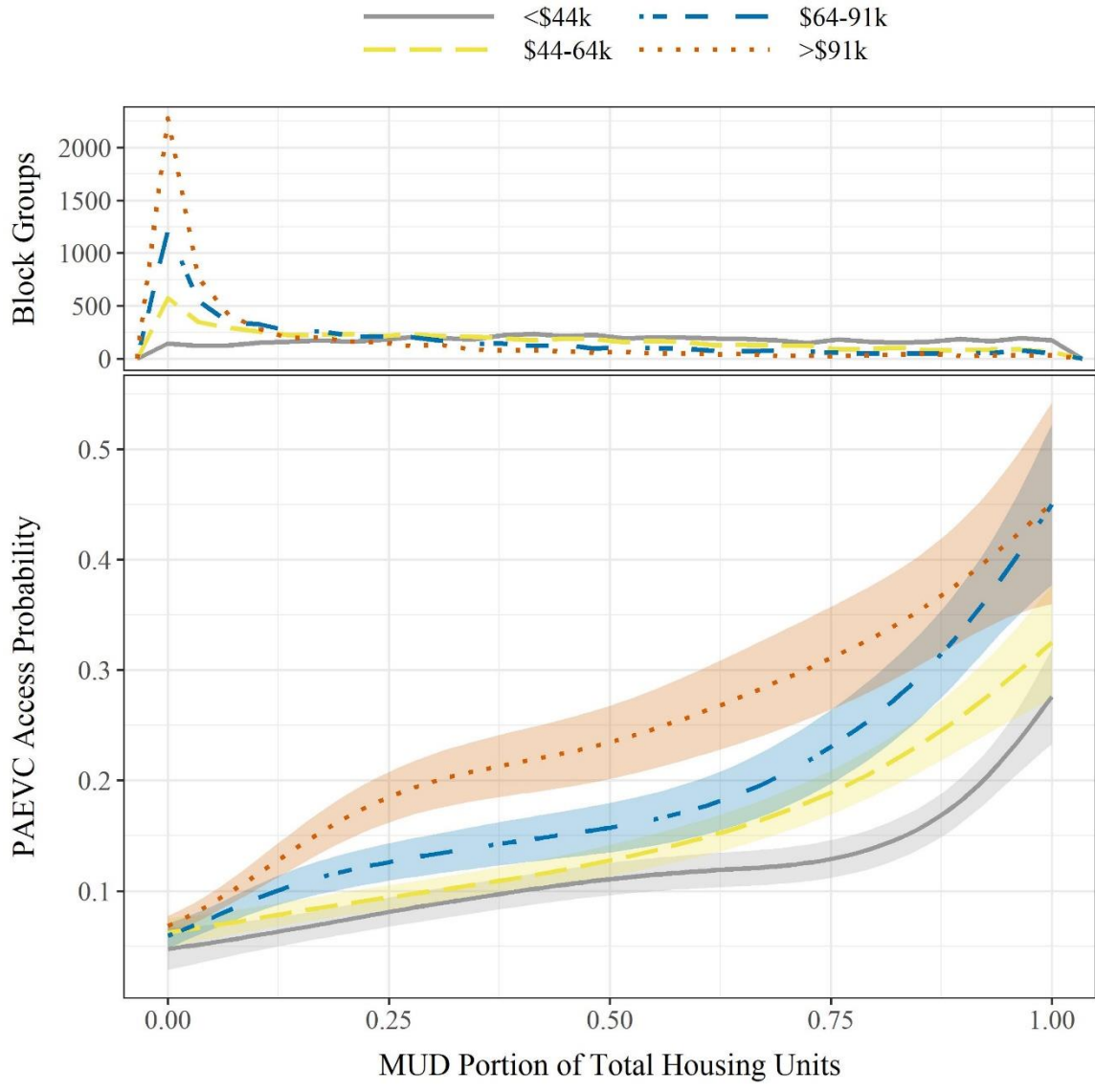


Figure 2-11 Relationship between the multiunit dwelling (MUD) portion of total housing units and the probability to public access electric vehicle charger (PAEVC) access by census block groups (CBG) with different median household incomes. **Top**) Frequency plot of CBGs. **Bottom**) Probability of having access to at least one PAEVC in the CBGs as a function of MUD housing unit rate. The semi-transparent bands represent the 90% confidence interval.

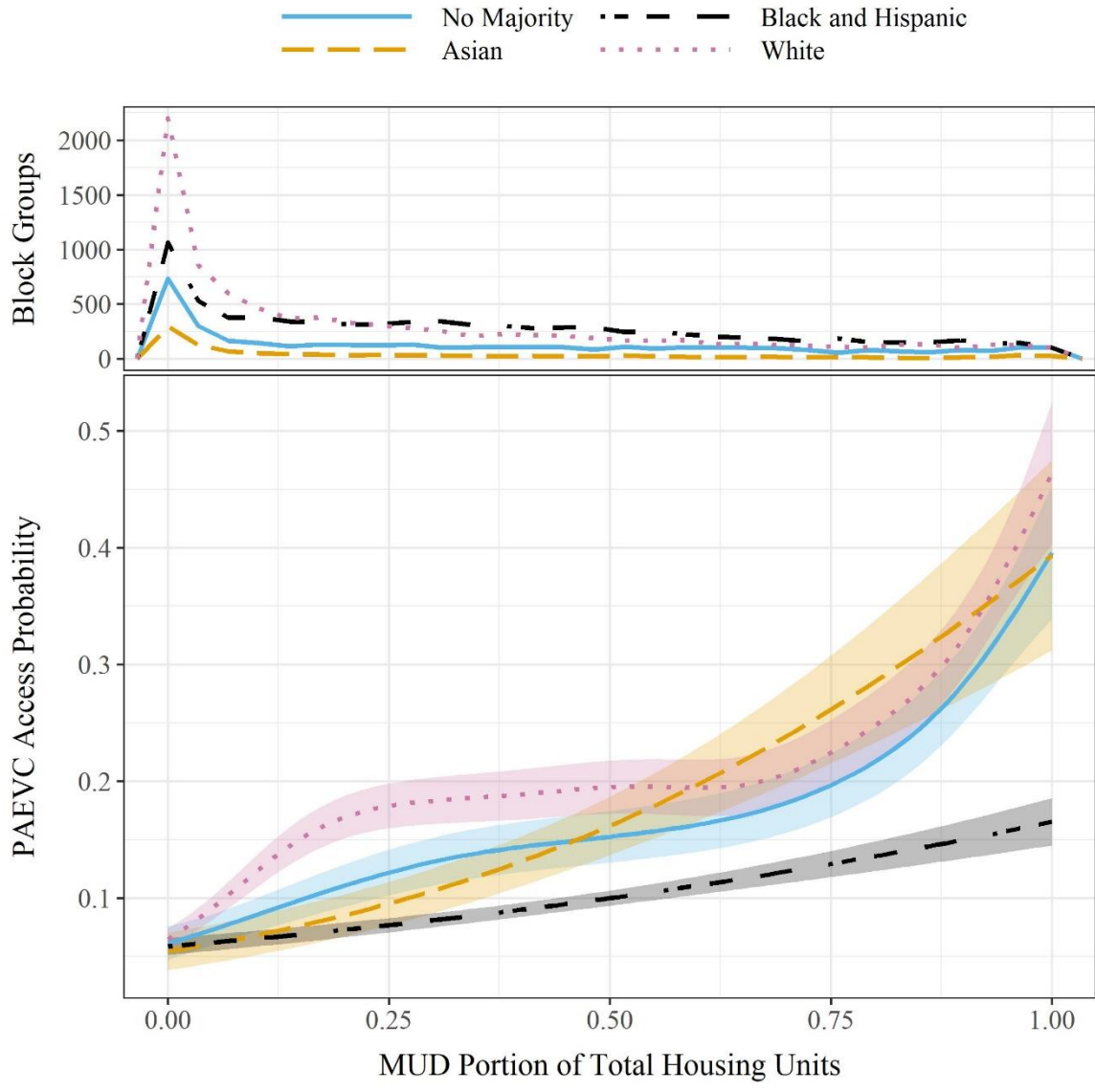


Figure 2-12 Relationship between the multiunit dwelling (MUD) portion of total housing units occupied and the probability to public access electric vehicle charger (PAEVC) access by census block groups (CBG) with different race and ethnic majorities. **Top**) Frequency plot of CBGs. **Bottom**) Probability of having access to at least one PAEVC in the CBGs as a function of MUD housing unit rate. The semi-transparent bands represent the 90% confidence interval.

One cautionary note should be taken when interpreting the results in the figures in this section. The trend lines at the tail-ends (i.e., high and low) of the X-axis should be

interpreted carefully as the trends could be driven by fewer CBGs. However, the disparity patterns pointed out earlier are still consistent if we only compared the trend lines at locations on the plot where there are higher and relatively similar amount of CBGs between groups (e.g., 500 to 1,000 meters away from freeway on Figure 2-7, 30% to 60% renter-occupied housing unit rate on Figure 2-10).

The results above indicate black and Hispanic-majority CBGs often have lower PAEVC access, in terms of the possibility of having at least one PAEVC station within the CBGs, compare to other CBGs across different distances to the nearest highway, renter-occupied housing unit rates, and MUD housing unit rates. And the PAEVC access disparities are most severe at higher renter-occupied and MUD housing unit rate locations.

CBGs with lower than the state median household income (i.e., less than \$64 thousand a year) also seem to have lower PAEVC access compared to the higher median household income CBGs across different renter-occupied housing unit rates, MUD housing unit rates, and slightly less so across different distances to the nearest highway. Combined with the race and ethnicity comparison result, Hispanic and black majority CBGs with lower median household income are even more likely to be underserved by the current PAEVC infrastructure compared to other groups.

Focusing on race and ethnicity. A multi-variable GAM model was performed to assess the probability of living in the CBG with at least one PAEVC across ethnic groups after adjusting for median household incomes, distances to the nearest freeway, MUD housing unit rates, and renter-occupied housing unit rates. Comparing across all CBGs

located within one-mile from the nearest freeway, relative to the no majority CBGs, white majority CBGs are 1.27 times (95% uncertainty interval: 1.11, 1.45 times) as likely to have access to PAEVCs and black and Hispanic majority CBGs are only 0.69 times (95% uncertainty interval: 0.59, 0.80 times) as likely to have access to PAEVCs within their respective CBGs (Table 2-3). This means white majority CBGs is 1.9 times more likely than black and Hispanic majority CBGs to have access to PAEVCs. Asian majority CBGs are slightly less likely (0.96 times as likely, 95% uncertainty interval: 0.75, 1.23 times) to have access to PAEVCs than the no majority CBGs but the difference is not statistically significant at the 0.05 level. This result aligns with Figure 2-8 to Figure 2-12 and further supports the differential PAEVC access based on the majority race and ethnicity of the CBGs.

Table 2-3. Relative model intercepts of the race and ethnicity linear categorical predictor variable. The estimate column shows the relative difference of the intercepts compared to the no majority reference case.

Covariate	Estimate (Natural Log of Odds Ratio)	Odds Ratio (Natural Exponential of Estimate)	Standard Error	P-value
Reference (No Majority)	-2.022	NA	0.058	<0.001
Asian	-0.040	0.961	0.124	0.747
Black and Hispanic	-0.378	0.685	0.076	<0.001
White	0.239	1.270	0.067	<0.001

The trends between the response variable (i.e., PAEVC access), and the predictor variables (i.e., median household incomes, distances to the nearest freeway, MUD

housing unit rates, and renter-occupied housing unit rates) are similar between the single variable models shown above and the multi-variable model (Figure 2-13). The median household income, MUD housing unit rate, and renter-occupied housing unit rate positively impact the PEVCS access. And the distance to the nearest highway negatively impact the PEVCS access.

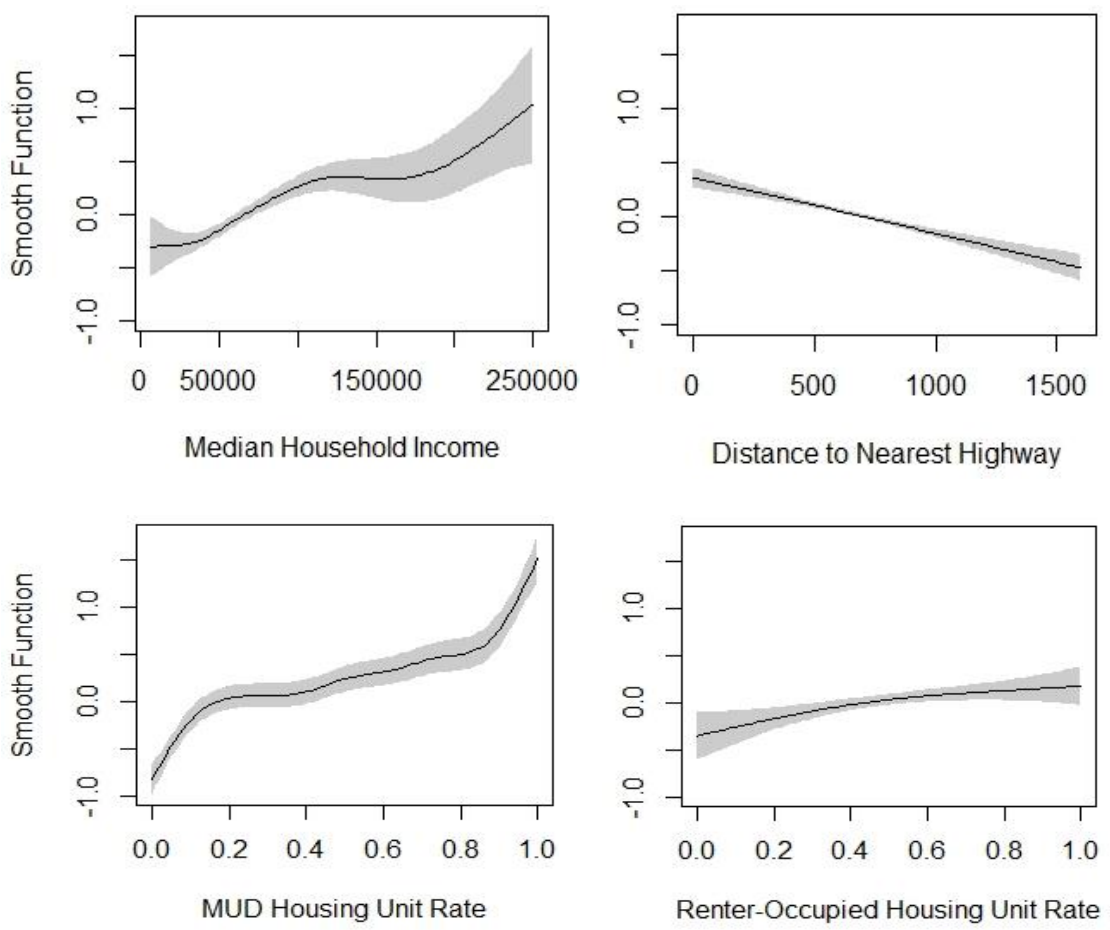


Figure 2-13. Estimated smoothed curves from the logistic binomial regression model with smoothing. The lines represent the estimated smoothed functions and grey bands represent the approximate 95% confidence bands (estimate± twice the standard error).

Analyzing infrastructure and service equity with sociodemographic factors alone may not be adequate in detecting the inequity of the PAEVC distribution. Unlike other infrastructure such access to internet, healthcare, and parks, where a person's place of residence—the main sampling unit in the census survey—could serve as the focal point of study, mobility and PAEVC infrastructure could be highly individualized as each person within each household could have a different travel pattern, travel distance, and even transportation mode. Place of residence may not tell the full story of PAEVC distribution equity since PAEVCs are utilized also when drivers are going to destinations away from their place of residence.

Since travel behaviors are largely related to the travel origins and destinations, by assuming most household trips originated from the residence, using POIs may serve as another way to investigate the equity in PAEVC infrastructure. The result of investigating PAEVC distribution equity using the POI approach is discussed in the next section.

2.4. Charger Distribution Equity Based on the Point of Interest Result & Discussions

The PAEVC distribution analysis based on grocery store brands reveals that Whole Foods, Trader Joe's, and Walmart have significantly higher mean PAEVC station counts within a 0.1-mile radius compared to the all grocery store baseline. On the other end, Vons, Costco, Aldi, and WinCo have significantly lower mean PAEVC station count compared to the baseline (Table 2-4). The result on fitness clubs/studios reveals that Equinox, Soul Cycle, and all yoga studios have significantly higher mean PAEVC station

count within a 0.1-mile radius compared to the fitness club and studio baseline (Table 2-5).

Table 2-4. Average number of public access electric vehicle charger (PAEVC) stations within 0.1 mile of each location of major grocery store chains in California. A plus sign (+) next to the grocery store name indicates significantly higher PAEVC stations available compared to the baseline; a minus sign (-) indicates the significantly lower PAEVCs available compared to the baseline. Both tested with a one-sided Mann-Whitney Test. NA indicates data unavailable.

Grocery Store Name	Mean PAEVC	Consumers' Checkbook Price Index	Median Household Income of All Locations	Sample Size	Standard Deviation
Whole Foods (+)	0.54	\$112	\$77,576	87	0.73
Co-op's	0.31	NA	\$41,217	16	0.79
Trader Joe's (+)	0.21	\$82	\$77,083	148	0.52
Walmart (+)	0.16	\$80	\$61,399	256	0.38
Target	0.16	\$87	\$66,016	232	0.49
Sprouts	0.13	\$90	\$77,108	77	0.55
Grocery Outlet	0.10	\$70	\$54,625	82	0.37
Safeway	0.10	\$102	\$78,347	241	0.33
Vons (-)	0.08	NA	\$67,153	210	0.34
Costco (-)	0.05	\$68	\$68,011	107	0.25
Aldi (-)	0.00	\$61	\$62,732	27	0.00
WinCo (-)	0.00	\$71	\$59,625	23	0.00
Baseline	0.12	\$100*	\$65,781	2533	0.43

* Baseline all grocery store Consumers' Checkbook Price Index

If we look at the grocery stores that have significantly different mean PAEVC station count than the baseline, stores with higher mean PAEVC station count seem to have higher Consumers' Checkbook price index and are located in CBGs with higher median household income. Whole Foods, with the highest price index and the second-highest median of median household income of all the CBGs containing stores (Table 2-4), likely is frequented by higher-income customers. None of the ALDI and Winco stores, likely frequented by lower-income customers as indicated by the lower price index, have any PAEVC within 0.1 miles. Note, Walmart and Costco should be evaluated with special considerations. The higher PAEVC stations available at Walmart locations likely are contributed by Walmart's early EV technology adopter role and its active effort to expand PAEVC access at its location (Walmart, 2019) and less driven by the income and the associated EV ownership of its clientele. The low price index of Costco, a special case being a warehouse store, likely has less relationship with the income level of its customers but is driven by the large volume of its products.

The same pattern is consistent with fitness clubs/studios. The three fitness locations (i.e., Equinox, Soul Cycle, and yoga studios) with significantly higher mean PAEVC stations compared to the baseline also have the highest membership/class fees (Table 2-5). Planet Fitness locations, although not significantly lower than the baseline, have the lowest membership fee, lowest mean PAEVC station count, and are located at CBGs with the lowest median of median household incomes.

Table 2-5 Average number of public access electric vehicle charger (PAEVC) stations within 0.1 miles of the selected fitness club or studio locations for California. A plus sign (+) indicates the fitness location has significantly higher PAEVC count compared to the baseline using a one-sided Mann-Whitney test.

Location	Mean PAEVC	Monthly Membership/ Class Fee	Median Household Income of All Locations	Sample Size	Standard Deviation
Equinox (+)	1.2	\$185	\$85,990	30	1.8
Soul Cycle (+)	1.2	\$160*	\$100,905	23	1.1
YMCA	0.34	\$ 47	\$80,576	38	0.9
All Yoga Studio (+)	0.32	\$ 90**	\$71,274	93	0.8
24 Hour Fitness	0.25	\$ 30	\$75,919	73	0.7
Crunch Fitness	0.15	\$ 11	\$78,272	13	0.4
LA Fitness	0.12	\$ 25	\$76,293	41	0.5
Planet Fitness	0.05	\$ 10	\$52,411	20	0.2
Baseline	0.22	NA	\$76,204	668	0.7

* Soul Cycle 5 Classes package; assuming members attend five classes a month.

** Class price from The Yoga Studio (<https://theyogastudio.biz/classes/pricing>) and Yoga Barren (<https://www.yogabaron.com/yoga-prices>) both suggest \$18 per class when purchasing packaged classes; assuming members attend five classes a month.

Lastly, comparing across income, race, and ethnicity groups, grocery stores and fitness club/studios located in CBGs with lower than the state median household income have slightly lower PAEVC access than higher median household income (Figure 2-14). In addition, grocery stores and fitness clubs/studios located in CBGs with black and

Hispanic majority CBGs consistently have lower PAEVC access than store locations in other CBGs (Figure 2-15).⁴

From the business perspective, the income based PAEVC access disparity pattern makes economic sense for PAEVC network companies and site managers, as most current EV drivers have higher incomes and are thus more likely to visit these locations (e.g., Whole Foods, Equinox). Also, the stores may try to cater toward and attract these drivers as an advertisement. The pattern demonstrates that early PAEVC infrastructure surrounding POIs, if not having the tendency to cater to the higher income early adopters, is at least differentially unavailable to lower-income customers at specific locations. However, race and ethnicity based PAEVC disparity is concerning and more obvious. The Hispanic ethnic group is the most dominant ethnic group in California but has the least availability of and access to PAEVCs.

⁴ Black-majority CBGs are combined with Hispanic CBGs since there are only 9 store locations that are located in black-majority CBGs.

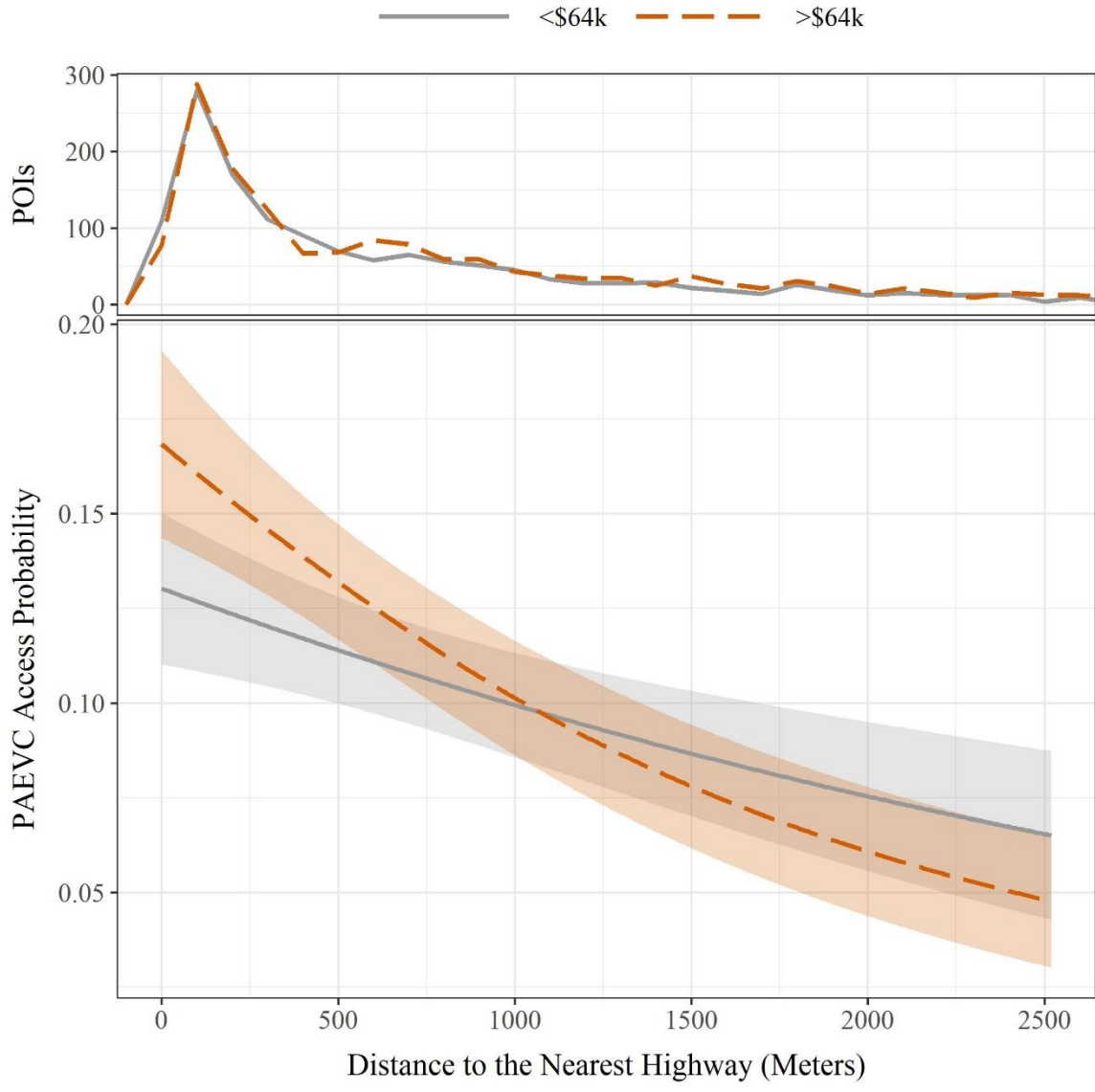


Figure 2-14 Comparison of public access electric vehicle charger (PAEVC) access between grocery stores and fitness clubs/studios located at census block groups with more and with less than the state median household income across different distances to the nearest highway. **Top**) Histogram of the points-of-interest (POIs) **Bottom**) Probability of having access to at least one PAEVC station within a 0.1-mile radius as a function of highway proximity. The semi-transparent bands represent the 90% confidence interval.

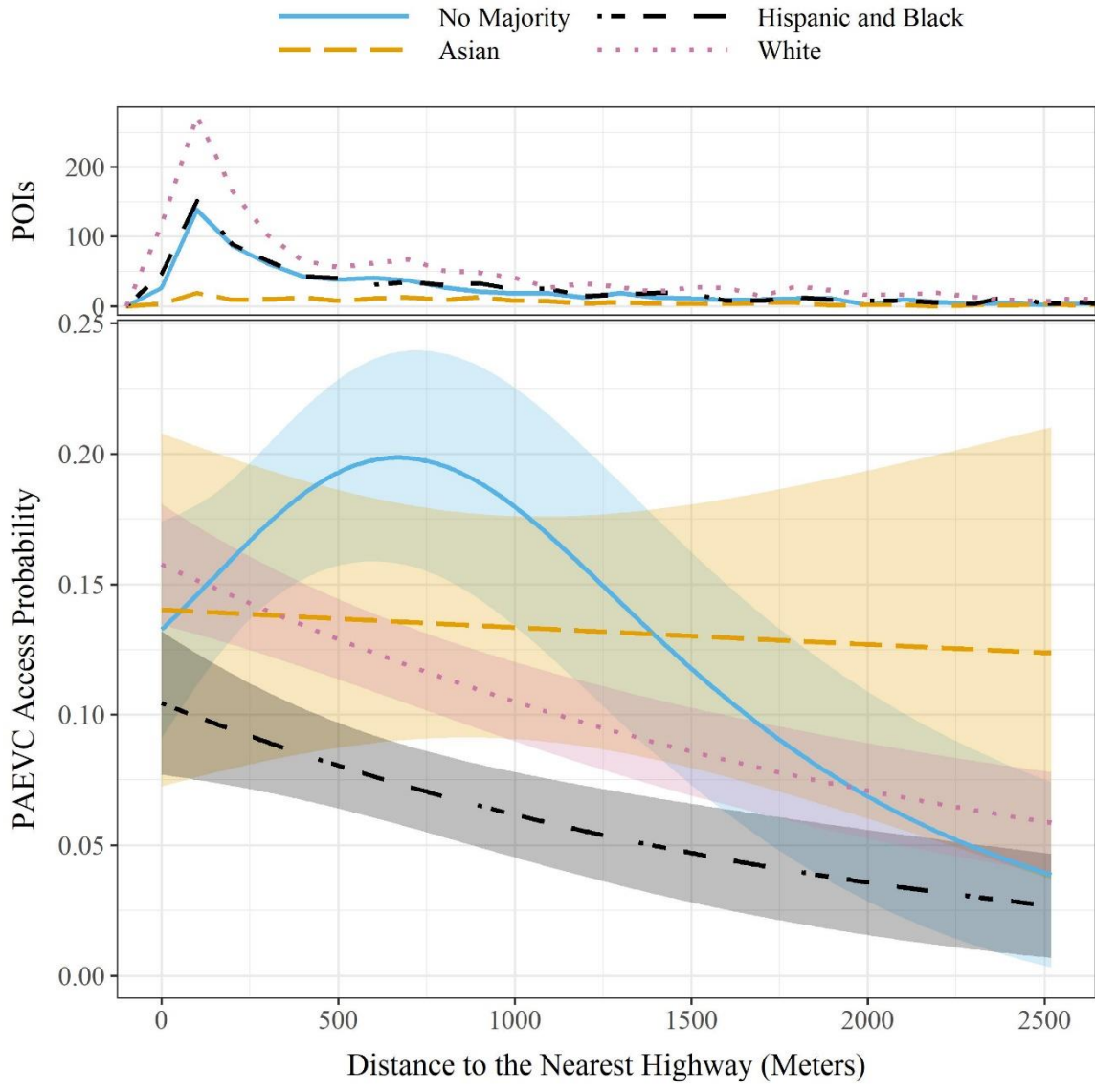


Figure 2-15 Comparison of public access electric vehicle (PAEVC) access between grocery stores and fitness clubs/studios located at census block groups with different race and ethnic majorities across different distances to the nearest highway. **Top**) Histogram of the points-of-interest (POIs) **Bottom**) Probability of having access to at least one PAEVC station within a 0.1-mile radius as a function of highway proximity. The semi-transparent bands represent the 90% confidence interval.

The phenomenon of lower PAEVC availability at POIs with lower-income clienteles highlights an area of improvement to an equitable EV adoption with equitably distributed PAEVC infrastructure. If not addressed, this adoption barrier may result in the enduring uneven distribution of low carbon mobility, as Wells (2012) suggested, in which areas without or with lower availability of PAEVCS become marginalized and further impacted by issues such as the ensuing lower housing desirability (Wells, 2012). Furthermore, although PAEVC visibility may not be the determining factor of the general public's interest in EV adoption (Bailey, Miele, & Axsen, 2015), it may sway a potential EV driver's decision if the POIs they frequent do have available and convenient PAEVCS. Following this logic, if the PAEVC disparities exist at the POIs based on income and race of the CBGs, differential EV adoption may be further exacerbated between neighborhoods with and without PAEVCS.

Lower-income populations, compared to the rest of the populations, are more likely to reside further away from urban centers that are associated with higher housing prices. They are also more likely to reside in MUDs, which in general have lower rent. These households not only have less PAEVCS available near where they live, but also less PAEVCS where they more often visit compared to the higher-income households as demonstrated in this chapter. Without PAEVCS in and around their neighborhoods and destinations, access to charging at home is crucial in adopting and operating BEVs. However, home charging is more challenging or completely infeasible for residents in MUDs. To overcome this barrier, lower-income residents in MUD would likely need to

rely more heavily on on-route DC fast chargers or residential curbside charging if available.

CHAPTER 3: NEW AND USED BATTERY ELECTRIC VEHICLE TOTAL COST OF OWNERSHIP COMPARISONS

This chapter compares the total cost of ownership (TCO) of battery electric vehicles (BEVs) based on operating scenarios with different charging behaviors as well as different BEV depreciation scenarios. Three ownership periods are considered: a) new ownership from year zero (2019), to year five (2024), b) used ownership from year five (2024) to year ten (2029) and c) new ownership from year zero (2019) to year ten (2029). TCO, for the purpose of this analysis, includes the financing, fuel or electricity, maintenance, value depreciation, and electric vehicle supply equipment (EVSE) cost.

3.1. Method

The TCOs of new and used BEVs under different vehicle depreciation and operation scenarios were compared against each other and with the baseline internal combustion engine (ICE) vehicle's TCO. The analysis used three specific vehicle models—one BEV and two ICE vehicles—with the base model costs and fuel efficiencies. These models were the 2019 Nissan Leaf (\$29,900 and 112 miles per gallon equivalent), Altima (\$24,100 and 32 miles per gallon), and Sentra (\$18,580 and 32 miles per gallon). The Altima and Sentra were chosen to compare against Leaf, the first and longest in-production modern all-electric vehicle model, to demonstrate the TCO differences within the same vehicle make. The Altima and Sentra are mid-price and entry-level price range sedans, respectively, offered by Nissan, which could shed light on

the TCO comparison between BEVs and ICE vehicles with two different purchase prices. In addition, I also conducted a sensitivity analysis on a range of annual mileage driven and gasoline fuel costs.

The TCO for a vehicle was calculated as the sum of 1) total interest payments for financing scheme, 2) the fuel or electricity cost, 3) the maintenance cost, 4) the vehicle depreciation, 5) the insurance premium, and 6) the applicable new BEV financial incentives (Equation 1) over the assumed five and ten years of ownership.

Equation 1 Total cost of ownership calculation

Total Cost of Ownership

$$= \textit{Financing} + \textit{Fuel} + \textit{Maintenance} + \textit{Depreciation} + \textit{Insurance} \\ - \textit{Financial Incentives}$$

The financing cost was a function of the purchase price of the vehicle and the financing scheme undertaken by the owner. For used vehicles, the purchase price relied on the vehicle depreciation curve that was generated as part of the analysis (discussed in section 3.1.1). The used ICE vehicle price in 2024, five years from now, was projected using the average residual value percentage at year five. The used BEV price was projected with two scenarios: 1) first-generation BEV depreciation scenario (referred to as “BEV early depreciation scenario”) where the 2019 model year BEVs depreciate similarly to the early model BEVs (e.g., first-generation Nissan Leaf and 2) historic vehicle depreciation scenario where the 2019 model year BEVs depreciate similarly to most ICE vehicles.

The financing terms scenarios used in the analysis were 1) 100% upfront payment and 2) the long term high-interest rate scenario (4% annual percentage rate for 60 months with 10% down payment). The amortized financing payments were converted to a net present value lump sum in 2019 USD with the net present value formula (Equation 2)

Equation 2 Net present value formula

$$\text{Net Present Value} = \sum_{y=0}^n \frac{\text{annual amortized payment}}{(1+r)^y}$$

Where y is the number of the years of the vehicle ownership, n is the auto loan term in years, and r is the annual percentage rate for the auto loan.

The amortized payment amount per year used in the above equation was calculated using Equation 3.

Equation 3 Annual payment amortization formula

$$\text{Annual Amortized Payment} = P * \frac{r(1+r)^n}{(1+r)^n - 1}$$

where P is the initial capital cost of the vehicle, r is the interest rate per year, and n is the total number of periods.

The fuel cost was calculated based on 12,000 miles driven a year. The electricity fuel cost was calculated based on the different charging scenarios and vehicle fuel efficiencies. The scenarios include 100% home charging (H100), 80% home and 20% public charging (80H20P), 50% home and 50% public charging (H50P50), 20% home and 80% public charging (20H80P), and 100% public charging (100P). The breakdown of the percent charging at Level 2 versus DC fast chargers varies for the different scenarios (Table 3-1). The total annual fuel cost used for the TCO was calculated as the

annual mileage driven divided by the fuel efficiency times the fuel cost per unit based on the charging scenarios. The cost for home charging was assumed to be the average California electricity price in May 2019—\$0.188 per kWh (U.S. Energy Information Administration, 2019b). The cost of public charging was calculated based on the average prices from two large public EV charging network companies, Blink and EVgo. The Level 2 public charging price was assumed to be \$0.392 per kWh and the DC fast charge price was assumed to be \$0.56 per kWh (Blink Charging Co., 2019; EVgo Services LLC, 2019). The gasoline price was assumed to be the average February 2019 to July 2019 gasoline price in California—\$3.658 per gallon (U.S. Energy Information Administration, 2019a). The vehicle fuel efficiencies were obtained from the U.S. Environmental Protection Agency (U.S. Environmental Protection Agency, 2019). Additionally, a one-time upfront cost of \$1,250, the average of the price range provided by the U.S. Department of Energy (U.S. Department of Energy, n.d.) for a home EVSE, was added to the scenarios with home charging. Lastly, gasoline and electricity costs were assumed change at the ten-year average rate. The cost of gasoline was assumed to change -0.7% per year—the average rate of change from 2009 to 2018 (U.S. Energy Information Administration, 2019a). The cost of electricity was assumed to change 1.3% per year—the average rate of change from 2008 to 2017 from the three largest investor owned utility companies: Southern California Edison, Pacific Gas & Electric, San Diego Gas & Electric (California Public Utilities Commission, 2019). The change in the cost of electricity was assumed to impact the cost of public charging as a direct pass through cost to the customers from public charger network companies.

Table 3-1 Assumed percentage breakdown of public charging at Level 2 and direct current (DC) fast charger for different operation scenarios used in the total cost of ownership analysis

Charging Scenarios	Level 2	DC Fast Charge
100% Home	0%	0%
80% Home 20% Public	20%	0%
50% Home 50% Public	40%	10%
20% Home 80% Public	70%	10%
100% Public	80%	20%

The maintenance cost was assumed to be \$1,186 (Edmonds, 2017) per year for ICE vehicles and 48% less (i.e., \$520 per year) for BEVs. The BEV maintenance cost ratio was derived by averaging the BEV to ICE vehicle maintenance cost ratio from various studies reviewed in a review journal article on the maintenance cost of BEV (Logtenberg, Pawley, & Saxifrage, 2018). The depreciation cost was calculated using the vehicle value depreciation curve (method detailed in the next section), which was the purchase price of the vehicle less the residual value as a percentage of the original value (in 2019 USD) at the last year of the ownership considered in the TCO analysis.

Insurance cost for each of the new and used models was obtained by using Geico's online quoting with the minimum legally required coverage and highest comprehensive and collision deductible (i.e., \$2,500). Lastly, for new BEV scenarios, new BEV financial incentives were deducted from the TCOs and reported separately. As discussed in section 1.2, new BEV consumers could qualify up to \$10,000—\$7,500 of Federal tax credit and \$2,500 state rebate—of financial incentives. However, the

incentives will not continue indefinitely as they are meant to promote the early BEV market.

3.1.1. Vehicle Value Depreciation Curve

Vehicle value depreciation curves were generated based on the used vehicle price data collected from AutoTrader.com and the historical Manufacturer Suggested Retail Price (MSRP) from MSN Autos. The data included both ICE and BEV models (Table 3-2). The ICE models were selected based on the most comparable model to the BEV counterparts from the same automaker to the author's best knowledge. For example, the comparable model to a Nissan Leaf was assumed to be a Nissan Altima, a mid-price range sedan in Nissan's model lineup. Additionally, whenever possible, the ICE vehicles were selected if the same model had both electric and non-electric versions. For example, the Fiat 500, an ICE vehicle, and the Fiat 500e, a BEV, were selected for this reason.

For each used vehicle price data point from Autotrader.com, the age of the vehicle was calculated by subtracting the model year from 2020. For each model, the mean MSRP of each model year was calculated by averaging the MSRP of all available model specifications of the model year on MSN Autos.⁵ The mean MSRP was adjusted for inflation—converted to 2019 USD—by multiplying the mean MSRP by the Consumer Price Index factor. The Consumer Price Index factor was calculated as the 2019 January Consumer Price Index divided by the Consumer Price Index of the year of the corresponding MSRP year from the U.S. Bureau of Labor Statistics. Finally, the residual

⁵ With the exception to the Ford Focus RS, a racing specification with significant higher MSRP than the mean MSRP. For consistency purpose, the Ford Focus RS was excluded from the analysis all together

value of the used vehicle as a percentage to the inflation adjusted MSRP of the model year (“residual value percentage”) was calculated by dividing the listed sale price on Autotrader.com by the MSRP, in 2019 USD, of the model year.

Table 3-2. Data collected from autotrader.com. BEV stands for battery electric vehicle and ICE stands for internal combustion engine vehicle.

Vehicle Make & Model	Drive	Sample Size	Model Year Range
Chevy Bolt	BEV	244	2017 - 2019
Chevy Malibu	ICE	3,522	1997 - 2019
Chevy Spark	ICE	1,041	2013 - 2019
Chevy Spark EV	BEV	190	2014 - 2016
Fiat 500	ICE	968	2012 - 2019
Fiat 500e	BEV	266	2013 - 2019
Ford Focus	ICE	3,340	2000 - 2018
Ford Focus EV	BEV	118	2012 - 2018
Kia Soul	ICE	3,087	2010 - 2020
Kia Soul EV	BEV	153	2015- 2019
Nissan Altima	ICE	4,416	1995 - 2019
Nissan Leaf	BEV	963	2011 - 2019
Tesla Model S	BEV	796	2012 - 2019

3.1.2. Uncertainty in the Total Cost of Ownership

I included three types of sensitivity analysis to assess the uncertainty of the estimated TCO. First, likely the largest uncertainty, is the purchase price and the residual value of the vehicle. The purchase price of new vehicles has relatively lower uncertainty

compared to used vehicles as the MSRPs are listed on the manufacturer's website. The purchase price and the residual value of used vehicles, however, could be highly uncertain due to factors such as different vehicle mileage and different wear and tear. To present the purchase price and residual value uncertainty in the result, high and low TCO thresholds were included. These thresholds were calculated by finding the largest and smallest difference between the 90% prediction interval of the purchase price and residual value. For example, a high uncertainty threshold for the TCO was calculated by the high end of the 90% prediction interval of the purchase cost (or just the MSRP for a new vehicle) and the low end of the 90% prediction interval of the residual value while keeping other variables constant. The gas price sensitivity analysis was performed for gas prices ranging from \$2 to \$6 per gallon while keeping other variables constant. The electricity price sensitivity analysis was performed for price ranging from \$0.14 to \$0.53 per kWh which corresponds to Pacific Gas and Electric's winter off-peak pricing and summer peak pricing in the EV time-of-use rate schedule respectively (Pacific Gas and Electric Company, 2019a). The electricity price sensitivity analysis was only applicable to the electricity used at home since public chargers currently charge a flat rate regardless of the time. The annual mileage driven sensitivity analysis was performed for mileage ranging from 6,000 to 30,000 miles while keeping other variables constant.

3.2. Result & Discussions

The result of the individual BEV value depreciation analysis suggests Tesla Model S and Chevy Bolt depreciate more similarly to the average ICE vehicle included in

this study (Figure 3-1). The pattern seems to suggest Model S, a luxury BEV, and Bolt, a late or current model BEV, are able to retain their value better than the early model BEVs. For this reason, the first-generation BEV depreciation curve in the early depreciation scenario excludes Model S and Bolt data.

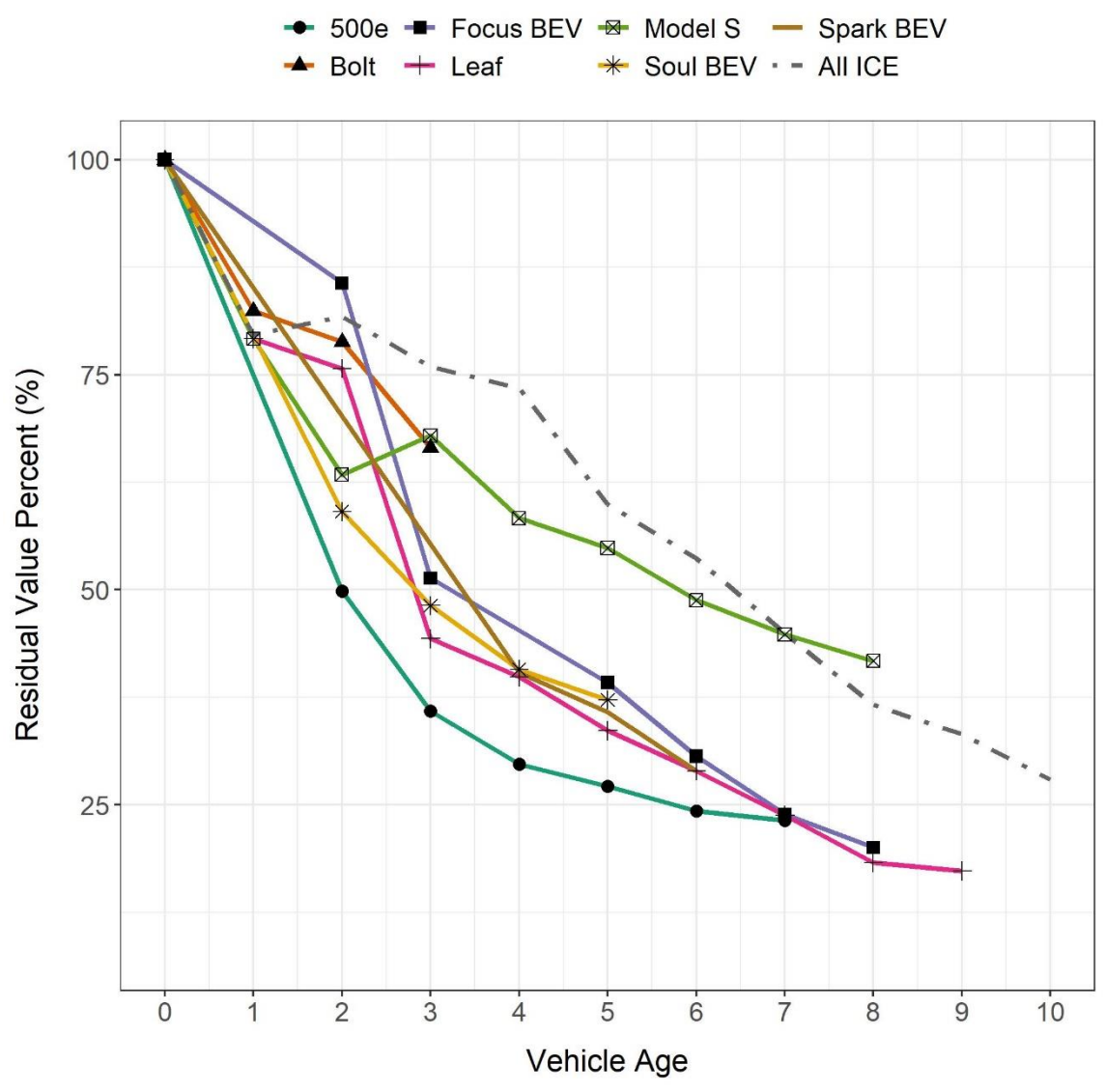


Figure 3-1 Battery electric vehicle (BEV) value depreciation by the model compared to the internal combustion engine (ICE) vehicles.

Looking at the depreciation curves generated for the analysis, the first-generation early model BEV depreciated faster than their ICE vehicle counterparts for the first five years (Figure 3-2). For the first five years of operation (i.e., brand new, zero-year-old vehicles to five-year-old vehicles), on average, BEV and ICE vehicles depreciated at 15.7% and 6.6% per year, respectively. Notably, the sharp decline in BEV value from year two to year three accounted for 30.8% of the original vehicle value resulting in a residual value of 44% of the original MSRP. Comparing to ICE vehicles, from year two to year three, the depreciation was only 5.8% of the vehicle value. ICE vehicles did not reach the same level of residual value of a year three BEV (i.e., 44%) until year seven or eight. From year three to year four, the 90% confidence intervals of ICE vehicle and BEV depreciation curves do not overlap; which was the only occurrence between year zero to year nine. Finally, starting around year four until year nine where BEV data stop, both ICE and BEV depreciated at slower annual rates of 8.0% and 4.0%, respectively.

There are a few reasons that may explain the sharp depreciation rate for BEVs in the first few years of ownership. First, the large incremental vehicle technology improvement—especially the battery range—from model year to model year could make the previous year's model much less desirable and valuable. Second, in addition to the incremental vehicle technology improvement, financial incentives could also play a role in the resale value in the vehicle. A potential BEV buyer would be unlikely to purchase a used BEV if the differential cost between a new BEV and used BEV is smaller than the financial incentive itself. A study also found the rebate eligible vehicle models had lower listing used vehicle prices in Thailand under a new vehicle financial rebate scheme

(Noparumpa & Saengchote, 2017). Third, as discussed earlier, BEV adopters tend to be from higher-income demographic groups making them less likely to be used car buyers, thus resulting in a smaller secondary BEV market with smaller demand. Again, the depreciation rate at this scale may not be applicable to the current generation BEVs, which is evident from the depreciation curves of Chevy Bolt and Tesla Model S (Figure 3-1). However, the first-generation BEVs' high depreciation rate may continue for the following reasons: 1) BEV and battery technology continue to have large improvements between model years, 2) the tax incentives continue for longer than it should without readjusting its incentive structure, and 3) not enough buyers enter the secondary BEV market.

Since the oldest BEV model available is only nine-year-old at the time of this analysis, the first-generation BEV residual curve for year ten was extended from year eight and nine assuming the same linear depreciation rate (shown as the dotted line segment in Figure 3-2) and the uncertainty bands of year nine were used for year ten.

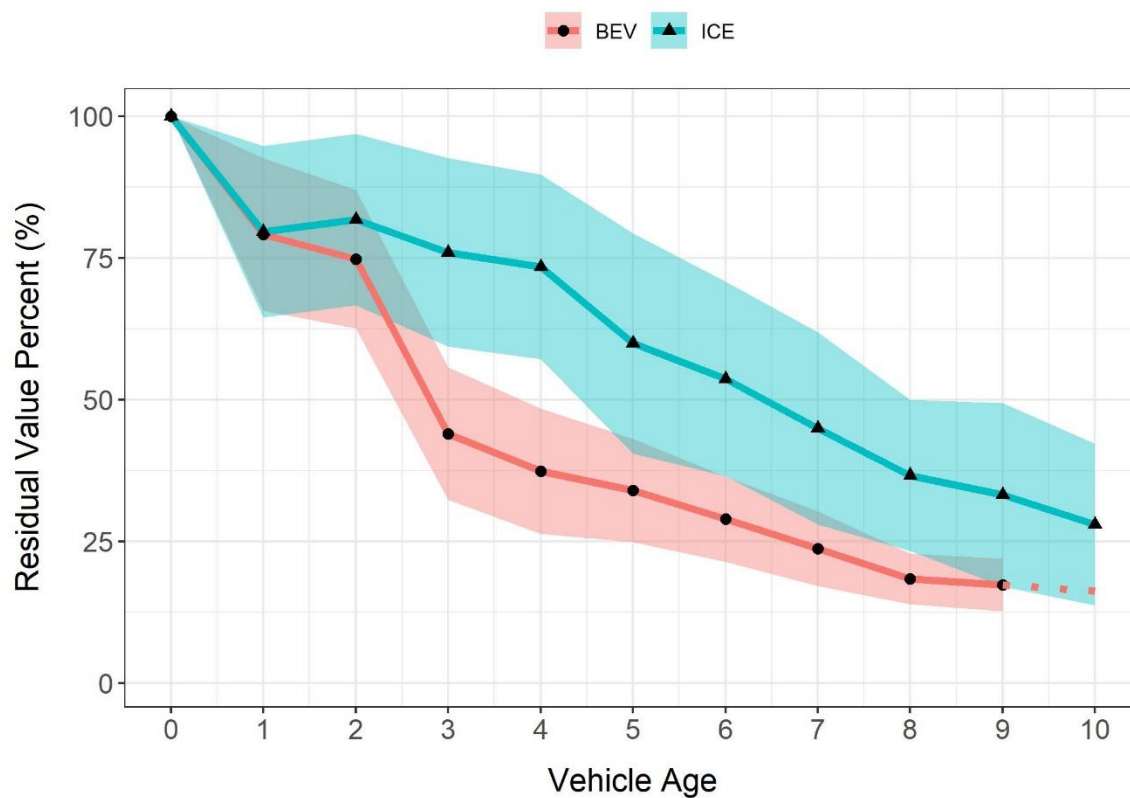


Figure 3-2 Inflation adjusted vehicle residual value as the percent of the original Manufacturer Suggested Retail Price based on the vehicle age with the 90% confidence interval. The dotted red line is the extrapolated depreciation curve.

The same pattern of BEVs depreciating faster than ICE vehicles can be observed when comparing the comparable models side by side. All six models of BEV included in the analysis depreciated faster than its ICE vehicle counterparts (Figure 3-3). This result is consistent with online reports (Halvorson, 2019; Svaldi, 2018) stating that the first-generation BEVs depreciated much faster than the ICE vehicles.

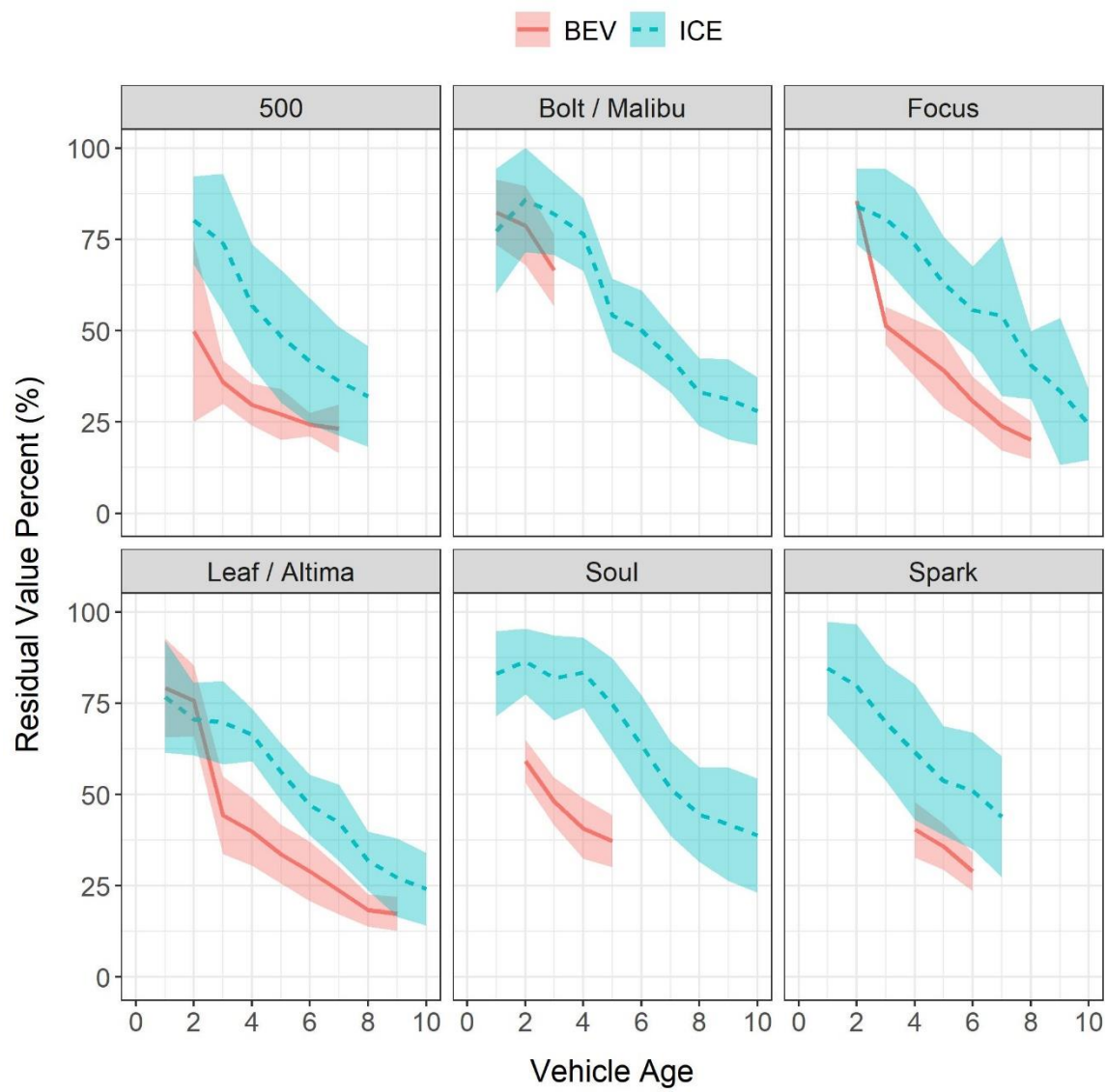


Figure 3-3 Vehicle value depreciation curves of the battery electric vehicle (BEV) models and corresponding comparable internal combustion engine (ICE) vehicle by models. Some vehicle models were only made for a few years thus the depreciation curves do not start from year 0.

3.2.1. Used 2019 Nissan Leaf Five-Year Total Cost of Ownership

BEV early depreciation scenario: The story of the projected TCOs of a used 2019 Leaf from 2024 to 2029 could change based on the vehicle depreciation scenarios.

The projected TCOs under the BEV early depreciation scenario are always lower than the ICE vehicle baseline, primarily due to the lower used BEV purchase cost under such a scenario. The used BEV has lost more value during the previous ownership. The difference in the TCOs of the used Leaf could be \$2,500 to \$6,700 cheaper lower than the ICE vehicles under the BEV early depreciation scenario. Under the BEV early depreciation and upfront payment scenario, the TCO of the used 2019 in H20P80 (refer to Table 3-3 for scenario acronyms) scenario is \$2, 500 lower than the Sentra. Under the BEV early depreciation and financing scenario, the TCO of the used 2019 Leaf in H100 scenario is \$6,700 lower than the Altima. (Table 3-4 & Figure 3-4).

Table 3-3 Operation scenario acronyms and descriptions

Scenario Acronym	Scenario Description
H100	100% charging at home
H80P20	80% charging at home, 20% charging at public chargers
H50P50	50% charging at home, 50% charging at public chargers
H20P80	20% charging at home, 80% charging at public chargers
P100	100% charging at public chargers

Historic vehicle depreciation scenario: By projecting the used BEV purchase cost with the historical vehicle depreciation scenario, the TCOs of the used 2019 Leaf are more expensive than the TCO of the Altima if more than half of the charging is done publicly (i.e., H50P50, H20P80, and P100). Only in the H100 operating scenario did the TCO of the used Leaf resemble the TCO of the Sentra (Table 3-4 & Figure 3-4). As discussed above, the late model BEVs, including the 2019 Leaf, will likely depreciate

similarly to the historical vehicle depreciation trend, which means the historical vehicle depreciation scenarios in Figure 3-4 may be more likely to occur. And under the historical vehicle depreciation scenarios for most operation scenarios, the TCOs of used 2019 Leaf are comparable to the used 2019 Altima from 2024 to 2029.

Table 3-4 Total costs of ownership of new and used 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra and Altima from 2019 to 2024 and from 2024 to 2029 under BEV early depreciation (ED) and historical vehicle depreciation (VD) scenarios and financing and upfront payment scenarios. Unit in \$1,000 2019 USD. H stands for home charging and P stands for public charging. The number following P and H indicates the percent of the charging taking place at each location. Note the battery electric vehicle financial incentives worth up to \$10,000 are not shown in the table. To calculate the post-incentive TCOs for new Leaf, deduct \$10,000 from the TCOs.

Charging Scenario	ED Financing		ED Upfront Payment		VD Financing		VD Upfront Payment	
	Used	New	Used	New	Used	New	Used	New
P100	\$24.1	\$42.3	\$22.6	\$37.8	\$29.6	\$34.6	\$26.8	\$30.0
H20P80	\$24.2	\$42.6	\$22.7	\$38.0	\$29.7	\$34.8	\$27.0	\$30.2
H50P50	\$23.0	\$41.4	\$21.5	\$36.9	\$28.5	\$33.6	\$25.7	\$29.1
H80P20	\$21.5	\$40.0	\$19.9	\$35.4	\$26.9	\$32.2	\$24.2	\$27.6
H100	\$20.7	\$39.2	\$19.1	\$34.7	\$26.1	\$31.4	\$23.4	\$26.9
Altima	\$27.4	\$32.0	\$25.2	\$28.3	\$27.4	\$32.0	\$25.2	\$28.3
Sentra	\$25.0	\$28.6	\$23.3	\$25.8	\$25.0	\$28.6	\$23.3	\$25.8

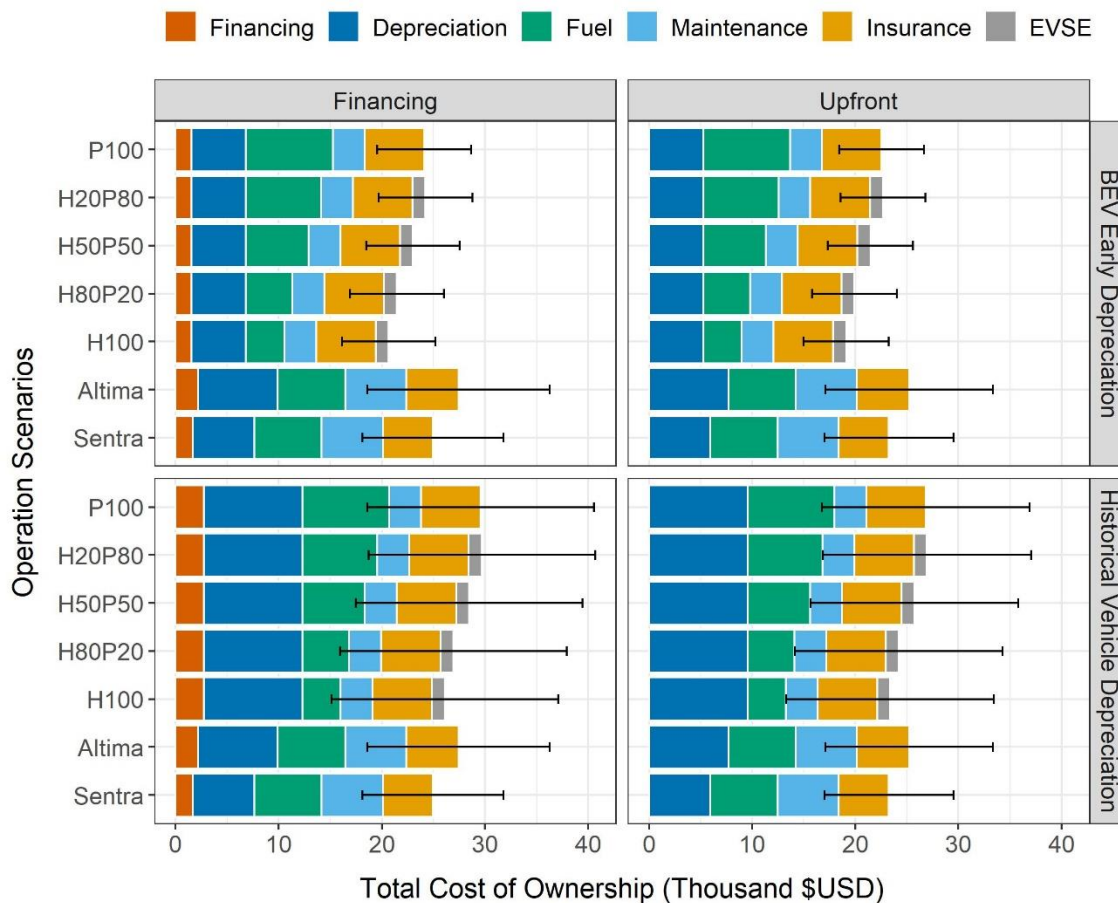


Figure 3-4 Cost break down of the total costs of ownership (TCOs) of the used 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2024 to 2029 with the Leaf purchase and resale price projected using battery electric vehicle (BEV) early depreciation and historical vehicle depreciation curves. The uncertainty bands represent the TCOs based on the high and the low depreciation cost. H stands for home charging and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location. The order of the bar segments follows the legend. Financing (left) side of the plot starts with “Financing” segment. Upfront (right) side of the plot starts with “Depreciation” segment.

The large uncertainty bands are the results of the high uncertainty in the capital cost of the vehicle as well as the resale price at the end of the ownership evaluation period. Considering the large uncertainty, the differences between the TCOs of the used

2019 Leaf, Altima, and Sentra are not definitively clear, but at least it suggests the TCOs of used BEVs are comparable to, if not cheaper than, used ICE vehicles.

In the BEV early depreciation scenario, except for very low annual mileage (e.g., 6,000 miles), the TCOs of the ICE vehicles are always higher than the Leaf TCO. In the historical vehicle depreciation scenario, at 12,000 miles per year—the annual mileage used for the TCO analysis above—the Sentra has the lowest TCO in the financing scenario. However, by 18,000 miles driven per year, the Sentra's TCO has exceeded the BEV operation scenarios with at least 50% home charging (Figure 3-5).

Comparing across the BEV operation scenarios, a higher portion of public charging results in a higher TCO, as expected. For example, the net present value of the fuel cost over the five year of ownership for the H100 scenario is \$3,716 compared to \$8,418 for P100 with the assumed 12,000 miles driven per year. Important to note, the P100 and H20P80 scenarios are the only operation scenarios where the fuel costs exceed the ICE vehicle scenario fuel cost of \$6,529. Even at 30,000 miles per year in the historical vehicle depreciation, P100 scenario still has higher TCO than the ICEs (Figure 3-5). The commonly known BEV fuel-saving operation advantage does not hold if the driver relies more, or exclusively, on charging at public charging stations.

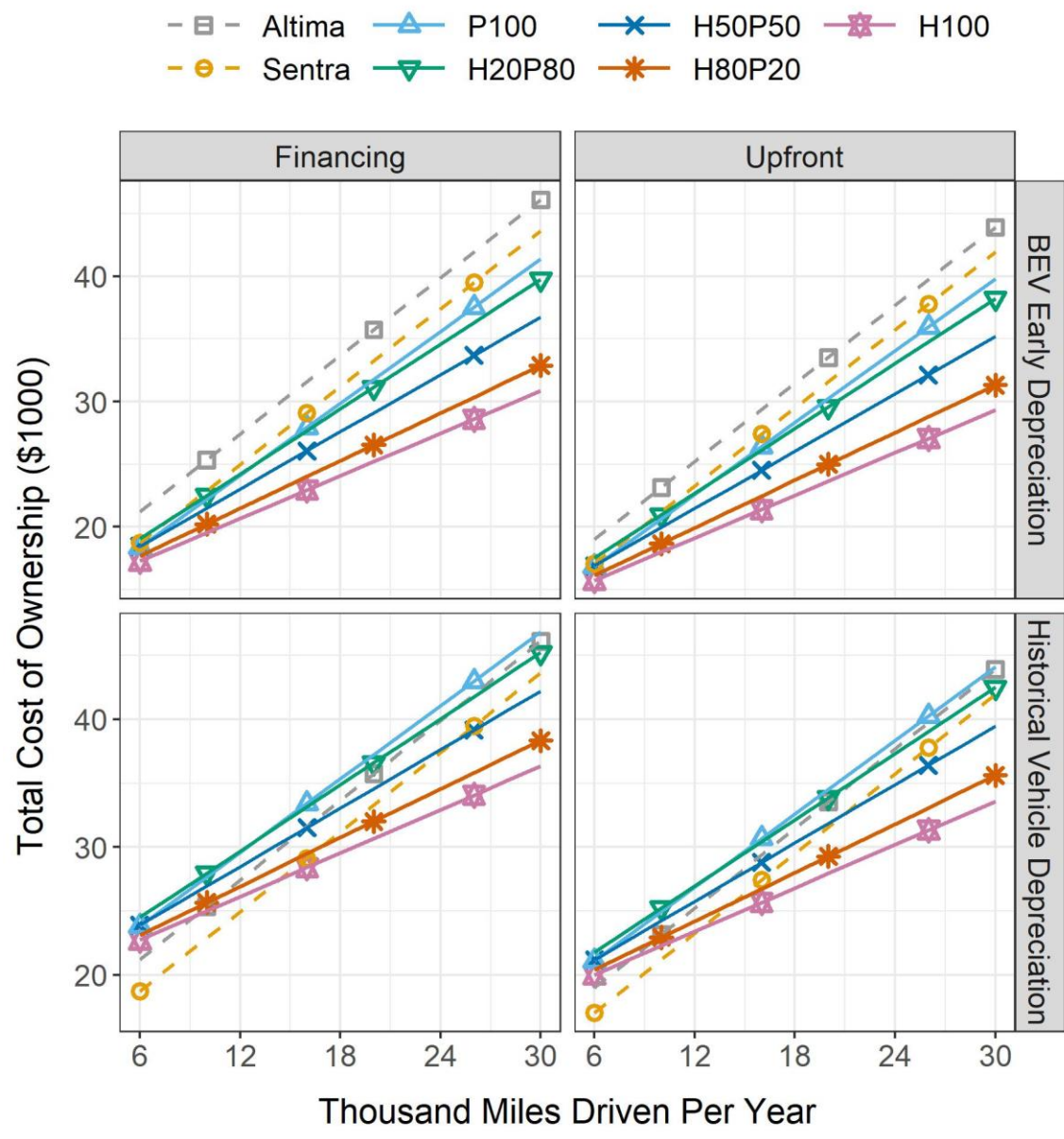


Figure 3-5 Total costs of ownership based on varying annual mileage driven of the used 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2024 to 2029. H stands for home charging and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

When the gas price is \$4.2 per gallon—approximately \$0.4 higher than the current California average gas price, both the Sentra and Altima in all scenarios become more expensive to own compared to the used Leaf that charges exclusively at home. At \$6 per gallon, both Sentra and Altima become more expensive to own compared to the TCOs of Leaf in almost all scenarios (Figure 3-6).

As expected H100 scenario is the scenario most sensitive to electricity pricing since the electricity price was only adjusted for the electricity used for home charging. At \$0.53 per kWh, H100 scenario has the highest TCO in almost all financing and depreciation scenarios. But note a BEV that charges 100% at home is unlikely to always charge at peak price time (i.e., two to nine pm). At \$0.14 per kWh (i.e., the off peak EV pricing), H100's TCO is cheaper than Sentra in three out of the four finance and depreciation scenarios. This suggests the EV time-of-use off-peak pricing, which is lower than the current state average, could make owning BEV more economic than even an ICE with a purchase cost that is almost \$9,000 lower.⁶

⁶ With the historical vehicle depreciation curve, the five-year-old leaf was projected to cost \$23,739 and the five-year-old Sentra was projected to cost \$14,752)

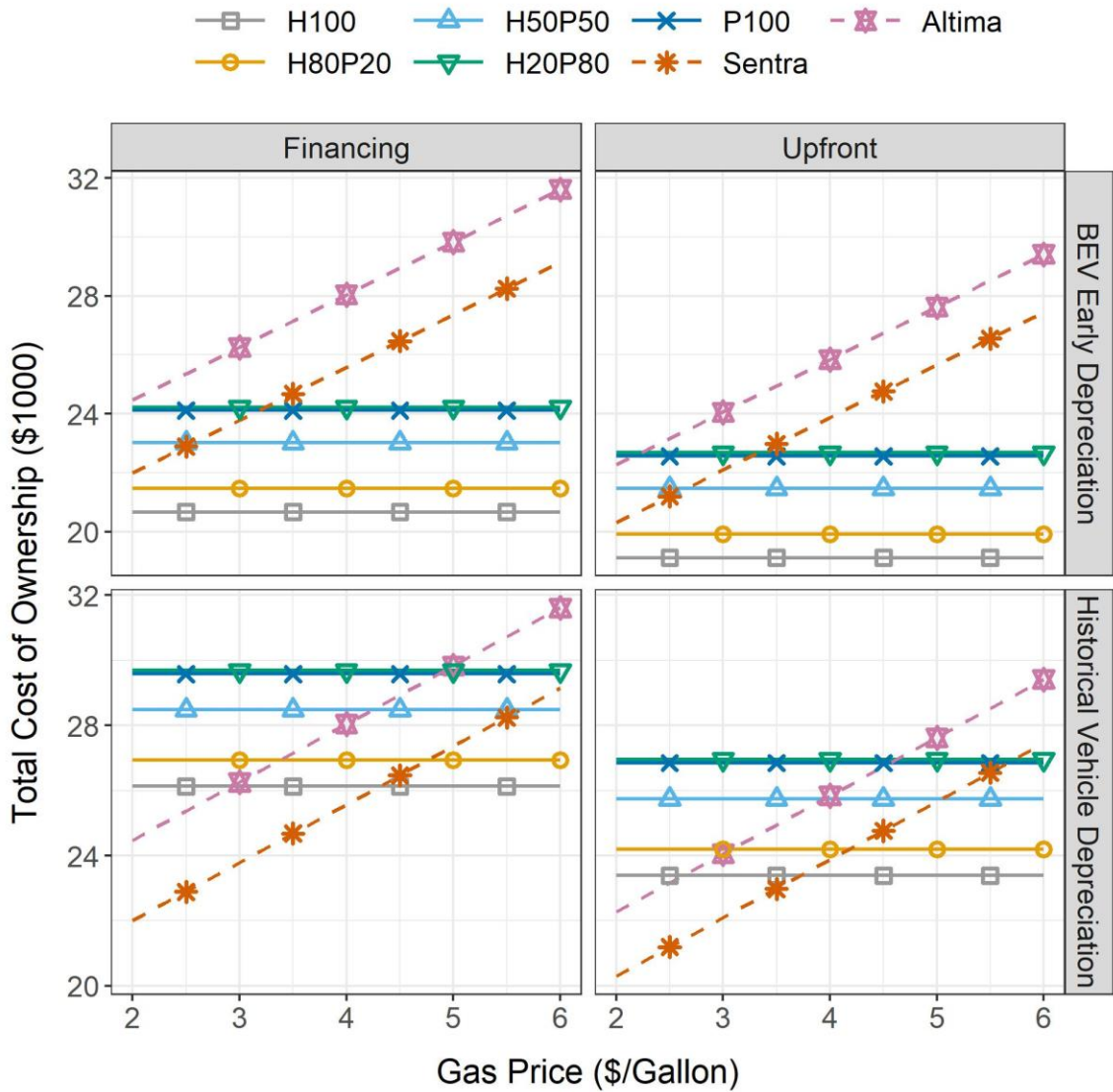


Figure 3-6 Total costs of ownership comparison based on a range of gasoline prices of the used 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2024 to 2029. H stands for home charging and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

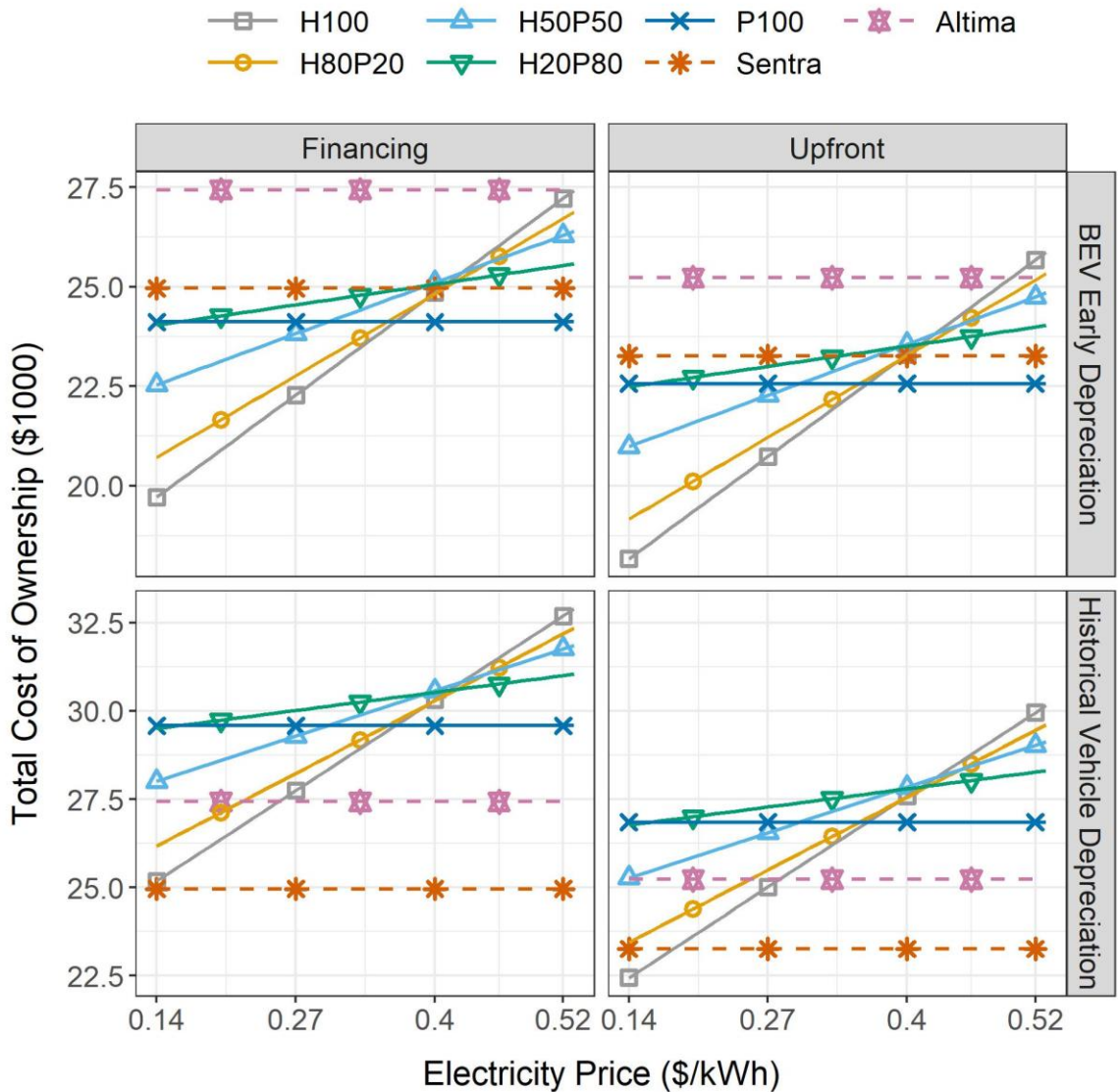


Figure 3-7 Total costs of ownership comparison based on a range of electricity prices of the used 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2024 to 2029. H stands for home charging and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

3.2.3. New 2019 Nissan Leaf Five-Year and Ten-Year Total Cost of Ownership

The federal tax incentive and California state rebate for new BEV purchases, which currently total up to \$10,000, reduce the TCOs of new Leafs to lower than the Altima in all scenarios and Sentra in all historical vehicle depreciation scenarios (Figure 3-8). At most, the incentives account for 37% of the new Leaf TCO in the H100 upfront payment historical vehicle depreciation scenario and 29% on average across all new BEV scenarios. Under the historical vehicle depreciation upfront payment scenario, the TCO of a new Leaf with the financial incentives could be as low as \$16,900, which is approximately 60% of the TCO of the Altima and 66% of the TCO of the Sentra in the same scenario (Table 3-4). Without the financial incentive, the TCOs of new Leafs are already comparable to the Altima in the historical vehicle depreciation scenario, but higher than the Sentra and Altima in the BEV early depreciation scenario. Most importantly, compared to the used Leaf TCOs, a new Leaf is always cheaper to own after deducting the \$10,000 financial incentives from the TCOs (i.e., deducting \$10,000 from the TCOs of the new Leaf ownerships in Table 3-4) if BEVs depreciate similarly to the historical vehicle depreciation trend.

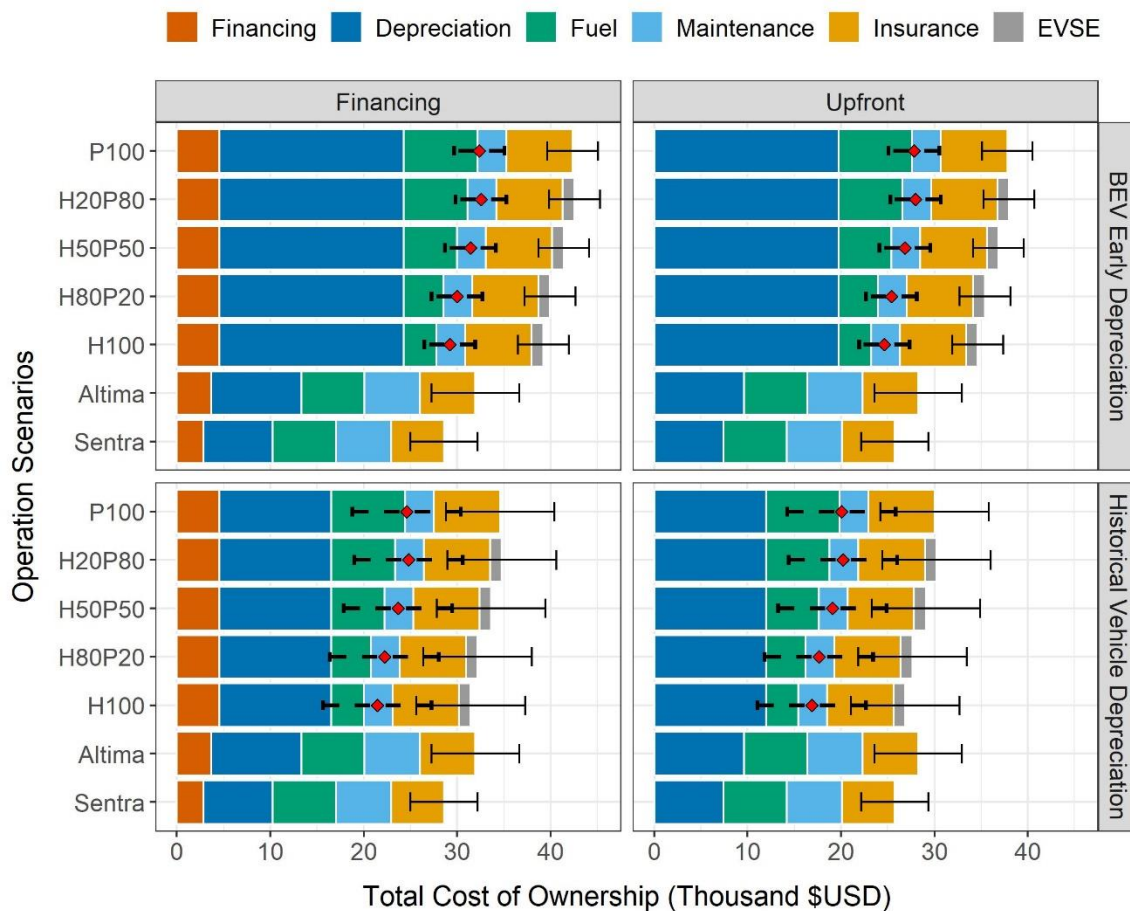


Figure 3-8 Cost breakdown of the total costs of ownership (TCOs) of the new 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Altima and Sentra from 2019 to 2024 with the Leaf purchase and resale price projected using battery electric vehicle (BEV) early depreciation and historical vehicle depreciation curves. The uncertainty bands represent the TCOs based on the high and the low depreciation cost. The red diamonds represent the TCOs after the BEV rebate and tax credit, and the dashed lines represent the corresponding uncertainty. H stands for home charging and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location. The order of the bar segments follows the legend. Financing (left) side of the plot starts with “Financing” segment. Upfront (right) side of the plot starts with “Depreciation” segment.

The uncertainty bands on the new Leaf TCOs are narrower due to the lower uncertainty of the purchase cost of the brand-new vehicles, which was informed by the listed MSRP on the manufacture’s website. However, the uncertainty bands, with and

without the financial incentives, still overlap in most scenarios between the Leaf and the ICE vehicles. The exceptions are the H100 with incentives and Altima in historical vehicle depreciation curve with upfront payment scenario (bottom right box in Figure 3-8) and the Sentra's TCO and all BEV scenarios without incentives in the BEV early depreciation curve scenario (top boxes in Figure 3-8). Interestingly, the Leaf's TCOs after financial incentives in the BEV early depreciation scenario (top boxes in Figure 3-8) are similar to the TCOs of the ICE vehicles, which compensated for the high depreciation cost. This may suggest that the first-generation BEVs' high depreciation rate could persist if the financial incentives on new BEVs continue to be structured and administered as they have been over the past decade.

The Leaf's TCOs with the financial incentives become significantly lower than the ICE vehicles' TCOs when the evaluating period for the TCOs is extended to ten years (Figure 3-9).⁷ Furthermore, even in the most expensive BEV operating scenario (i.e., P100), the TCO without the financial incentives is still comparable to the Altima's TCO. Interestingly, with the 10-year evaluation period, TCOs in the BEV early depreciation scenario and historical vehicle depreciation scenario start to resemble each other as the result of the two depreciation curves converging around year nine (Figure 3-2).

⁷ The tabular TCO cost for the ten-year ownership and the sensitivity analysis are included in Appendix C

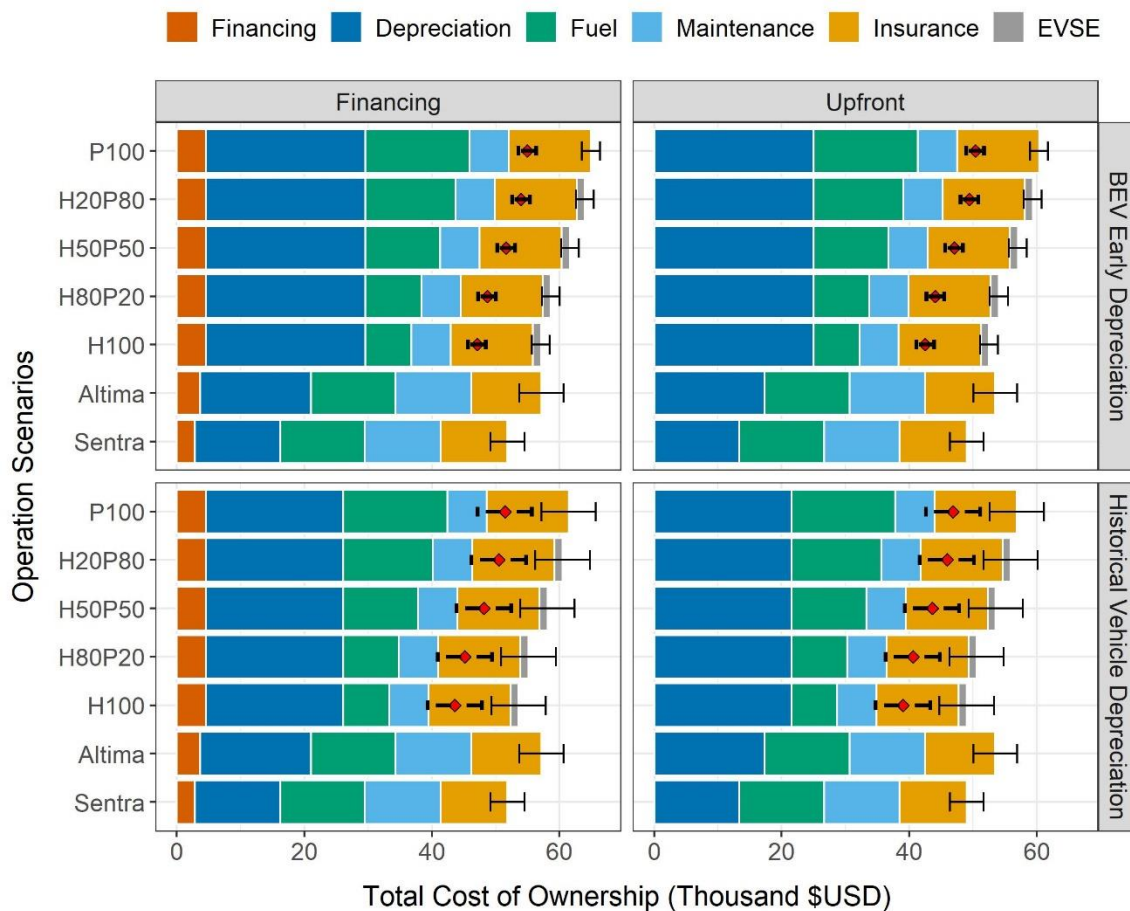


Figure 3-9 Cost breakdown of the total costs of ownership (TCOs) of the new 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Altima, and Sentra from 2019 to 2029, with the Leaf purchase and resale price projected using battery electric vehicle (BEV) early depreciation and historical vehicle depreciation curves. The uncertainty bands represent the TCOs based on the high and the low depreciation cost. The red diamonds represent the TCOs after the BEV rebate and tax credit, and the dashed lines represent the corresponding uncertainty. H stands for home charging and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location. The order of the bar segments follows the legend. Financing (left) side of the plot starts with “Financing” segment. Upfront (right) side of the plot starts with “Depreciation” segment.

Similar to the used Leaf’s TCOs, the more mileage driven a year, the more economically favorable BEV ownership is compared ICE vehicles. The BEV TCO trends

in the mileage sensitivity figures (Figure 3-10 & Figure 3-11) have smaller slope than the ICE due to the cheaper operation cost per mile for BEVs compared to ICE vehicles.

Looking at the gas price, in the BEV early depreciation scenario, even at \$6 per gallon, all Leaf operating scenarios without financial incentives have higher TCOs than the ICE vehicles (Figure 3-12). This suggests BEVs' high depreciation cost in early depreciation scenarios is making owning BEV uneconomic even compared to a \$6 per gallon gas price. And at the lowest gas price evaluated in the analysis (i.e., \$2 per gallon), both TCOs for the Altima and Sentra are higher than all Leaf operating scenarios with financial incentives in the historical vehicle depreciation scenario (Figure 3-13).

Like the result of the gas price sensitivity analysis, without the financial incentives, TCOs of the Leaf are always higher than the TCOs of the ICE vehicles between \$0.14 to \$0.53 per kWh in the BEV early depreciation scenario (top box of Figure 3-14). And with the financial incentives, TCOs of the Leaf are always lower than the ICE vehicles in the historical vehicle depreciation scenario (bottom box of Figure 3-15).

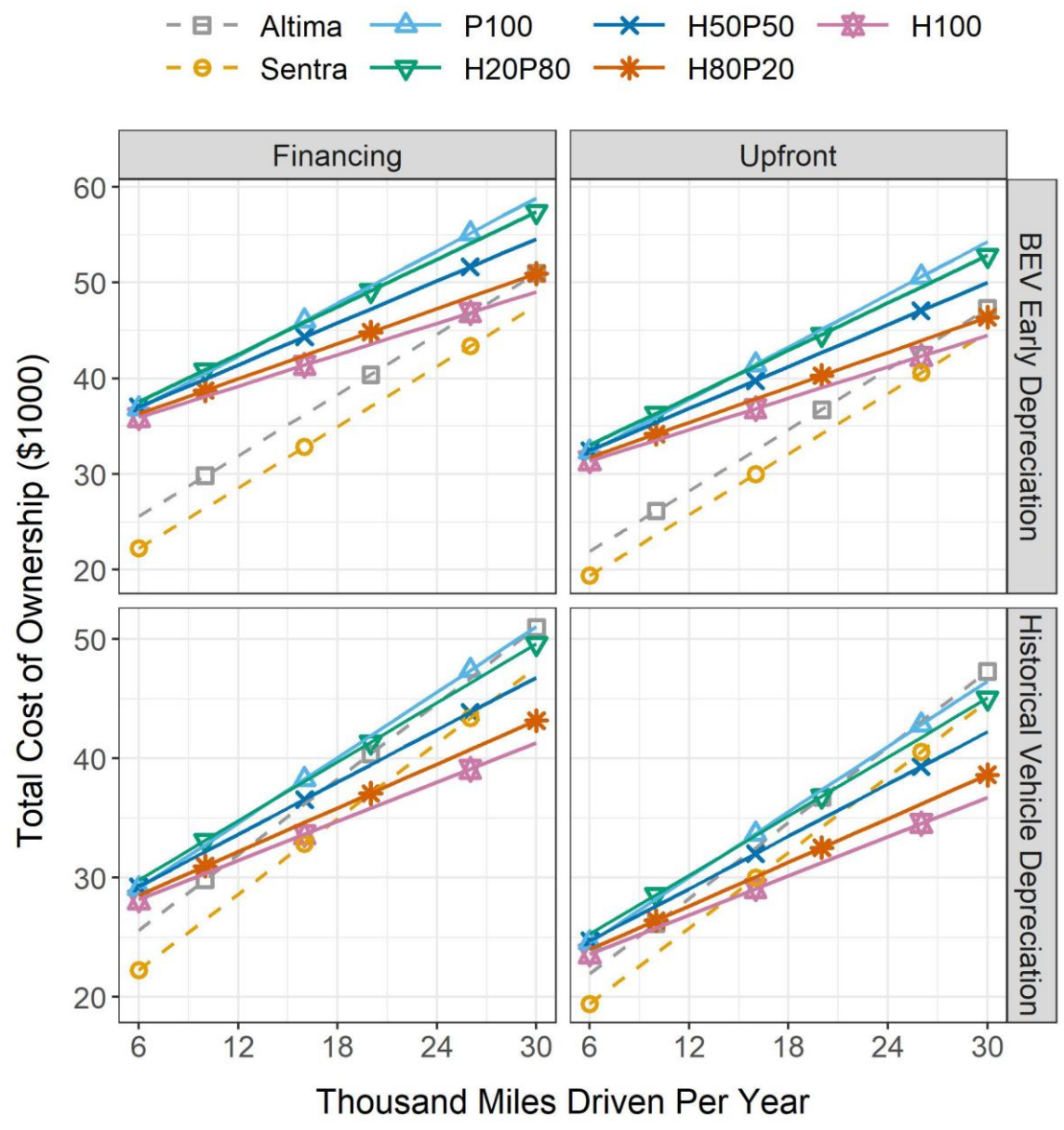


Figure 3-10 Total costs of ownership (TCOs) based on varying annual mileage driven of the 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2019 to 2024. H stands for home charging and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

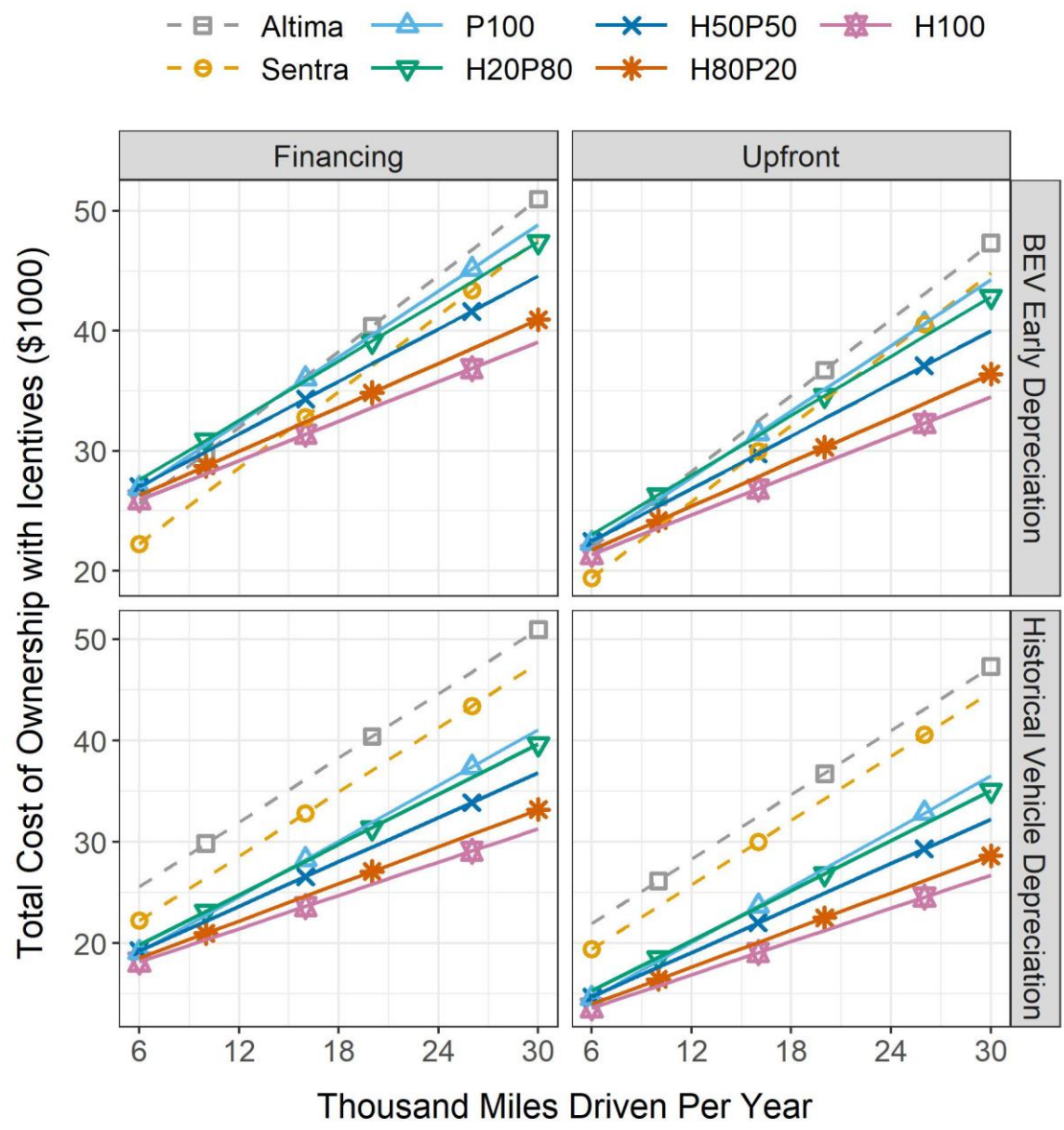


Figure 3-11 Total costs of ownership (TCOs) with \$10,000 financial incentives based on varying annual mileage driven of the 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2019 to 2024. H stands for home charging and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

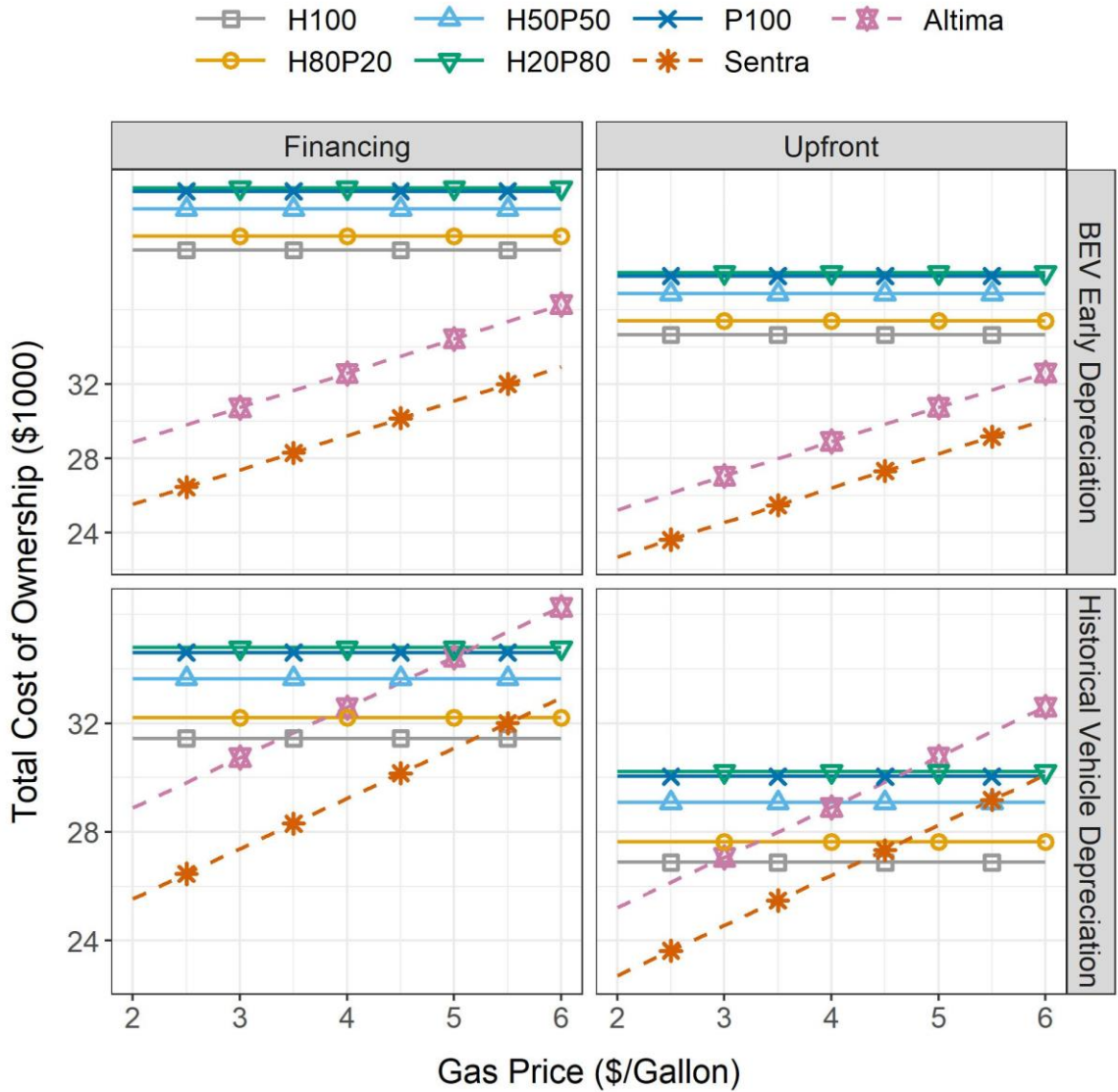


Figure 3-12 Total costs of ownership (TCOs) based on a range of gas prices of the 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2019 to 2024. H stands for home charging, and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

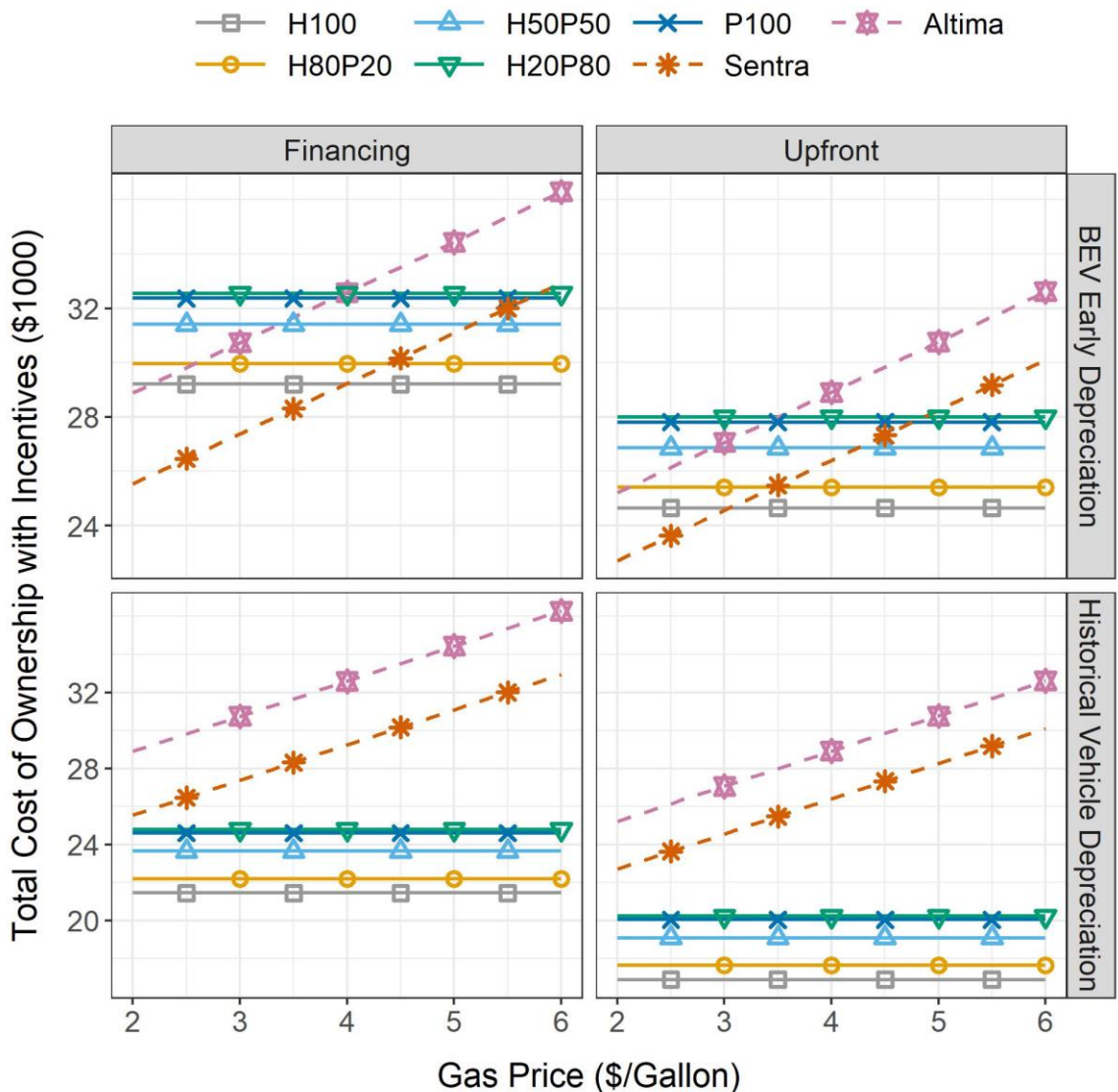


Figure 3-13 Total costs of ownership (TCOs) with \$10,000 financial incentives based on a range of gas prices of the 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2019 to 2024. H stands for home charging, and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

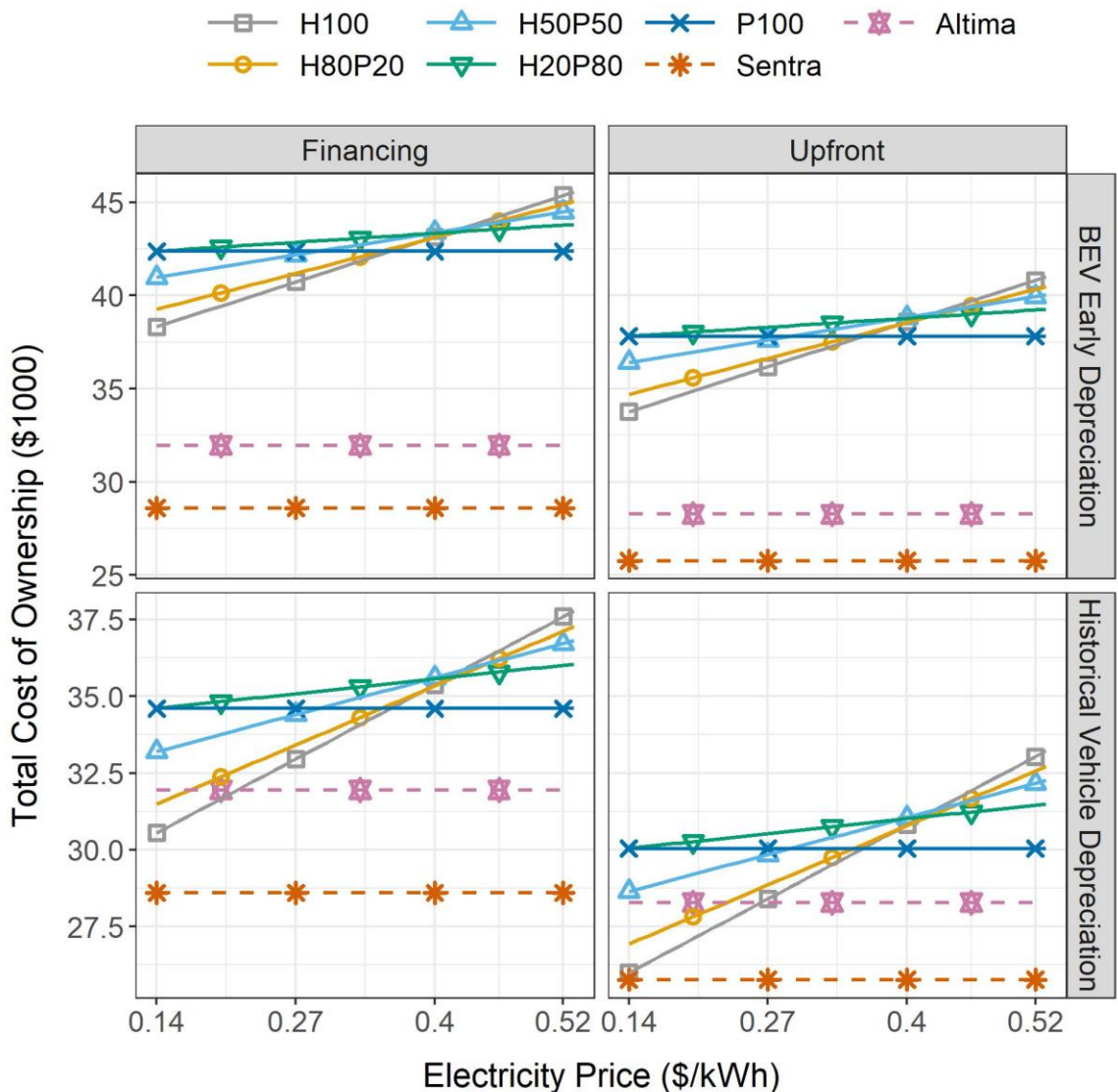


Figure 3-14 Total costs of ownership (TCOs) based on a range of electricity prices of the 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2019 to 2024. H stands for home charging, and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

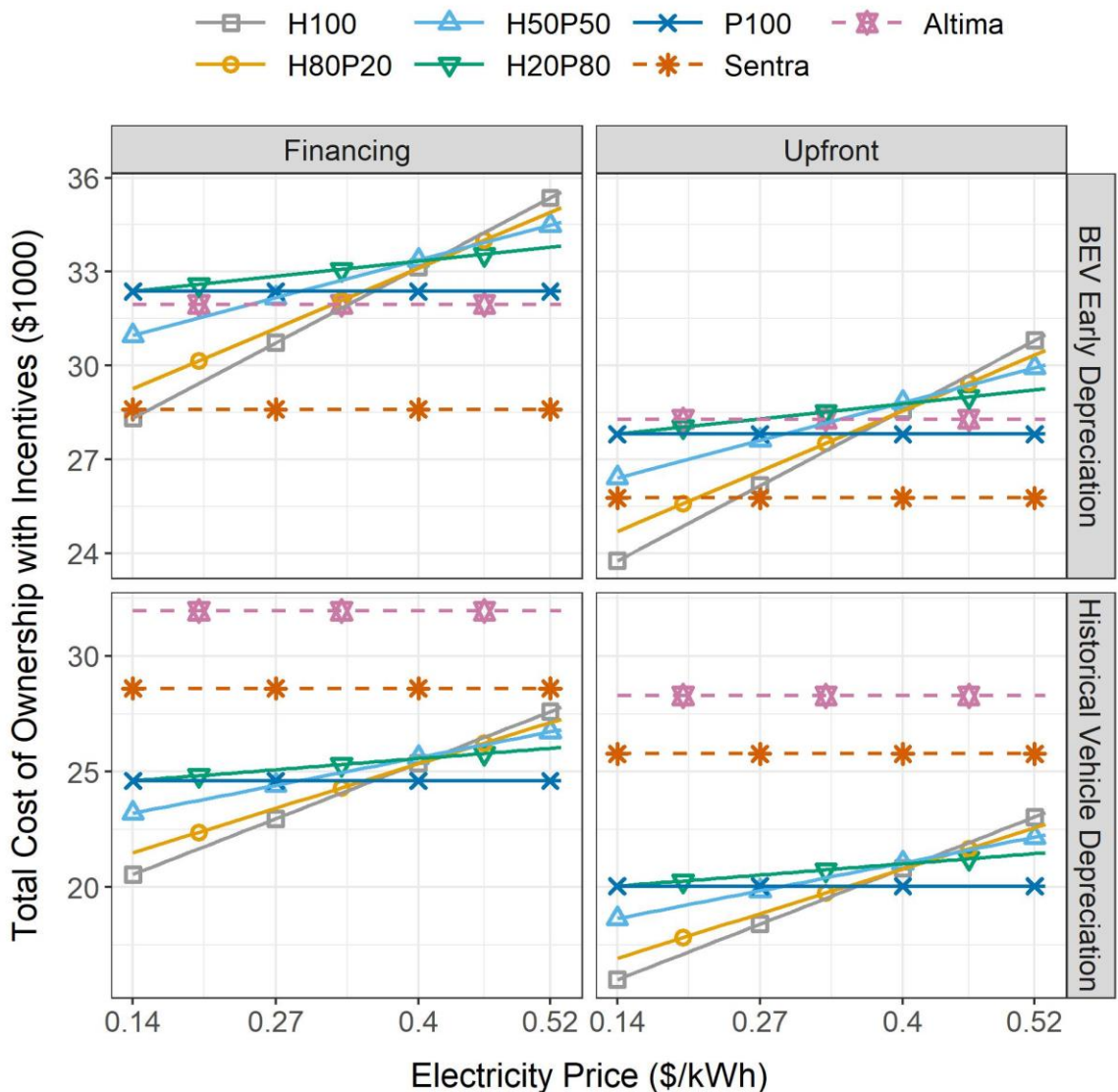


Figure 3-15 Total costs of ownership (TCOs) with \$10,000 financial incentives based on a range of electricity prices of the 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2019 to 2024. H stands for home charging, and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

3.2.5. Equity and Economic Implications

The results from Chapter Three suggest the TCOs of new and used Leafs are already comparable to ICE vehicles that have lower and much lower new vehicle purchase costs (i.e., the Altima and Sentra, respectively) if the current generation BEVs hold their values better and depreciate similarly to the historical vehicle depreciation trend. If the early and high depreciation rate of BEVs in the first three years is caused mostly, but not solely, by the financial incentives on the new BEVs, we could infer that shifting the incentives toward the used BEV market could cause BEVs at a broader market scale to depreciate more slowly (e.g. at a rate that may be similar to the historical ICE vehicle trend) while achieving the same policy outcome of increasing the amount of BEV drivers.

Public money has been successful in creating a primary market for BEVs despite the fact that the owners tend to belong to higher income and more highly educated demographic groups. In the case describe above, where public money is shifted to used car buyers as well, a single new BEV consumer, without the new BEV incentives, would still benefit from a lower TCO that is comparable to ICE vehicles as the result of lower depreciation cost. A used BEV consumer, without using an incentive, will still enjoy a used BEV TCO that is comparable to ICE (i.e., bottom plots of Figure 3-4 and Figure 3-8).

The residual value of the used BEVs could increase partly due to sellers taking notice of the rebates and marking up the sale price in addition to the increasing demand for used BEVs. However, there may be an unintended protection mechanism for used

BEV sale price markup—the abundance of the used ICE vehicles. Used BEV sellers may wish to increase the BEV sale price by as much as the used BEV rebate. However, the used vehicle buyers may decide, after all, to purchase ICE vehicles if the post-rebate used BEV price were higher than the price of used ICE vehicles. Thus, as long as there is an abundance of used ICE vehicles in the market, which will be true for at least the next 10 years if BEV sales increase substantially, used BEV prices would likely increase but still be lower than ICE vehicles after the rebate. On the other hand, used ICE vehicles may start seeing their prices drop in the attempt to attract used vehicle buyers that are now less likely to buy used ICE vehicles. This could result in a higher and faster depreciation in new ICE vehicles, causing higher ICE vehicle TCOs, which would then discourage new ICE vehicle ownerships.

Another economic impact of subsidizing used BEVs could be an increase in the value of used BEVs beyond historical vehicle residual values. This would then result in a new BEV depreciation curve in which BEVs hold their values better than ICE vehicles. In this case, the TCO for a used BEV could potentially become higher, even higher than ICE vehicles, resulting in a potential adverse effect for used BEV adoption. One possible way to avoid such outcome is to structure the used BEV incentive based on the income level of the buyer.

BEV drivers that charge more often at public chargers would typically have the highest TCO compared to all other BEV operating scenarios and ICE vehicle scenarios, which creates another equity issue. For demographic groups that do not live in residences with off-street parking, much of the cost savings from operating BEVs would be offset

from relying more heavily on PAEVCs, especially if a higher portion of the more expensive fast charging is needed. Additionally, although not analyzed in this chapter, the TCO would become even higher for drivers purchasing vehicles under longer financing terms. Both factors, higher public charging reliance and longer financing terms, are more likely to happen for the lower-income and lower credit score individuals.

New vehicles have higher TCOs in general compared to used vehicles, but, under specific cases, a used Leaf could be \$2,800 more expensive to own compared to a new Leaf over the five years of ownership even without new vehicle financial incentives. For example, under the historical vehicle depreciation scenario, a new Leaf purchased by paying the full upfront cost and that is charged 100% at home costs \$26,900 over five years of ownership, compared to \$29,700 for a used Leaf that is financed and is only charged 20% at home (Table 3-4). Even when all else is equal, both charging 100% at home and paying for the vehicle upfront, a new Leaf is only \$3,500 more expensive to own compared to the used Leaf in the historical vehicle depreciation scenario (Table 3-4). And when the new vehicle financial incentives are factored in, the new vehicle ownership cost is reduced by as much as \$10,000. As shown in the TCO cost table above (i.e., deduct \$10,000 from the new vehicle TCOs in Table 3-4), it is almost always cheaper to own a new Leaf with financial incentives compared to a used one in the scenario where BEVs depreciate similarly to the historical vehicle depreciation trend.

CHAPTER 4: INVENTORY OF LIGHT & UTILITY POLES FOR CURBSIDE ELECTRIC VEHICLE CHARGER RETROFIT FOR HUMBOLDT COUNTY, CA

Chapter Two identified public access electric vehicle charger (PAEVC) access and availability disparities for lower-income populations and Hispanic and black-majority neighborhoods. Furthermore, it argued these disparities create even further challenges for groups without off-street parking and the ability to charge at home, which emphasized the need for additional PAEVC access in these areas. Chapter Three further investigated and showed that cost savings associated with BEV adoption are reduced with higher reliance on public charging. Both chapters point to the importance of an alternative PAEVC infrastructure that could reach communities that are underserved by the current PAEVC infrastructure.

Chapter Four created an inventory of multi-unit dwellings (MUDs) with five or more units that do not have access to off-street parking in population centers in Humboldt County (i.e., city of Eureka and city of Arcata, accounting for 35% of the county's population [Humboldt County, n.d.]). The inventory also includes a list of light and utility poles that are potential candidates for retrofitting EV chargers on curbsides. This chapter also proposes a ranking system based on the shareability of these potential retrofitted curbside chargers by MUDs. And finally, examples of high utilization potential residential curbside charging zones in Eureka are identified using the ranking system presented in the chapter.

The economic feasibility of the retrofitted residential curbside chargers is outside the scope of the study, but it is reasonable to believe that there would be cost savings from retrofitting curbside chargers on light or utility poles compared to deploying a similar number of pole-mounted standalone chargers. PAEVCs, both in parking garages and on the curbsides, are more costly compared to home chargers due to the installation cost, including trenching and electrical upgrades (Agenbroad & Holland, 2014). Retrofitting the chargers on light and utility poles could potentially reduce or even avoid the trenching and electrical upgrade costs by tapping into the existing infrastructure, making them less costly compared to the conventional PAEVCs. Furthermore, if the municipality takes on ownership of the light/utility pole retrofitted curbside chargers, the permitting and installation process could be streamlined and made more efficient, especially for public spaces in residential areas.

Technically, adding Level Two chargers to utility poles should be more straightforward than adding chargers to light poles, as the connected distribution circuit should not have any issue to take on another 6.6 kW of electricity load—the typical power consumption of a Level Two charger. However, most streetlights will first need to be retrofitted to light-emitting diode (LED) lights, as the cities used as examples below, such as Los Angeles, did, to create excess capacity on the circuit. A typical residential high pressure sodium (HPS) street lamp uses about 70 to 100 watts (W), and a typical collector road HPS street lamp uses about 150 W (Los Angeles Bureau of Street Lighting, 2019b). These HPS streetlights can be retrofitted with LED lights that use conservatively half of the power, as seen from the currently utilized LED lights replacement for Los Angeles. A

typical Level Two charger uses approximately 6.6 kW, which could be supported by retrofitting approximately 165 residential streetlights or 88 collector road streetlights or some combination of the two. Eureka has over 2,000 street lights (City of Eureka, n.d.) which, if are all retrofitted to LED streetlights, could support adding roughly 12 Level Two chargers onto the light poles without any major electrical upgrade. Level Two chargers operate with 240 volts, and since most streetlights, at least at the residential level, operate at 120 volts, a transformer with at least 30-amp capacity—the typical amperage of Level Two chargers—would need to be installed along with the charger. And finally, a separate electric meter is needed to distinguish the energy consumption between the street light and the charger.

Some municipalities, such as Los Angeles and Berkeley, are already piloting and implementing light/utility pole retrofitted curbside EV chargers. Los Angeles Department of Water and Power (LADWP) retrofitted an EV charger on a utility pole (Figure 4-1). The installation took less than one day with four crew members (Kinney, 2017). LADWP also partnered with the Los Angeles Bureau of Street Lighting and retrofitted 132 streetlights with PAEVCs (example in Figure 4-2 and Figure 4-3) across the city (Los Angeles Bureau of Street Lighting, 2019a).⁸ Berkeley is piloting a curbside EV charger project for residents without off-street parking to install chargers on public curbsides at the resident's expense (City of Berkeley, 2018).

⁸ A map of all light pole public electric vehicle chargers by Los Angeles Bureau of Street Lighting could be found at the following url http://bsl.lacity.org/smartcity-ev-charging_map.html and in Appendix D



Figure 4-1 The Los Angeles Department of Water and Power's public curbside charger (circled in red) located at 1773 East Century Blvd, Los Angeles. Image from Google Street View.



Figure 4-2 The Los Angeles Bureau of Street Lighting's public curbside charger (circled in red) located at 932 S Wilton Pl., Los Angeles next to multiunit dwellings. Image from Google Street View.



Figure 4-3 Close up view of public electric vehicle supply equipment located at 932 S Wilton Pl., Los Angeles. Image from PlugShare.com.

4.1. Method

4.1.1. Multiunit Dwelling Off-street Parking Availability and Surrounding Light and Utility Pole Surveying for Arcata and Eureka in Humboldt County

The MUD off-street parking availability and surrounding light and utility pole inventory in shapefile format for Eureka and Arcata in Humboldt County were created using satellite images in QGIS. The satellite image survey was done by utilizing publicly available parcel data from the Humboldt County GIS Department and Google satellite images. These data were supplemented by Google Street View in Google Maps when needed. First, the parcels of MUDs with five or more units were identified using the Humboldt County parcel data. Every identified MUD with five or more units was then visually inspected for off-street parking availability. For the purpose of this analysis, a

MUD was deemed to have off-street parking availability if one of the following is true: 1) the presence of clearly marked parking spaces on the property within the parcel 2) the presence of parked cars on non-public roads in the property within the parcel 3) the presence of at least three cars parked in close proximity with one another in an off-street space on the property within the parcel 4) the presence of clearly marked parking spaces in the immediate structures outside of the parcel that is contiguous part of the property.

Once all MUDs without off-street parking availability (MUDNP) were identified, another satellite image survey was carried out specifically for the MUDNPs. For each MUDNP, the light and utility poles located on the same block and the same side of the street were digitized (Figure 4-4). The shadows of the light and utility poles were often used to assist the identification. In cases where the street block structure was less prominent, the typical block size judged from the surrounding areas was used to define the survey area for identifying light and utility poles. In a higher uncertainty situation, Google Street View was used for closer visual inspection of the presence or absence of light or utility poles that were otherwise unable to be discerned from satellite images. Lastly, all the light and utility poles surrounding MUDNPs in Old Town Eureka were identified using Google Street View since they were covered and overshadowed by taller buildings.



Figure 4-4 Example multi-unit dwelling (MUD) parcel without off-street parking availability and the identified light or utility poles located on the same side of the street on the block.
Data sources: Google satellite image base map and Humboldt County parcel shapefile from Humboldt County GID department website.

4.1.2. Availability of Light and Utility Poles Surrounding Multi-Unit Dwellings without Off-Street Parking

The digitized MUD and light and utility pole shapefiles were imported to R Studio and processed with the “sf” package. The MUD polygons were buffered for 0.1 miles, and the utility/light poles within the buffered polygons were counted for each parcel. And then the summary statistics including the percentages of MUDs with and without off-street parking and average poles within 0.1 miles of MUDs were calculated.

4.2. Result & Discussions

Eureka has more MUDs with five or more units without off-street parking (MUDNP) compared to Arcata (Table 4-1). More than half (66%) of the MUDs with five or more units in Eureka do not have off-street parking, which highlights the difference in the housing structure characteristics between the two cities as well as the additional barriers to adopting BEVs for MUD residents in Eureka.

Table 4-1. Summary of off-street parking availability and surrounding light and utility poles for multi-unit dwellings (MUD) with five or more units in Arcata and Eureka in Humboldt County, California.

Location	Off-Street Parking	N	Poles within 0.1 miles of MUD
			Mean/Median
Arcata	No	25	5/4
Arcata	Yes	107	2/2
Eureka	No	137	18/17
Eureka	Yes	71	8/5

The MUDNPs in Eureka, however, do have more light and utility poles within 0.1 miles compared to Arcata (Table 4-1), demonstrating the potential of using these poles to retrofit curbside chargers and support EV adoption in these areas. More than 75% of the MUDNPs in Eureka have at least ten light or utility poles within 0.1 miles (Figure 4-5). On the other side, 75% of the MUDNPs in Arcata have seven or less light and utility poles within 0.1 miles (Figure 4-5). With the relative abundance of the poles compared to

Arcata, MUDNPs in Eureka would be more likely to have suitable locations for retrofitting curbside EV chargers.

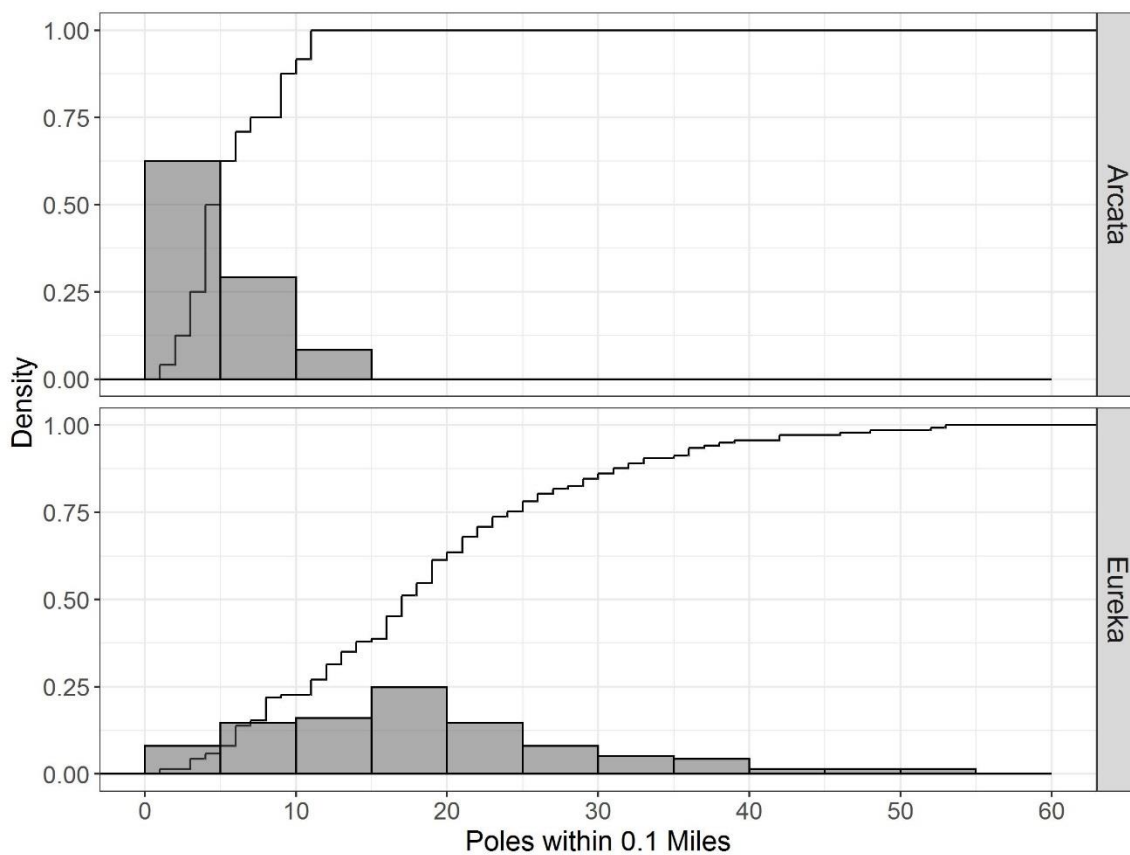


Figure 4-5. Distribution of the count of light and utility poles within 0.1 miles of all identified MUD without off-street parking in Arcata and Eureka in Humboldt County, California. The step lines represent the cumulative density.

If a curbside charger is retrofitted in Eureka on one of these poles, on average it could be shared by four MUDNPs. Half of the poles within 0.1 miles of a MUDNP in Eureka could be shared by two to five MUDNPs (Figure 4-6). This result shows the potential of higher curbside charger utilization in Eureka. Furthermore, there are 12 poles in Eureka that, if retrofitted to curbside chargers, could be shared by more than 10

MUDNPs within 0.1 miles. These 12 high-co-sharing potential poles are located in the high charger utilization potential Zone B as depicted in Figure 4-7.

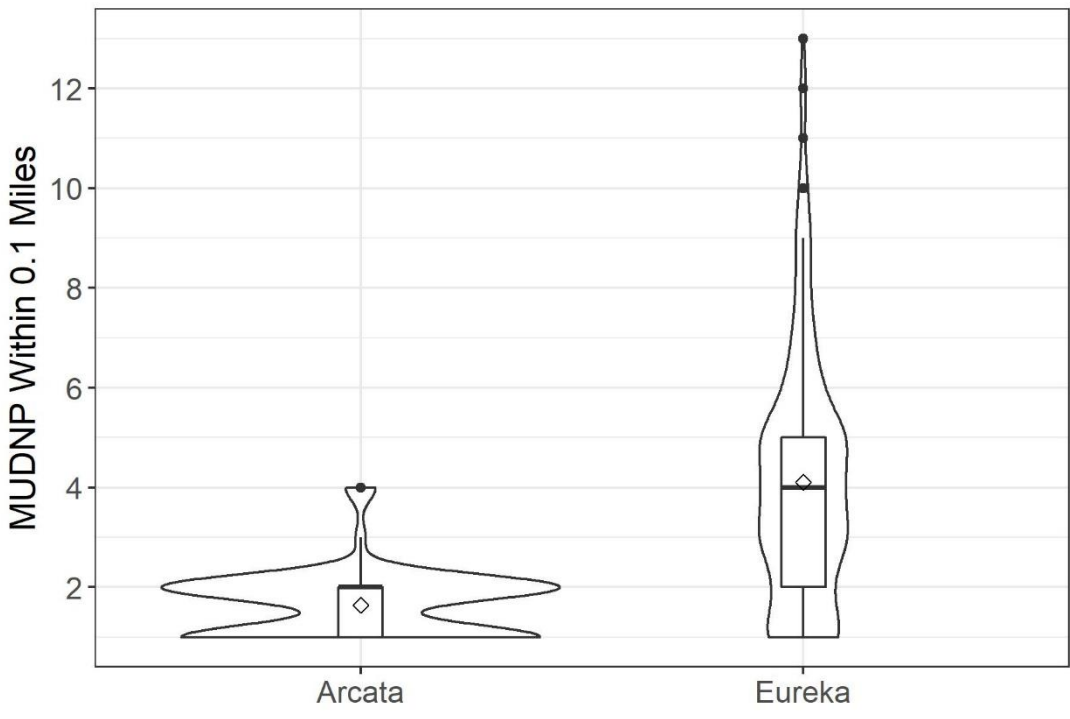


Figure 4-6. Boxplots of the count of multi-unit dwellings without off-street parking (MUDNP) within 0.1 miles of all identified light and utility poles surrounding MUDNP in Arcata and Eureka in Humboldt County, California. The diamond represents the mean. The x-axis spread represents the distribution kernel density.

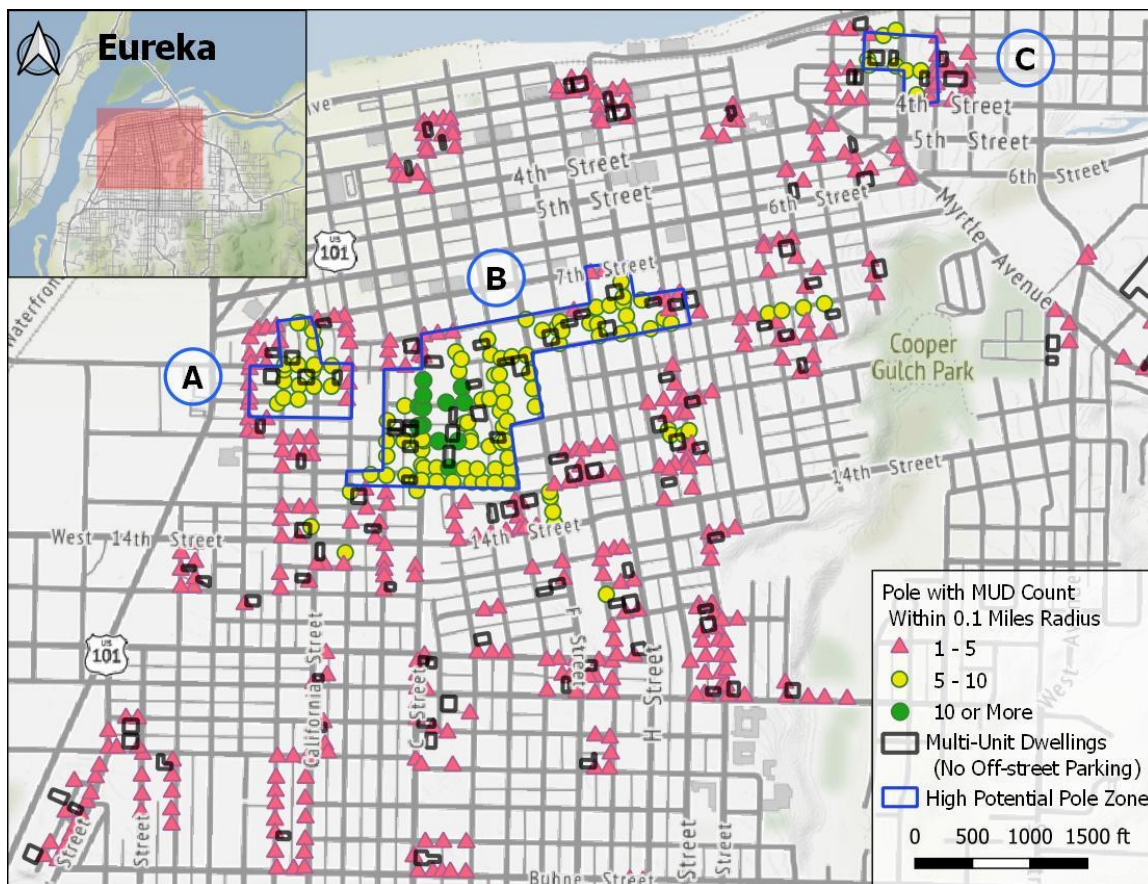


Figure 4-7. Multi-unit dwelling (MUD) without off-street parking and the surrounding light or utility poles in Eureka, CA. The shape of the point symbol represents the count of MUDs within 0.1 miles of the pole. Three high potential zones for pole retrofitted curbside chargers are enclosed within the blue polygons.

High shareability potential Zone A is centered on the block located on Washington, Pine, Grant, and California Street, just south of West 7th Street and East of Broadway in Eureka (Figure 4-8). High potential Zone B is the largest zone in terms of both geographic size and the amount of high potential poles. It is located south of 8th Street and East of B Street in Eureka (Figure 4-9). High potential Zone C is the smallest zone in terms of geographic area and is located between Q Street and S Street just to the East of Old Town Eureka (Figure 4-10). All three zones are located near commercial

zones and businesses compared to other MUDNPs and their surrounding poles which may be because MUD density is likely to increase with the proximity to city centers. The proximity to businesses could potentially increase the utilization rates of these retrofitted curbside chargers by allowing them to supply to both daytime destination public charging demand and nighttime residential charging demands.

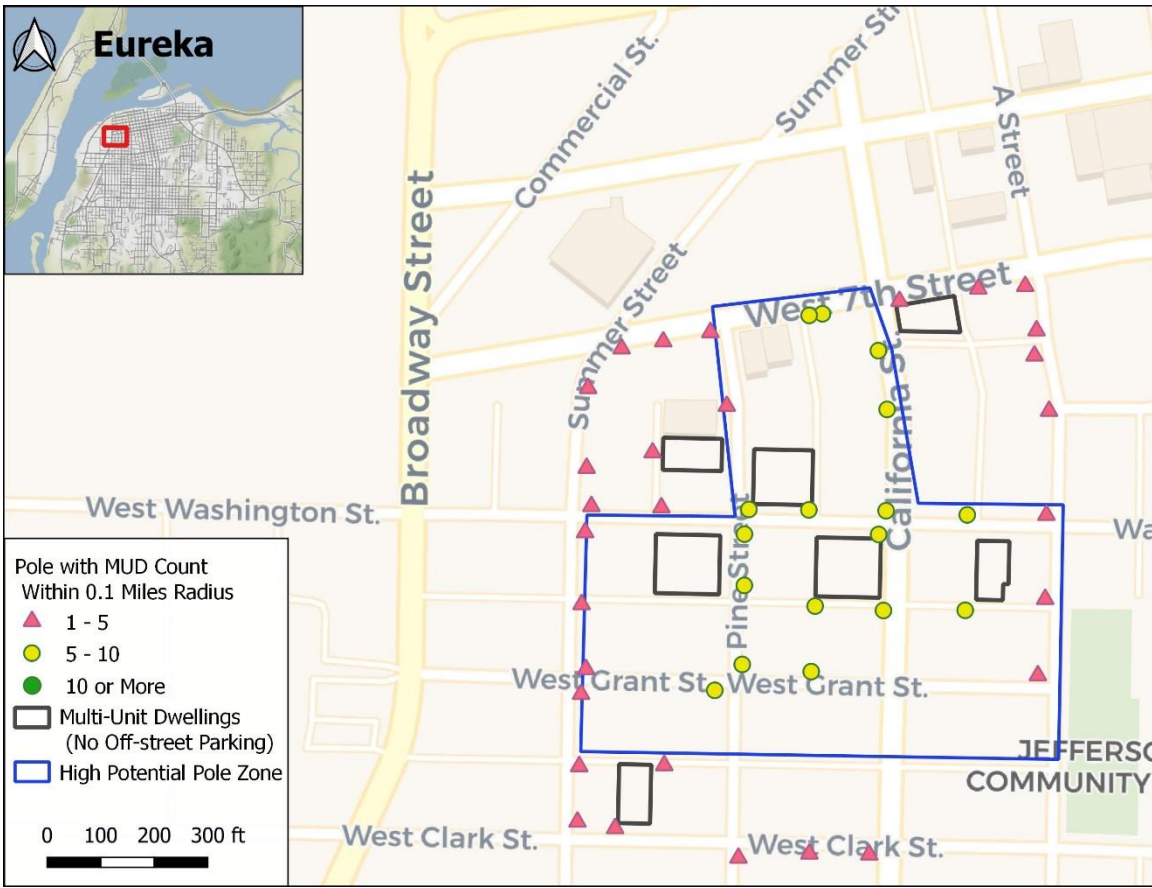


Figure 4-8 High shareability potential Zone A for retrofitting curbside chargers on utility/light poles in Eureka, California.

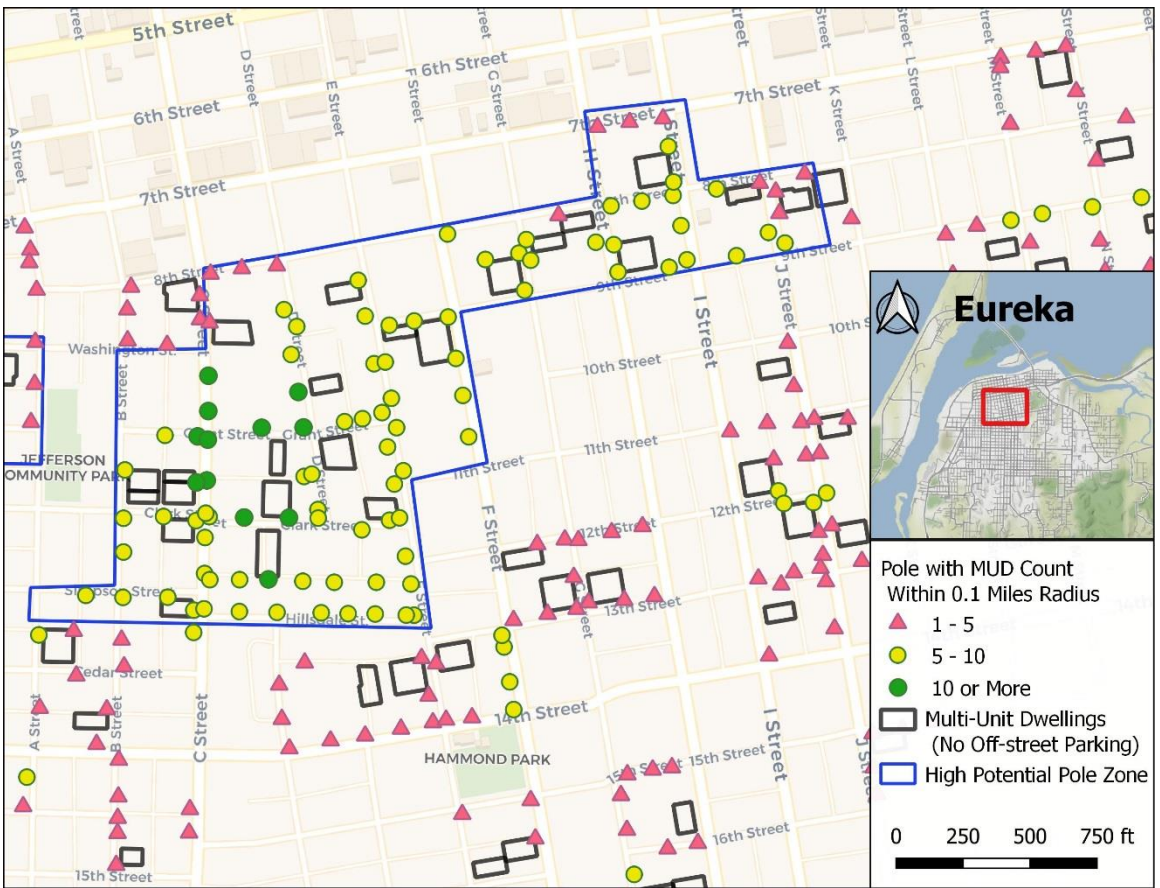


Figure 4-9 High shareability potential Zone B for retrofitting curbside chargers on utility/light poles in Eureka, California.

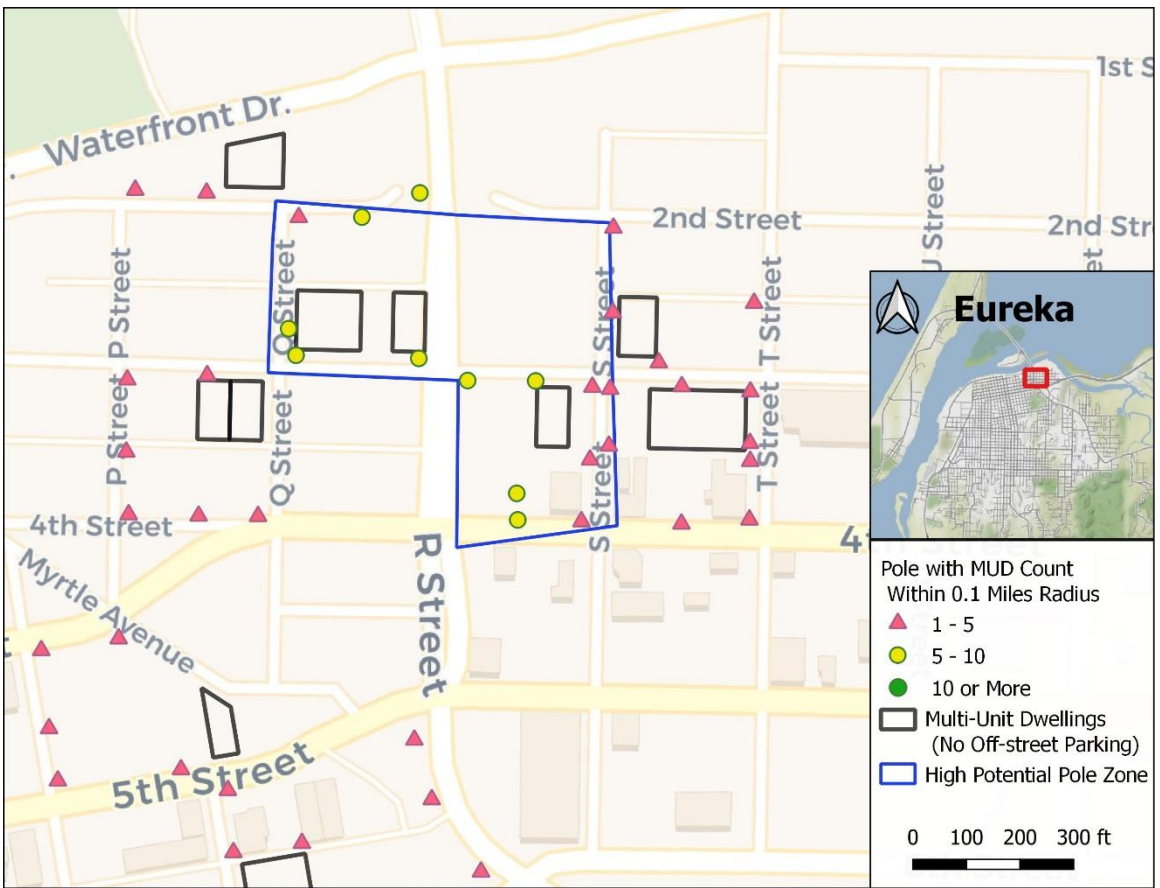


Figure 4-10 High shareability potential Zone C for retrofitting curbside chargers on utility/light poles in Eureka, California.

If the City of Eureka decides to pilot retrofitting curbside chargers for the earlier stage of BEV adoption, the process could be application-based similar to the Berkeley pilot project. The specific technical and economic feasibility of the retrofitted curbside chargers will likely be highly site-dependent. Lastly, pilot projects can provide useful feedback and utilization data to inform further development.

CHAPTER 5: CONCLUSION, POLICY RECOMMENDATIONS, AND FUTURE RESEARCH

Chapter Two of this study found access disparities in the public access electric vehicle chargers (PAEVCs), implying that the current PAEVC infrastructure is leaving specific demographic groups behind. Census block groups (CBGs) with majority black and Hispanic population and CBGs with lower median household incomes (“underserved CBGs”) have lower possibilities to have access to at least one PAEVC station within the CBGs compared to other CBGs located at the similar distance from the nearest freeway. At similar renter and multiunit dwelling (MUD) rates, the same underserved CBGs—black and Hispanic majority CBGs and lower income CBGs—still have the lowest PAEVC access among all CBGs, and the disparities are most severe at higher MUD and renter-occupied housing unit rate locations. Taken together, residents living in MUDs in low income and black and Hispanic majority CBGs would experience higher electric vehicle (EV) adoption barriers as they have both lower access to home charger being MUD residents and lower PAEVC access as shown in the chapter.

In addition to the lack of PAEVC access near homes, underserved groups also face lower PAEVC access at the selected points-of-interest (POIs) (i.e., grocery stores and fitness club/studios). Within the selected grocery and fitness chains, some chains (i.e., Wholefood’s and Equinox) more commonly associated with higher income customer clienteles were found to have higher PAEVC availability than all-store baselines. However, most of the POI chains investigated were not significantly higher or

lower than the PAEVC availability baselines. When the PAEVC access and availability of all grocery and fitness POIs were compared based on the CBGs they are located in, the same disparity pattern persists for underserved CBGs with lower median household income and a Hispanic and/or black majority.

Chapter Three found, in the case where the current-generation BEVs depreciate at a rate that matches historic ICE vehicle depreciation, BEVs' total costs of ownership (TCOs) for both new and used ownership would be comparable to ICE vehicles. And new BEVs with financial incentives could be significantly cheaper to own compared to new ICE vehicles and even cheaper than used BEVs. Alternatively, if the current-generation BEVs depreciate like the first-generation BEVs, used BEVs could be cheaper to own compared to the used ICE vehicles and new BEVs would need to capture financial incentives to be comparable to new ICE vehicles. The generous BEV financial incentives, accounting for 33% of the new vehicle MSRP and as high as 51% of the TCO under a specific scenario, are likely contributing to the early depreciation pattern of the first-generation BEVs as discussed in the chapter. Surprisingly, the new BEV five-year TCO with financial incentives, in many cases, could be lower than the used BEV five-year TCO.

The TCO analysis also shows that heavier reliance on public charging would reduce, or even eliminate, the BEV operation cost saving compared to an ICE vehicle. And, as results from Chapter 2 suggests, PAEVC access disparities are most severe at locations with higher renter-occupied and MUD housing unit rates, meaning that potential BEV owners living in underserved CBGs would likely have higher BEV TCOs.

The conclusion from Chapter Three highlights the need to reevaluate and potentially restructure BEV financial incentives because the impacts on BEV early depreciation and the regressive result of enabling new vehicle ownerships for buyers that are more likely to have higher income.

Finally, Chapter Four proposed a potential alternative PAEVC infrastructure that focuses on BEV charging access for the residents in multi-unit dwellings without off-street parking (MUDNP) that are mostly being underserved by the current PAEVC infrastructure. The alternative charging infrastructure could rely heavily on the existing electric and physical infrastructure by retrofitting charging stations on electric and utility poles.

Given the current PAEVC infrastructure, BEV market, and incentive structure, a potential BEV buyer with lower income, living in a MUD in an underserved CBG, and only able to afford the upfront cost of a used BEV, would likely end up paying more to own and operate the BEV than an average BEV owner today. BEV ownership by this buyer would also be much more inconvenient, as there are less PAEVCs he or she would be able to access around their residence and the grocery store where they often shop. Added together, the financial and behavioral barriers would deter BEV adoption for underserved demographic groups and could further reinforce the infrastructure buildout for early EV adopters or the more affluent demographic groups that we are starting to see.

5.1 Policy Recommendations

Many of the issues discussed in this thesis study do have policies that aim to address them. However, many of them could and should be restructured to address equity concerns identified in this thesis.

5.1.1. Current Policies and Programs

SB535 and AB 1550 have been the main California policies that generated public funding aimed at increasing PAEVC availability and BEV adoption. The bills mandate that at least 25% of the Greenhouse Gas Reduction Fund (GGRF) from the California Cap-and-Trade program fund state programs that seek to reduce GHG emissions in disadvantaged communities and 10% to low-income households (CAL. HSC.CODE § 39713). The original of the AB 1550 bill text proposed to allocate 25%, instead of the 10% that was approved, to low-income households (The Greenlining Institute, 2015). The GGRF has funded multiple programs that subsidized PAEVC installations and at least partially attempted to address the related equity issue by mandating a portion of the fund to go to disadvantaged communities. However, few programs were designed solely to focus on addressing the PAEVC access and BEV adoption equity issues in disadvantaged and lower-income communities. Furthermore, the programs that do have equity components often do not achieve a higher funding levels for lower-income and disadvantaged communities required by the bill text.

An example where we should see further equity commitment is the California Clean Vehicle Rebate Project (CVRP). CVRP issued and approved to date \$720 million

worth of rebates (California Air Resources Board, 2019), which is approximately 7% of the GGRF, and \$130 million or 18% has been rebated to new vehicle buyers in low-income communities. However, new vehicle buyers in low income communities are not necessarily low income households, the CVRP statistics show half of the rebate recipients in disadvantaged communities had annual household income of \$100,000 or higher while these households only accounted for less than 15% of the households indicated the intent to buy new vehicles in these communities (Center for Sustainable Energy, 2015). Combining with the rebates for disadvantaged communities, CVRP has rebated 25.3%—0.3% higher than the bill requirement—to these equity groups.

Another example of only a fraction of the public funding being allocated to the underserved groups is the rate payer funded Pacific Gas and Electric Company (PG&E) EV Charge Network program, which aims to install EV chargers at workplaces and MUDs. The program does not require the installed chargers to be accessible to the public. The program, fully subscribed, has a \$130 million budget, and 23 out of 201 (11.4%) installation sites to date are located in MUDs in disadvantaged communities (PG&E, 2019). The top three areas with the most applicants are San Jose, San Francisco, and Oakland, where PAEVCs are already more abundant.⁹ The program design and the Public Utilities Commission review process should, in the future, consider the fact that more luxurious MUDs, even located within disadvantaged communities, should not be provided with as much incentives as all other MUDs. The tenants in these luxurious

⁹ For the reference, using the CalEnviroScreen 3.0, no census tracts in the entire county of Humboldt would not be considered as disadvantaged communities under this program.

MUDs would already have a demand for the chargers, and the public goods fund should be prioritized and allocated to increase access in areas that would otherwise unlikely have them.

The Clean Vehicle Assistance Program mentioned in Chapter One is one program example that is specifically targeting disadvantaged and lower-income communities. However, the program funding (i.e., \$5 million) is dwarfed by the similar, but new vehicles only, CVRP (i.e., program budget of \$720 million with an additional \$238 million) mentioned earlier. There have been modifications to the CVRP aiming to address the issue raised here. The CVRP implemented an income cap limiting rebates to individuals with \$150,000 annual income or less and increased the rebate amount (i.e., additional \$2,000) for qualifying low-income applicants.

Furthermore, programs like PG&E's EV Charge Network (e.g., San Diego Gas and Electric's Power Your Drive and Southern California Edison's Charge Ready) solely target and rely on property owners or managers to apply. Although the chargers, installation, and infrastructure could be paid for by the utilities—worth up to \$118,000 for installing 10 chargers, according to PG&E—there are still costs associated with the program participation such as the upfront one-time participation fee (e.g., PG&E's participation payment of \$11,500). It is reasonable to assume that property owners and managers, guided by their financial interests, would have little to no incentives to apply for the program if few or no property residents drive BEVs—which is more likely the case for MUDs with predominantly lower-income residents.

At the federal level, the only BEV financial incentive is the federal EV tax credit for new EVs, which does not have an income cap nor additional incentives for lower-income households. The tax credit nature of the incentive precludes individuals with lower income from taking full advantage, as they may not owe enough federal tax to receive the full credit. For example, to fully capture the \$7,500 tax credit, a single tax filer would have to make \$53,000 in the tax year or higher with other tax deductions.¹⁰ Additionally, being a tax credit, the EV buyer would not receive the financial incentive until the tax refund time, which sometimes could potentially be more than a year from the date of the vehicle purchase. For lower-income consumers who are much likely to have a higher sensitivity to the capital purchase cost of EVs, the delayed financial incentives would further fail to encourage their EV adoption.

5.1.2. Higher Subsidies and Strategic Placement of Public Electric Vehicle Charging Stations in Disadvantaged and Lower-Income Communities

In addition to the current policies, more and enhanced policies need to ensure or encourage equitable charger access across income, race, and ethnicity groups. A potential way to achieve this outcome is to allocate a larger proportion of the GGRF funding to provide more and higher subsidies for the currently underserved communities. More importantly, PAEVC stations need to be strategically located so that POIs serving mainly lower-income customer clientele could have PAEVC access as well. Simply specifying the chargers to be installed in a general geographic area (e.g., census tracts used by California Environmental Protection Agency's CalEnviroScreen, which defines the

¹⁰ Calculated with the 2019 federal single filer tax bracket

disadvantaged and low-income communities in California) may not adequately address PAEVC distribution equity. For example, the POIs with more current BEV owners frequenting them would have a better PAEVC business case. Thus, these stores (e.g., a Trader Joe's as opposed to an ALDI) are more likely to install chargers that are subsidized by the public money, even within the disadvantaged or low-income census tract.

5.1.3. Financial Incentives for Used Electric Vehicles

Policies should also increase the incentives for used BEV purchase to promote BEV adoption beyond the early adopters and into the predominantly used car buying consumer base, which includes lower-income communities. Administering the BEV financial incentives exclusively for new vehicles makes sense for the earlier adoption stage to create the market for BEVs. However, used EVs should start being allocated with a higher proportion of the public funding available for EV purchase incentives. Furthermore, as argued in Section 3.2, shifting some incentives away from new BEVs to used BEVs could potentially increase the residual values of the used BEVs, making BEV depreciation rates more similar to the historical ICE vehicle depreciation trend, thereby promoting a stronger used BEV market while making new BEV ownership more attractive at the same time. Used vehicle sellers may try to inflate used BEV sale prices due to the incentives, but this could be buffered by the large stock of used ICE vehicles making the post-rebate used BEV price potentially still lower than used ICE vehicles. Finally, the existing database on vehicle ownership transfers could be used to ensure each

BEV would only receive one used BEV incentive to prevent people taking advantages of loopholes.

From an environmental and climate standpoint, lower-income and disadvantaged communities are more likely to purchase older, cheaper, and lower fuel efficiency used vehicles. The potential greenhouse gas emissions abatement from incentivizing this group of drivers to adopt EVs could likely be higher than continuing to differentially support higher income and already more environmentally conscious drivers to adopt BEVs. A program could be devised to promote the early retirement of old inefficient vehicles and encourage program participants to switch to EVs including BEVs. Such a program could be funded by the fees collected from the sales of new inefficient vehicles. Program criteria would need to be established to ensure the carbon footprint embedded in new vehicle production is offset by the avoided emissions that would otherwise be emitted in the remaining effective vehicle life time of the retired vehicle.

Lastly, incentive programs should not be limited to the purchase of used EVs. The forthcoming AB 193 mandated battery replacement program could also be subsidized to reduce the cost of replacing EV batteries near or at the end of its useful lifetime. This could help boost potential buyers' confidence in the range of the used EVs, increase the residual value of used EVs, and increase EV adoption overall.

5.1.4. Encourage and Streamline Public-Private Partnership for Public Electric Vehicle Charging Infrastructure Build Out

Policies should also address the additional challenges faced by residents in MUDs and MUDNPs. Alternative charger locations could be implemented under public

programs and public ownerships, such as the light pole chargers installed in Los Angeles. For example, partnerships between municipalities and utility companies could make the installation process more efficient to serve a broader range of current and potential EV drivers. As discussed above, the current utility company PAEVC programs (e.g., PG&E's EV Charge Network) hinge on the property owner's willingness to install the EV chargers. If the municipalities and utility companies could form public and private partnerships, EV chargers could potentially be installed at any available public space including light poles and utility poles.

5.2 Future Research

Further research is needed for policies to more efficiently, effectively, and equitably address the issues discussed in this thesis. First, research should assess the destination POI charging demand from drivers with low home charging access. Research should also explore the residential ("over-night") charging demand of areas with a higher portion of MUDNP. These results could inform the appropriate amount of funding and incentives to be allocated to locations with high charging demand from the potential EV adopters without access to home charging that may be unaccounted for in other charging demand studies.

Economic research on EV incentives' impacts on the EV depreciation trend and used EV market is also needed. By better understanding this relationship, funding for EV purchase incentives can be better allocated between new and used EV markets to achieve more efficient and equitable EV adoption.

More research and pilot projects are needed to investigate the economic and technical feasibility of retrofitting EV chargers on light/utility poles, especially under a public-private partnership. In addition, studies can also utilize the data generated from the Los Angeles Bureau of Street Lights' light pole PAEVC pilot to better understand the factors (e.g., the surrounding area demographics) impacting the utilization rates.

Lastly, research on greenhouse gas emissions abatement from increasing EV adoption in lower-income communities could inform policymakers on how to allocate the state's GGRF to more efficiently, and, more importantly, equitably achieve higher greenhouse gas emissions abatement per public dollar.

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APPENDIX A. URBAN AREA MAP OF CALIFORNIA

The map presented in Figure A-1 shows the urban areas and clusters in California as defined by the U.S. Census Bureau.

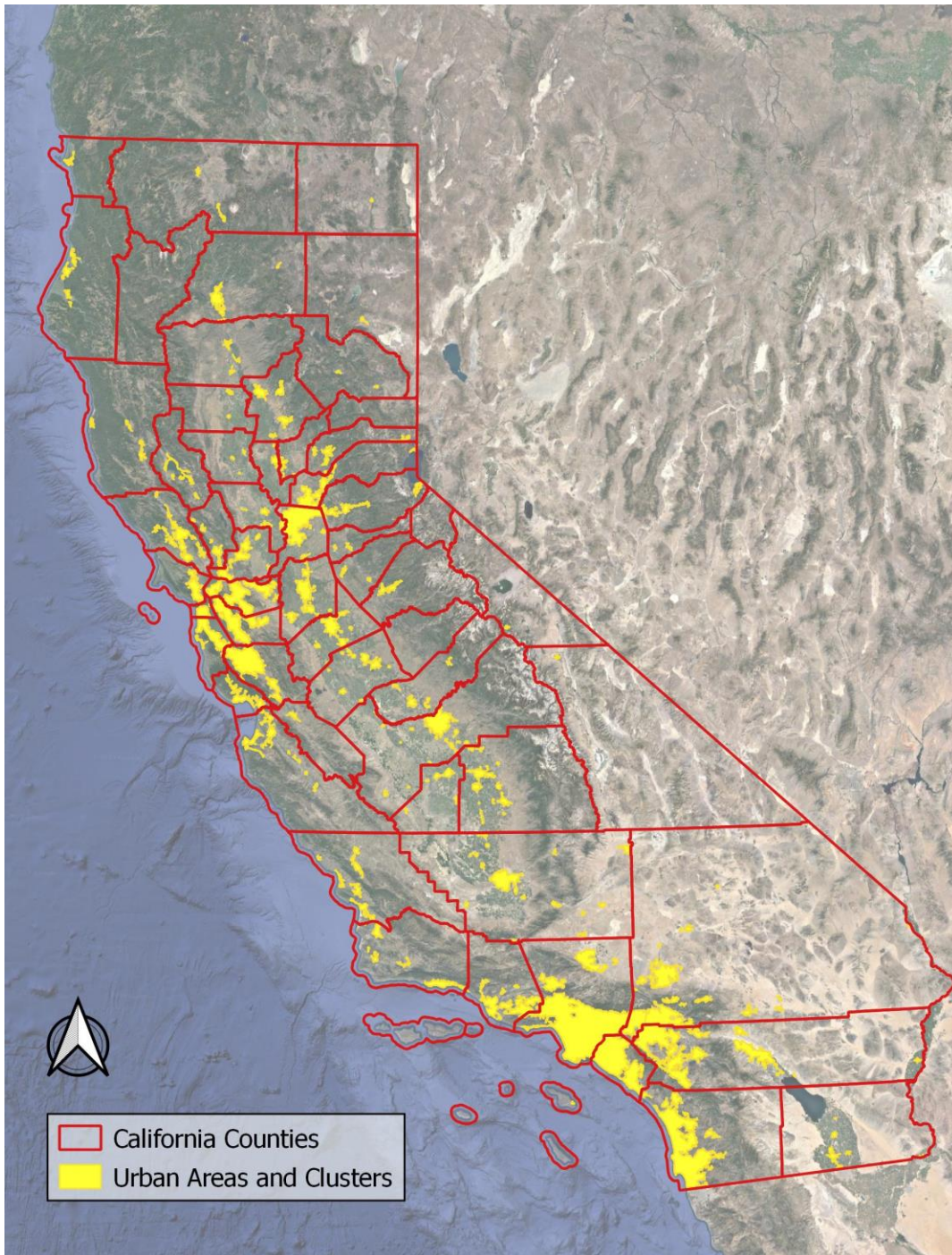


Figure A-1 Urban Areas in California. Urban Area shapefile obtained from U.S. Census Bureau.

APPENDIX B. COUNTY POPULATION AND PUBLIC ELECTRIC VEHICLE
SUPPLY EQUIPMENT COUNT REGRESSION RESULT

Table B-1 shows the linear regression residual for public access electric vehicle chargers as predicted by the county's population for all 58 counties in California.

Table B-1 Top to bottom counties ranked by the predicted public access electric vehicle charger (PAEVC) station count residual. The predicted values were generated based on the linear regression on PAEVC station count as the function of county populations.

County	PAEVC Count	Population Size	Residual	Average of CBG Median Household Income
Santa Clara	465	1,884,335	218	\$110,934
Orange	518	3,133,727	113	\$86,611
San Mateo	193	751,017	89	\$114,713
Napa	106	134,680	80	\$81,923
Sonoma	142	491,560	71	\$71,978
San Luis Obispo	105	264,107	63	\$66,317
San Francisco	179	850,282	63	\$98,956
Alameda	254	1,603,627	42	\$87,713
Marin	74	252,925	33	\$115,416
Santa Barbara	97	437,357	33	\$75,168
San Diego	435	3,213,618	20	\$73,319
Yolo	54	204,119	20	\$64,710
Monterey	81	419,636	19	\$65,326
Humboldt	28	112,244	5	\$44,990

County	PAEVC Count	Population Size	Residual	Average of CBG Median Household Income
Placer	57	357,048	3	\$80,153
El Dorado	32	159,786	3	\$76,341
Santa Cruz	45	269,477	2	\$74,712
Mendocino	16	65,872	-1	\$48,294
Nevada	17	86,434	-2	\$60,078
Siskiyou	9	24,325	-3	\$41,223
Mono	5	8,035	-5	\$61,984
Amador	5	20,489	-6	\$56,155
Madera	17	124,886	-7	\$45,677
Del Norte	4	23,875	-8	\$45,761
Plumas	2	9,563	-8	\$46,536
Tuolumne	6	41,391	-8	\$54,655
Lassen	2	11,876	-8	\$48,688
Modoc	1	4,104	-8	\$41,857
Sierra	0	680	-9	\$40,234
Colusa	2	18,385	-9	\$57,429
San Benito	5	51,090	-10	\$75,198
Inyo	0	11,883	-10	\$59,485
Calaveras	2	27,757	-10	\$62,475
Solano	52	428,126	-11	\$71,664
Tehama	4	50,186	-11	\$42,512

County	PAEVC Count	Population Size	Residual	Average of CBG Median Household Income
Glenn	0	21,853	-11	\$43,643
Kings	14	146,483	-13	\$50,637
Yuba	3	62,121	-13	\$45,484
Lake	2	60,103	-14	\$38,059
Butte	17	212,030	-18	\$46,592
Sutter	1	86,841	-19	\$54,668
Ventura	96	840,391	-19	\$84,520
Shasta	8	146,926	-19	\$46,204
Contra Costa	130	1,111,748	-19	\$92,155
Sacramento	171	1,475,015	-24	\$63,341
Imperial	1	162,653	-28	\$45,168
Merced	11	258,506	-30	\$46,014
Los Angeles	1239	10,044,116	-41	\$67,190
Stanislaus	29	523,765	-46	\$51,945
Riverside	253	2,303,612	-47	\$62,374
Fresno	75	908,815	-49	\$48,676
Tulare	13	432,251	-50	\$44,345
San Joaquin	37	690,218	-59	\$54,211
Kern	25	828,872	-88	\$50,631
San Bernardino	135	2,079,861	-137	\$58,015

APPENDIX C. TABULAR RESULT OF TOTAL COST OF 10 YEAR OWNERSHIP
AND SENSITIVITY ANALYSIS

Appendix C includes the 10-year total cost of ownership of the 2019 Nissan Leaf compared to Nissan Altima and Nissan Sentra internal combustion engine vehicle baselines and the sensitivity analyses based on varying gas price, electricity price, and total miles driven annually. See Table C-1 and Figures C-1 to C-6.

Table C-1 Total cost of ownership (in \$1,000 2019 USD) of 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Altima, and Sentra from 2019 to 2029 under battery electric vehicle early depreciation (ED) and historical vehicle depreciation (VD) scenarios and financing and upfront payment scenarios. The cost in parenthesis indicates factors in the rebate and tax credit. H stands for home charging and P stands for public charging. The number following P and H indicates the % of the charging taking place at each location. Note the battery electric vehicle financial incentives worth up to \$10,000 are not shown in the table. To calculate the post-incentive TCOs for new Leaf, deduct \$10,000 from the TCOs.

Charging Scenario	ED Financing	ED Upfront Payment	VD Financing	VD Upfront Payment
P100	\$64.9	\$60.4	\$61.4	\$56.9
H20P80	\$64.0	\$59.4	\$60.5	\$55.9
H50P50	\$61.6	\$57.1	\$58.1	\$53.6
H80P20	\$58.6	\$54.1	\$55.2	\$50.6
H100	\$57.1	\$52.5	\$53.6	\$49.0
Altima	\$57.2	\$53.5	\$57.2	\$53.5
Sentra	\$51.9	\$49.0	\$51.9	\$49.0

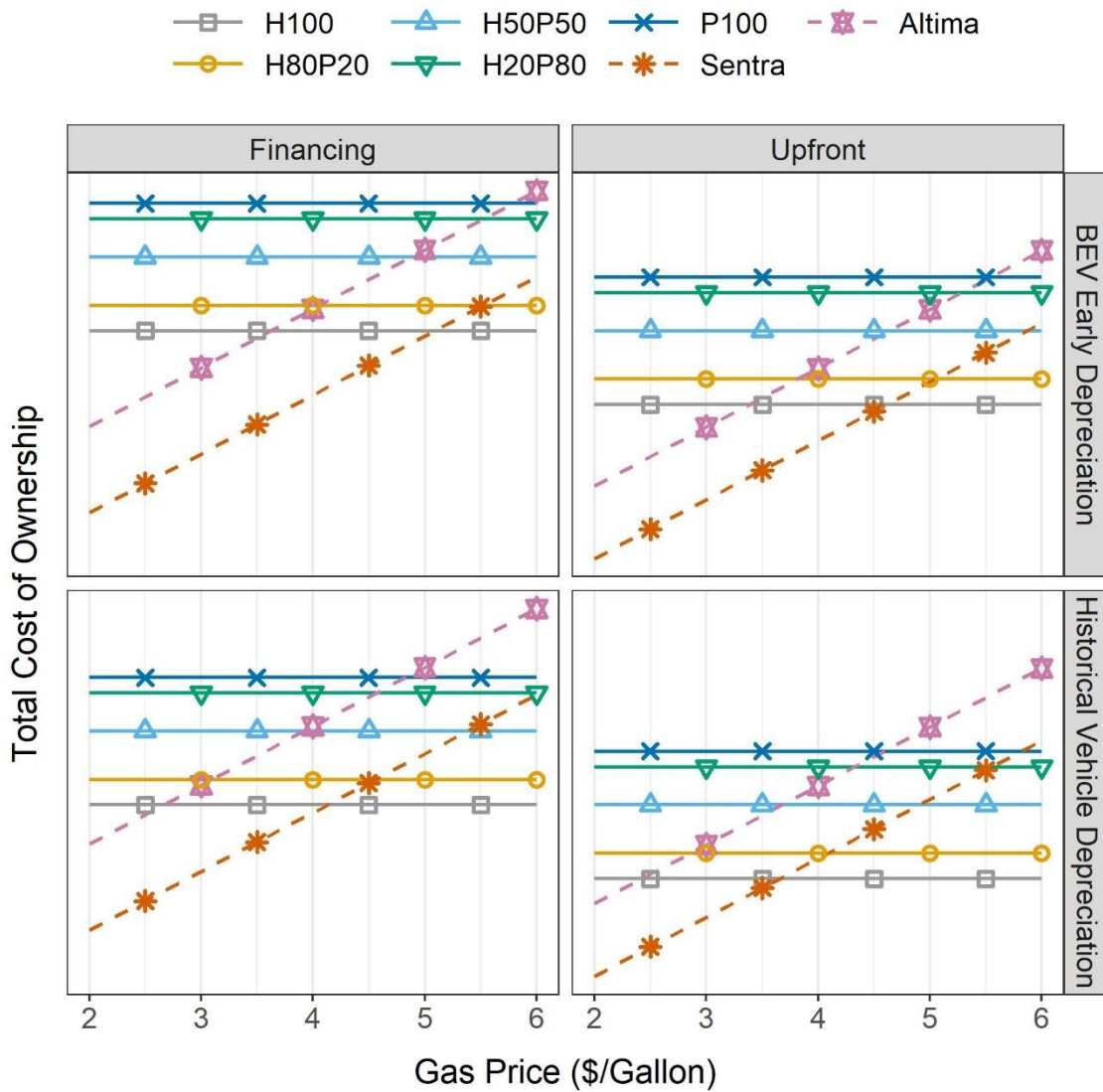


Figure C-1 Total costs of ownership based on a range of gas prices of the 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2019 to 2029. H stands for home charging and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

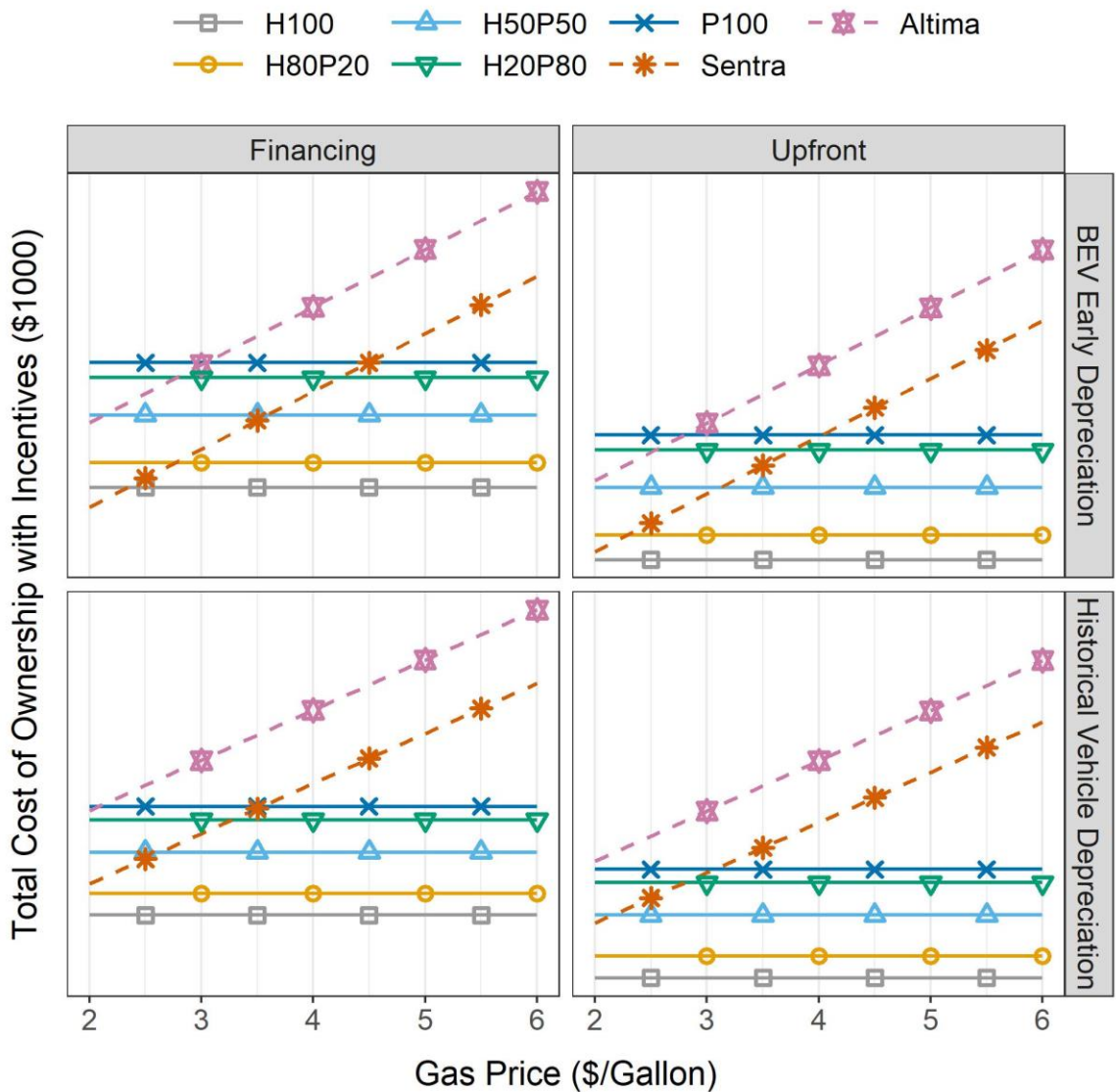


Figure C-2 Total costs of ownership with \$10,000 electric vehicle financial incentives based on a range of gas prices of the 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2019 to 2029. H stands for home charging and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

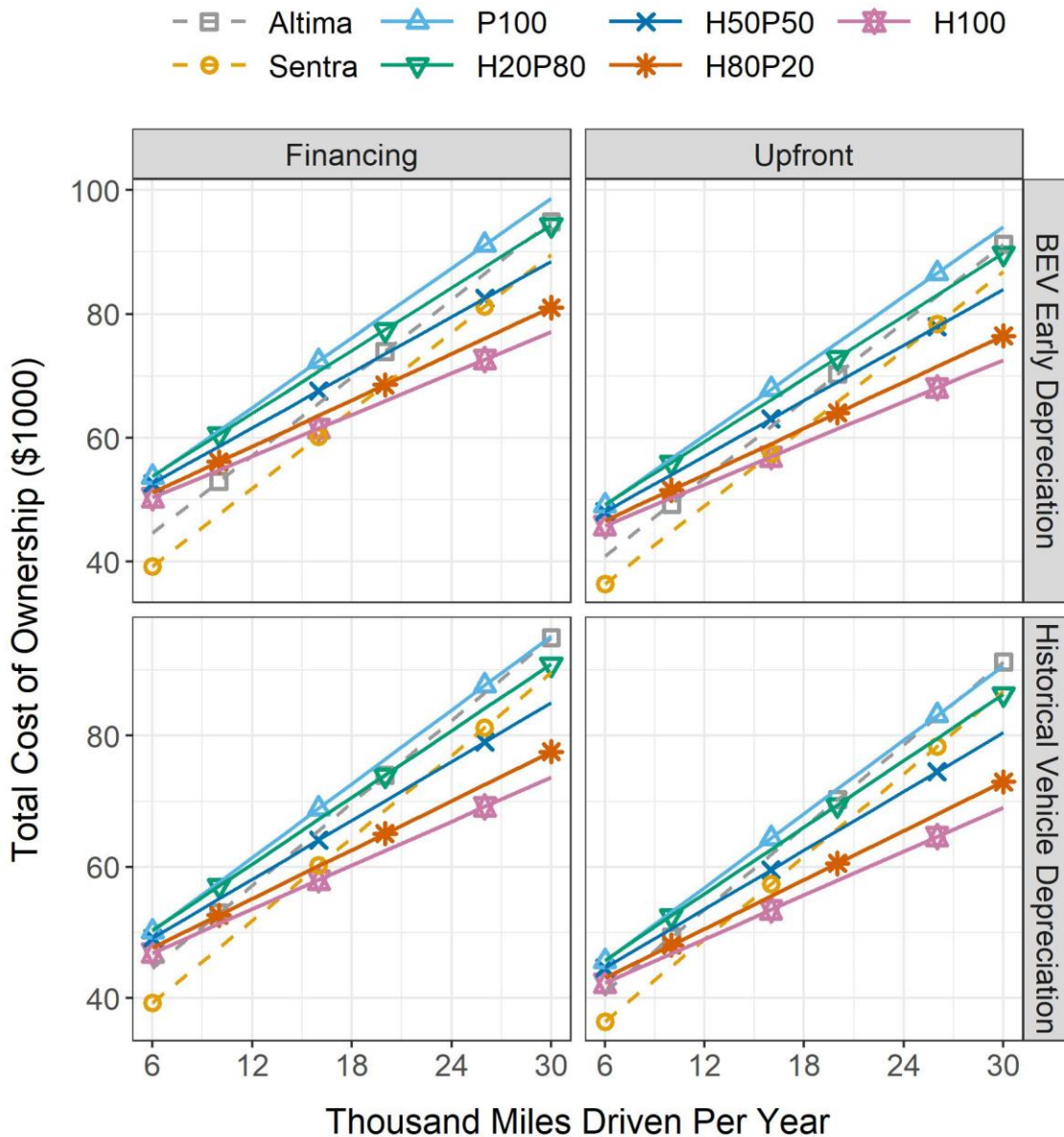


Figure C-3 Total costs of ownership based on varying annual mileage driven of the 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2019 to 2029. H stands for home charging and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

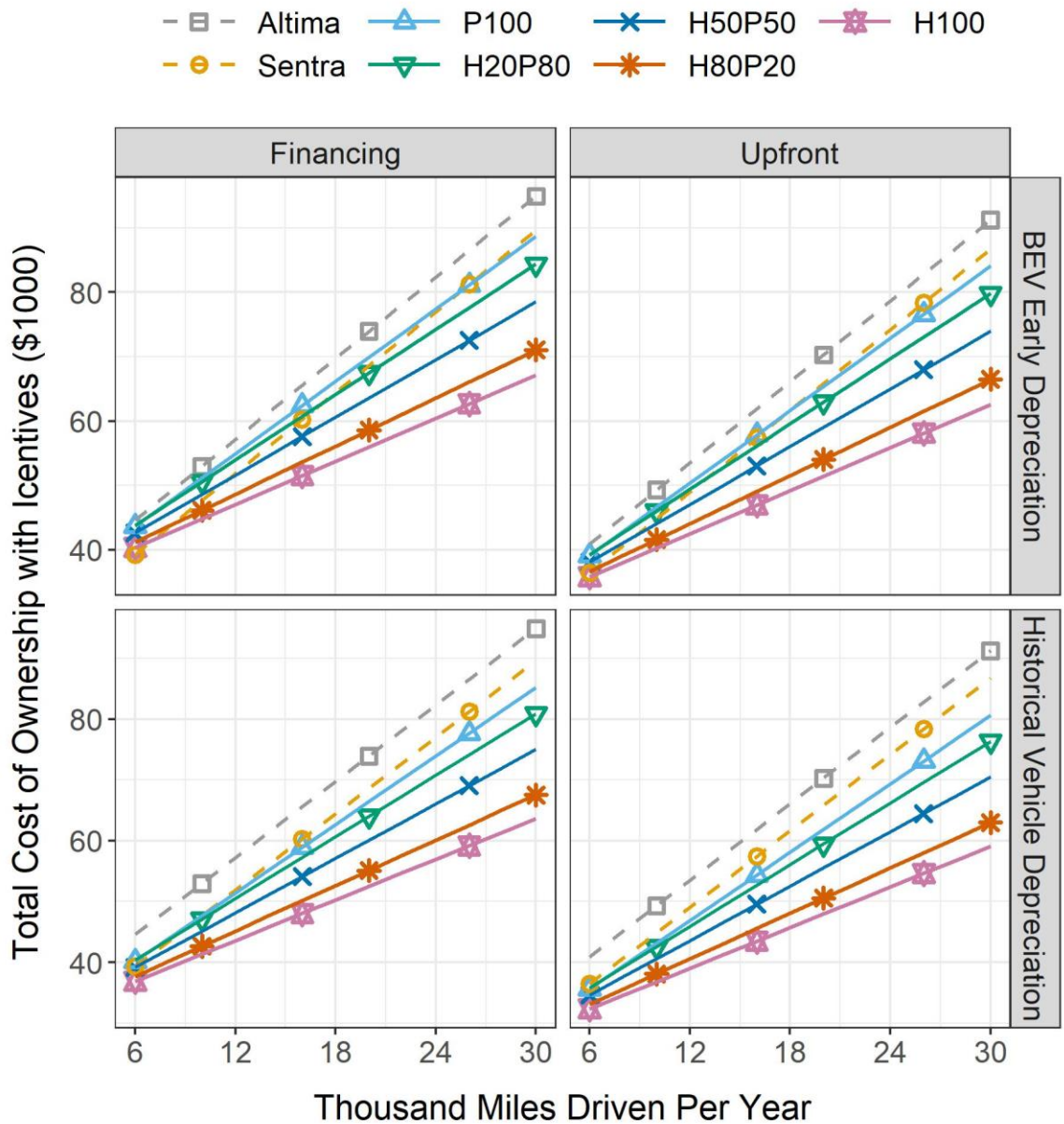


Figure C-4 Total costs of ownership with \$10,000 electric vehicle financial incentives based on varying annual mileage driven of the 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2019 to 2029. H stands for home charging and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

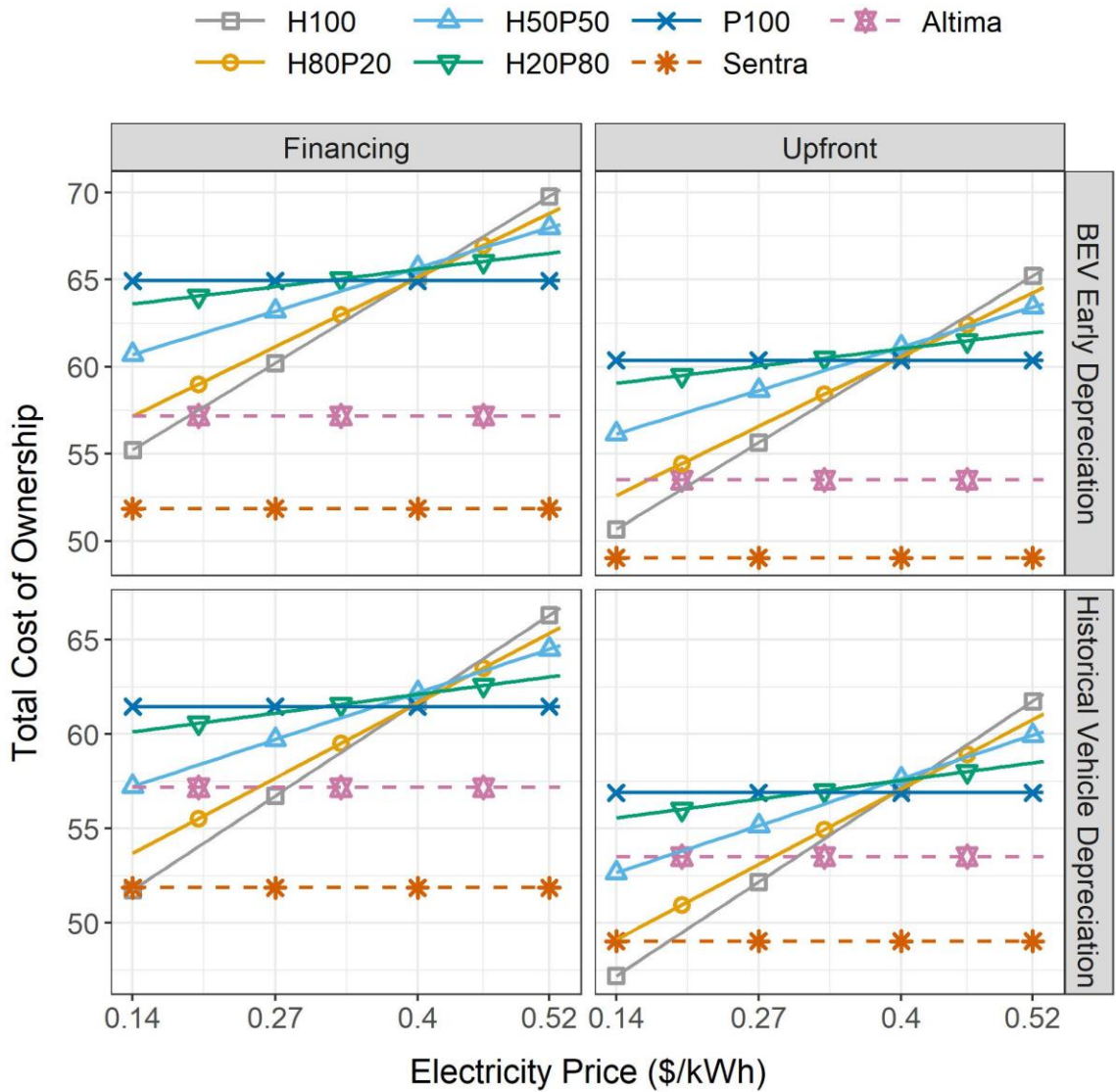


Figure C-5 Total costs of ownership (in \$1,000) based on varying electricity price of the 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2019 to 2029. H stands for home charging and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

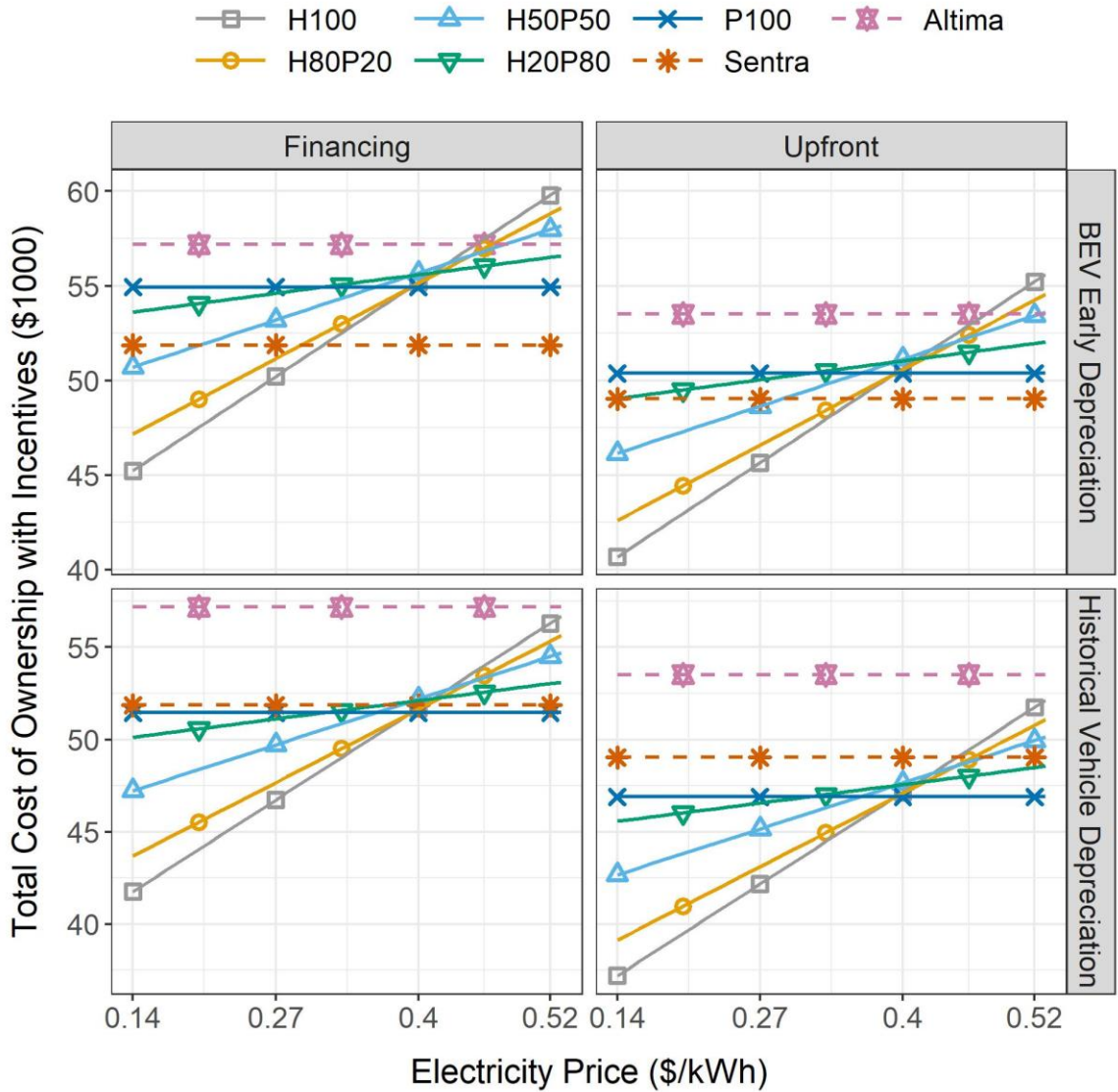


Figure C-6 Total costs of ownership with \$10,000 electric vehicle financial incentives based on varying electricity price of the 2019 Nissan Leaf (P100, H80P20, H50P50, H20P80, and P100 scenarios), Sentra, and Altima from 2019 to 2029. H stands for home charging and P stands for public charging. The number following P and H indicates the percentage of charging taking place at each location.

APPENDIX D LOS ANGELES CITY OWNED ELECTRIC VEHICLE CHARGERS

The map presented in Figure D-1 shows the public access electric vehicle chargers (PAEVCs) installed by the city of Los Angeles. The “BSL” locations are PAEVCs installed on light poles.

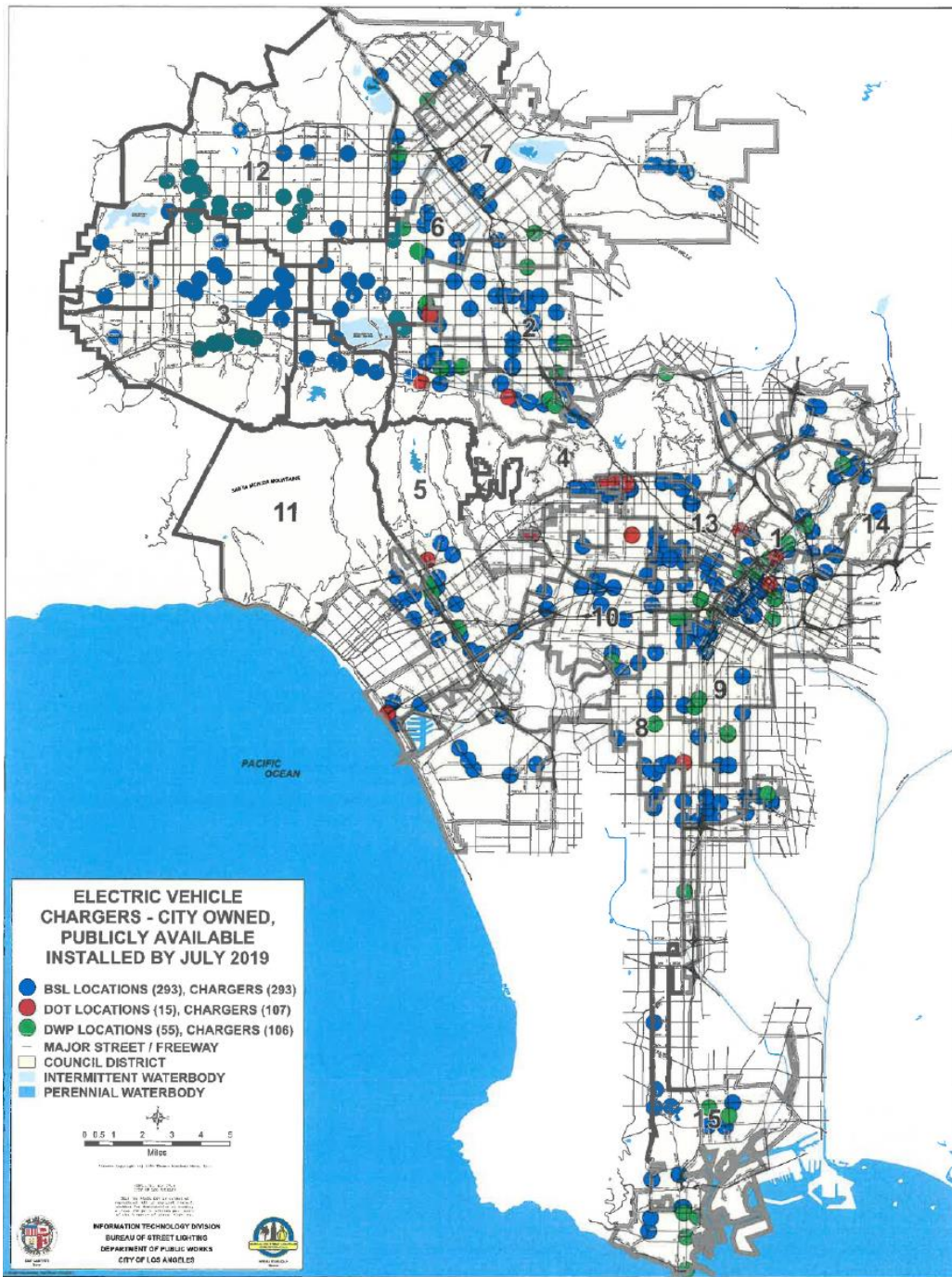


Figure D-1 Map of the public electric vehicle supply equipment owned by the city of Los Angeles. Adapted from the Los Angeles Bureau of Street Lighting (Los Angeles Bureau of Street Lighting, 2019a).