Who Receives Environmental Benefits from Driving Electric Vehicles?

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Abstract

Electrification of on-road transportation is a prominent strategy for emissions reduction. The distribution of environmental benefits from electric vehicles (EVs) largely depends on the regions to which EVs are driven. I develop a structural model of the U.S. auto market and use data from California to study household decisions with respect to both EV adoption across multiple vehicles and trip-specific vehicle selection. Combining the model-predicted probability of EV driving with simulated optimal travel routes, I construct a measure of the cumulative EV mileage at a highly granular geographic level, which captures the spatial distribution of environmental benefits. I show that higher-income communities receive more benefits. However, this disparity is less pronounced than that observed in EV adoption rate, suggesting a positive environmental spillover effect from EV driving. In the counterfactual policy experiments, I compare the effect of EV purchasing subsidies (both universal and targeted to low incomes) with charging station investments under various spatial deployment scenarios. The results suggest that investment in charging infrastructures generates more environmental benefits than purchase subsidy policies. Furthermore, place-based charging station policies can promote a more equitable distribution of these benefits.

Keywords: Electric Vehicles, Environmental Benefits, Environmental Justice, Demand Estimation, Spatial Spillover

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1 Introduction

Electrifying the transportation sector is a prominent strategy for reducing carbon emissions and urban pollution. As such, governments around the world have implemented various policies to incentivize the adoption of electric vehicles (EVs). During this electrification transition, equity issues in EV policies are becoming increasingly salient in public and academic discussions. Financial incentives disproportionately favor high-income households, as they account for the majority of EV purchases and receive the majority of EV subsidies. Compounding these purchase inequities, the environmental benefits of EVs may be unevenly distributed due to disparities in EV adoption and access to charging infrastructure.

This paper focuses on an important yet understudied aspect of EV adoption in the U.S.: the environmental benefits of driving EVs. Specifically, I study the distribution of emission reduction from EVs in different geographical areas and evaluate the efficiency and equity of EV policies.[1] Two observations motivate my analysis. First, the majority of US households that adopt an EV also tend to own at least one other internal combustion engine (ICE) vehicle (Davis, 2023).[2] This suggests that the household arranges a vehicle for various travel destinations, thereby determining where to drive the EV. Second, EV charging infrastructure is disproportionately deployed in relatively high-income and non-minority communities.[3] In turn, disproportionate access to charging infrastructure tends to localize EV use to regions with readily available facilities (Sheldon, 2022).[4] Given that pollutants are emitted primarily near roadways, the distribution of environmental benefits from EVs replacing ICE vehicles depends on both the locations where EVs are adopted and the regions to which these EVs are driven.

Therefore, I study both EV adoption and spatial EV driving behaviors in a unified framework.

[1]Existing studies predominantly emphasize EV adoption and the efficacy of policies to promote such adoption, leaving the spatial distribution of environmental benefits and equity concerns understudied (Rapson and Muehlegger, 2023; Sheldon, 2022). In this paper, the term efficiency of policies denotes their effectiveness when provided with the same financial resources, in advancing total EV adoption and environmental benefits. On the other hand, the equity of policies refers to the extent of even distribution of effects across various demographic groups.

[2]Allowing households to own multiple vehicles is crucial in my context because about 90% of U.S. households with EVs also own gasoline or diesel vehicles (Davis, 2023). In addition, 60% of U.S. households with EVs also owned non-electric SUVs, trucks, or minivans.

[3]For example, reports show that approximately 72% of public EV charging ports are located in counties within the top income quintile (Source: Autoweek), and the majority of accessible charging stations are in predominantly White areas (Source: The Washington Post). The media even refers to low-income and minority areas as EV charging "deserts." I will present more robust empirical evidence regarding this phenomenon for California in Section 2.3.

[4]I provide more survey and empirical evidence on the importance of public charging stations on EV usage in Appendix.

Specifically, I present and estimate a structural model of the U.S. auto market that incorporates rich demand-side features, consisting of a sequence of discrete choices with respect to household vehicle fleet, EV adoption, and trip-vehicle matching. I combine EV adoption and driving simulations from this model with optimal travel routes from Google Maps. This method enables me to construct a measure of cumulative EV mileage at a highly granular geographic level. With this novel measurement, I can produce the first analysis in the literature on the spatial distribution of environmental benefits and associate it with various EV policies.

For the empirical context of this study, I select California for two reasons. First, California accounts for approximately 37% of total EVs in the U.S.[5] Second, California has one of the cleanest electricity grids, which means that emissions from on-road transportation are a primary concern when evaluating the cleanliness of EVs relative to ICE (Holland et al., 2016). To estimate the demand model, I use data from two primary sources: (1) National Household Travel Surveys regarding vehicle fleets and geo-referenced travel diaries on trip-specific vehicle choices; and (2) aggregated market data on new vehicle sales in California from 2016 to 2019.

The model uses a nested discrete choice framework. Households first determine the number of vehicles to own and the fuel-type composition–either EVs or ICE–for their vehicle portfolio. Next, households choose vehicle makes and models (e.g., 2015 Nissan Leaf) conditional on the pre-determined fuel type. Finally, they maximize travel utility by determining which vehicle to drive for each trip based on trip-level attributes (e.g., travel distance, fuel cost, and the convenience of charging infrastructure associated with a trip's origin and destination). The model incorporates rich heterogeneity, which is crucial for quantifying distributional implications.

I quantify the distribution of environmental benefits across census tracts in California by combining the model-predicted EV driving probability with simulated optimal travel routes from Google Map API, using around 800,000 hypothetical trips. These benefits are directly associated with reducing on-road transportation emissions.[6] In particular, I focus on ambient air pollutants, which are concentrated in the vicinity of roadways.[7] Near-roadway emissions play a critical role

[5]Source: Alternative Fuel Data Center, https://afdc.energy.gov/data.

[6]On-road transportation emissions generally consist of tailpipe emissions derived from fuel combustion and emissions from tire wear between wheels and roads. These emissions are distinct from those derived from electric generation, as studied in Holland et al. (2016) and Holland et al. (2019).

[7]The local ambient air pollutants (also known as "criteria air pollutant"), including Ground-level Ozone (O3), Particulate Matter (PM), Carbon Monoxide (CO), Lead, Sulfur Dioxide (SO2), and Nitrogen Dioxide (NOx), have limited geographic range of influence.

in urban pollution, given the substantial number of households in the U.S. located near highways, particularly those in low-income and minority communities.[8] I find that environmental benefits are negatively correlated with low-income percentages in communities, which implies that higher-income communities receive more benefits. However, this disparity is less pronounced than that observed in EV adoption, measured by raw EV share of the total vehicle inventory. Specifically, a ten-percentage-point increase in the share of low-income households (i.e., those below twice the poverty line) is associated with a 0.23 standard deviation decrease in EV share, whereas it is only associated with a 0.08 standard deviation decrease in environmental benefits. The wealthiest 20% of zipcode receives about 25% of the environmental benefits but purchased 50% of the electric vehicles. This pattern indicates that after higher-income households adopt EVs, they produce positive environmental spillover effects for the low-income communities through which they drive.

To study the efficiency and equity of EV policies, I simulate the effects of two commonly used policies—EV purchasing subsidies policies (e.g., federal tax credits and local EV rebate programs) and investments in charging infrastructure. For the former, I consider both a universal subsidy and a subsidy targeted at low-income households; for the latter, I examine various scenarios for the spatial deployment of charging stations. The estimated model reveals that the utility derived from vehicle usage (like EV charging convenience, fuel cost, driving experience, etc.) has a greater impact on lifetime consumer surplus than vehicle attributes (such as price, horsepower, weight, etc.). Therefore, access to charging infrastructure plays a pivotal role in explaining EV driving and, in turn, the desire to adopt EVs. These findings suggest that, overall, range anxiety and inadequate charging infrastructure are greater impediments to EV adoption than elevated purchase costs.

The counterfactual exercises yield the following results. First, I find that EV policies are more effective if they target middle-income households who already own vehicles. This is be-

Scientific research has shown that most pollutants decay to near-background levels within a few hundred meters – about 500-600 feet (WHO, 2021). In contrast, the global pollutant refers to the Greenhouse Gas (GHG) emissions, which are accumulated in the atmosphere and generate issues of climate change. See the EPA synopsis on Near Roadway Pollution, Criteria Air Pollutants, and Greenhouse Gas Emissions for more information.

[8]EPA reports over 45 million people in the U.S. living, working, or attending school within 300 feet of a roadway, airport, and railroad. Source: EPA. And low-income and minority communities face higher health risks due to emissions from nearby roadways. Source: U.S. Department of Transportation (DOT) and abcNews.

cause the majority of households likely to adopt an EV either already own a car and are contemplating purchasing a second one, or own two cars and are considering replacing one with an electric model. Second, when considering EV adoption as a policy objective, the targeted subsidy policy is more equitable, while less efficient. It substantially increases the adoption rate among low-income households with a minor decrease in overall adoption. Conversely, charging infrastructure investment can increase the EV adoption rate by approximately 50%, while the majority of new adoptions are attributed to high-income households. Third, when considering environmental benefits, charging infrastructure investment is more efficient and could also be more equitable under specific deployment scenarios. It is approximately three times more effective than current policies and purchasing subsidy policies in enhancing environmental benefits. Furthermore, place-based charging station policies aimed at disadvantaged communities (DAC) are more equitable compared to those of the baseline. Specifically, it reduces the correlation between environmental benefits and income by approximately 29%.

This paper makes three major contributions. First, it adds to the growing literature on EV economics and EV incentive policies.[9] One strand of research focuses on the demand side of the market, aiming to understand household adoption and usage behaviors, which includes substitution patterns between EVs and ICE (Muehlegger and Rapson, 2023; Xing, Leard, and Li, 2021); the extent to which EVs are used (Burlig et al., 2021; Davis, 2019; Sinyashin, 2021); and the impacts of energy prices (Bushnell, Muehlegger, and Rapson, 2022), consumer acceptance (Gillingham et al., 2023), and subsidy policies (Fournel, 2023; Muehlegger and Rapson, 2022) on EV adoption decisions. Another strand of studies focuses on the supply side, and employs industrial organization models to analyze automakers' behaviors by endogenizing firms' decisions on product attributes (Barwick, Kwon, and Li, 2022), carbon credit trading (Kwon, 2022), product entry (Armitage and Pinter, 2021), charging network compatibility (Li et al., 2019), and responses to policy dynamics (Hu, Yin, and Zhao, 2023; Lohawala, 2023).[10] My model extends the demand-side analysis on two important margins. First, I allow households to jointly

[9]See Selod and Soumahoro (2020) and Rapson and Muehlegger (2023) for a comprehensive review of the literature on electric vehicles and the key facts related to the electrification transition.

[10]Most studies consider equilibrium in the EV market. The dichotomy mentioned here is based on the direction in which the paper extends the baseline model. Meanwhile, there is also an important stream of studies that focus on the network effect in the EV market (Li et al., 2017; Liu, 2022; Springel, 2021)

choose multiple vehicles, resulting in more realistic EV adoption patterns. Compared to existing discrete choice vehicle demand models, my approach accounts for interaction effects within the vehicle fleet owned by a household. This aspect is essential for understanding EV demand, given that the majority of households adopting EVs own multiple vehicles. The model shows that the impact of purchase subsidies varies non-linearly among different income groups, with middle-income households being the most effectively targeted. Second, I consider geographic locations to which EVs are driven; doing so substantially enhances the explanatory power of the current model to explain the spatial distribution of EV adoption and usage. In terms of EV policy,[11] I study both the efficiency and equity effects of different EV policies. My approach documents the uneven deployment of EV charging infrastructure and analyzes its distributional implications. I also incorporate measures of consumer surplus and environmental benefits to enhance welfare consideration. Compared to pioneering works by Holland et al. (2016, 2019) that capture the environmental benefits of EVs, this paper delves deeper into emissions from on-road transportation rather than from electricity generation. On-road transportation emissions have been well documented to generate adverse health consequences in populations located near roadways (Anderson, 2020; Currie and Walker, 2011; Knittel, Miller, and Sanders, 2016).

Second, my paper relates to recent advances in the literature that explore the welfare effects of urban transportation policies and infrastructure investments. Typically, these studies account for spatial dimensions in residence and workplace choice as well as commuting flow.[12] Nevertheless, to the best of my knowledge, few papers have considered the spatial distribution of environmental outcomes. One of my contributions is incorporating the spatial flow of emissions, which allows me to analyze the distribution of environmental outcomes. In terms of modeling choice, I do not endogenize household sorting as equilibrium objectives. This simplification is justifiable in my context due to the low EV penetration rate in the U.S. (less than 3% in 2022) and thus it likely has a limited impact on equilibrium sorting. Therefore, my model relies less on tractable but restrictive gravity-type equations and allows for richer heterogeneity in preferences, which is important for analyzing the equity of policies. In this spirit, my methodology aligns more closely

[11]See Holland, Mansur, and Yates (2021), Davis and Sallee (2020), Li et al. (2022), Gillingham, Ovaere, and Weber (2021) and Linn (2022) for more discussion of EV policies and interactions between EV policies and other environmental regulations.

[12]See Redding and Turner (2015), Redding and Rossi-Hansberg (2017), and Diamond and Gaubert (2022) for reviews on recent advances in the urban transportation literature and the application of quantitative spatial equilibrium (QSE) models.

with that of Barwick et al. (2021). Their paper studies the equilibrium impact of transportation policies in Beijing by developing a sequential discrete choice model with choices of travel mode and residence location. They first estimate the travel mode problem and then incorporate the inclusive value of travel as an attribute of housing. In comparison, I incorporate the inclusive value of travel as an attribute of the vehicle portfolio.[13]

At the same time, my work joins the trend of using transportation big data in economic analysis (Selod and Soumahoro, 2020). Existing studies use optimal-routing software APIs to study the effects of traffic speed (Akbar et al., 2023a,b; Couture, Duranton, and Turner, 2018), ride-sharing (Gorback, 2020), congestion charge and pricing (Herzog, 2021; Kreindler, 2023), public transit infrastructure (Suri, 2022), city-center accessibility (Conwell, Eckert, and Mobarak, 2023), and urban sorting (Barwick et al., 2021). The majority of these papers use an optimal-routing algorithm to calculate the travel time and monetary cost of counterfactual trips and then use them for model estimations. In comparison, my methodological innovation is to use this algorithm to simulate the spatial diffusion of pollution and environmental benefits.

Finally, I contribute to the environmental justice (EJ) literature.[14] Empirical research has established that low-income and minority communities are disproportionately exposed to air pollution (Colmer et al., 2020; Tessum et al., 2021). Recent studies have explored the EJ implications of environmental policies and new technologies, including the Clean Air Act (Currie, Voorheis, and Walker, 2023), energy taxes (Borenstein and Davis, 2016; Pizer and Sexton, 2019), renewable energy policies (Reguant, 2019), carbon prices (Shang, 2023), and solar panel adoption (Dauwalter and Harris, 2023). In comparison, this paper is one of the few studies that analyzes EJ with respect to EV policies.

The rest of the paper is organized as follows. In Section 2, I describe the empirical context and data, and present key stylized facts that motivate and ground the subsequent structural analysis. In Section 3, I introduce my structural model and estimation strategy. After I present my estimation results and model analysis in Section 4, I then use Section 5 to study the spatial

[13]This strand of literature is an application of the empirical industrial organization method in urban transportation economics. Another recent example that studies the choice of transport mode and location of residence using a discrete choice model is Akbar (2022).

[14]See Banzhaf, Ma, and Timmins (2019a), Banzhaf, Ma, and Timmins (2019b), Bento (2013), Hsiang, Oliva, and Walker (2019), and Robinson, Hammitt, and Zeckhauser (2016) for a comprehensive review of causes, consequences, and police efforts with respect to EJ issues.

distribution of environmental benefits and Section 6 to conduct the counterfactual exercise on various policy scenarios. I conclude this paper with Section 7.

2 Policy Background and Data Description

The empirical context of this paper focuses on the state of California in the United States. In this section, I first discuss the U.S. EV market and policies, the scientific knowledge concerning on-road transportation emissions, and the institutional background related to urban segregation and inequality. I then describe the main datasets used. Finally, I present the set of stylized facts that motivate and ground the subsequent structural analysis.

2.1 Policy Background

The U.S. electric vehicle market. In this paper, electric vehicles (EVs) encompass both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). The alternative vehicle category examined is internal combustion engine vehicles (ICEs). By 2022, electric vehicle sales represented 9% of US passenger car sales and 23% in California. By the end of 2022, light-duty EV registrations in the US were over 3 million, with California accounting for 40% of that total.[15,16] In addition to the increase in total sales, the driving range and number of products of EV also have experienced dramatic growth. Since 2011, the median driving range of EVs has multiplied by 3.5 times. It was 73 miles on a single charge in 2011 and rose to 247 miles by 2022. During this period, the variety of products expanded from fewer than five to over 70.[17]

Existing studies have summarized that the majority of EV charging takes place at home, with public charging stations contributing to less than 20% of the total charging events.[18] While most charging can occur at home, the limited number of public charging stations remains a barrier to broader EV adoption because (1) many US residents live in multi-family units without access to a garage or plug, and (2) public charging stations in densely populated areas face extremely

[15] Source: AFDC and Atlas.

[16] Nevertheless, the EV penetration rate in the US remains comparatively low. The market share of EVs in the US still lags far behind Norway (over 80%), China (30.5%), and Europe (19.7%); furthermore, the overall share of EV registrations is just under 2% of the total vehicle population.

[17] Souce: EPA and Bloomberg.

[18] Source: Idaho National Laboratory.

high demand and are often overused Sheldon (2022). A recent survey conducted by the Forbes Wheel suggests that 30% of respondents depend on public charging networks, and range anxiety continues to be prevalent among EV owners.

Government EV Policies. The U.S. government has implemented various policies to incentivize the adoption of EVs. One category of policies aims to address barriers that deter households from transitioning from ICE to EV (demand-side policies). These include reducing the upfront costs of purchasing an EV and enhancing access to charging networks. [19]

One primary policy approach is EV purchase incentives. Both the federal and state governments offer tax credits or vehicle purchase rebates to subsidize and thus lower the up-front cost of an EV. Federal subsidies can go up to $7,500 for each new EV, but these begin to phase out once an automaker sells 200,000 EVs or accrue over $1.5 billion in tax credits.[20] At the state level, California boasts the most substantial program in the U.S., the Clean Vehicle Rebate Project (CVRP). It grants new EV purchasers rebates up to $4,500 based on income and vehicle classification. Importantly, to foster environmental justice and ensure a more equitable transition to transportation electrification, there has been a rise in subsidies specifically aimed at low-income and minority groups. For example, the Enhanced Fleet Modernization Program (EFMP) provides subsidies to low- and middle-income households within disadvantaged communities (DAC) to incentivize them to scrap older, dirtier vehicles for newer, cleaner, and more fuel efficient ones (Muehlegger and Rapson, 2022).[21]

Another policy approach is charging infrastructure incentives. At the federal level, the 2021 Bipartisan Infrastructure Law (BIL) designates $7.5 billion in subsidies for the development of a nationwide fast-charging infrastructure along major interstate routes. The 2022 Inflation Reduction Act (IRA) would further empower a basket of EV-related programs to strategically

[19] Another policy category targets the supply side, incentivizing automakers to enter the EV market, expand EV varieties, and enhance vehicle features like battery capacity and range. Notable examples of such policies include the Zero-Emission-Vehicle (ZEV) mandate and the Corporate Average Fuel Economy (CAFE) standards. This paper will primarily discuss the demand-side policies to examine the effects of policies on household adoption and travel behaviors. See Rapson and Muehlegger (2023) and *Electricity Laws and Incentives in Federal* summarized by AFDC for more a comprehensive review of the EV policies.

[20] The Inflation Reduction Act of 2022 modified the rules for this credit but introduced additional restrictions related to battery capacity, weight, and assembly location. Check IRS for detailed information.

[21] Disadvantaged communities in California are those most impacted by a combination of economic, health, and environmental challenges. These challenges encompass factors like poverty, high unemployment, air and water contamination, hazardous waste presence, as well as elevated rates of asthma and heart disease. These factors are compiled into a CalEnviroScreen (or CES) score. A community is designated as a disadvantaged community if its CES score is in the top 25th percentile. Source: CA OEHHA.

deploy EV charging infrastructure.[22] At the state level, California has launched a $30 million incentive to increase fast electric vehicle (EV) charging stations to target counties.[23]

On-road Transportation and Air Pollution. On-road transportation is the primary source of greenhouse gas emissions and local pollution, leading to negative health impacts to near-roadway residents.[24] Most local pollution has a limited geographic range of influence. Scientific research shows that most pollutants decay to near-background levels within a few hundred meters – about 500-600 feet (WHO, 2021).[25] Previous medical and economic studies have attested that local pollution from on-road transportation is directly associated with adverse health consequences, including asthma, cardiovascular diseases, premature death, and others (Anderson, 2020; Currie and Walker, 2011; Knittel, Miller, and Sanders, 2016).[26]

This paper focuses on the emission of local pollutants from on-road transportation. These pollutants, in general, consist of tailpipe emissions derived from fuel combustion and emissions from tire wear between the wheel and road. On the contrary, another major source of emissions associated with electric vehicles is the emissions from electricity generation, particularly when derived from fossil fuel combustion, such as coal. Engineering studies generally concur that in-use emissions from EVs are negligible. Even when accounting for power plant emissions and battery manufacturing, EVs typically generate fewer emissions over their lifetime compared to their ICE counterparts.[27] However, this difference can vary significantly across states, depending largely on the cleanliness and capacity of the local electricity grid (Holland et al., 2016, 2019). Therefore, an advantage of studying California as a context is its remarkably clean electricity grid. Specifically, coal comprises only 3% of its total power mix (compared to the national average of 19.5%), while renewable energy accounts for 33.6% (versus the national average of 21.5%).[28] This positions in-use emissions as the primary consideration when evaluating the

[22]Source: The U.S. Department of Transportation (DOT).
[23]Source: Golden State Priority Project.
[24]For example, gasoline and diesel fuel consumption account for 30% of total U.S. energy-related CO2 emissions in 2022. Meanwhile, the transportation sector contributes approximately 45% of nitrogen oxides (NOx) and 10% of volatile organic compounds (VOCs) and particulate matter (PM) in the U.S. In California, the transportation sector is the largest contributor to greenhouse gas emissions, making up over 40% of the total. Source: U.S. Energy Information Administration (EIA), U.S. Environmental Protection Agency (EPA), and California Air Resources Board.
[25]For example, Liu, Chen, and Xue (2019) shows that about 80% of NOx would be reduced at 300 meters from the road based on a metadata-based exponential decay rate.
[26]Please refer to the EPA synopsis regarding further medical research related to Near Roadway Pollution.
[27]Source EPA, Electric Vehicle Myths.
[28]Source: California energy commission and EIA.

environmental benefits of EV adoption.

2.2 Data Description

My empirical analysis and model estimation use a comprehensive dataset with several main elements.

Household Vehicle Fleet and Travel Behaviors. First, I use the 2017 National Household Travel Survey (NHTS) and its California add-on. The data offers detailed information on household income, demographics, automobile ownership, and vehicle miles traveled. Additionally, it features travel diaries that document every trip made during a survey day. This survey encompasses records from a total of 26,095 households and 55,793 participants in California. I also have access to confidential spatial data from the Transportation Secure Data Center (TSDC). This data includes the latitude and longitude of participants, as well as their travel routes, allowing for geocoding of the commute paths.

New Vehicle Sales and Attributes. The second dataset, purchased from IHS Automotive (formerly R.L.Polk), consists of quarterly new vehicle sales data, covering 25 urban Metropolitan Statistical Areas (MSA) in California from 2016 to 2019. I define a vehicle model by its make, model, model year, fuel type, and body style (e.g., 2018 Ford Fusion SE Gasoline Sedan). The data includes sales counts for 524 such vehicle models. Price is the Manufacturer's suggested retail price (MSRP). I calculate the discounted price for EVs by deducting the federal and state purchase incentives from the MSRP specific to each MSA. Vehicle attributes including weight, size, height, horsepower, miles per gallon (MPG), engine displacement, battery capacity, and others are compiled from Ward Intelligence and EPA. Manufacturer Incentives information is aquired from the Automotive News Market Data Book. I divide vehicles into eight segments (Convertible, Coupe, Hatchback, Pickups, Sedan, Sport Utility, Station Wagon, and Van) based on body styles and market orientations.

EV charging networks. Data related to the deployment of the EV charging network, which includes details like opening date, location, charging speed, and standard, is also sourced from the AFDC.[29] I aggregate charging station information to calculate the number of charging

[29] I have access to unpublished screenshots of this data, allowing for a more accurate historical perspective on the evolution of charging

ports in each zip code.

Commuting Flows. I use the 2012-16 Census Transportation Planning Package (CTPP) data, which provides commuter flows between residence and work census tracts. This data is aggregated from the American Community Survey (ACS) microdata for the corresponding years. I use the CTPP data that breaks down commuters by household income brackets.[30] I define a trip in the commuting matrix as the combination of origin and destination census tract pairs (OD pairs) and assume the coordinates for each OD pair to be the geographical centroids of the corresponding census tracts. I simulate counterfactual routes for each trip using an optimal-routing software API, following the methods developed by Akbar et al. (2023a). The detailed web-scraped algorithm is described in the Appendix. [31]

Air Pollution Data. To examine whether the environmental benefits measurements generated in this paper capture pollution reduction, I also leverage air quality data from the US Environmental Protection Agency's Air Quality Service data. I aggregate the monitor-level data to census tract and zip code-level following Alexander and Schwandt (2022). The key pollutant I consider includes: Nitrogen dioxide (NO_2), Particulate matters (PMx), Carbon monoxide (CO), and Sulfur dioxide (SO_2).

Auxiliary Data. I also combine a set of auxiliary data. The light-duty vehicle registration data over time at the zip-code level in California is compiled from the Zero Emission Vehicle and Infrastructure Statistics of the California Energy Commission; the distribution of household demographics is drawn from the 2016 to 2019 American Community Survey. The socio-economic variables, along with pollution and health-related variables for each census tract in California, are derived from the Environmental Justice Screening and Mapping Tool (EJScreen); The retailed gasoline price data for each MSA is compiled from the AAA Gas Price Archive. The electricity price data is from the CA Public Utilities Commission.

networks.

[30] Commuters are broken down into eight income groups: (1) under \$15,000; (2) \$15,000-35,000; (3) \$35,000-50,000; (4) \$50,000-75,000; (5) \$75,000 - 100,000; (6) \$100,000 - 150,000; (7) over \$150,000.

[31] To save computational time, I retain OD-pairs with more than four trip counts, following the rule of thumb in transportation literature.

2.3 Motivating Facts

In this section, I present three pieces of stylized facts in data that motivate and ground the subsequent structural analysis: (1) Inequality in EV adoption and EV charging deployment; (2) EV households hold more than one vehicle; (3) Low-income areas are exposed to trips originating from high-income areas.

Facts 1: Inequality in EV adoption and EV charging infrastructure deployment. In the process of EV adoption, two inequality issues merge. First, high-income households account for the majority share of EV purchases (Jacqz and Johnston, 2023; Rapson and Muehlegger, 2023). The upper panel of Figure 1 shows that the EV share, measured as the number of EVs per 1,000 registered vehicles, has increased over time, with a notably faster rate in higher-income communities (Sheldon, 2022). Potential reasons include the higher up-front cost of EVs compared to ICE vehicles, even when accounting for purchase incentives, and the greater acceptance of electric vehicles and energy efficiency technologies among higher-income households. These facts imply the importance of modeling heterogeneity in both preference and price elasticity.

Second, charging infrastructures are disproportionately deployed in relatively high-income and non-minority communities. The lower panel of Figure 1 shows that the log number of public Electric Vehicle Supply Equipment (EVSE) is negatively correlated with the percentage of low-income households in the zip code level. It suggests that the number of charging infrastructure is higher in high-income communities. This pattern of uneven deployment of charging infrastructure is also recognized by the media. For example, reports show that approximately 72% of public EV charging ports are located in counties within the top income quintile, and the majority of accessible charging stations are in predominantly White areas. The media calls low-income and minority areas EV charging "deserts".[32] Due to disparities in charging infrastructure deployment and concerns about EV range anxiety, EV use is often concentrated in areas with better charging accessibility (Sheldon, 2022). Consequently, the environmental advantages of EV adoption might predominantly benefit relatively high-income and majority-white communities.

Facts 2: EV households tend to hold more than one vehicle. The second stylized

[32]Source: Autoweek and The Washington Post.

fact delves into the relationship between EV adoption and the composition of household vehicle fleets using microdata from the 2017 NHTS. I plot the distribution of the number of vehicles in the household and separate the results by whether the household owns an EV. Figure 2 shows the results. It is evident that households with EVs generally own multiple vehicles and are less inclined to buy EVs as their primary and sole vehicle. Approximately 90% of U.S. households with an EV also have gasoline or diesel vehicles. This finding is consistent with Davis (2023), which also indicates that 60% of U.S. households with an EV also own a non-electric SUV, truck, or minivan. This fact informs an important modeling choice: the vehicle portfolio is an essential component to consider, as EV adoption often intertwines with other vehicle purchase decisions.

Facts 3: Lower-income areas are exposed to trips originating from higher-income areas. The third fact examines the connectivity between regions of varying income levels through commuting flows. Using route-level data from CTPP, I plot the non-parametric relationship between the average poverty rate at the Origin and Destination. Figure 3 plots the relationship for both routes with destination to DAC census tract and non-DAC census tract. Both lines have slopes that are less steep than the 45-degree line, with the non-DAC line being notably flatter. This suggests that high- and low-income regions are intricately connected, as a significant number of commuters from high-income areas travel to low-income regions. As a result, EV adoption by high-income households has the potential to yield positive environmental externalities for low-income areas.

3 Empirical Model

3.1 Model Structure

I develop a structural model of the U.S. auto market that incorporates rich demand-side features, following the sequential discrete choice framework of Barwick et al. (2021). The model consists of a sequence of discrete choices on vehicle portfolio, vehicle model, and trip-vehicle matching.

Appendix Figure A.2 presents the nested structure of the demand model, which consists of three separate problems: **(1) vehicle portfolio problem; (2) vehicle purchase problem;**

(3) vehicle usage problem. In the initial stage, households determine the number of vehicles to own and the fuel-type composition, choosing between EVs and internal combustion engine vehicles (ICE), for their vehicle fleet (vehicle portfolio). Next, households choose vehicle models conditional on the pre-determined fuel type on each choice occasion. Finally, given the alternative vehicles owned and trip pools, they maximize utility from travel by deciding which vehicle to drive for each trip based on trip-level attributes.

The model is solved in a backward fashion. Following Goldberg (1995), I calculate the Inclusive Value of Usage (IVU) from the vehicle usage problems and the Inclusive Value of a Vehicle (IVV) from the vehicle purchase problems. The expected utility, derived from vehicle attributes and usage, is then incorporated into the portfolio problem. The utility associated with a vehicle portfolio alternative is influenced by both IVU and IVV. This presents a trade-off between the relative price (or cost) and convenience (or benefit) among portfolio choices.[33]

Notation. Before proceeding to each segment of the model, I define three key notations that run through the entire section. $\mathcal{S}_i$ denotes the vehicle portfolio of household i. The vehicle portfolio is defined as a combination of the total number of vehicles and the classification of each vehicle as either EV or ICE. For example, $\mathcal{S}_i = \{2; EV, ICE\}$ represents owning two vehicles with one EV and one ICE, and $\mathcal{S}_i = \{3; EV, ICE, ICE\}$ means owning three vehicles with one EV and two ICEs. In this paper, I do not distinguish the order of vehicles. $\mathbb{S}_i$ denotes the choice set of vehicle portfolios. I consider seven potential vehicle portfolio alternatives, as they account for over 90% of the samples in the NHTS 2017 data,

$$\mathbb{S}_i = \Big\{\{\emptyset\}, \{EV\}, \{ICE\}, \{EV, ICE\}, \{ICE, ICE\}, \\ \{EV, ICE, ICE\}, \{ICE, ICE, ICE\}\Big\}$$

S_i denote the set of vehicle models owned by the household i given the vehicle portfolio, $S_i \in \mathcal{S}_i$. For example, given $\mathcal{S}_i = \{EV, ICE\}$, one possible case is $S_i = \{\text{2016 Nissan Leaf}, \text{2008 Toyota Camry}\}$. The choice $\{\emptyset\}$ is assumed to be the outside option. The distinction between $\mathcal{S}_i$ and S_i is central to me as it allows for rich substitution patterns and demographic heterogeneity in vehicle de-

[33] For instance, the value of purchasing an EV as a secondary vehicle is influenced by both the attributes of the EV (e.g., price and battery) and the value of expanding the set of vehicle choices for trips.

mand and usage choices, all while maintaining computational tractability. I discuss more about these issues in the Appendix.

3.2 Vehicle Usage Problem

Setting. Utility-maximizing households select a vehicle from their vehicle portfolio for each trip, based on trip-vehicle variables. The trade-off is on the relative convenience, fuel cost, and idiosyncratic tastes across alternatives. Household i's utility from trip d using vehicle v is specified as:

$$\begin{aligned}\max_{v \in S_i} U_{idv} = \gamma_{0v} + \sum_{l \in \{O,D\}} C_{idv}\big(\Psi^l_{iv}, Nstation^l_{id}, Purpose_{id}\big) + \gamma_{1v} \cdot Distance_{id} \\ + \gamma_{2v} \cdot Purpose_{id} + FuelCost_{idv} + X_{idv} \cdot \mathbf{\Gamma_v} + \varepsilon_{idv}\end{aligned} \tag{1}$$

And

$$\gamma_{kv} = \bar{\gamma_k} + \gamma_k \cdot 1_v(EV)\,, \quad \mathbf{\Gamma_v} = \bar{\mathbf{\Gamma}} + \mathbf{\Gamma} \cdot 1_v(EV)$$

where S_i is the set of vehicles owned by the household i. I group all choices that aren't related to driving as the outside option (such as walking, biking, and public transit). The variable $Distance_{id}$ is the travel distance of the trip d, and $Purpose_{id}$ is an indicator variable for commuting to work. The vehicle-specific fuel cost, $FuelCost_{idv}$, is calculated as follow:

$$\begin{aligned}FuelCost_{idv} = \gamma_3 \cdot Distance_{id} \times GPM_v \times GasPrice_i \\ +\gamma_4 \cdot Distance_{id} \times ElectricityRate_i \times 1_v(EV)\end{aligned}$$

where GPM, an abbreviation for gallon per mile, gauges the fuel economy of the vehicle. $GasPrice_i$ and $ElectricityRate_i$ are the retailed gasoline price and electricity rate at home zip code. The vector X_{idv} includes household-trip-vehicle-specific controls (such as the interaction between demographics variables and vehicle attributes).[34] $1_v(EV)$ denotes whether vehicle v is an EV. Therefore, coefficients γ_{kv} and $\mathbf{\Gamma_v}$ capture the relative utility among the outside option,

[34]Note that this model is based on the conditional Logit choice problem. Therefore, any terms without household-trip-vehicle-specific variations (such as the level term of travel distance and income) do not enter the decision problem.

driving an ICE, driving an EV, and their interactions with both household demographics and trip-specific variables.

The function $C_{idv}(\cdot)$ measures the relative convenience of EV, which depends on the $Purpose_{id}$ and the accessibility to charging infrastructure at both the origin and destination of the trip. I measure the accessibility with the log of the total number of charging ports ($Nstation_{id}$) within the zip code. I assume the following functional forms. The convenience function is parameterized as the interaction polynomial of $Nstation$ and $Purpose$:

$$C_{idv}(\,\cdot\,) = \Psi^l_{1,iv}\,Nstation^l_{id} + \Psi^l_{2,iv}Nstation^l_{id} \times Purpose_{id}$$

This specification reflects the idea that the significance of charging facilities can vary according to travel purposes. To model households' idiosyncratic tastes, I allow for both observed heterogeneity and random coefficients in the parameter Ψ^l_{iv},

$$\Psi^l_{iv} = (\bar{\psi}^l + \sum_{r=1}^{R} \boldsymbol{z}_{ir}\psi^l_r \;+\; v^l_i\,\psi^u) \cdot 1_v(EV)$$

where z_{ir} is a vector of household demographics; v^l_i is the unobserved terms that follow a standard normal distribution. $\bar{\psi}^l$ is the mean value of the parameter. ψ^l_r and ψ^u are observed and unobserved heterogeneity coefficients, respectively. ε_{idv} is assumed to be the i.i.d. error term with the Type-one extreme value (T1EV) distribution.

Inclusive Value. The ex-ante expected value of trip (before the realization of trip-specific shocks) for household i and trip d with the given set of vehicles owned S_i is:

$$I_{id}(S_i) = E_{\epsilon_{idv}}\Big(\max_{v\in S_i} U_{idv}\Big)$$

The expectation is taking over ε_{idv}. The estimated model also allows me to simulate the expected value of trips for any counterfactual set of vehicles and vehicle portfolio scenarios. Denote $\widetilde{S}_i$ as any hypothetical vehicle set. Therefore, $\widetilde{S}_i \in \mathcal{S}_i$ represents the observed vehicle set in data, while $\widetilde{S}_i \notin \mathcal{S}_i$ represents the counterfactual vehicle sets. The trip value for the counterfactual vehicles set is,

$$I_{id}(\widetilde{S}_i) = E_{\epsilon_{idv}}\Big(\max_{v\in\widetilde{S}_i} U_{idv}\Big)$$

The inclusive value of the usage of a specific vehicle portfolio $\mathcal{S}$, $IVU_i(\mathcal{S}_i)$, is calculated as the weighted average of the expected value of trip across (1) counterfactual scenarios of vehicles set; and (2) all trips:

$$IVU_i(\mathcal{S}_i) = \begin{cases} \mathbb{E}_{D(d)}\Big(I_{id}(S_i)\Big) & \text{if } S_i \in \mathcal{S}_i \\ \mathbb{E}_{D(d)}\mathbb{E}_{G(\widetilde{S}_i|\widetilde{\mathcal{S}}_i)}\Big(I_{id}(\widetilde{S}_i)\Big) & \text{if } \widetilde{S}_i \notin \mathcal{S}_i \end{cases}$$

where $D_i(d)$ is a set of trips for all members of the household i. I assign each trip the same weight in the baseline and consider the purpose-specific and gender-specific weight in the robustness.

$G(\widetilde{S}_i|\widetilde{\mathcal{S}}_i)$ is the empirical distribution of counterfactual vehicles set. For observed vehicle sets, the IVU is simply the (weighted) average of $I_{id}(S_i)$ across all trips. For the counterfactual vehicle portfolios, I obtain $G(\widetilde{S}_i|\widetilde{\mathcal{S}}_i)$ using nearest neighbor matching techniques. Given the set of household demographics w_{ir},[35] I first employ the principal component analysis (PCA) method to reduce the dimensionality of covariates and calculate a propensity score. The demographics include household income, household size, race, a dummy variable indicating the presence of young children, and home ownership status. Then I match each household with its three nearest neighbors whose observed portfolio is $\widetilde{\mathcal{S}}_i$. The potential set $\widetilde{S}_i$ comprises the observed vehicle sets from all three neighbors, and the probability function is formulated using inverse distance metrics. For instance, consider a household that owns a 2001 Ford Fusion and a 2015 Toyota Camry (both ICEs). To determine the counterfactual set of vehicles they might have owned if they had chosen a combination of an ICE and an EV, I identify three households with similar demographics who made the choice of owning both an EV and an ICE in the observed data.

[35]Note that the set of household demographics used in observed heterogeneity preference and matching is different.

3.3 Vehicle Purchase Problem

Households solve vehicle purchase problems based on their preferences for vehicle attributes. They choose vehicle models conditional on the pre-determined fuel type of vehicle (EV versus ICE). The vehicle purchase problem is modeled following recent empirical literature on differentiated products (Beresteanu and Li, 2011; Berry, Levinsohn, and Pakes, 1995; Petrin, 2002). The market in this paper is defined as the MSA of California for a specific quarter.

Demand Side. The utility of household i from vehicle model j (in market m) is defined as a total of average utility (δ_j), a consumer-specific component (μ_{ij}), and an idiosyncratic taste shock (ϵ_{ij}):

$$u_{ij} = \delta_j + \mu_{ij} + \epsilon_{ij} \tag{2}$$

Note that all variables include market m in subscript. I do not write m explicitly to ease the exposition. The average utility common to all consumers (in a given market) is derived from price p_j and observed attributes X_j, such as weight, size, height, horsepower, miles per gallon (MPG), engine displacement, battery capacity, and fixed effects. ξ_j is unobserved characteristics.:

$$\delta_j = X_j\,\bar{\beta} - \bar{\alpha}\,ln(p_j) + \kappa\,1(g_i \in EV) + \xi_j \tag{3}$$

where $\bar{\beta}$ and $\bar{\alpha}$ are mean preference parameters on attributes and price. I include an EV dummy, $\kappa\,1(g_i \in EV)$, to measure the relative difference in mean utility between EV and ICE groups.

The consumer-specific deviation from the mean is a function of household demographics, including observable characteristics ($\boldsymbol{z}_{ir}$) and unobservables (v_{ik}),

$$\begin{aligned} \mu_{ij} &= \alpha_i ln(p_j) + \sum_{k=1}^{K} x_{jk}\left(\sum_{r=1}^{R} \boldsymbol{z}_{ir}\beta_{kr} \;+\; v_{ik}\,\beta_k^u\right) \\ \alpha_i &= \alpha_1 \cdot \ln(y_i) + v_0\,\alpha^u \end{aligned} \tag{4}$$

where α_i measures consumer i's idiosyncratic preference for price change. I model α_i depending on log household income, y_i, and a random term. α_1 is expected to be positive as higher-income buyers tend to be less sensitive to price. With a slight abuse of notation, x_{jk} is the kth product attribute for product j. $\mathbf{v}_i = (v_{i1}, v_{i2}, ..., v_{iK})$ is a mean zero vector of random variables with a multi-normal distribution. I scale v_{ik} such that $E(v_{ik}^2) = 1$.

Finally, I assume the idiosyncratic taster shock ϵ_{ij} to follow an i.i.d T1EV distribution, and I normalize the utility of the outside option (not buying a vehicle) as zero of all consumers. Given this assumption, I can derive the aggregate demand function and the market share of new vehicles as:

$$s_j = \int_{\Omega_i} \frac{\exp(\delta_j + \mu_{ij})}{1 + \sum_{j'} \exp(\delta_{j'} + \mu_{ij'})} \, dF(\Omega_i) \tag{5}$$

where, $\Omega_i = (\boldsymbol{z}_i, v_i)$, $F(\Omega_i)$ is the empirical distribution of household characteristics calculated based on the ACS microdata.

Supply Side. As shown in Beresteanu and Li (2011), the demand side problem can be estimated without solving the firm's problem and market equilibrium. However, the supply side model plays a role in counterfactual analysis, where the price is solved as an equilibrium objective. Therefore, I model the supply side based on the literature concerning differentiated products. In this framework, oligopolistic automakers endogenously set prices and engage in Bertrand competition, aiming to maximize their periodic profit, all while taking the product mix as given.

Following the standard BLP literature, the equilibrium price vector can be solved from the first-order condition of the automaker's profit maximization problem. In matrix notation, it is,

$$\mathbf{p} = mc(\mathbf{q}) + \triangle^{-1} Q(\mathbf{p}, \theta) \tag{6}$$

where $Q(\cdot)$ is the aggregated demand function. $\triangle$ represents the gradient matrix of the aggregated demand function to the price vector,

$$\triangle_{jl} = \begin{cases} -\partial q_j / \partial p_l & \text{if product } j \text{ and } l \in \text{same firm} \\ \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Contrasted with recent EV literature that endogenizes firms' decisions on product attributes (Barwick, Kwon, and Li, 2022), carbon credit trading (Kwon, 2022), and product entry (Armitage and Pinter, 2021), I maintain a parsimonious supply-side structure. I choose this model choice for two reasons. First, this paper focuses on the demand side of the EV market and studies the EV driving behavior. I extend the demand side analysis by incorporating both flow data from new vehicle sales and stock data related to the vehicle population. Therefore, I avoid complex supply-side structures to ensure computational tractability. Second, I am interested in EV purchase subsidies and charging infrastructure investment. These policy tools are arguably less likely to shift automaker's decisions on products mix. However, a potential limitation is that my model may offer limited explanatory power for other policies, such as the ZEV regulation, attribute-based subsidies, and Corporate Average Fuel Economy standards.

Inclusive Value. The ex-ante expected value of fuel type $g \in \{\text{EV, ICE}\}$ (before the realization of vehicle-model-specific shocks) for household i in market m with demographics $\boldsymbol{z_i}$ is specified as follow:

$$IVV_{im}(g|\boldsymbol{z_i}) = \mathbb{E}_{\mathbf{v}_i}\left\{\ln\left[\sum_{j\in g}\exp\Big(\delta_{jm} + \mu_{ijm}(\boldsymbol{z_i})\Big)\right]\right\}, \quad g \in \{\text{EV, ICE}\} \tag{8}$$

The expectation is over the realization of random terms on price and attribute coefficients, $\mathbf{v}_i$. I calculate 8 using the simulation method with 250 Halton draws. Intuitively, $IVV_{im}(EV|\boldsymbol{z_i})$ represents the expected utility for a household i in market m with demographics $\boldsymbol{z_i}$, who is determined to purchase an EV but hasn't yet visited the dealers to decide among models such as the 2017 Tesla Model 3, the 2016 Nissan Leaf, or other EV variants.

3.4 Vehicle Portfolio Problem

The utility for household i with demographics $\boldsymbol{z_i}$ choosing vehicle portfolio $\mathcal{S}_i$ is specified as,

$$\begin{aligned}
\max_{\{\mathcal{S}_i \in \mathbb{S}_i\}} V_i(\mathcal{S}_i) &= \widetilde{V_i(\mathcal{S}_i)} + \varepsilon_i(\mathcal{S}_i) \\
\widetilde{V_i(\mathcal{S}_i)} &= \lambda_i(\mathcal{S}_i) + \rho_1 \cdot IVV_i(\mathcal{S}_i) + \rho_2 \cdot IVU_i(\mathcal{S}_i) \\
IVV_i(\mathcal{S}_i) &= \sum_{g \in \mathcal{S}_i} \phi^T \cdot IVV_i(g)
\end{aligned} \tag{9}$$

Note that Equation 9 is a conditional logit model wherein all variables are contingent on demographics $\boldsymbol{z_i}$. I omit the conditional function notation to avoid redundancy. λ_i is the portfolio-specific random coefficient, which captures the average preference for a specific portfolio. I allow unobserved heterogeneity in λ_i to capture idiosyncratic preference, such as warm glow preference or peer effect on adopting EV.

The nature of IVU is that it always increases with the number of vehicles in the portfolio, as households are always better off having more vehicles to choose from. Therefore, IVU represents the benefit of a portfolio. In contrast, IVV measures an attribute-adjusted price, which represents the cost factor in this trade-off. The coefficients of interest ρ_1 and ρ_2 capture the importance of the IVV and IVU to household i's portfolio decisions. For example, if ρ_2 is close to zero, it indicates that households don't derive significant utility from travel. In other words, they don't highly value the option of driving compared to walking or the flexibility of choosing a car for a specific trip. $\varepsilon_i(\mathcal{S}_i)$ is drawn from an i.i.d. T1EV distribution.

IVV of a vehicle portfolio, $IVV_i(\mathcal{S}_i)$, is specified as the summation of IVV of each vehicle consisting of the portfolio. In the real world, considering that vehicles are durable goods, the portfolio problem involves dynamic decision-making. Nonetheless, in this paper, I adopt a static model for reasons of computational simplicity. To address the dynamic nature of purchase order and timing, I adjust the simulated IVV in a reduced-form manner. Specifically, I discount the IVV of each vehicle by raising it to the power of vehicle age T, using an adjustment parameter, ϕ. This operation addresses two issues. First, there's the issue of time inconsistency: the IVV is derived from new vehicle sales data spanning 2016 to 2019, yet many vehicles in the NHTS sample predate 2016. Second, older vehicles are more susceptible to measurement error issues.

I assume that the inclusive values are independent of the purchase occasions, that is to say, the first purchase of $\mathcal{S} = \{2; ICE, EV\}$ is the same as the first purchase $\mathcal{S} = \{1; ICE\}$. It is a reasonable case as the future purchase should not impact the current purchase decision. However, this assumption also implies that the second purchase of $\mathcal{S} = \{2; ICE, EV\}$ is the same as the first purchase $\mathcal{S} = \{1; EV\}$. With the exogenous distribution of $\mathcal{S}$, this case is unrealistic as the household values less the range of the EV if the household already owns an ICE for a long-distance road trip. However, this assumption is less restrictive in my model as I endogenize the vehicle portfolio $\mathcal{S}$. Therefore, any interactions between choice occasions are captured explicitly with observed or unobserved heterogeneity in the vehicle portfolio choice problem. As I will show in the next section, for example, if $\mathcal{S} = \{1; EV\}$ is the optimal choice, a household must have a small share of long-distance trips (a relatively high $V_i(\mathcal{S} = \{1; EV\})$) or a strong taste on EV (a high realization of $\varepsilon_i(\mathcal{S} = \{1; EV\})$) to offset the dis-utility from the range anxiety. Therefore, I can estimate a standard vehicle demand model following the BLP method separately from the vehicle portfolio and the usage problem.

3.5 Full Market Equilibrium

I have characterized the firm problem and the equilibrium of the new vehicle market (incremental market). Since my model integrates both new vehicle sales and vehicle stock, I also model the used vehicle market to close the full equilibrium. Specifically, I model the used vehicle market using a reduced-form function $U(\cdot)$ that connects aggregated vehicle stock to aggregated new vehicle market share:

$$s_g = U\Big(A_g(\mathcal{S}_i)\,;\,\bar{Q}_{new}, \bar{Q}_{used}\Big), \quad g \in \{\text{EV, ICE}\} \tag{10}$$

where $A_g(\mathcal{S}_i)$ is the aggregated EV share in total registered vehicles and $\bar{Q}_{new}, \bar{Q}_{used}$ are total number of new and used vehicles. Model details and accounting issues are discussed in the Appendix. Equation 10 captures the fact that the used vehicle market comprises 28.2% of conventional vehicle sales in the US, while being relatively insignificant for EVs.[36]

[36]Source: Bureau of Transportation Statistics.

I choose this parsimonious model for two reasons. First, the demand model can be identified and estimated without solving for the full equilibrium. Consequently, a simplified used vehicle market diminishes the computational burden in the counterfactual exercise. I will discuss this issue more in the next section. Second, I lack data on the used vehicle market sales and prices. Therefore, parameters with any rich structure cannot be well-identified. See Bento et al. (2009) for the model on used vehicle market equilibrium.

4 Estimation Results

4.1 Estimation and Identification

I estimate the vehicle usage problem from the household trip diary data from the NHTS 2017 dataset. The Combining Equation 1 with the T1EV assumption derives the vehicle-specific choice probability conditional on the trip, which is used to formulate the maximum likelihood function. Parameters set $\Theta_1 = \{\Psi^l_{iv}, \gamma_{kv}, \mathbf{\Gamma_v}\}$ is estimated using the simulated maximum likelihood estimator (Train, 2009). The identification assumption of the parameters Ψ^l_{iv} is that unobserved variables, which are correlated with the deployment of the charging network, do not influence the relative utility across vehicles. This assumption is arguably reasonable in my model for two reasons. First, unobserved confounders might correlate with aggregated EV demand, but they are unlikely to influence vehicle usage behavior conditional on adopting an EV. Second, I employ the intensity of EV subsidies at the trip destination zip code as an instrument for the number of charging stations, based on the network effect in EV charge station deployment (Li et al., 2017; Springel, 2021). Even though I cannot use Instruments in my Logit model, I compare the difference of estimation between the Probit model and the IV-Probit model (Newey, 1987). I find that the IV estimator produces larger coefficients, suggesting that the assumption results in a more conservative estimation.

For the vehicle purchase problem, I denote linear parameters as $\theta_1 = \{\bar{\alpha}, \bar{\beta}\}$ and non-linear parameters as $\theta_2 = \{\alpha_1, \beta_{kr}, \alpha^u, \beta^u_k\}$. Following the BLP literature, given a vector of θ_2, I use the contraction mapping algorithm to recover the mean utility δ_j that equalizes predicted market shares with observed market shares. Then, I use δ_j as the dependent variable and recover θ_1

within a linear instrumental variable framework. I use standard BLP instrument variables, IV, including the mean of vehicle characteristics of other products produced by automakers and the mean of characteristics of competitor products. Denote the error terms from the linear framework as $e(\theta_1, \theta_2)$. Therefore, the first set of moment conditions is:

$$M_1 = E\Big[e_{jm}(\Theta_2) \,|\, IV_{jm}\Big] = 0$$

Following Beresteanu and Li (2011), the second set of micro-moment conditions matches the model predictions with the observed probability of households in income group $\boldsymbol{y}$ purchasing a new vehicle across each of the 25 MSAs. The observed new vehicle market size is calculated from the NHTS 2017 dataset.

$$M_2 = E\Big[\sum_{j\neq 0} s_{ijm}(\boldsymbol{y}) - Pr_{im}(\boldsymbol{y}) \,|\, \Theta_2\Big] = 0$$

The third and fourth sets of micro-moment conditions match with the model-predicted and observed EV market shares for each income and racial group.

$$M_3 = E\Big[\sum_{j\in \text{EV}} s_{ij}(\boldsymbol{y}) - Pr_i(\text{EV}|\boldsymbol{y}) \,|\, \Theta_2\Big] = 0$$
$$M_4 = E\Big[\sum_{j\in \text{EV}} s_{ij}(\boldsymbol{r}) - Pr_i(\text{EV}|\boldsymbol{r}) \,|\, \Theta_2\Big] = 0$$

where $\boldsymbol{r} = \{\text{White, Black, Asian, Others}\}$ is set of racial groups. Parameter set $\Theta_2 = \{\theta_1, \theta_2\}$ is estimated using the GMM estimator by stacking the moment conditions $M1$ to $M4$.

The model objective, κ, which captures the relative difference in mean utility between the EV and ICE groups, is not exactly identified. This challenge arises because I use both flow and stock data to model consumer preferences toward EVs. κ can be identified either from the EV share in new vehicle sales (the flow moment) or the EV share in the overall vehicle population (the stock moment). I assume that κ is identified from the vehicle portfolio problem with the stock moment. Therefore, the relative market share between EV and ICE does not inform the relative inclusive value, $IVV_{im}(EV|\boldsymbol{z_i}) - IVV_{im}(ICE|\boldsymbol{z_i})$. Instead, it is pinned down by the coefficients of the portfolio fixed effect and the used-vehicle market as depicted in equation 10. This is the key difference between my model and the nested-Logit model as in Goldberg (1995).

For the vehicle portfolio problem given ϕ, parameter set $\Theta_3 = \{\lambda_i(\mathcal{S}_i), \rho_1, \rho_2\}$ is estimated using the maximum likelihood estimator and the NHTS 2017 data. The parameter ϕ itself is estimated by maximizing the information criteria of the MLE.

4.2 Results

4.2.1 Vehicle Usage Problem

Table 1 presents estimates of Equation 1 with four specifications. The first three columns use standard conditional Logit specification while the last one allows for the random coefficients. Three parameters of interests are: $EV\times\ Nstation^O$, $EV\times\ Nstation^D$, and $EV\times\ Nstation^D$ $\times Work$

Column (1) presents the baseline variables. Column (2) incorporates fuel type and body style fixed effects. Column (3) further introduces a series of interactions between EV and household demographics. The increase in the log-likelihood function suggests that augmenting the model with additional controls and fixed effects improves the model's fit. All three parameters in the convenience function are positive and precisely estimated and the coefficients are stable across columns. Accessibility to charging infrastructure at both the trip's origin and destination enhances the appeal of driving an EV. Furthermore, the coefficient for the triple interaction $EV\times\ Nstation^D\ \times Work$ is positive and substantial. This suggests that having more charging ports at the workplace is a crucial factor in encouraging households to use EVs. As illustrated in the previous section, the identification of station parameters comes from the comparison between trip destinations that have access to different numbers of charging stations. To deal with the potential endogeneity of the charging network, I use the number of EV subsidy recipients from CVPR and EFMP in the destination zip code as an instrument for the number of EV charging ports. I reestimate the choice problem with the same controls as Column (3) using probit models and report the results in Appendix Table A.2.[37] Using instrument variables to correct the potential generates large estimates, which suggests that Table 1 tends to provide relatively

[37]The IV-probit model is estimated using method by Newey (1987).

conservative estimates.

The coefficients on other variables align with expectations. The fuel cost parameter is negative, indicating that increased spending results in disutility. However, its relatively small magnitude suggests that while fuel cost might be a significant factor in vehicle adoption, it might not be as crucial when deciding which vehicle to drive. The coefficients for $EV \times Distance$ are negative, which confirms the presence of range anxiety: people are hesitant to use EVs for longer trips due to concerns about battery range.

My preferred specification is presented in Column (4). Incorporating random coefficients significantly enhances the log-likelihood value. The standard deviations of the three main variables are notably greater than their means, indicating substantial unobserved preference heterogeneity across households.

4.2.2 Vehicle Purchase Problem

Table 2 presents estimates of the BLP problem. I present three specifications. The first two columns display point estimates and standard errors using the standard Logit model without addressing the endogeneity of the vehicle price. The second specification addresses the endogenous price problem by employing the BLP instrumental variables mentioned earlier. The third specification uses the BLP-Logit model. In all specifications, I incorporate fixed effects for MSA, quarter-year, vehicle segment, and MSA-by-EV. Standard errors are clustered at the MSA level. Most of the coefficients in Table 2 are precisely estimated.

In the standard Logit specification, the average price coefficient, $\bar{\alpha}$, is -0.840. When accounting for price endogeneity using the IV Logit specification, the coefficient changes to -1.527. This suggests that neglecting to address price endogeneity can substantially bias the estimation of price elasticity. The interaction between EV and price is positive, indicating that purchasers are less responsive to the price of EVs compared to ICE vehicles, potentially because of the restricted variety in the EV segment. Coefficients on other vehicle attributes are consistent with expectations. For instance, all else being equal, consumers favor ICE vehicles with higher horsepower and larger engine displacement, while they gravitate towards EVs with a more substantial battery capacity and extended range. The coefficient for Dollars per Mile (DPM) is negative, which indicates that vehicles with superior fuel efficiency (and consequently a lower DPM) are more valued by consumers, all other things being equal. This finding underscores the importance of fuel efficiency in consumers' vehicle preferences and is consistent with the results of Beresteanu and Li (2011).

The preferred specification is the BLP-Logit model. In terms of household-specific utility, I incorporate interactions between price and income to account for heterogeneous price elasticity. I also introduce interactions between the EV dummy variable with both income and racial groups. Additionally, I account for random coefficients related to prices, the EV dummy, and a constant term. The coefficient for $\ln(price) \times \ln(income)$ is positive, suggesting that higher-income households exhibit lower price elasticity. The positive coefficient of $\ln(price) \times \ln(income)$ indicates that higher-income households have a stronger preference for EVs. Regarding racial-specific heterogeneity, I observe that Black households have a lower preference for EVs compared to White and other racial groups, while Asian households show a notably stronger preference for EVs. The observed differences may also be influenced by variations in wealth, homeownership rates, and taste across different racial groups. These findings are consistent with the results of a survey conducted by Idaho National Laboratory.

The random coefficient on price is significant, suggesting considerable unobserved heterogeneity in price elasticity among consumers. As a result, utilizing the BLP-Logit model is crucial for inferring this distribution of price elasticity and for accurately deriving consumer surplus.

4.2.3 Vehicle Portfolio Problem

Lastly, I present the results of the vehicle portfolio problem in Table 3. As key variables IVV and IVU are simulation objectives from prior estimations, I calculate the standard error using the bootstrap method to account for the computational error. The coefficients of interest are ϕ, ρ_1, and ρ_2. Column (1) is an inferior specification, which includes only IVU. The nature of IVU is that it always increases with the number of vehicles in the portfolio. This is because households always derive greater utility from a wider range of vehicle choices. Therefore, in specification 1, without portfolio fixed effects and IVV, only the benefits of a portfolio are considered, omitting the associated costs. As a result, both the estimated coefficients and the log-likelihood function are significantly smaller compared to the other specifications. Column (2) incorporates IVV. IVV measures an attribute-adjusted price, which represents the cost of having more vehicles. With both benefit and cost factors in the model, ρ_1 and ρ_2 are well-identified and estimated. I estimate ϕ using a parsimonious specification as in Column 2. By maximizing the log-likelihood ratio (LR), I pin down $\phi = 0.86$.

Column (3) further includes portfolio fixed effects. As a result, the log-likelihood function increases remarkably compared to the previous Columns. Column (4) allows for random coefficients in portfolio fixed effects and serves as my preferred specification. The positive estimates of ρ_1 and ρ_2 show that both inclusive values from usage and attributes play important roles in portfolio decision-making. Appendix Table A.1 reports more results. A notable result is that when the vehicle purchase problem is specified without heterogeneity and random coefficients (standard Logit problem), the implied IVV is not identified from the portfolio fixed effects. Therefore, ρ_1 is identified from the idiosyncratic component of IVV that deviates from the average inclusive value, which is captured by the fixed effects.

4.3 Analysis on the Model Results

The following sections discuss the implications of the model on household behavior and the projected welfare disparities across income groups.

Price Elasticity, Welfare and Travel Behavior. I first explore the variation in price elasticity across income groups and the distribution of consumer surplus, as presented in Table 4. The price elasticity for EVs varies significantly, ranging from -7.12 for households with an income below \$30,000 to -0.43 for households with an income above \$175,000, with an average of -3.21. This suggests that high-income households are considerably less responsive to price changes. Additionally, the overall price elasticity for EVs is lower than that for ICE vehicles. These combined patterns explain why EVs are more frequently adopted by high-income households. My price elasticity estimation is comparable to that of in Muehlegger and Rapson (2022) using transaction-level data on the universe of new and used EVs purchased by California buyers.[38]

Then, I discuss about the households' welfare. The consumer surplus (CS) for income groups

[38]It is also consistent with the other demand estimations related to electric vehicle market Linn (2022); Xing, Leard, and Li (2021).

$\boldsymbol{y}$ is calculated using the formula as in Small and Rosen (1981):

$$CS(\boldsymbol{y}) = \mathbb{E}_{i\in\boldsymbol{y}}\left\{\frac{1}{\bar{MU}_i}\left[\ln\Big(\sum_{\{\mathcal{S}_i\in\mathbb{S}_i\}}\exp(\widetilde{V_i(\mathcal{S}_i)})\Big)\right]\right\}$$

where $\bar{MU}_i$ is the average marginal (dis)utility of price for i across all vehicle models. $\widetilde{V_i(\mathcal{S}_i)}$ is defined in Equation 9. Note that the formula for consumer surplus already accounts for the vehicle price. And by construction, the consumer surplus for the outside option $\{\emptyset\}$ (no vehicle and never drive) is \$0. The calculations reveal that the lifetime consumer surplus derived from the entire vehicle portfolio is significantly higher for high-income households. The post-purchase consumer surplus over vehicle portfolio lifetime (approximately 15 years) for the median-income household (\$62,500) is about \$23,244 (relative to the outside option). And CS for low-income households (those with incomes below \$30,000) is approximately one-third of the median. This partially explains why low-income households tend to reside closer to roadways and are more inclined to use public transit.

Finally, I examine EV usage behaviors measured by the probability of driving an EV conditional on owning an EV. The model predicts that on average, the household has a 44% probability of using an electric car, with low-income households being more likely to drive an EV. This is largely because low-income households tend to own fewer vehicles compared to those with higher incomes. This pattern suggests an underexplored benefit of encouraging low-income households to adopt EVs since they utilize them more extensively. Previous literature ignores this observation as they do not explicitly model the portfolio choice problem.

Decomposition between IVU and IVV Next, I decompose the household utility of each portfolio alternative into IVU, IVV, and other factors. This allows for a comparison of the relative significance between vehicle attributes and vehicle usage value. Specifically, I use the formula $\widetilde{V_i(\mathcal{S}_i)} = \lambda_i(\mathcal{S}_i) + \rho_1 \cdot IVV_i(\mathcal{S}_i) + \rho_2 \cdot IVU_i(\mathcal{S}_i)$, where $\rho_1 IVV_i(\mathcal{S}_i)$ captures utility components stemming from vehicle attributes (IVV), $\rho_2 IVU_i(\mathcal{S}_i)$ captures utility components stemming from usage (IVU), and $\lambda_i(\mathcal{S}_i)$ are components that cannot be explained by either usage or vehicle. To convert the utility into monetary value, I divided each utility component by α_i.

Figure 7 shows the decomposition for the median income household. The utility from the outside option is 0 and it serves as the benchmark. Two findings emerge. First, the total utility (black bar) for all EV-related and triple ICE portfolios is less than the outside option, which is consistent with the overall low EV adoption rates. Second, the IVV utility for all portfolios is negative, while the IVU utility is positive. This comparison reveals the underlying trade-off in the vehicle portfolio choice problem. IVU captures the relative benefit of the portfolio, which derives from the convenience value of having a vehicle fleet. In contrast, IVV captures the cost, which derives from the attributes-adjusted prices.

4.4 Model Fit

Before moving to the policy analysis, I assess my model's performance by examining its model fit to both targeted and untargeted moments.

4.4.1 Within Sample Moments

First, I evaluate how closely the model matches with the within-sample moments. This includes the share of each vehicle portfolio alternative segmented by income group, racial group, and by MSA.

Figure 4 compares the model-predicted choice probability with the observed share in the data for three portfolios associated with EV, $\{EV\}$, $\{EV, ICE\}$, and $\{EV, ICE, ICE\}$. I categorize households into two groups based on whether their household income is below or above the median income. Except for the EV, ICE category in the low-income group, the model predictions align closely with the actual data. This indicates that my model tends to overpredict the appeal of the EV, ICE option for lower-income households. Figure 5 breaks down the data into four racial groups: White, Black, Asian, and Others. The observed and model-predicted shares are closely aligned for each portfolio across all racial groups. These comparisons demonstrate that the model effectively captures the demographic difference in EV adoption patterns. The results illustrate that, even though I do not explicitly incorporate demographic variables in the vehicle portfolio problem, demographics influence the model through variations in the IVV and IVU. The findings underscore the effectiveness of my sequential and nested model structure. This structure enables capturing rich substitution patterns and observed heterogeneity in vehicle adoption, all while preserving computational tractability.

As spatial dimension is core to my paper, I delve into the model's capability to predict geographic variances in EV adoption. The results are shown in Appendix Figure A.3. The X-axis represents the data, while the Y-axis showcases the model's predictions. The dashed line indicates the 45-degree line. Most of the data points closely align with this 45-degree line, suggesting a strong fit between the model and the actual data across various geographical dimensions.

4.4.2 Out-of-Sample Prediction

I also check the model's out-of-sample prediction power by examining how well the model fits the EV adoption trend over time in Data. I measure the EV trend using the EV share in the total registered vehicle. Given that the portfolio problem model is based on the cross-sectional data from NHTS 2017 (surveyed in 2016), I use the EV share in stock data from 2017 to 2021 as the test set. The algorithm is as follows: In step one, using the time-series data from EV charging networks and new vehicle sales, I compute projected values for both IVU and IVV. In step two, with the derived IVU and IVV values, I input them into the vehicle portfolio model to forecast the choice probability for various portfolios over time. In step 3, I translate the estimated portfolio shares to predict EV shares over time.

The results are shown in Figure 6. The thin grey line represents the data, while the wider line illustrates the model's predictions. Broadly speaking, the model successfully captures approximately 60% to 80% of the increasing trend in EV adoption over time. The remaining unexplained component is attributed to fixed effects and structural errors.

I further decompose the predictable increases into portions attributed to IVU and IVV. To achieve this, I isolate one channel at a time by keeping the respective variable constant at its 2016 level. The results indicate that the added convenience from a more accessible charging network, represented by IVU, plays a more significant role in the rise of EV adoption.

5 Environmental Benefits of EV Driving

5.1 Conceptual Framework

Before proceeding, I develop a simple framework to describe the relationship between EV adoption, travel behaviors, and urban pollution dissemination, as well as how policy impacts the spatial distribution of environmental benefits. Consider a city comprising two interconnected regions: Region 1 and Region 2. Each region has a representative household. Residents in one region commute to the other, dispersing emissions. Without loss of generality, let ω denote the population share in Region 1. Let q_i, where $i = \{1, 2\}$, denote the proportion of total travel mileage within the residential region.[39] Let D_i, where $i = \{1, 2\}$, denote the vehicle miles traveled (VMT) in the case of two Regions.

Each representative household adopts an EV with a probability p_i. For households that own an EV as part of their vehicle portfolio, the likelihood they drive the EV from origin i to destination j is s_{ij}. The set of exogenous policies is represented by the vector $\mathcal{P}$.

Now, I define the total on-road transportation emissions in Region 1, E_1, as follows:

$$E_1(p_1, p_2, s_{11}, s_{21}) = \underbrace{\omega \cdot q_1 \cdot D_1 \left\{ \underbrace{p_1 \cdot (1 - s_{11}) \cdot e_1}_{\text{regions 1 EV households who drive ICE}} + \overbrace{(1 - p_1) \cdot e_1}^{\text{Region 1 non-EV households}} \right\}}_{\text{Emission from Region 1 residence}}$$

$$+ \underbrace{(1 - \omega) \cdot (1 - q_2) \cdot D_2 \left\{ \underbrace{p_2 \cdot (1 - s_{21}) \cdot e_2}_{\text{Region 2 EV household who drive ICE}} + \overbrace{(1 - p_2) \cdot e_2}^{\text{Region 2 non-EV households}} \right\}}_{\text{Emission from region 2 residence}} \tag{11}$$

where e_i represents the per unit emission from ICE driving for households owning only ICE vehicles. I assume the EVs generate zero emissions.[40]

Equation 11 decomposes Region 1's total emission into those originating from Region 1 (first line) and Region 2 (second line). Within each origin, emissions are further divided between

[39] $q_i = 1$ represents a special case where the two regions are isolated and households travel exclusively within their residential region.
[40] Engineering studies generally agree that in-use emissions from EVs are negligible

households owning only ICE vehicles and those with both EVs and ICE.

Assumption 1. ***No Sorting.*** *EV policies δ do not affect relative population share, commuting matrix, and total VMT, that is, $\partial\omega/\partial\delta = 0$, $\partial q_i/\partial\delta = 0$, $\partial D_i/\partial\delta = 0$.*

Assumption 1 states that any EV policies will not change household residence, workplace, and commuting choices. The assumption is justifiable in my context due to the low EV penetration rate in the U.S. (less than 3% of total vehicle stock in 2022) and thus has a limited impact on equilibrium sorting. The simplification enables me to study EV policies under partial equilibrium.[41]

Definition 1. ***Environmental Benefits.*** *The environmental benefit of EV adoption in Region 1, EB_1, is*

$$\begin{aligned} EB_1 &= E_1(p_1, p_2, s_{11}, s_{21}) - E_1(0,0,0,0) \\ &= \omega \cdot q_1 \cdot D_1 \left\{ p_1 \cdot s_{11} \cdot e_1 \right\} + (1-\omega) \cdot (1-q_2) \cdot D_2 \left\{ p_2 \cdot s_{21} \cdot e_2 \right\} \end{aligned} \tag{12}$$

Based on the definition, the objectives of interest in this paper include: (1) Inequality of distribution of environmental benefits $EB_1 - EB_2$; (2) Effects of EV policies, $\partial EB_i/\partial\mathcal{P}$; (3) Distributional Effects of EV policies $\partial EB_1/\partial\mathcal{P} - \partial EB_2/\partial\mathcal{P}$.

5.2 Calculating EV Exposure and Environmental Benefits

By combining EV adoption and travel behaviors simulated from the model with travel routes from optimal-routing software, I calculate the objectives of interest in the described conceptual framework under the real-world scenario and analyze the spatial distribution of environmental benefits.

The geographical unit I consider is the census tract, c. I calculate the environmental benefits based on the total mileage replaced by EVs when traveling through area c and following the multi-region extension of Equation 12. Specifically, the environmental benefit from EV adoption

[41] In the general equilibrium cases that account for residential sorting, every variable previously mentioned is an equilibrium objective and can be expressed as a function of $\mathcal{P}$.

EB_c^{EV} is,

$$EB_c^{EV}(r,i,\mathcal{S}_i) = \underbrace{L_{rc}^{od}}_{\text{Optimal Route}} \cdot \underbrace{Pr\big(n_r(\boldsymbol{y})\big)}_{\text{Commuting Matrix}} \cdot \underbrace{Pr(\mathcal{S}_i)}_{\text{Portfolio Problem}} \cdot \underbrace{Pr(EV_r^{Driving}|\mathcal{S}_i)}_{\text{Usage Problem}} \cdot \widetilde{e(ICE)}_i$$
$$EB_c^{EV} = \sum_{r\in\mathcal{R}} \sum_{\boldsymbol{y}} \sum_{i\in\mathcal{O}(r,\boldsymbol{y})} \sum_{\mathcal{S}_i\in\mathbb{S}_i} EB_c^{EV}\big(r,i,\mathcal{S}_i\big) \tag{13}$$

where

- $EB_c^{EV}(r,i,\mathcal{S}_i)$: Environmental benefits in c generated from simulated household i with vehicle portfolio $\mathcal{S}_i$, traveling along route r.

- L_{rc}^{od}: The length of the line segment that overlaps between route r and census tract c.

- $n_r(\boldsymbol{y})$: Trip counts for r in income groups $\boldsymbol{y}$.

- $Pr(\mathcal{S}_i)$: Model predicted probability of choosing $\mathcal{S}_i$.

- $Pr(EV_r^{Driving}|\mathcal{S}_i)$: Model predicted probability of driving EV conditional on choosing $\mathcal{S}_i$.

- $\widetilde{e(ICE)}_i$: Emission per mile from ICE driving for households who adopt EVs.

- $\mathbb{S}_i$, $\boldsymbol{y}$, $\mathcal{O}(r,\boldsymbol{y})$, and $\mathcal{R}$: set of portfolio alternatives, set of income bins, set of simulated household in the origin zip code of r and income bins $\boldsymbol{y}$ and, set of total routes.

I normalize the EB variable using its standard deviation, $\widetilde{EB_c^{EV}} = EB_c^{EV}/\sigma$. Three features distinguish my calculation of environmental benefits from that in previous studies. First, I focus on the emission of local pollutants from on-road transportation (vehicle in-use) as opposed to emissions from electricity generation (Holland et al., 2016, 2019). Second, I emphasize local pollutants, which have a limited geographic range of influence and are directly linked to adverse health consequences. In contrast, other studies focus on greenhouse gases, such as CO2 (Sinyashin, 2021). Third, I analyze the normalized EB calculation instead of converting it into monetary units or tons (Jacqz and Johnston, 2023; Li, 2018). The main reason is that I am more interested in the distributional effect, and the unit do not matter. Moreover, such conversions often rely on engineering estimates, which can suffer inaccuracy and arbitrariness. In my context, given the low rate of EV adoption, the values obtained through conversion tend to be relatively small. This makes the inherent inaccuracies particularly crucial, and at times they can overshadow the results.

5.3 Spatial Distribution of Environmental Benefits

Figure 8 depicts the geographical distribution of normalized environmental benefits and EV exposure in California.[42] Regions with high EV exposure include coastal census tracts and counties with high median income like Santa Clara and Santa Jose. Big metropolitan areas, such as San Francisco and Los Angeles, also exhibit high EV exposure.[43]

To delve deeper into the distribution of environmental benefits, I examine the correlation between these benefits and income levels, as measured by the percentage of low-income households at the census tract level. Figure 10 plot the relationship fitted using a local polynomial function as a black solid line. For comparison, I also illustrate the relationship between the local EV share in registered vehicles (normalized) and the percentage of low-income residents, denoted by a grey dashed line. Two interesting findings emerge. First, the downward-sloping relationship suggests that high-income communities experience greater EV mileage, thereby benefiting more from EV adoption. Specifically, the difference in EV environmental benefits between the wealthiest and poorest communities is approximately 0.6 standard deviations. Second, the environmental inequality measured by EV exposure is less severe than the observed inequality in EV adoption. And the difference becomes more noticeable at the lower end of the income distribution, particularly among the top income groups. Specifically, a ten-percentage-point increase in the share of low-income households (i.e., those below twice the poverty line) is associated with a 0.23 standard deviation decrease in EV share, whereas it is only associated with a 0.08 standard deviation decrease in environmental benefits. My calculation shows that the wealthiest 20% of zipcode receives about 25% of the environmental benefits but purchased 50% of the electric vehicles. So higher income region generate positive environmental externality. This pattern implies that households owning EVs are predominantly situated in the highest-income

[42] I use the word "environmental benefit" and "EV exposure" interchangeably in this paper.

[43] For an interactive map detailing a household income in California, please refer Median income Map by the Census Bureau.

communities. Nevertheless, these households export the positive environmental externality to lower-income communities when they drive their EVs and commute across these regions, for instance, via interstate highways that traverse these areas.

Appendix Figure A.7 further examines the correlation between EV exposure and other demographics. Consistent with Figure 10, environmental benefits of EVs show a weaker correlation with other socio-economic variables than EV adoption rates. Interestingly, I do not find a strong negative correlation between EV environmental benefits and minority percentage, which implies the distribution of environmental benefits is quite equal across racial groups. This is due to the fact that people of color tend to live in closer proximity to major roadways, and as a result, are more exposed to EV mileage traveled on those routes. Another pattern that emerges is the positive correlation between EB and both the population and the number of employers. It suggests that a significant portion of the narrative is driven by EV trips to and through densely populated areas and business districts, regions that are also typically more exposed to on-road transportation pollution.

These findings underscore the significance of travel behavior and commuting patterns when examining environmental justice concerns related to EV adoption and evaluating the equity issues of EV policies.

5.4 EV Exposure and Air Quality

In this section, I explore the correlation of my model-based EV exposure measurement and air quality. In particular, I examine whether it performs better than the original local Specifically, I investigate if it outperforms the initial local EV share measures in quantifying the environmental advantages of EVs in reducing air pollution. To this end, I estimate the following two-way fixed effects model using monthly, zipcode-level data of air pollution and EV exposure. Specifically, I regress the log of pollution level at zipcode c in time t on the local share of EV $EVshare$ or the exposure of EV EB^{EV} and zipcode fixed effects c and time fixed effects t. Then, I conduct a comparison between the estimated coefficients β_1 and β_2.

$$\begin{aligned} \log(Pollution_{ct}) &= \beta_1 \, EVshare_{ct} + \mathbf{X_{ct}}\Gamma + \lambda_c + \eta_t + \varepsilon_{ct} \\ \log(Pollution_{ct}) &= \beta_2 \, EB^{EV}_{ct} + \mathbf{X_{ct}}\Gamma + \lambda_c + \eta_t + \varepsilon_{ct} \end{aligned} \tag{14}$$

Figure 9 shows the estimated β_1 in red and β_2 in blue. I normalized both $EVshare$ and EB^{EV} using their standard deviation. The coefficients represent the impact of a one standard deviation change in either measure on the percentage change in pollution. I show results for different pollutants including NO_2, $PM_{2.5}$, PM_{10} and SO_2, with NO_2 as the main outcome of interest as it mainly comes from vehicle tailpipe emissions. The result clearly shows that my model-based EV exposure (β_2) is more correlated with pollution reduction than EV adoption share (β_1). SO_2 serves as a placebo test as vehicle tailpipe emissions are not a major source of it. The result shows that EB^{EV} can also better recover the null effect on SO_2. The comparison shows that EB^{EV} serves as a better measurement of environmental benefits than $EVshare$. This is because the model-based approach captures the spatial spillover of environmental benefits from EV driving explicitly and alleviates the bias of EV adoption measurement.

6 Policy Experiments

6.1 Counterfactual Policies

To evaluate the efficiency and equity of EV policies, I examine two types of policy that mainly focus on the demand side of the EV market: purchase subsidy and charging infrastructure investment. The benchmark for comparison is the 2016 EV incentives in California, which combined federal income tax credits with the California Vehicle Rebate Program, as detailed in Section 2. Moreover, I ensure that the total financial cost for counterfactual policies remains consistent with the benchmark, enabling a fair comparison across various policy scenarios. For each type of EV policy, I consider different scenarios that allow the policy to target specific groups of households and locations (place-based). I summarize the policy scenarios below. For EV purchase subsidies, the first scenario involves eliminating all such subsidies. The second scenario is a targeted subsidy policy where only households with incomes below the median are eligible for the subsidy.

For EV charging infrastructure investment, I assume that the government eliminates all current subsidies and reallocates those funds towards subsidizing charging infrastructure. The subsidy required per station for the construction of a new station (marginal cost of the subsidy) is taken from the upper bound estimate in Li et al. (2017), \$ 55,000 per station. The monetary value is adjusted to the 2016 US dollar terms. I consider four scenarios concerning the spatial distribution of charging stations. In the first scenario, new stations are allocated proportionally to the current distribution of charging infrastructure across each zip code. The second scenario allocates new stations based on population share within the zip codes. The third scenario evenly distributes new stations across all zip codes. In the fourth scenario, a place-based policy is considered, with new stations disproportionately allocated to disadvantaged communities (DAC). Specifically, 50% of the new stations are designated for DAC and then are evenly distributed between zip codes within DAC.

For any policy combination $\mathcal{P} = \{\mathcal{N}, \delta\}$, $\mathcal{N}$ represents the spatial distribution of charging infrastructure, and δ denotes the spatial distribution of purchase subsidies. The counterfactual equilibrium is defined as a new vector, $\{p_j,\ \kappa\}$, which denotes vehicle prices and EV-specific shocks in the new vehicle market, respectively. This vector clears both the new vehicle sale market (Equation 6) and the used vehicle market (Equation 10).

6.2 Effects of EV Policies on Adoption and Welfare

I first examine the effects of EV purchase subsidies on adoption by comparing the status quo with the case of eliminating all federal and state purchase subsidies. Figure 11 depicts the results for each income group based on the NHTS data. The solid black line illustrates that removing subsidies leads to a 0.25 percentage point decline in the EV share among total vehicles, representing roughly 22% of the present EV share. This decrease can be attributed to the elevated EV prices, thus resulting in a diminished inclusive value of the vehicle. Interestingly, the relationship between the effectiveness of purchase subsidies and income is nonlinear. The U-shaped pattern suggests that purchase subsidies are most effective for middle-income households.

This trend becomes more evident when I adjust for the number of households within each income group (as shown by the dashed line and the right axis). Contrary to this, the conventional BLP approach typically predicts a downward-sloping relationship, given that lower-income households usually exhibit higher price elasticity and, consequently, are more responsive to subsidies.

The difference is that in my model, the inclusion of vehicle portfolio choices and the inclusive value of usage allow for richer and more realistic substitution patterns. Figure 13 explores the relative substitution patterns across vehicle portfolios. This is done by comparing the changes in the choice probability of each portfolio against the benchmark. Intuitively, the figure highlights area from where the market share is being drawn to account for the increase in market share of any given alternative. I specifically look into two scenarios: the elimination of subsidies and the investment in charging infrastructure (Station Policy 1). The figure reveals that EV policies predominantly impact the market share of the portfolio option $\{EV, ICE\}$. And the fluctuations in the market primarily divert from/to the options $\{ICE\}$ and $\{ICE, ICE\}$. It means most households considering the adoption of an EV typically either have a car and are thinking about acquiring a second one, or they possess two cars and are considering exchanging one for an electric model. Hence, for low-income households who own one or no vehicles, adopting an EV is less appealing due to the comparatively lower usage value derived from EVs.

Table 5 summarizes the effects of counterfactual policies on EV stock share, measured by the deviation from the status quo and consumer surplus. As anticipated, redirecting subsidies to target low-income households leads to an increase in their adoption of EVs, while adoption among high-income households decreases. Overall, the total adoption sees only a slight decline. In stark contrast, reallocating financial resources from purchase subsidies to charging station investments significantly boosts EV adoption across all income groups, with the most pronounced increase observed in the high-income group. For example, policy scenario 1 increases the overall adoption by more than 40% compared to the current level. Policy scenario 2 suggests that the impact of investing in charging stations is more pronounced when the new stations are placed in areas with higher population density. It almost doubles the effect of the policy 1. This result aligns with the observations summarized in Sheldon (2022), which highlight that concerns about range anxiety and the difficulty in locating charging stations predominantly arise in densely populated urban areas.

The lower panel of Table 5 presents the results for consumer surplus. In all scenarios, the overall increase in consumer surplus is modest compared to the financial costs of the policies. This can be attributed to the still relatively low EV adoption rate. Similar to their impact on adoption rates, infrastructure policies are more effective in transmitting financial subsidies into enhanced welfare compared to purchase subsidies.

Lastly, I analyze the distributional effects of various policies. Evidently, the targeted purchase subsidy policy produces the most equitable outcome, although it compromises efficiency in terms of a lower overall adoption rate. Within the spectrum of infrastructure policies, policy scenarios 3 and 4 delve into equitable strategies for deploying charging stations. A comparison between policies 1 and 4 reveals that, when new charging facilities are strategically placed in DAC areas, the uptick in EV adoption is primarily driven by low-income households. Notably, the overall adoption rates across these two policies are relatively similar.

6.3 Effects of EV Policies on Environmental Benefits

Table 6 reports the impacts of EV policies on the distribution of environmental benefits (EB). I calculate EB using Equation 13. I normalize the average of EB in the status quo to 1, therefore the results highlight changes in EB induced by the policies relative to the baseline. As illustrated in Section 5, high-income households tend to be exposed to disproportionately greater EB. Across a spectrum of counterfactual policies, targeted purchase subsidies yield minimal change compared to the baseline. Even though there's an increase in EV adoption among low-income households, the environmental benefits they experience don't see a corresponding rise. In fact, every income bracket observes a marginal decline in environmental benefits. One possible explanation is that low-income households generally drive fewer miles (Jacqz and Johnston, 2023), resulting in fewer environmental benefits from EV adoption. A caveat in this paper is that I do not endogenize the driving mileage (VMT problem) as West (2004) and Bento et al. (2009), therefore, my model could undervalue the importance of total driving mileage on EV adoption.

In line with the trends of EV adoption, charging station policies result in a significant increase in total environmental benefits (EB). The most effective approach is deploying based on population distribution (Station Policy 2). It is followed by an even distribution (Station Policy 3), allocation favoring DAC (Station Policy 4), and finally, based on current deployments (Station Policy 1). Furthermore, among the four station policies, the place-based policy that allocates more new stations to DACs produces the most equitable outcome.

Panel B decomposes EB by the origins of the trips. Only less than 7% of EB is generated from trips originating within the same zip code, while about 60% arises from trips originating from a different county. This pattern suggests that the majority of environmental benefits are derived from longer commutes or inter-county travel, emphasizing the importance of commuting flow in analyzing urban pollution diffusion and EV environmental benefits distribution.

Finally, to assess the impact of EV policies on the equitable distribution of environmental benefits, I examine the changes in the relationship between EB and the percentage of low-income households at the census tract level, resulting from EV policies. Figure 14 displays the effects of two policies: targeted purchase subsidies and place-based charging infrastructure investments, together with the benchmark. The two policies influence the distribution of EB through distinct mechanisms. Purchase subsidies serve as a "push" effect, increasing the overall probability of EV driving. In contrast, charging infrastructure policies act as a "pull" effect, drawing EV mileage to specific geographic areas. Both policies diminish the slope of the relationship, suggesting a more equitable spatial distribution of EB across regions with varying income levels. However, the targeted subsidy only slightly flats the slope. In contrast, the effect of station policies is more pronounced, especially for the poorest communities. A more rigorous quantitative comparison using regression analysis can be found in Appendix Table A.4. This comparison suggests that place-based charging station policies can promote a more equitable distribution of these benefits among income and racial groups.

7 Conclusion

The inequitable distribution of charging infrastructure in the U.S. is a notable yet often overlooked issue. This disparity raises environmental justice concerns regarding the benefits of EVs, as well as equity issues related to EV policies. This paper studies the spatial distribution of environmental benefits from EV and the distributional effects of EV policies. I develop a new structural model of the U.S. auto market that allows me to study both EV adoption and spatial usage behavior in a unified framework and to incorporate rich observed and unobserved heterogeneity, both of which are crucial for quantifying distributional implications. By combining EV adoption and travel behaviors simulated from this model with travel routes simulated from optimal-routing software, I analyze the spatial distribution of environmental benefits. My analysis generates three sets of conclusions. (1) The model underscores the significance of utility derived from vehicle usage, as opposed to mere vehicle attributes, in EV adoption. Consequently, the role of charging infrastructure becomes paramount. (2) Environmental benefits are negatively correlated with low-income and minority percentages in communities. Higher-income households adopting EVs produce positive environmental externalities for lower-income communities through which they drive. (3) Investments in charging infrastructure generate approximately three times more environmental benefits than current policies. Furthermore, place-based charging station policies can promote equitable distribution of these benefits among income and racial groups.

The paper sheds light on environmental justice issues in the electrification transition. My model has implications for both the efficiency and equity of EV policies. For adoption, I highlight the importance of vehicle portfolios in determining optimal policy targets. For environmental benefits, I demonstrate that the underlying mechanisms of purchase subsidies and charging infrastructure investments differ significantly, leading to pronounced variations in distributional outcomes. The 2021 Bipartisan Infrastructure Law designates $5 billion in subsidies for the development of a nationwide fast-charging infrastructure along major interstate routes. An additional $2.5 billion is set aside to encourage construction in disadvantaged, low-income, and rural communities. My findings provide both theoretical justification and empirical evidence in favor of promoting charging infrastructure investment. It further supports the strategic allocation of funds to disadvantaged communities.

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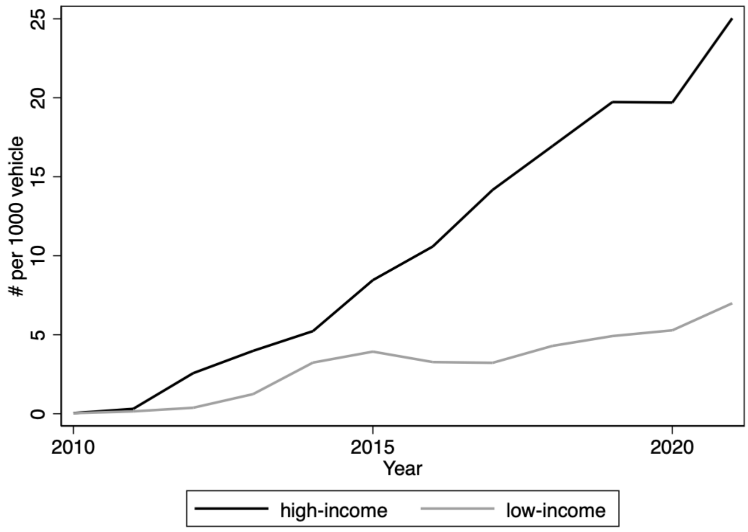
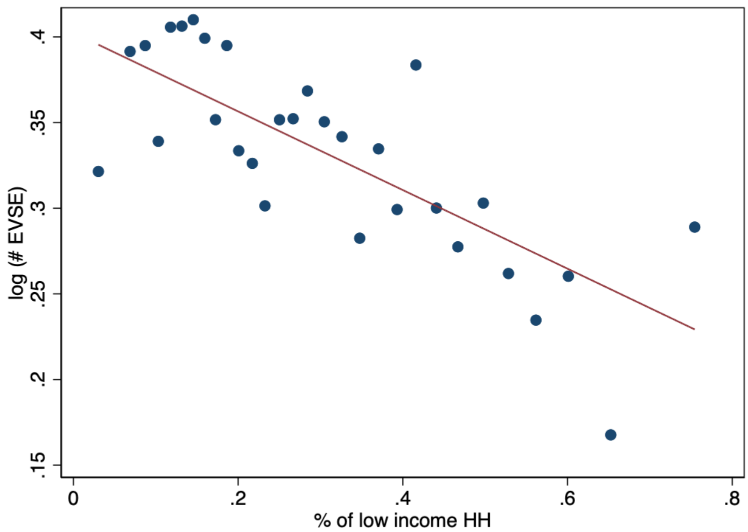
Figures and Tables

Figures



(a) EV adoption in high- and low income communities



(b) Relationship between income and charging network deployment

Figure 1: Inequality in EV adoption and changing network deployment

Notes: This figure depicts the disparity in EV adoption and the deployment of EV charging infrastructure. The upper subplot illustrates the EV share among total registered vehicles over time, specifically in high-income and low-income communities. Income levels are measured based on the percentage of households earning below twice the poverty line. The lower subfigure shows the relationship between the log number of charging infrastructures and the percentage of low-income households. The upper subfigure uses the zip code-level data. The lower subfigure uses census tract-level data. The Electric vehicle supply equipment (EVSE) is a measure of EV charging ports.

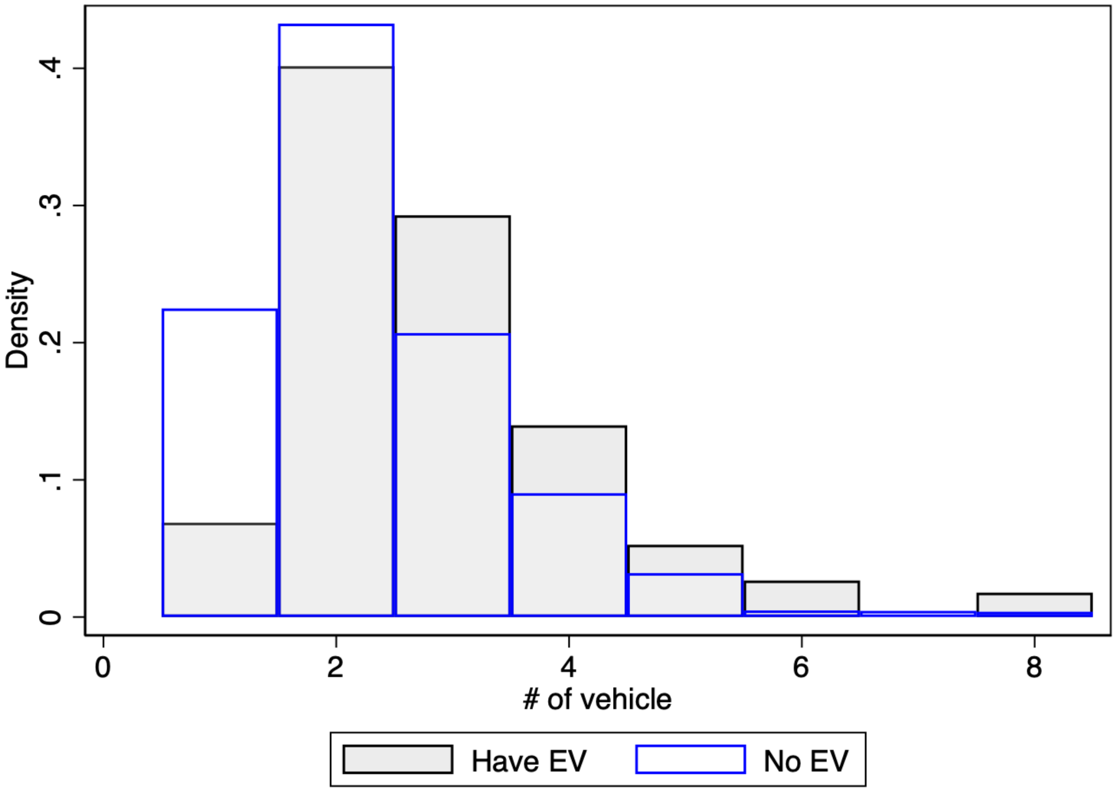


Figure 2: Distribution of number of vehicles

Notes: This figure shows the distribution of the number of vehicles in households using NHTS 2017 data. The grey bar stands for households with at least one EV and the white bar stands for households without any EV.

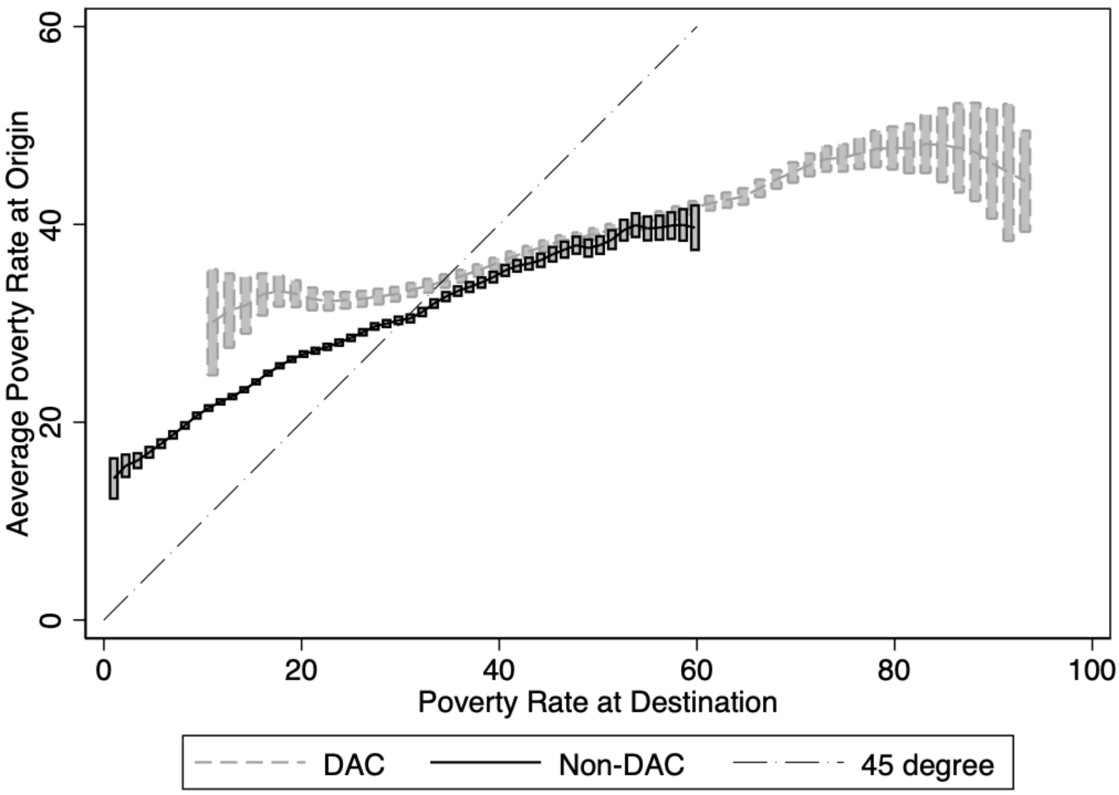


Figure 3: Relationship between Income Level at Origins and Destinations

Notes: This figure plots the relationship between the poverty rate at the origins and destinations of commuting routes. The dashed and solid lines represent relationships fitted using a local polynomial function, while the bands around the lines indicate the 95% confidence interval. The dashed line stands for routes with disadvantaged communities (DAC) as a destination, while the solid line stands for routes with non-disadvantaged communities (Non-DAC) as a destination

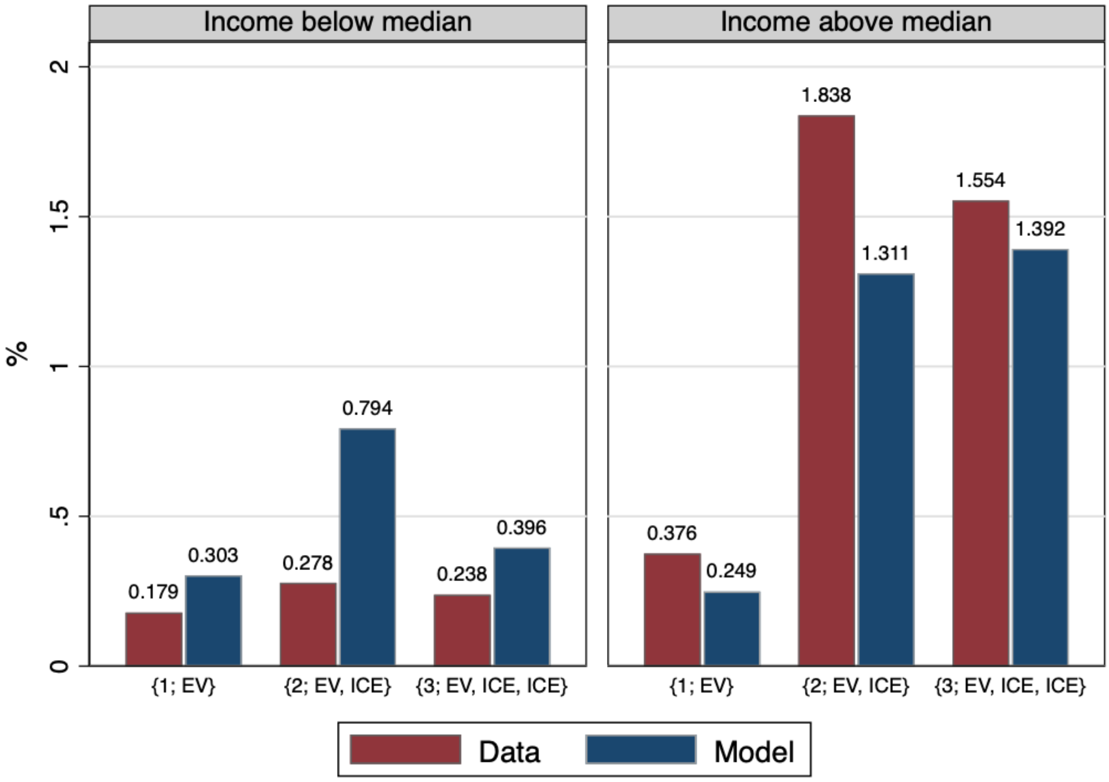


Figure 4: Model Fit: Portfolio Share in Data and Model by Income Group

Notes: This figure compares the model-predicted choice probability with the observed share in the data for three portfolios associated with EV, $\{EV\}$, $\{EV, ICE\}$, and $\{EV, ICE, ICE\}$. I categorize households into two groups based on whether their household income is below or above the median income. The red bar is the data and the blue bar is the model.

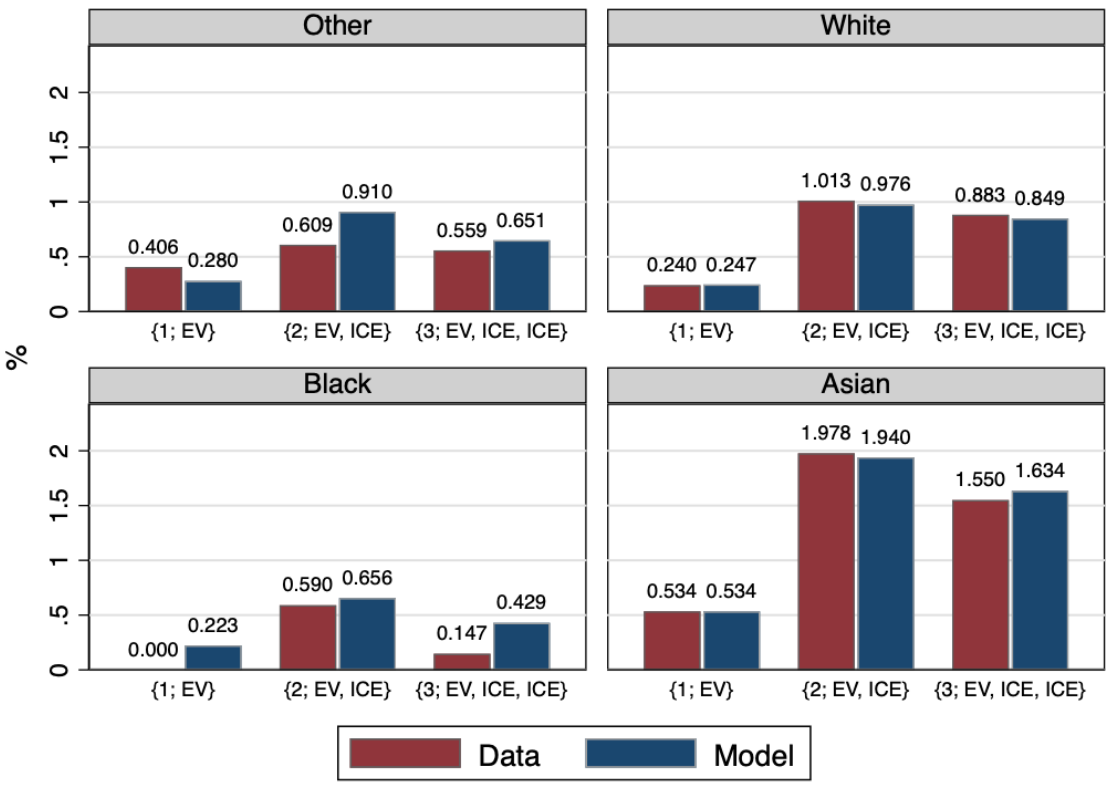


Figure 5: Model Fit: Portfolio Share in Data and Model by Race

Notes: This figure compares the model-predicted choice probability with the observed share in the data for three portfolios associated with EV, $\{EV\}$, $\{EV, ICE\}$, and $\{EV, ICE, ICE\}$. I break down the data into four racial groups: White, Black, Asian, and Others. The red bar is the data and the blue bar is the model.

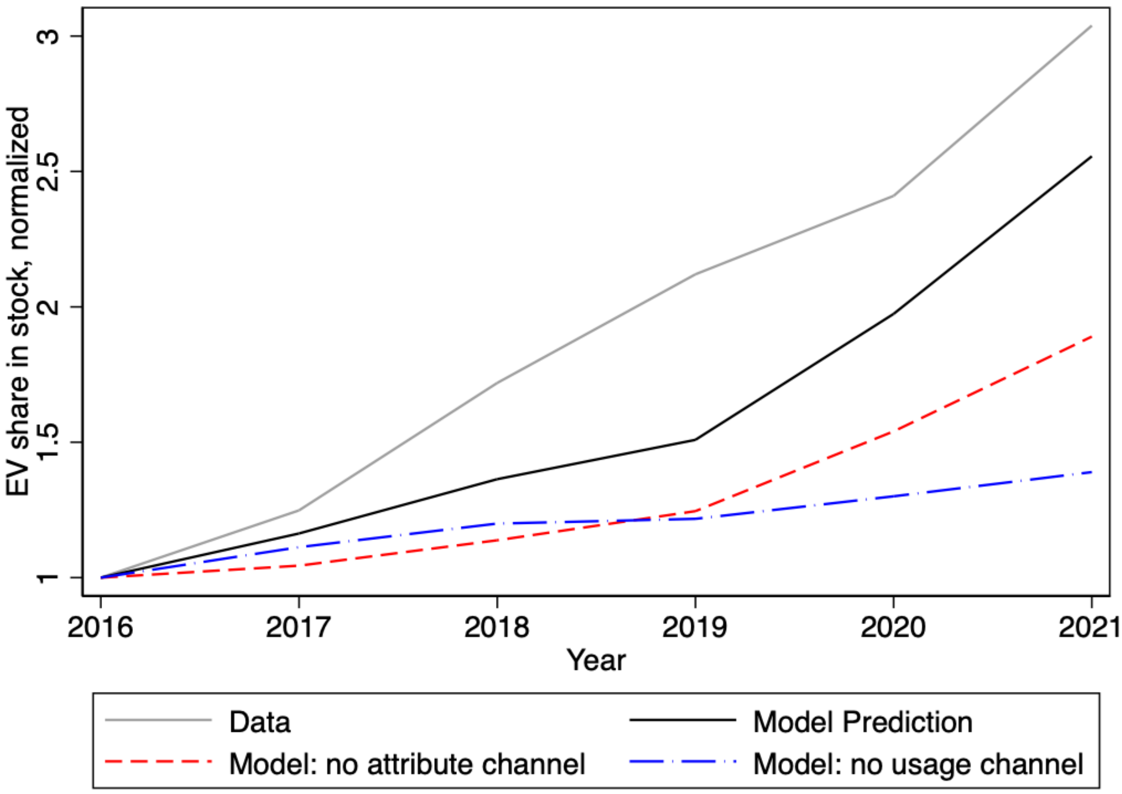


Figure 6: Model Fit: Out-of-Sample Prediction

Notes: This figure compares the model-predicted choice probabilities with the observed data shares from 2017 to 2021. The model's estimation is based on 2016 data, showcasing out-of-sample prediction results. For comparative purposes, I've normalized both the 2016 data and model to 1. The data is depicted by the thin grey line, while the model's predictions are represented by the bolder black line. I further isolate one channel at a time by keeping the respective variable constant at its 2016 level. The red line is the trend without IVV change and the blue line is the trend without IVU change.

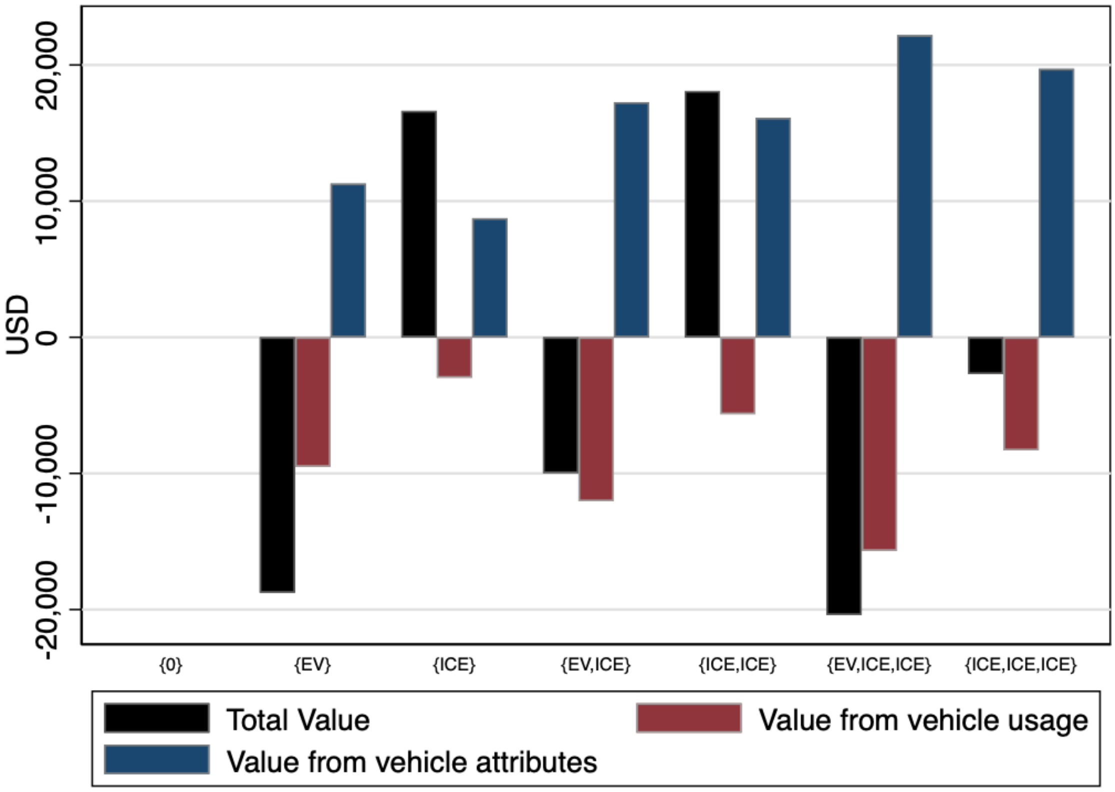


Figure 7: Decompose Utility to Vehicle Usage and Vehicle Vehicle Attributes

Notes: This figure illustrates the decomposition of utility for each portfolio alternative, breaking it down into vehicle usage (IVU) and vehicle attributes (IVV) components. For illustrative purposes, the results are shown using a median income household (with an income of $62,500). To express the utility in monetary terms, I divide each utility component by α_i. The black bars represent the total value; the red bars depict the value derived from IVV, and the blue bars indicate the value sourced from IVU. The difference between the total value and the sum of the IVV and IVU values represents the value captured by the fixed effects. By design, the utility of $\{\emptyset\}$ is normalized to zero.

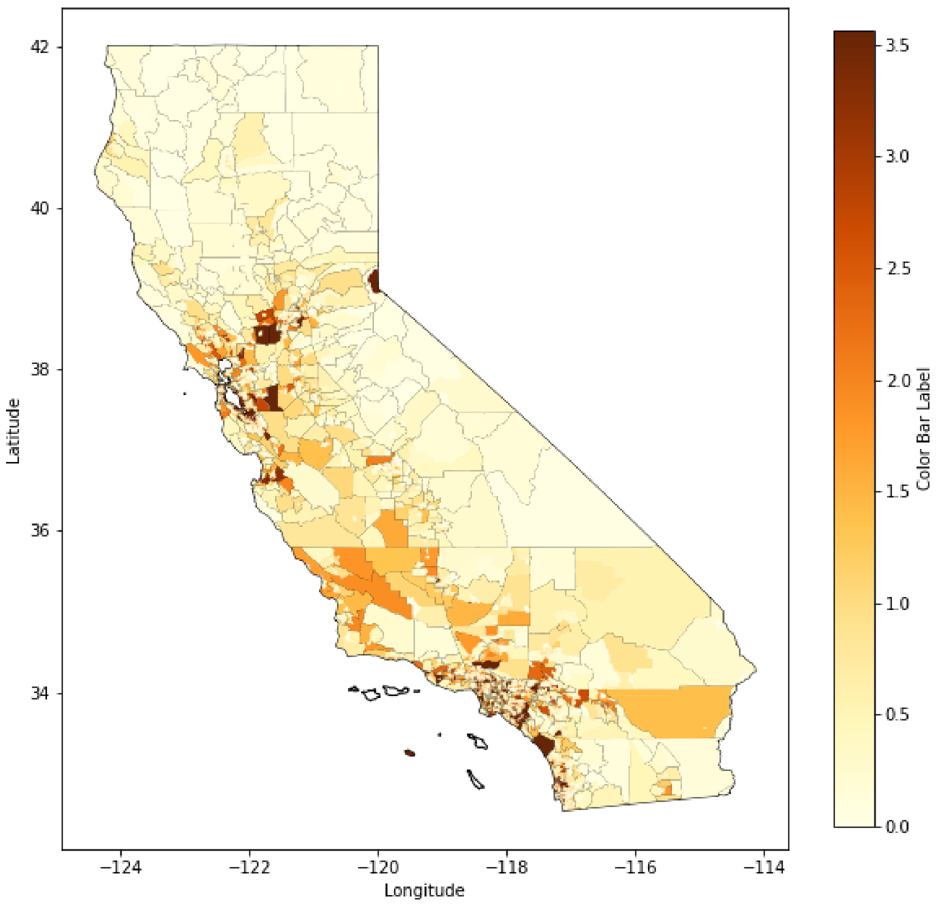


Figure 8: Spatial Distribution of Standardized Environmental Benefits across Census Tracts in California

Notes: This figure depicts the geographical distribution of normalized environmental benefits and EV exposure in California under the status quo.

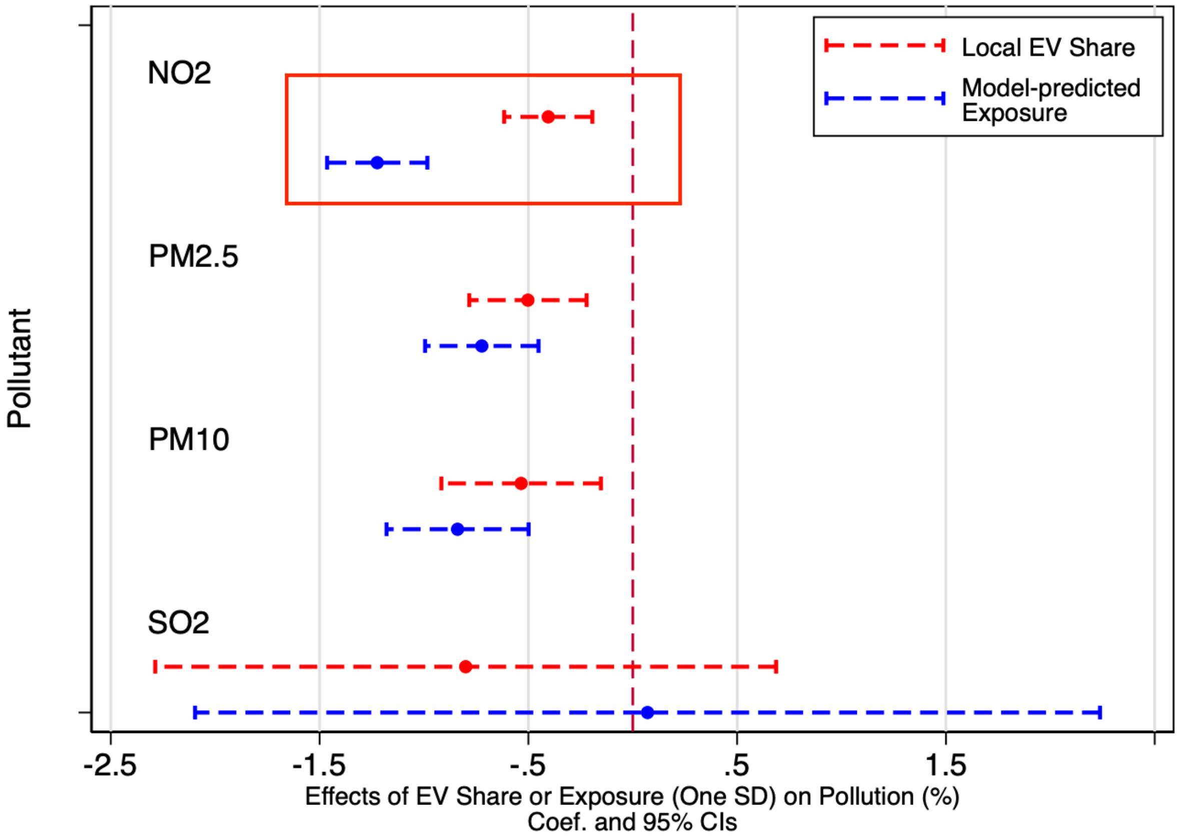


Figure 9: Comparison

Notes: This figure plots coefficients and 95% confidence interval of regression monthly, zipcode-level pollution on either local EV share or model-based EV exposure following Equation 14. I standardized two explanatory variables by dividing by their respective standard deviations for comparison. The coefficients represent the impact of a one standard deviation change in either measure on the percentage change in pollution. The NO_2 is the main outcome of interest as vehicle tailpipe emissions are the major sources of NO_2.

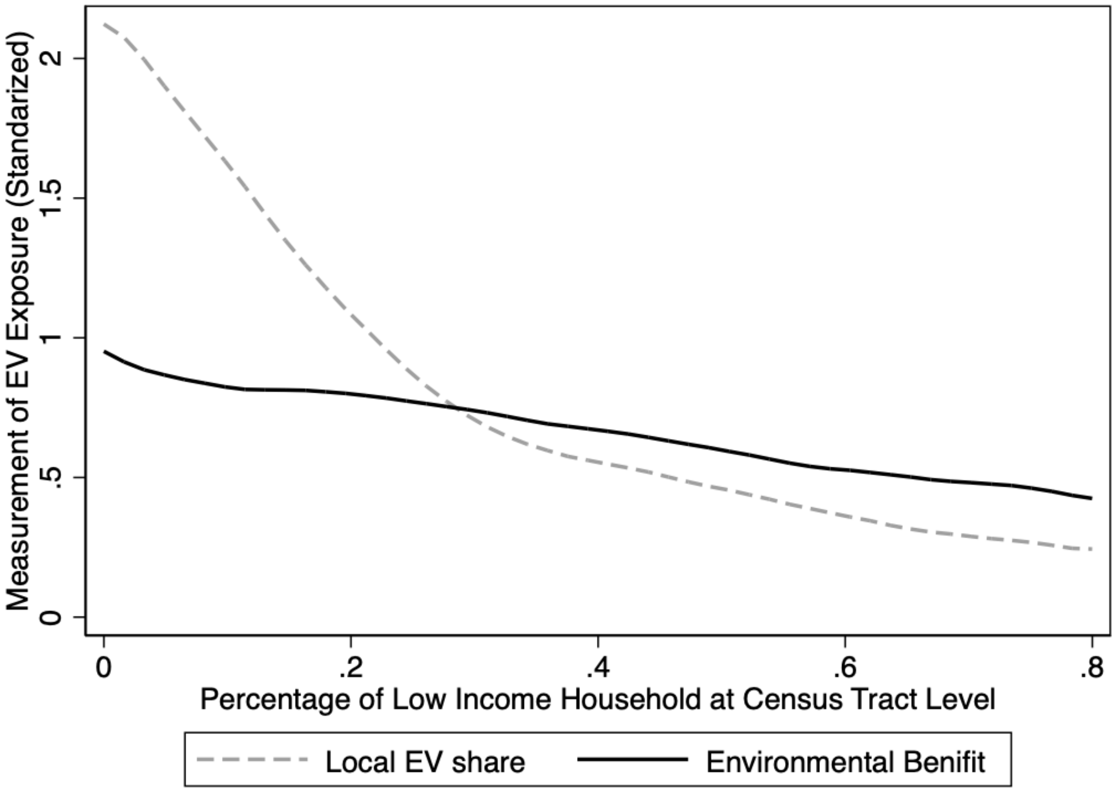


Figure 10: EV Exposure and Low Income Percentage at Census Tract Level

Notes: This figure plots the relationship between environmental benefits and income levels, as measured by the percentage of low-income households (below twice the poverty line) at the census tract level. I fit the relationship using a local polynomial function as a black solid line. For comparison, I also illustrate the relationship between the local EV share in registered vehicles (normalized) and the percentage of low-income residents, denoted by a grey dashed line.

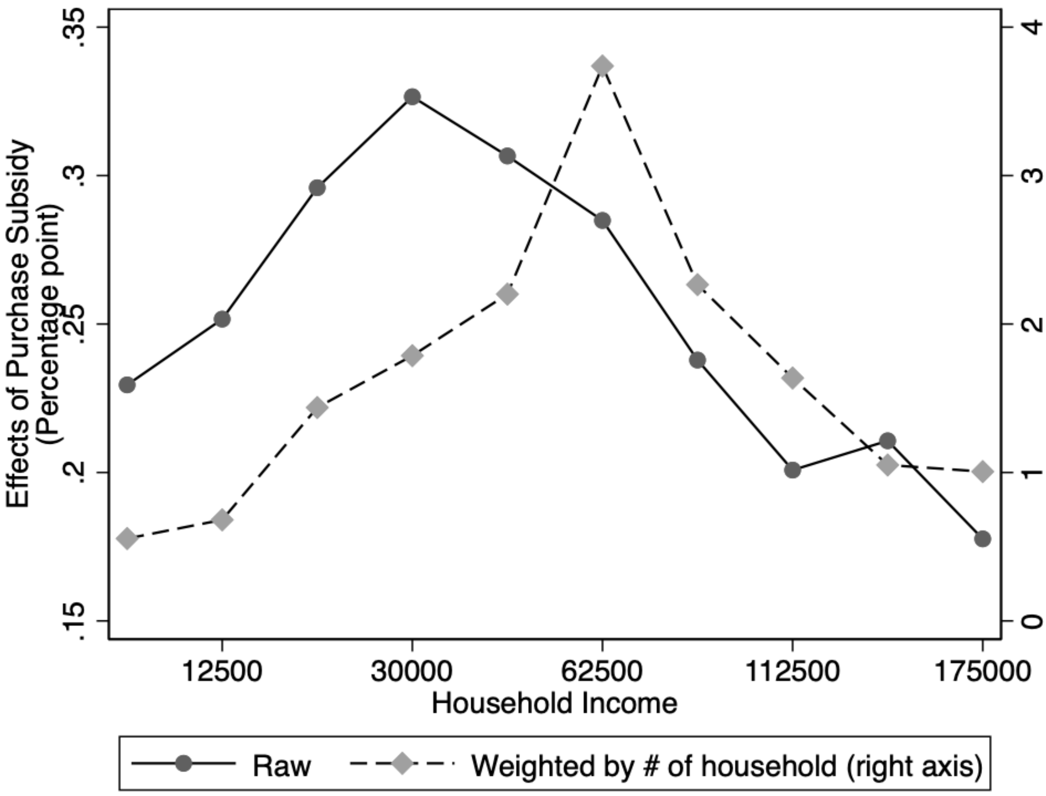


Figure 11: Effects of EV Purchase Subsidies on EV Adoption by Income Groups

Notes: This figure depicts the effects of EV purchase subsidies on the adoption. The effect is measured by comparing the status quo with the case of eliminating all federal and state purchase subsidies. I show results for each income group based on the NHTS data. The solid black line represents the raw results, while the dashed line depicts the results weighted by the number of households in each income group.

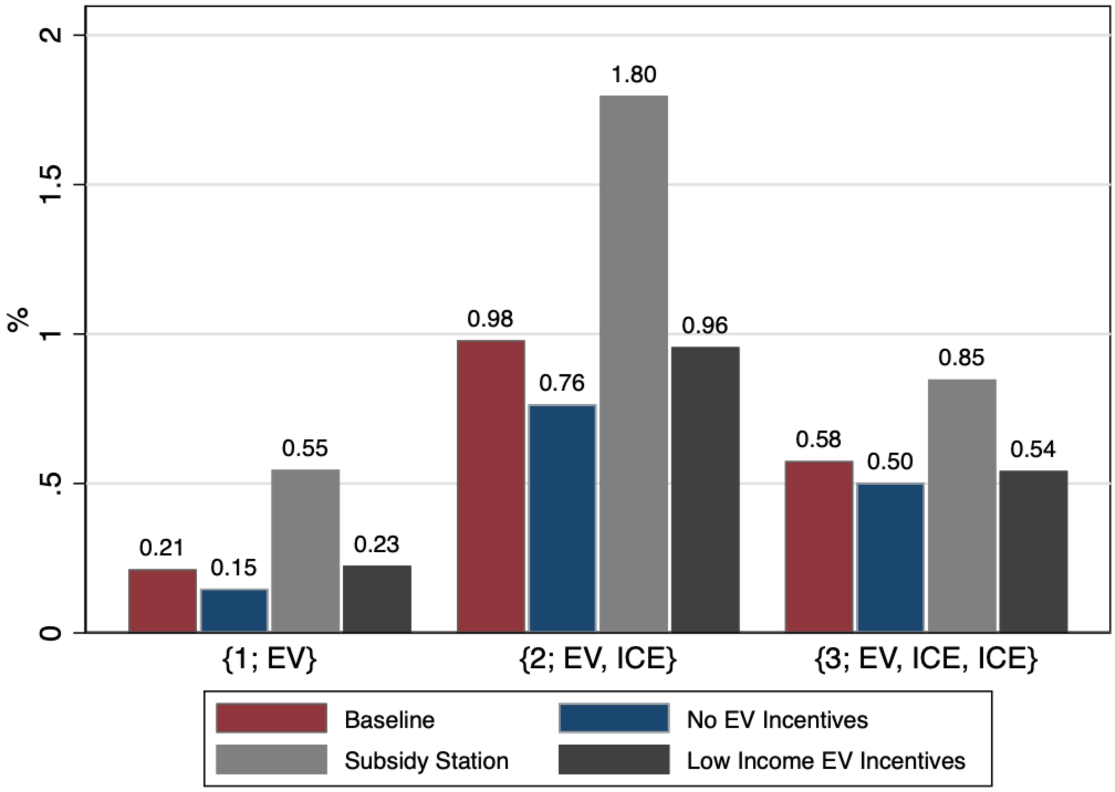


Figure 12: Effects of Counterfactual EV Policies on EV Adoption

Notes: This figure illustrates the effects of EV policies on the choice probability for each portfolio alternative by presenting the difference in choice probability for each portfolio relative to the benchmark. I show results for three portfolios associated with EV, $\{EV\}$, $\{EV, ICE\}$, and $\{EV, ICE, ICE\}$.

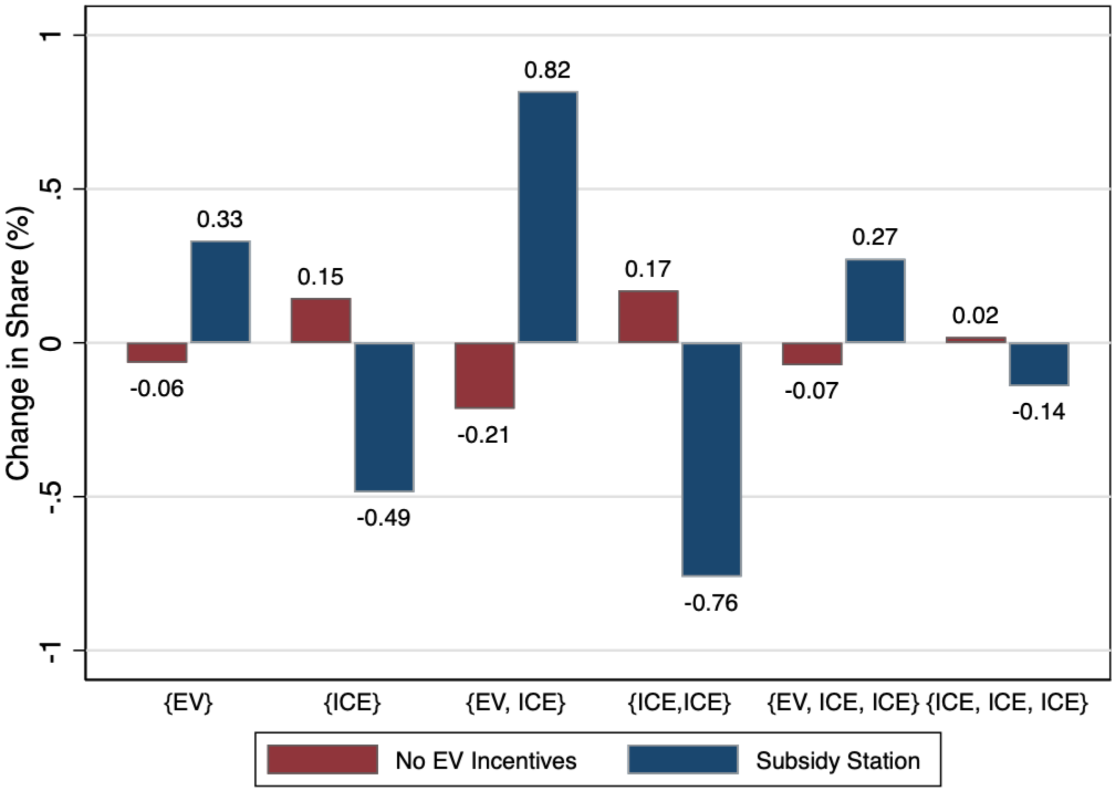


Figure 13: Effects of EV Policies on Choice Probability of Each Portfolio

Notes: This figure explores the relative substitution patterns across vehicle portfolios. It shows the effects of EV policies on the choice probability for each portfolio alternative by presenting the difference in choice probability for each portfolio relative to the benchmark. Intuitively, the figure highlights from where the market share is being drawn to account for the increase in market share of any given alternative.

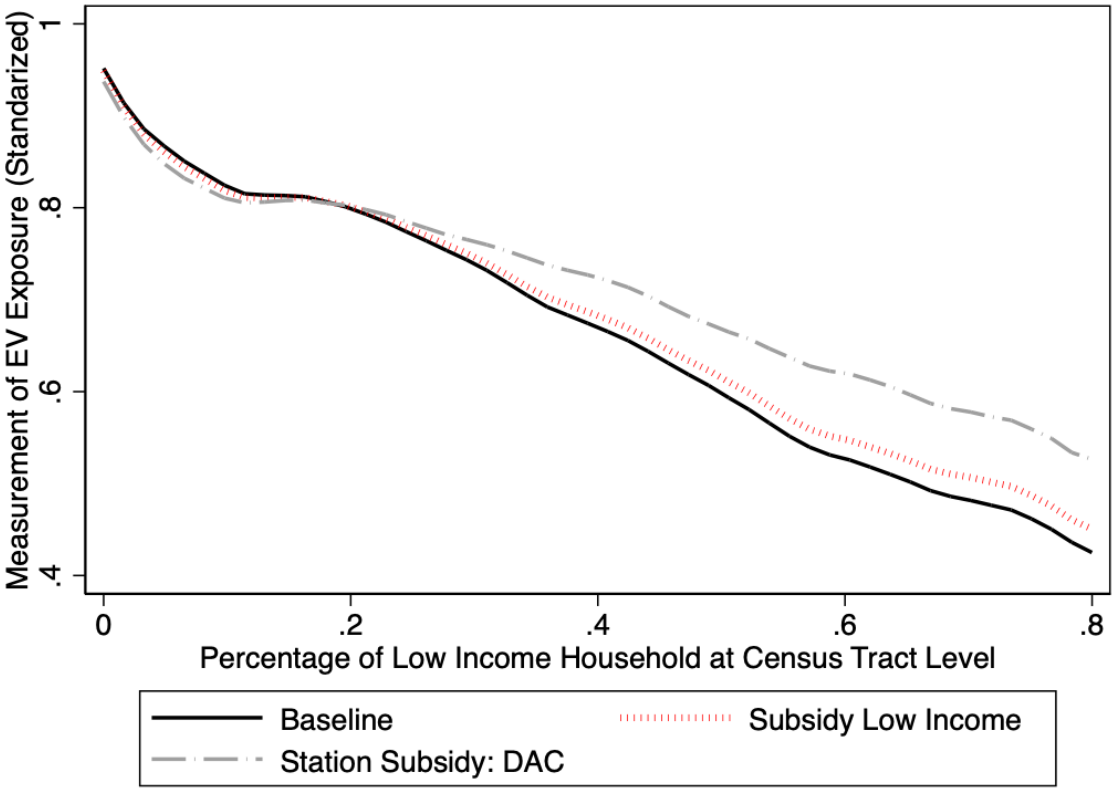


Figure 14: Counterfactual Policies: EV Exposure and Low Income Percentage at Track Level

Notes: This figure shows the impact of EV policies on the relationship between environmental benefits and the percentage of low-income households at the census tract level.

Tables

Table 1: Estimation Results of Vehicle Usage Problem: Maximum Likelihood Estimation

	(1) Logit	(2) Logit	(3) Logit	(4) Logit-Random Coef.
Parameters				
Vehicle age	0.00131	-0.0487	-0.0487	-0.0488
	(0.000)	(0.001)	(0.001)	(0.001)
Fuel cost	-0.00136	-0.0107	-0.0107	-0.0107
	(0.000)	(0.001)	(0.001)	(0.001)
EV × distance	-0.00135	-0.00215	-0.00236	-0.00371
	(0.001)	(0.001)	(0.001)	(0.001)
EV × $Nstation^O$	0.129	0.137	0.136	0.136
	(0.026)	(0.026)	(0.026)	(0.064)
EV × $Nstation^D$	0.0697	0.0778	0.0784	0.0297
	(0.027)	(0.027)	(0.027)	(0.070)
EV × $Nstation^D$ × work	0.237	0.229	0.222	0.523
	(0.049)	(0.050)	(0.051)	(0.270)
Random Coefficients				
EV × $Nstation^O$				0.754
				(0.212)
EV × $Nstation^D$				-0.760
				(0.217)
EV × $Nstation^D$ × work				-3.460
				(1.800)
Fuel type FE	No	Yes	Yes	Yes
Body style FE	No	Yes	Yes	Yes
EV × demographics	No	No	Yes	Yes
Log-likelihood	-200274.42	-184895.52	-184885.9	-184853.51

Notes: The unit of observation is household-trip-vehicle alternatives. Vehicle alternatives for each household are any vehicle in the vehicle fleet plus the outside option (not driving). The number of observations is 582,000. The dependent variable is the utility of any specific trip-vehicle combination. Demographics include household income, household size, sex, race, and home ownership status. Body style FEs include subcompact cars, compact cars, midsize and large cars, sports cars, vans, trucks, and others. Fuel types FEs include gasoline, diesel, plug-in hybrid, battery electric, hybrid, and others. The omitted category is an outside option. The first three specifications are conditional multinominal logit while the last one adds random coefficients. The distribution of preference on the charging network is specified as a standard normal distribution. Standard errors are displayed below parameter estimates

Table 2: Estimation Results for Vehicle Purchase Problem: GMM Estimation

	(1)		(2)		(3)	
	Logit		IV-Logit		BLP-Logit	
Variable	Coefficient	SE	Coefficient	SE	Coefficient	SE
Parameters in mean utility						
log(price)	-0.840	0.008	-1.527	0.009	-19.455	0.048
EV $\times$ log(price)	0.221	0.021	0.757	0.014	0.237	0.059
EV $\times$ log(Nstation)	-0.038	0.024	0.022	0.004	0.075	0.018
Dollars per mile (DPM)	-3.919	0.154	-0.066	0.104	-3.875	0.648
Horsepower/weight	4.778	0.200	9.213	0.153	3.073	1.081
Liter	0.097	0.004	0.131	0.003	0.198	0.015
Displacement $\times$ EV	-0.196	0.011	-0.209	0.006	-0.388	0.034
log(range)	0.081	0.005	0.106	0.003	0.074	0.011
Parameters in the household-specific utility						
log(price) $\times$ log(income)					3.304	0.091
log(income)					-6.742	0.308
log(income) $\times$ EV					0.638	0.036
EV $\times$ White					0.085	0.089
EV $\times$ Black					-2.137	1.185
EV $\times$ Asian					1.959	0.214
Random Coefficients						
σ(log(price))					1.921	0.037
σ(EV)					0.205	0.934
σ(Const)					0.391	1.597
Fixed Effects						
Time	Yes		Yes		Yes	
MSA	Yes		Yes		Yes	
MSA $\times$ EV	Yes		Yes		Yes	
Segment	Yes		Yes		Yes	

Notes: The table reports GMM estimation of vehicle purchase problem. The data is quarterly new vehicle sales data, covering 25 urban Metropolitan Statistical Areas (MSA) in California from 2016 to 2019. The unit of observation is vehicle-model-MSA-quarter. Standard errors (SEs) are clustered at the MSA-quarter level.

Table 3: Estimation Results of Portfolio Choice Problem: Maximum Likelihood Estimation

	(1) Logit	(2) Logit	(3) Logit	(4) Logit Random coef.
IVU - Usage	0.187	0.878	1.152	1.541
	(0.023)	(0.045)	(0.066)	(0.070)
IVV - Attribute: BLP-Logit		0.222	0.122	0.224
		(0.005)	(0.005)	(0.009)
Portfolio FE	No	No	Yes	Yes
Portfolio-by-CBSA FE	No	No	No	Yes
Log-likelihood	-38615.42	-33593.95	-24719.78	-24542.87
Random Coefficients: Portfolio dummies				
estimation of $\phi = 0.86$, standard error = 0.00246				

Notes: This table shows the maximum likelihood estimation of the vehicle portfolio problem. The data is NHTS 2017 data. The unit of observation is household portfolio alternatives. The number of observations is 139,419. I consider seven potential vehicle portfolio alternatives: $\{\emptyset\}$, $\{EV\}$, $\{ICE\}$, $\{EV, ICE\}$, $\{ICE, ICE\}$, $\{EV, ICE, ICE\}$, $\{ICE, ICE, ICE\}$. Column (1) is an inferior specification, which is meant to show why IVV is necessary. The estimations are implemented in two procedures. In the first step, I estimate ϕ. I estimate ϕ using a parsimonious specification as in Column 2. By maximizing the log-likelihood ratio (LR). Then I use the same ϕ across Columns (2) to (4). In the second step, I estimate the conditional multinomial logit problem. The standard errors are calculated using the clustered bootstrap method to account for the computational error.

Table 4: Price Elasticity, Welfare and Travel Behavior by Income Group

	Price Elasticity		Welfare	Travel Behaviors
	EV	Non-EV	CS ($)	% EV Trips
Blow $30000	-7.119	-7.302	7,602.34	48.578
$30000 to 62500	-4.512	-4.667	14,793.37	46.799
$62500 to 112500	-2.963	-3.111	27,706.65	44.694
$112500 to 175000	-1.812	-1.952	51,754.99	40.316
Above $175000	-0.427	-0.558	1138,524.38	38.966
Median	-3.282	-3.431	23,244.42	46.352

Notes: This table reports model-predicted price elasticity and consumer surplus over vehicle portfolio lifetime (approximately 15 years) for different income groups. All monetary values are in 2016 dollars.

Table 5: Counterfactual EV Adoption and Welfare by Income Group

Income Groups	Subsidy Low	Station Policy 1	Station Policy 2	Station Policy 3	Station Policy 4
			△ EV Stock Shares (%)		
Blow $ 30000	0.172	0.092	0.402	0.167	0.177
$ 30000 to 62500	0.150	0.507	1.098	0.619	0.577
$ 62500 to 112500	-0.232	0.905	1.758	1.116	0.964
$ 112500 to 175000	-0.222	1.169	1.994	1.300	1.088
Above $ 175000	-0.127	1.355	2.362	1.690	1.381
Average	-0.026	0.846	1.598	1.027	0.879
			△ Consumer Surplus ($ per Household)		
Blow $ 30000	8.1	13.4	28.2	16.1	16.9
$ 30000 to 62500	12.3	61.7	105.2	62.7	60.0
$ 62500 to 112500	-7.1	155.9	265.1	168.7	148.9
$ 112500 to 175000	-46.0	348.7	518.7	333.7	304.6
Above $ 175000	-172.0	7558.3	12124.9	8583.8	7764.3
Average	-37.4	1443.3	2314.6	1623.7	1468.9

Notes: All policy scenarios maintain the same financial cost. In the Subsidy Low Policy, I consider a case in which all purchase subsidies are eligible for households with income below the median level. In Station Policy 1, new stations are allocated proportionally to the current distribution of charging infrastructure across each zip code. Station Policy 2 allocates new stations based on population share within the zip codes. Station Policy 3 evenly distributes new stations across all zip codes. In Station Policy 4, a place-based policy is considered, with new stations disproportionately allocated to disadvantaged communities (DAC). Specifically, 50% of the new stations are designated for DAC and then are evenly distributed between zip codes within DAC.

Table 6: Counterfactual Environmental Benefit by Group

Income Groups	Baseline	Subsidy Low Income	Station Policy 1	Station Policy 2	Station Policy 3	Station Policy 4
			Panel A: By Income Group			
Blow $ 30000	0.690	0.670	1.638	3.307	2.527	2.388
$ 30000 to 62500	0.784	0.759	1.881	3.724	2.854	2.661
$ 62500 to 112500	0.957	0.921	2.307	4.508	3.462	3.184
$ 112500 to 175000	1.157	1.108	2.799	5.380	4.134	3.760
Above $ 175000	1.386	1.320	3.371	6.478	5.001	4.465
			Panel B: By Origin of Trips			
Same Zipcode	0.057	0.056	0.140	0.248	0.191	0.175
Same County	0.577	0.558	1.382	2.611	2.012	1.838
Origin in non-DAC	0.864	0.824	2.095	4.019	3.120	2.735
Average	1.000	0.961	2.413	4.703	3.614	3.308

Notes: All policy scenarios maintain the same financial cost. The baseline represents the status quo in California with universal federal tax credits and state vehicle purchase rebates. In the Subsidy Low Policy, I consider a case in which all purchase subsidies are eligible for households with income below the median level. In Station Policy 1, new stations are allocated proportionally to the current distribution of charging infrastructure across each zip code. Station Policy 2 allocates new stations based on population share within the zip codes. Station Policy 3 evenly distributes new stations across all zip codes. In Station Policy 4, a place-based policy is considered, with new stations disproportionately allocated to disadvantaged communities (DAC). Specifically, 50% of the new stations are designated for DAC and then are evenly distributed between zip codes within DAC.

Appendix

A Figures and Tables Appendix

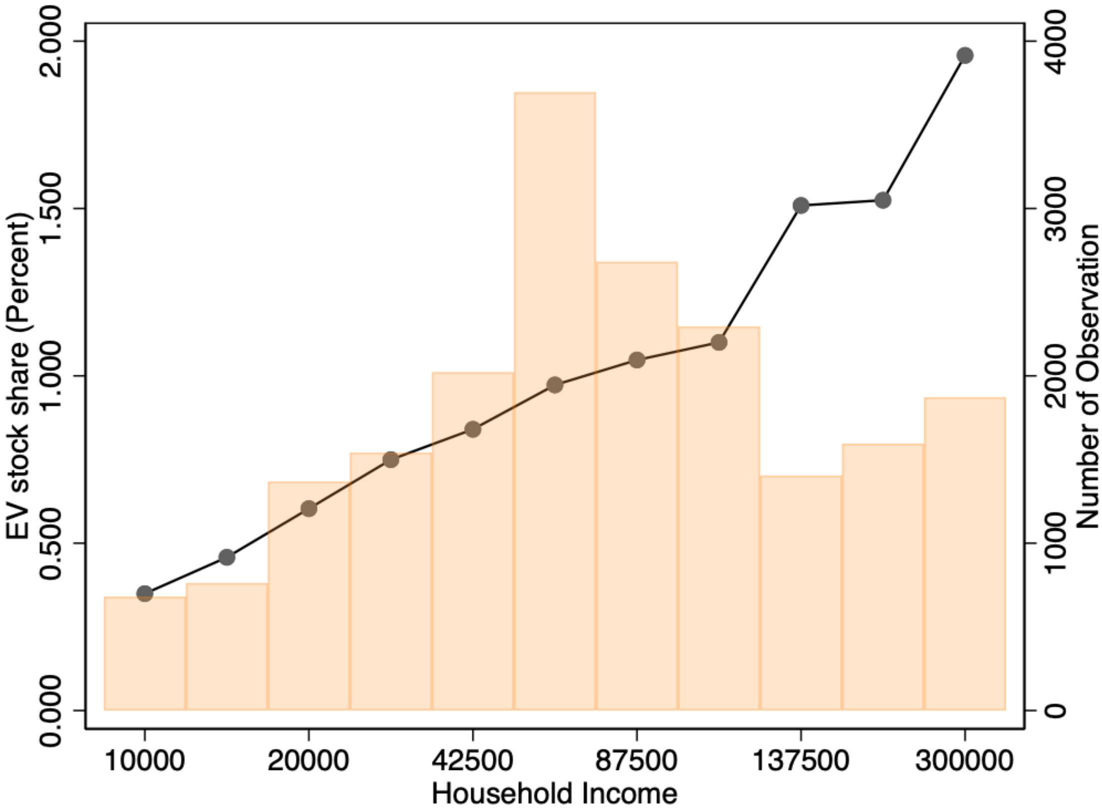


Figure A.1: EV Stock Share by Income Group in NHTS 2017

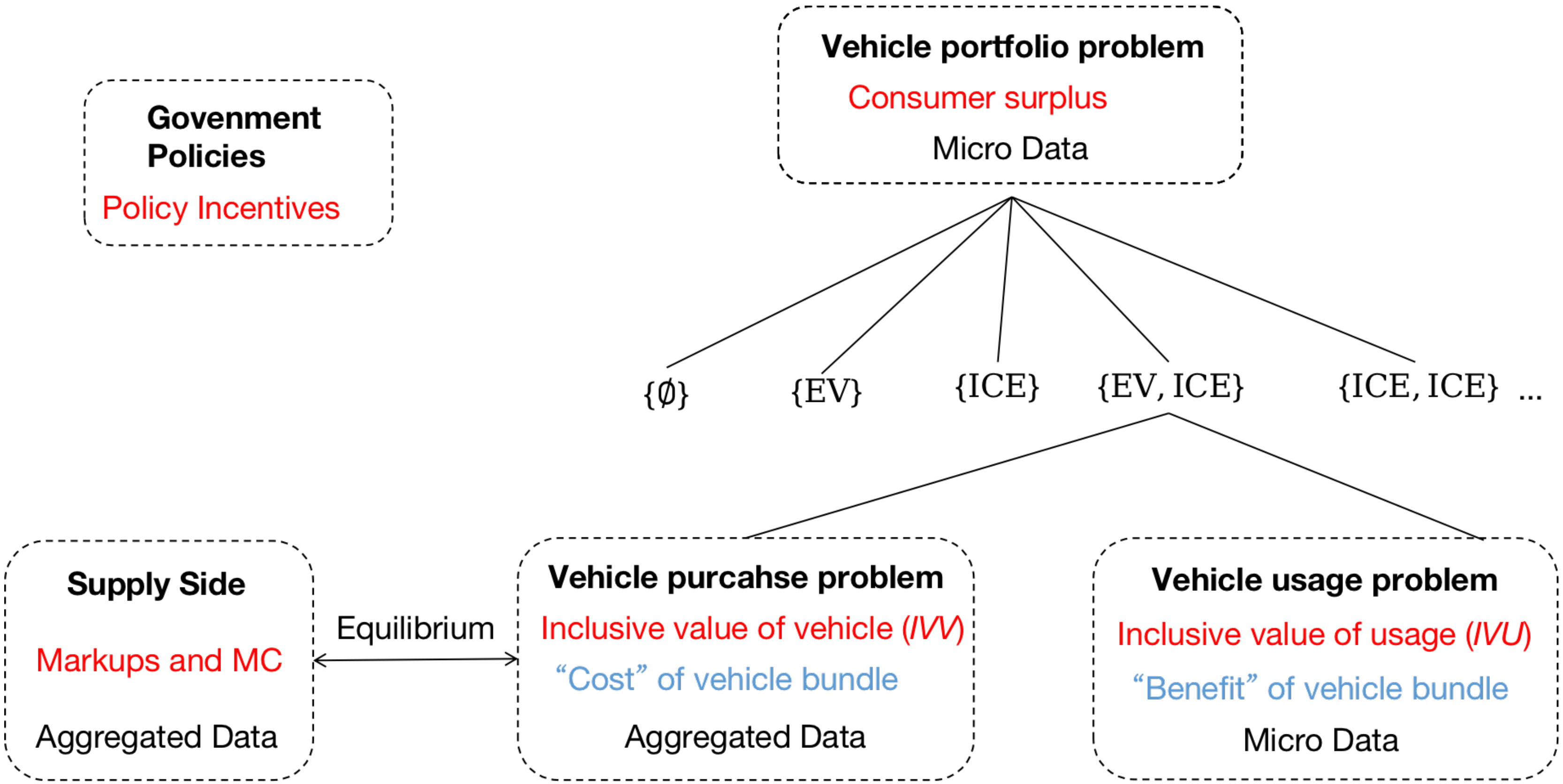


Figure A.2: Structure of the Model

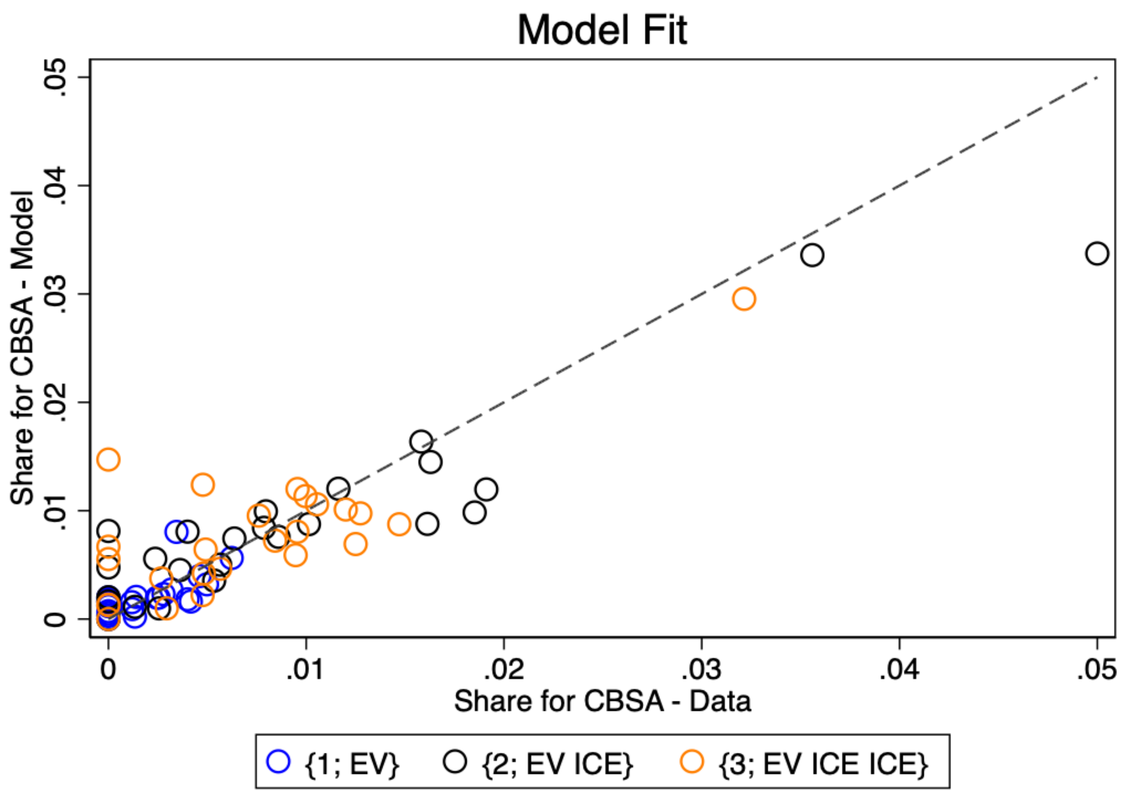


Figure A.3: Model Fit: Portfolio Share in Data and Model by Core-based Statistical Area (CBSA)

Notes: This figure compares the model-predicted choice probability with the observed share in the data for three portfolios associated with EV. The x-axis is the data and the y-axis is the model. The data includes 25 CBSAs, with each circle representing one CBSA. The blue circles are $\{EV\}$, the black circles are $\{EV, ICE\}$, and oranges circles are $\{EV, ICE, ICE\}$.

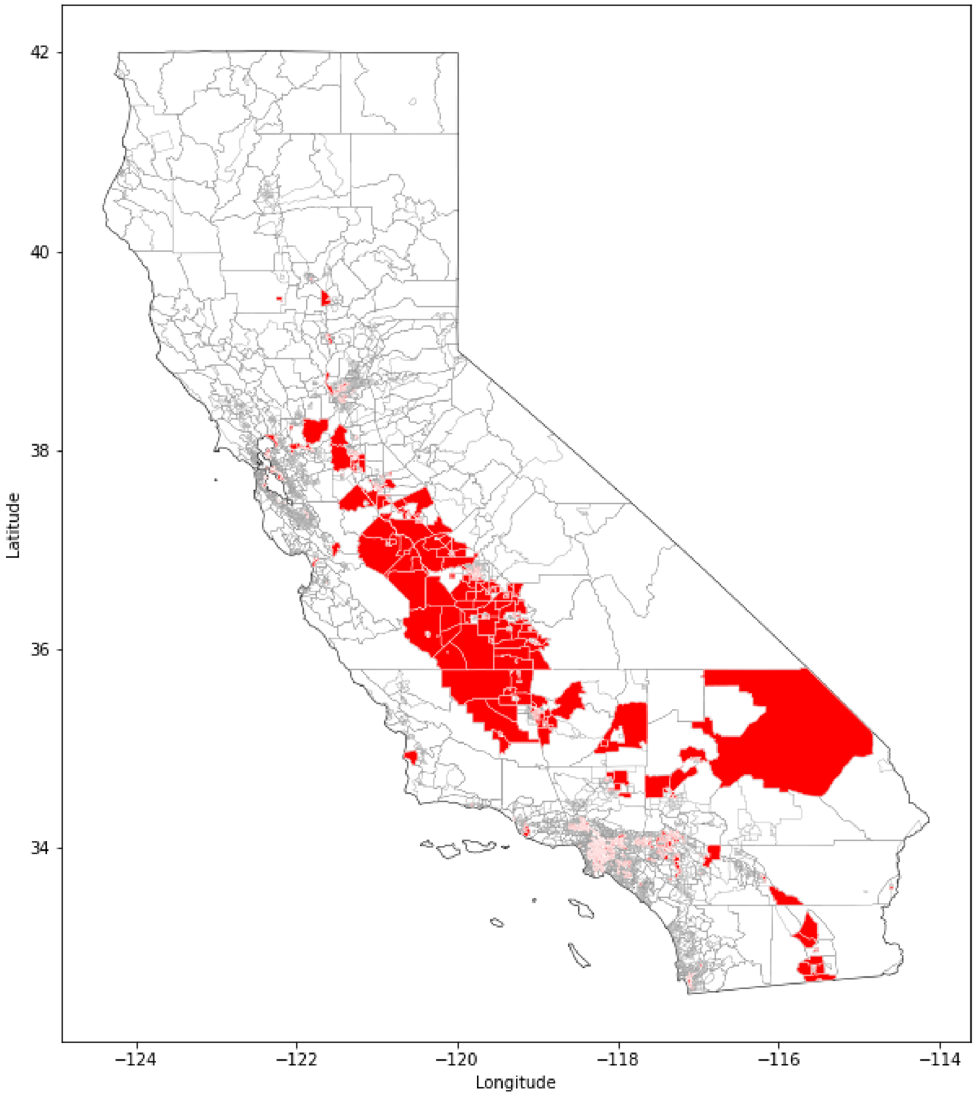


Figure A.4: Disadvantaged Communities Regions in California

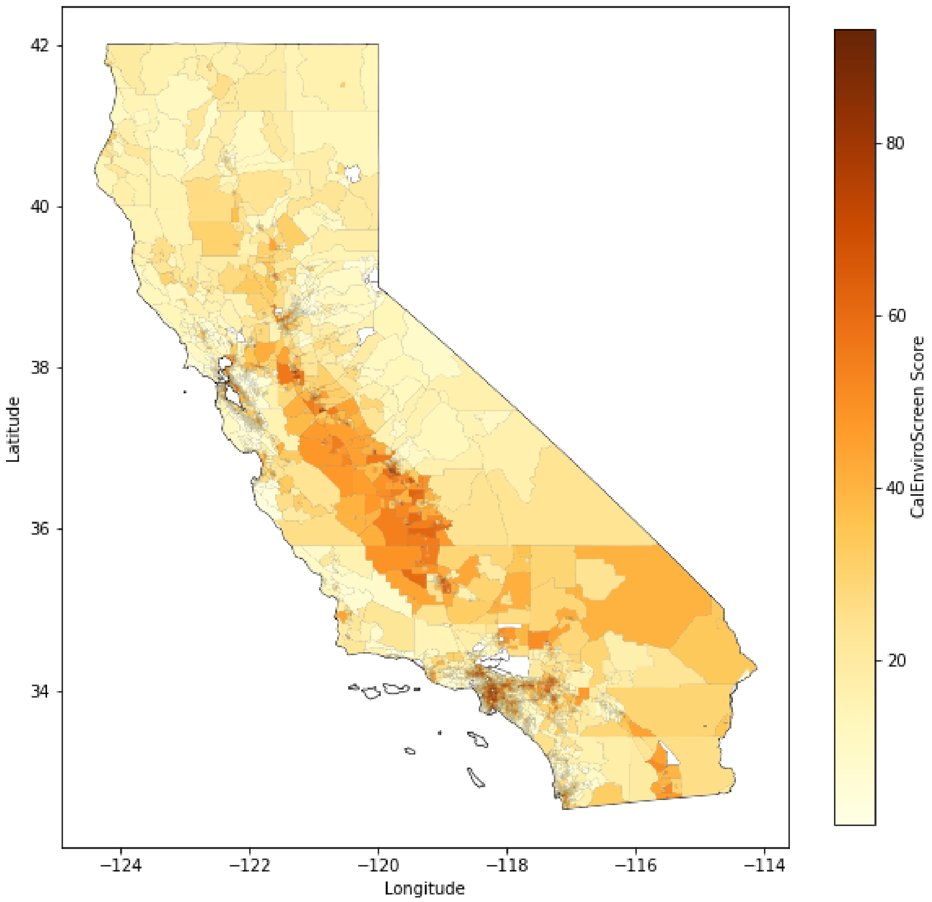


Figure A.5: Disadvantaged Communities and CalEnviroScreen

Notes: This figure shows the distribution of the CalEnviroScreen (or CES) score. Source: CA OEHHA.

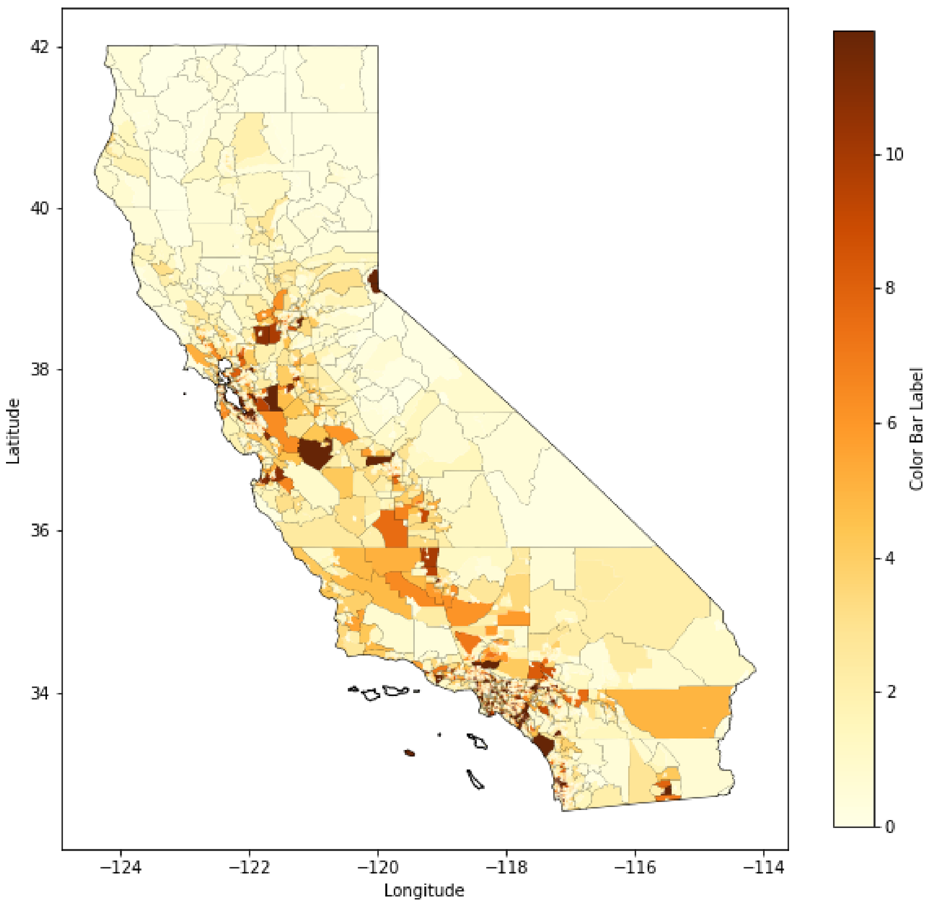
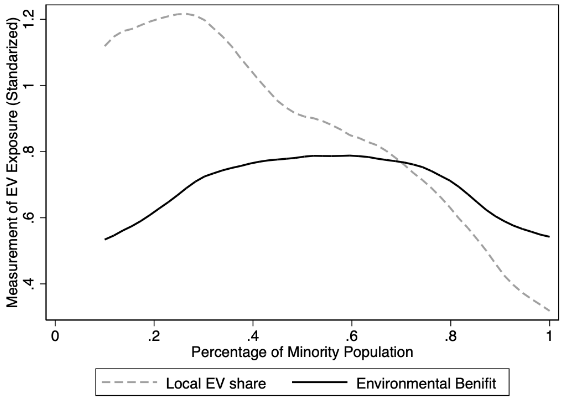
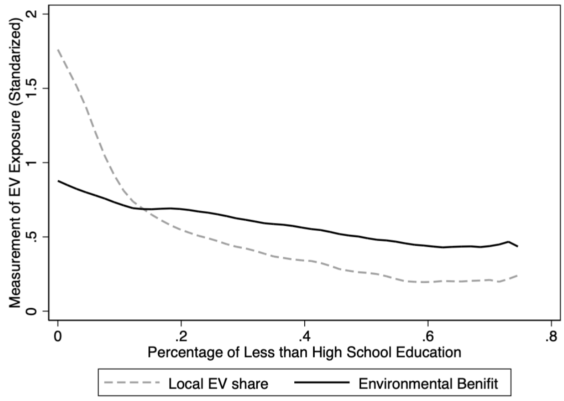


Figure A.6: Spatial Distribution of Standardized Environmental Benefits across Census Tracts in California: Counterfactual, Station Policy 4

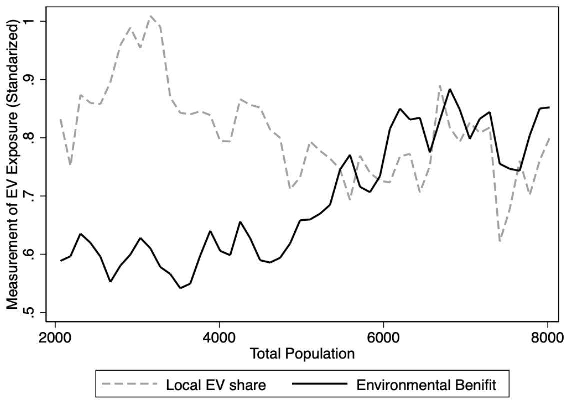
Notes: This figure depicts the geographical distribution of normalized environmental benefits and EV exposure in California under Station Policy 4, which deploys stations disproportionately to disadvantaged communities (DAC). I normalize the environmental benefits level of staus quo scenarios.



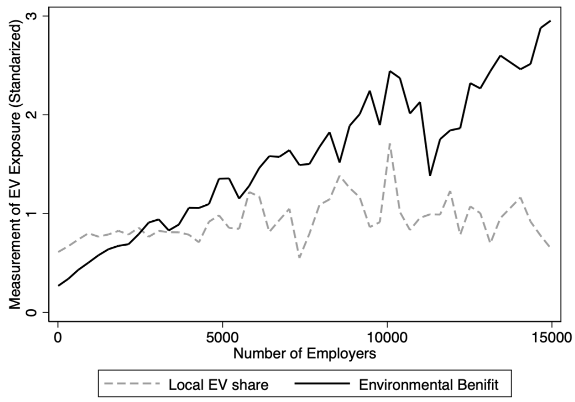
(a) EV Exposure and Race



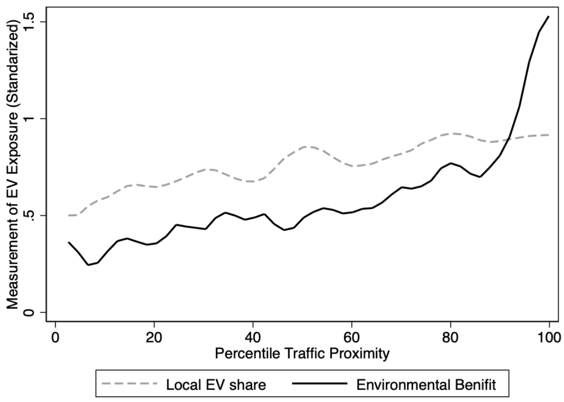
(b) EV Exposure and Education



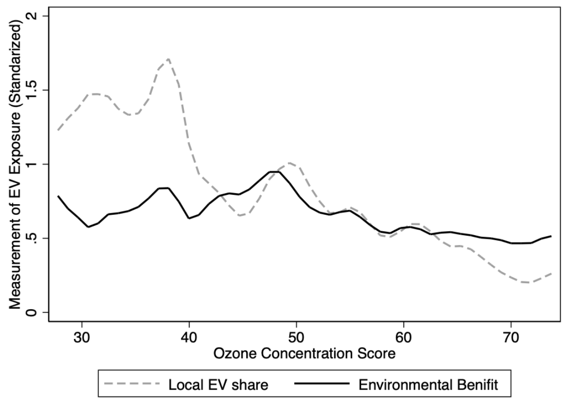
(c) EV Exposure and Population Size



(d) EV Exposure and Employment Size



(e) EV Exposure and Traffic Proximity



(f) EV Exposure and Pollution

Figure A.7: Relationship Between EV Exposure and Other Demographics

Notes: This figure plots the relationship between EV exposure and various demographic and socio-economic variables at the census tract level. The y-axis of all subplots is EV exposure. I compare two measures: environmental benefits calculated by this paper (black line) and local EV share in registered vehicles (grey dashed line). Subfigure (a) is the percentage of the minority population. Subfigure (b) is the percentage of the population with education attainment less than high school. Subfigure (c) is the total population. Subfigure (d) is the total number of employers calculated using the CTPP data. Subfigure (e) is the percentile of traffic proximity from the EJScreen data. Subfigure (f) is the ozone concentration score from the EJScreen data. I fit the relationship using a local polynomial function.

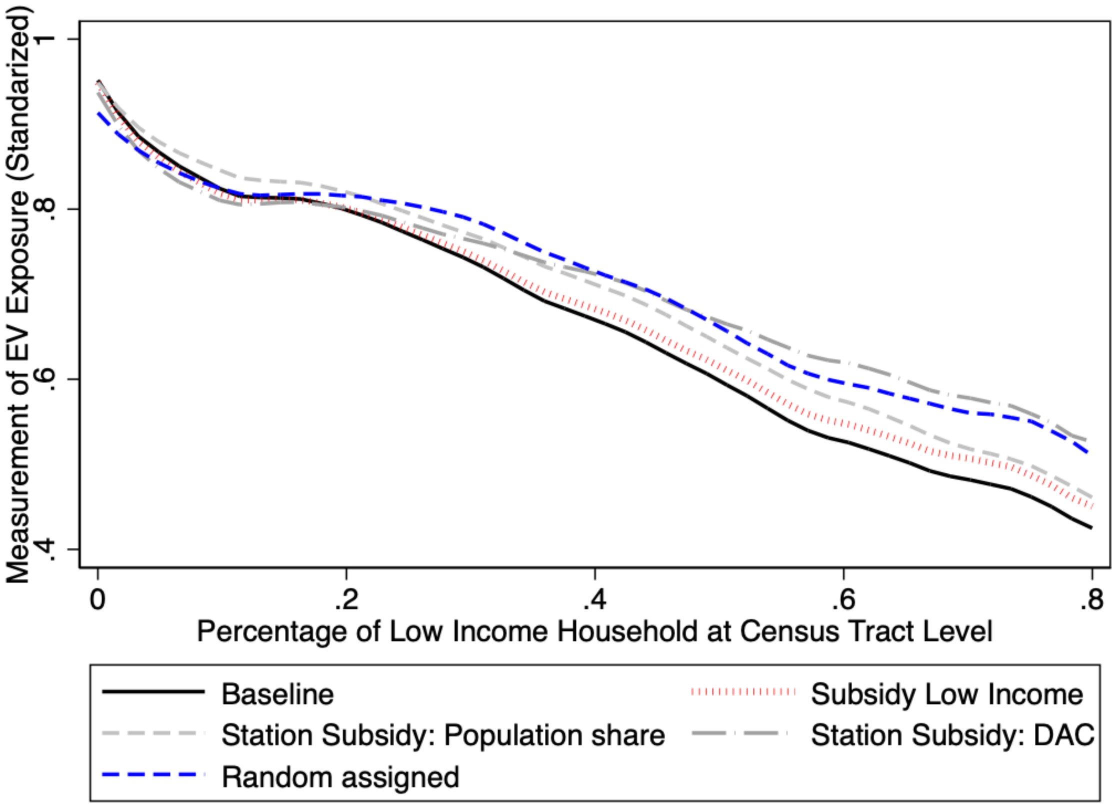


Figure A.8: EV Exposure and Low-Income Percentage at Track Level: More Scenarios

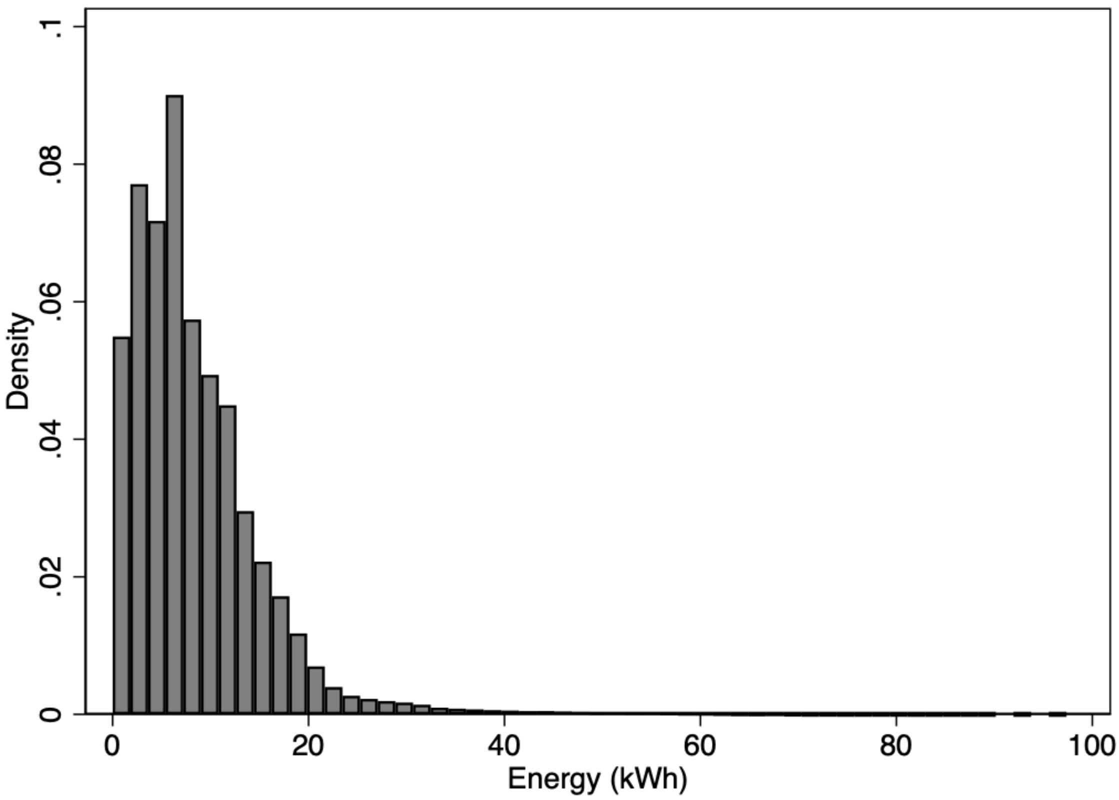
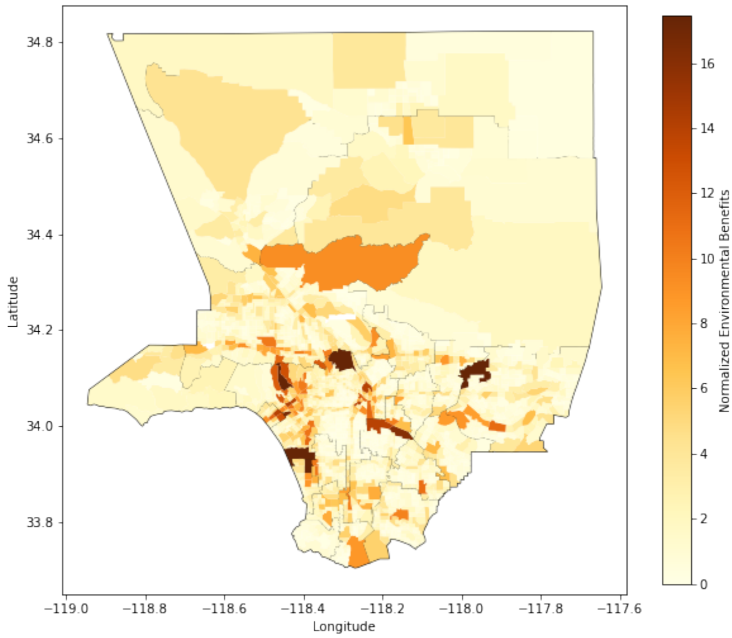
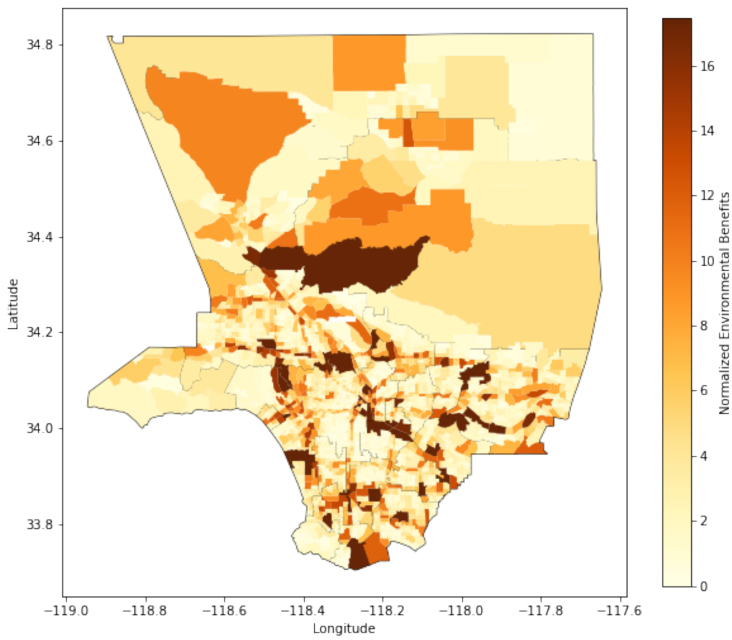


Figure A.9: Histogram of Energy Consumer per Charging Event at Public Charging Stations

Notes: This figure shows the distribution of energy consumers per charging event at public charging stations using transaction-level charging data from public charging stations in Palo Alto, California. The average energy consumption is less than 8 kWh. The full charging energy consumption is about 70 kWh for most popular EV models (Nissan Leaf, Chevrolet Bolt, Telsa Model 3) and over 100 kWh for premium EV models (Tesla Model Y).



(a) Charging Station Policy 1: Based on Current Station Distribution



(b) Charging Station Policy 2: Based on Population Density

Figure A.10: Spatial Distribution of Standardized Environmental Benefits across Census Tracts in Los Angeles

Notes: This figure depicts the geographical distribution of normalized environmental benefits and EV exposure in Los Angeles under two different Station Policies: policy 1 is based on current station distribution; policy 2 is based on population density. I normalize the environmental benefits level of staus quo scenarios.

Table A.1: Estimation Results of Portfolio Choice Problem: Additional Results

	(1) Logit	(2) Logit	(3) Logit	(4) Logit	(5) Logit	(6) Logit
IVV: logit	0.0446	-0.118				-0.0643
	(0.003)	(0.008)				(0.008)
IVV: random coef.			0.145	0.120		
			(0.003)	(0.005)		
IVU					1.068	0.898
					(0.060)	(0.068)
Portfolio FE	No	Yes	No	Yes	Yes	Yes
Log-likelihood	-38389.19	-25746.57	-35521.53	-25229.97	-25538.67	-25476.44

Notes: This table shows the maximum likelihood estimation of the vehicle portfolio problem. The data is NHTS 2017 data. The unit of observation is household portfolio alternatives. The number of observations is 139,419. I consider seven potential vehicle portfolio alternatives: $\{\emptyset\}$, $\{EV\}$, $\{ICE\}$, $\{EV, ICE\}$, $\{ICE, ICE\}$, $\{EV, ICE, ICE\}$, $\{ICE, ICE, ICE\}$. The standard errors are calculated using the clustered bootstrap method to account for the computational error.

Table A.2: Impact of Trip and Vehicle Attributes on Choice Probability: Maximum Likelihood Probit Model

	(1) Probit	(2) Probit-IV
Vehicle age	-0.0292	-0.0292
	(0.000)	(0.000)
Fuel cost	-0.00485	-0.00484
	(0.000)	(0.000)
EV × distance	0.0112	0.0156
	(0.007)	(0.007)
EV × $Nstation^O$	0.0742	0.221
	(0.016)	(0.132)
EV × $Nstation^D$	0.0437	0.349
	(0.017)	(0.121)
EV × $Nstation^D$ × work	0.120	0.216
	(0.030)	(0.050)
EV × electricity rate	-0.0712	-0.0960
	(0.038)	(0.040)
Fuel type FE	Yes	Yes
Body style FE	Yes	Yes
EV × demographics	Yes	Yes
Log-likelihood	-347299.5	
Log-pseudolikelihood		1611538.17

Notes: The unit of observation is household-trip-vehicle alternatives. Vehicle alternatives for each household are any vehicle in the vehicle fleet plus the outside option (not driving). The number of observations is 582,000. The dependent variable is a binary variable whether the vehicle is chosen. The utility of any specific trip-vehicle combination. Demographics include household income, household size, sex, race, and home ownership status. Body style FEs include subcompact cars, compact cars, midsize and large cars, sports cars, vans, trucks, and others. Fuel types FEs include gasoline, diesel, plug-in hybrid, battery electric, hybrid, and others. The first specification uses the standard Probit model. The second specification uses IV probit model following Newey (1987)'s method. Robust standard errors are displayed below parameter estimates.

Table A.3: Counterfactual Results by Income Group

Income Groups	Origin Type	Baseline	Station Policy 1	Station Policy 2	Station Policy 3	Station Policy 4
Blow $ 30000	All	0.684	1.631	3.276	2.511	2.360
Blow $ 30000	DAC	0.106	0.241	0.542	0.388	0.470
Blow $ 30000	non-DAC	0.578	1.390	2.734	2.123	1.891
$ 30000 to 62500	All	0.777	1.872	3.692	2.838	2.633
$ 30000 to 62500	DAC	0.101	0.232	0.528	0.377	0.456
$ 30000 to 62500	non-DAC	0.676	1.640	3.164	2.460	2.177
$ 62500 to 112500	All	0.954	2.308	4.496	3.463	3.172
$ 62500 to 112500	DAC	0.114	0.266	0.583	0.417	0.498
$ 62500 to 112500	non-DAC	0.840	2.042	3.913	3.046	2.674
$ 112500 to 175000	All	1.158	2.810	5.387	4.153	3.763
$ 112500 to 175000	DAC	0.128	0.301	0.642	0.461	0.543
$ 112500 to 175000	non-DAC	1.030	2.509	4.745	3.692	3.221
Above $ 175000	All	1.401	3.417	6.557	5.081	4.517
Above $ 175000	DAC	0.133	0.313	0.670	0.481	0.565
Above $ 175000	non-DAC	1.268	3.104	5.887	4.599	3.953

Table A.4: Descriptive Regression of EV Exposure on Demographics

	Baseline	Station policy 1	Station policy 2	Station policy 3	Station policy 4
Pct. Low Income (<2X poverty line)	-0.777***	-0.809***	-0.729***	-0.797***	-0.548***
	(0.102)	(0.099)	(0.097)	(0.099)	(0.099)
Pct. Minority Population	-0.0985**	-0.171***	0.0617	-0.0115	0.163***
	(0.049)	(0.049)	(0.053)	(0.052)	(0.051)
PM 2.5 Concentration Score	0.0519***	0.0372***	0.0567***	0.0494***	0.0819***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Disadvantage Community	-0.0596**	-0.0956***	-0.0202	-0.0497*	0.115***
	(0.027)	(0.026)	(0.029)	(0.028)	(0.029)
Controls	Y	Y	Y	Y	Y
Observation	7797	7797	7797	7797	7797

B More Background

B.1 EV policies in CA

Federal tax incentives, as well as basic state laws and incentives, are sourced from the Department of Energy's Alternative Fuels Data Center (AFDC). California EV purchase incentives are collected from The Clean Vehicle Rebate Project (CVRP) database. Following Muehlegger and Rapson (2022), I also collect data on disadvantaged community designations from CalEPA and Enhanced Fleet Modernization Program (EFMP) rebate data from the California Air Resource Board (ARB). Both the CVRP and EFMP data are publicly available at the transaction level. I calculate the average EV subsidy from these two programs for each MSA and EV model.

B.2 Charging Technologies

The other side of the EV market is the charging facilities. Homeowners and employers have the option to set up chargers for private use. The expense for installing a Level 2 charging port typically ranges from \$1,150 to \$2,750.[44] Additionally, entities such as EV manufacturers (like Tesla), EV charging network companies (like ChargePoint), utility firms, and public facilities offer public charging stations accessible to the general public, usually operating on a pay-to-charge basis. By the end of 2022, the US had approximately 58,000 public charging stations, totaling over 130,000 charging ports. However, this equates to fewer than 3 charging ports for every 10,000 individuals in the US, with even scarcer availability in less affluent regions.[45]

In terms of charging technology, there are two primary kinds: Level 2 and Level 3 (also called Direct Current Fast Charging, DC). The primary difference between them is the charging speed.[46] A Level 2 charger can charge an EV in 4-8 hours to drive 150 miles, whereas a Level 3 charger can achieve the same range in 15-30 minutes. Level 2 chargers make up approximately 88% of all public charging stations.[47]

B.3 Importance of Public Charging Stations

One common myth related to the current EV (Electric Vehicle) adoption and usage pattern is that most EV owners charge at home, making public charging stations unimportant. The primary observation supporting this impression is that the average daily commuting distance in the US is about 40 miles, while most EV models have a range of more than 150 miles. In this section, I will argue against this misconception from three different aspects.

First, multiple recent consumer surveys show that "range anxiety" and "inability to find

[44] Source: MOTORTREND

[45] Source: ADFC.

[46] Level 1 charging involves a corded nozzle that plugs into a standard 120V electrical outlet. Due to its slow charging speed, it often falls short of the needs of most EV owners and is consequently viewed as outdated technology.

[47] See Li et al. (2019) for more discussion on the compatibility issues related to the charging technologies.

public charging ports" are consistently among the top three reasons for reluctance to adopt EVs (e.g., Autolist, 2023). An important factor is that a significant proportion of households residing in multi-family apartments or single-family houses with outdated electrical systems face challenges when trying to install home chargers. This phenomenon is more pronounced in major metropolitan areas such as New York and Los Angeles.

Second, the insufficiency of public charging stations is more likely the reason for the infrequent use of public chargers, rather than the consequence. Evidence is provided by the Idaho National Laborator. Through their survey, they found that, in general, about 13 to 16% of the charging events used public chargers. However, for those who have access to both home and public chargers at their workplace, this ratio increases to 32 to 39%. Sheldon (2022) also reviewed studies indicating that congestion at public charging stations is more likely to occur in densely populated regions.

Third, unlike gasoline vehicles, not everyone is comfortable depleting an electric vehicle's battery entirely. Based on a survey (by Verra Mobility, 2023), almost all consumers expect their EV to cover at least 60 miles before needing a charge. This expectation stems from the fact that the range for EVs, while relatively stable, depends on various factors such as temperature, terrain (like ascending a mountain), and the use of amenities like the air conditioner. Using transaction-level charging data from public charging stations in Palo Alto, California, I demonstrate in Appendix Figure A.9 that very few charging events result in a full charge. Most drivers charge only about one-tenth of the total range during one visit. This pattern suggests that EV charging behaviors tend to involve high-frequency but low-quantity charges, emphasizing the importance of both home and public chargers.

B.4 Urban Segregation and Disparity Exposure to Pollution

Urban Segregation by income and race is a central characteristic of U.S. cities (Shertzer and Walsh, 2019) and forms the key context of this paper. Segregation leads to inequity problems in poverty, education, intergenerational mobility, and most relevant to this paper: urban pollution. Existing studies have documented that low-income and racial minority neighborhoods are exposed to disproportionately higher levels of airborne and water pollution (Colmer et al., 2020; Tessum et al., 2021). In particular, they face higher health risks due to emissions from nearby roadways.[48] Two reasons are potentially related to this pattern. First, highways and factories that produce air pollution are more likely to be located in predominantly low-income or racial minority neighborhoods due to historical events and government policies (Kodros et al., 2022). Second, low-income and minority populations are more likely to sorting close to roadways for the convenience of public transportation and commuting (Glaeser, Kahn, and Rappaport, 2008). Therefore, in the context of urban segregation, the uneven spatial distribution of electric vehicle usage directly correlates with unequal access to environmental benefits across demographic

[48]U.S. Department of Transportation (DOT) and abcNews

groups (Garcia et al., 2023; Visa et al., 2023).

C Model Appendix

C.1 Used Vehicle Market and Full Market Equilibrium

This paper utilizes both vehicle stock data (from NHTS) and flow data (aggregated new vehicle sales) to estimate preferences for EVs. An over-identification issue may arise. When estimating the model, these two data sources could create discrepant moments regarding EV preference. Furthermore, when simulating policy effects, multiple pairs of EV shock and flow data might satisfy the equilibrium condition. Therefore, an additional condition is required to bridge the EV stock and flow data and to regulate the degree of freedom. The used vehicle market Equation 10 serves this role.

Equation 10 states that there exists a one-to-one mapping between the share of new vehicles s_g and the share of stock in the total population of vehicles A_g that clears the used vehicle market. I specify Equation 10 in a simple linear specification as:

$$s_g = \nu_1 \cdot A_g(\mathcal{S}_i) + \nu_2 \cdot A_g(\mathcal{S}_i)1(g \in EV), \quad g \in \{\text{EV, ICE}\} \tag{B.1}$$

where parameters $\nu_1 > 0$ and $\nu_2 > 0$ essentially how much of newly purchased vehicles are new vehicles.

The above equation closes the model. Therefore, I can define the full market equilibrium as follows

Definition 2. ***Full Market Equilibrium:*** *Given parameter set $\{\Theta_1, \Theta_2, \Theta_3\}$, and exogenous policy vector $\mathcal{P}$, the market equilibrium is defined as (i) the set of vehicle portfolio and model choice, $\{\mathcal{S}_i, S_i \in \mathcal{S}_i\}$ for each household i; (ii) the vector of new vehicle price $\mathbf{p}$; (iii) EV preference shiftier κ on the new vehicle market, such that: (1) vehicle usage problem, vehicle purchase problem, and vehicle portfolio problem are solved. (2) new vehicle market (Equation 6) is cleared. (3) The used vehicle market (Equation 10) is cleared.*

C.2 Model Choice

Based on the stylized facts presented in Section 2.3, the distributional effects of EV policies arise not just from the adoption of the EV, but also from the selection of the vehicle fleet and the utilization of the EV. Thus, the structured model is designed to address three empirical aspects: (1) EV adoption (choice of vehicle model); (2) EV usage, conditional on vehicle fleet selection; and (3) Vehicle portfolio decision.

The overarching challenge related to modeling the multiple vehicle choice problem is an enormous number of potential auto bundles. For example, with J different vehicle models and only two purchase occasions, there are $1 + J + J(J+1)/2$ bundles. This number increases exponentially if one allows for additional purchase occasions. A notable attempt to address this problem is Bento et al. (2009). They build upon the discrete-continuous choice literature (Dubin and McFadden, 1984; West, 2004) and the multiple-discrete choice literature (Dubé, 2004; Hendel, 1999) to estimate a joint model of multiple vehicle ownership and vehicle mileage travel (VMT). However, two caveats of their model prevent me from directly borrowing their framework. First, they do not allow for interaction among fleets of automobiles held by households; for example, the difference in utility between holding a single EV and an EV as a second vehicle depends on household demographics and travel behaviors. As I care about the distribution effect of EV policies, these interaction effects are crucial to evaluating which types of households receive the subsidy. Therefore, I explicitly model the vehicle portfolio choice (or called vehicle bundle choice) and incorporate the idea of "complementarity value" as Gentzkow (2007) and Archsmith et al. (2020).

Second, Bento et al. (2009) do not allow for unobserved product characteristics that are correlated with price. Recent papers about oligopolistic differentiated automobile markets have shown that ignoring endogenous price generates unrealistic substitution patterns. (Berry, Levinsohn, and Pakes, 1995; Petrin, 2002). As I would like to study the distributional effect of EV subsidies, it is crucial to obtain an unbiased estimation of price elasticities. Therefore, I use aggregate product-level data and the BLP method to estimate price parameters separately from the vehicle bundle and the usage problem.

Furthermore, I aim to model the locations where EVs are used and understand the relationship between vehicle usage and trip attributes, such as distance and the presence of charging stations at both the origin and destination. Therefore, for the vehicle usage problem, I depart from the continuous-discrete choice framework and use a trips-specific vehicle choice model given the vehicle bundle of the household.

The model's major drawback is that it employs sequential, two-step estimators instead of the full information, one-step structural approach suggested by Bento et al. (2009). They argue that the two-step approach ignores the cross-equation restriction implied by a unified behavior model and might yield different estimates for the same structural primitives. To deal with it, I discuss the functional form of the underlying utility problem and the assumptions to make the empirical model consistent with a unified behavioral model. I also examine how the welfare analysis is sensitive to the imposed structure of the model.

C.3 Comparing My Model with Related Papers

In this section, I briefly discuss how my framework relates to and differs from previous papers.

Related to Repeated Discrete Choice Model: Hendel (1999), Dubé (2004), and Bento et al. (2009):

The repeated discrete choice framework does not allow for interaction between two choice occasions. As quote in Bento et al. (2009), "*A main drawback is that it does not allow for interaction effects among the fleet of autos held by households*". Given that the vehicle portfolio and the interaction between EV and ICE are crucial for EV adoption decisions, this framework cannot be directly applied to my study.

Related to Gentzkow (2007):

First, while preserving computational tractability, my framework is conceptually richer but sacrifices some of the flexibility inherent in Gentzkow's approach, particularly concerning unobserved correlations in consumer preference. Gentzkow's key innovation lies in accounting for these unobserved correlations across alternatives, enabling a distinct identification of substitution patterns stemming from them. Such correlations are paramount in the context of newspapers, given their non-durable nature and relatively low prices. Hence, the demand for newspapers and online news can be significantly influenced by both cross-sectional (like brand loyalty) and time-series unobserved shocks (such as sudden events). In contrast, vehicles, being substantially more expensive, render these unobserved shocks less significant. For instance, it's unrealistic for consumers to simultaneously purchase an electric car and a gasoline car from the same brand simply out of brand loyalty.

Second, a feature I would like to capture is the interaction between the number of vehicles (vehicle portfolio) and the choice of vehicle type (EV or ICE). The advantage of my data is that I have an additional layer of outcome – vehicle usage conditional on vehicle portfolio. The vehicle usage data enables me to identify specific preference parameters associated with trip-level attributes. Given that vehicles are durable goods, their perceived value at the time of purchase is intrinsically linked to anticipated future use, which, in turn, closely correlates with the attributes of prospective trips. For long-lasting products like vehicles, there's a notable difference between stock share and flow share (new registrations). Household survey data offer insights into stock, while new registration data capture the flow. However, in the context of the newspaper market, as in Gentzkow (2007), this difference is relatively inconsequential.

Third, Gentzkow (2007) uses a full-information, one-step structural approach, while I use a multi-step, nested logit structure that is closer to Goldberg (1995). Gentzkow (2007)'s estimation method is not possible for my analysis due to the expansive potential choice set, coupled with the dimensionality challenges presented when considering portfolios.

Related to Bento et al. (2009)

The key difference between my approach and Bento et al. (2009) is that I combine both NHTS microdata and aggregated new vehicle sales data.

First, While NHTS provides detailed information about vehicle make-model-year, it essentially captures vehicle stock rather than flow. One needs to match with historical vehicle (20 years in their paper) attribute data that are purchased from third-party data vendors. I cannot afford that at this moment.

Second, Bento et al. (2009) uses a repeated discrete choice model framework. In contrast, I've made the simplifying assumption that interactions between different vehicle models, such as between Nissan Leaf and Honda Civic, are analogous to those between models like Tesla Model 3 and Toyota Camry. Thus, granular model-specific information isn't as crucial in my approach.

Third, the highly nonlinear-in-parameters structure of their conditional indirect utility functions limits the possibility of estimating a model with a full set of alternative specific constants (δ) as BLP. Therefore, they could include only a small set of attributes. See their footnote 23.

Fourth, there are no unobserved vehicle attributes ξ_j in Bento et al. (2009), which being said, there are no attributes that are observed to consumers but not to econometricians.

Related to Archsmith et al., 2020

Archsmith et al., 2020 use a different framework that models the substitution pattern at the attribute level instead of the product level. This methodology is possible for them because they have administrative vehicle registration data and unusually rich variation in vehicle attributes