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HOUSEHOLD FLEET CHOICE AND USAGE

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To my parents, for their unwavering support.

To my husband, for keeping me fed during the job market.

To my son, who arrived just in time to see me finish.

“All models are wrong, but some are useful.”

— George E. P. Box

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Nels—People say completing a PhD challenges and transforms you; they say the same

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ABSTRACT

This paper offers new insights into crafting effective emission policies by examining demand for household vehicle fleets. I find evidence that fleet-level adjustment in fuel economy preferences is closely linked to the usage potential of electric vehicles. I estimate a role-dependent model of fleet choice, which allows for trip optimization and captures complementarity preference for vehicle attributes based on travel demands. The shift toward high-fuel-efficiency driving tends to dominate complementary preference for high-range electric vehicles and large utility vehicles, and failure to account for within-fleet substitution underestimates the effectiveness of emission policies.

CHAPTER 1

INTRODUCTION

Transportation is the largest source of greenhouse gas (GSG) emissions in U.S., with light-duty vehicles accounting for 17% of total emissions (EPA). Within this sector, large utility vehicles (LUVs) including sport utility vehicles (SUV), pick-up trucks and minivans, are the biggest contributor, accounting for 11% of national total.¹ Since private vehicle ownership is nearly universal in the U.S., and these vehicles travel extensively, it is critical to reduce emissions in the transportation sector.²³ While advances in vehicle efficiency are essential, policies must also address how much, and how, Americans drive.

In many contexts, households select more than one unit of a product, such as financial assets, housing, spousal jobs, and vehicles. These decisions often occur sequentially or simultaneously, resulting in interdependent preferences. For automobiles, households rarely purchase identical vehicles; instead, they assemble fleets tailored to diverse needs, combining, for example, a compact car for commuting with a larger vehicle for family travel. Consequently, fleet-level complementarities emerge based on usage. This portfolio perspective is important for policy: interventions targeting individual vehicles—such as electric vehicle subsidies or scrappage incentives—implicitly assume that changes in a single vehicle attribute independently influence utility. In practice, however, such policies can affect choices and usage of the remaining fleet [Archsmith et al., 2020, Wakamori, 2015, Munk-Nielsen, 2022]. Therefore, understanding fleet-level household preferences is essential for effective policy design.

Electric vehicle (EV) adoption is an important strategy for reducing transportation emissions but is closely linked to broader household vehicle fleet decisions. Empirical evidence

1. See <https://www.epa.gov/ghgemissions/transportation-sector-emissions>.

2. According to Pew Research, about 92% of U.S. households own at least one car, and 60% own more than one. See <https://www.pewresearch.org/short-reads/2024/11/14/1-in-10-americans-rarely-or-never-drive-a-car/>.

3. Light-duty vehicles traveled over 3 trillion miles in 2023—three times the distance traveled in the 1970s (AFDC). See <https://afdc.energy.gov/data/10315>.

indicates that nearly 90% of EVs in the United States are owned by multi-vehicle households that also possess at least one internal combustion engine vehicle [Davis, 2023]. This highlights that the environmental impact of EV adoption depends not only on the attributes of the EV itself but also on its role within the overall household fleet composition.

This paper develops a two-step model that jointly captures household vehicle fleet composition and trip-level usage patterns. The framework allows the attractiveness of a household fleet to depend directly on expected usage, which incorporates key attributes of EVs such as fuel efficiency and driving range limitations. While prior literature has primarily focused on the environmental impacts of which vehicles households select [Klier and Linn, 2012, Archsmith et al., 2020], comparatively less attention has been paid to the role of usage patterns and the influence of policy interventions on fleet-level emissions. By examining usage-based preferences for household vehicle fleets, this study addresses this gap. Although the application here is to vehicles, the modeling framework is broadly applicable to other multi-product household choices, such as appliances or housing, where the value of individual items depends on both their complementarity within the set and their patterns of use.

I conduct this study in the context of the Texas automobile market, which is among the largest markets in the United States for both electric and gasoline vehicles. The analysis draws on two primary data sources: (1) vehicle registration records from the Texas Department of Motor Vehicles (DMV) for the years 2015 to 2022, which are used to construct household vehicle fleets; and (2) the 2017 and 2022 National Household Travel Surveys (NHTS), which provide information on vehicle fleet composition and trip-level vehicle usage.

I examine the complementary relationship between EV adoption and subsequent vehicle fuel economy. Consistent with prior findings on attribute substitution [Archsmith et al., 2020], the results show that acquiring an EV reduces households' sensitivity to fuel economy in their subsequent vehicle purchase. This behavioral pattern reflects households' demand for a diverse set of vehicle attributes that fulfill varied travel needs, and also parallels findings

in the literature on vice and virtue products, where consumers are known to indulge in “vice” products after engaging in “virtuous” consumption [Khan and Dhar, 2006].

My analysis provides new evidence that such fleet-level adjustments are closely tied to the usage potential of EVs within the fleet—specifically, the all-electric drivable range that represents high fuel-efficiency travel. Battery electric vehicle (BEV) adoption primarily drives these adjustments, whereas plug-in hybrid electric vehicles (PHEVs), due to their limited electric range, do not significantly influence subsequent vehicle fuel economy. Notably, an increase of 100 miles in electric range corresponds to a 6.4 MPG reduction in the fuel economy of the subsequent vehicle, approximately equivalent to replacing a gas-powered sedan with a midsize or standard SUV. On the other hand, greater range capabilities means EVs can accommodate a wider variety of trips. The tension makes the emission outcomes ambiguous: adopting EVs with high range capabilities may inadvertently encourage the subsequent purchase of less efficient vehicles but also allow more high fuel-efficiency travel.

To capture the interactions between EV range capabilities and overall fleet efficiency, I estimate a model of usage-dependent fleet choice. The model accommodates households owning up to two vehicles, which represent about 80% of those in the data. The framework includes two stages. First, households determine the number and type of vehicles to own.⁴ Second, households optimize trip assignments by matching vehicles to trip characteristics such as distance, fuel costs, and range constraints. An key feature of the model is to incorporate and endogenize the usage values of EVs and traditional vehicles from travel patterns in the second stage. Preferences for vehicle attribute are also shaped by expected usage intensity—households anticipate how well the attributes will map onto their travel needs as opposed to simply choose attributes in isolation. This structure enables a nuanced assessment of how different policy interventions influence household fleet composition and usage.

4. For example, a household choose to combine a new 2024 Volkswagen ID.4 EV with 290 miles of range and a three-year-old gasoline-powered Chevrolet Traverse with 5000 miles of odometer reading.

The estimation results show that the cost associated with depleting a BEV’s driving range plays a central role in shaping the usage value of EV fleets. This cost reflects the inconvenience of locating public chargers, the need for additional trip planning, and concerns over range uncertainty. Therefore, single-EV fleets yield lower usage value than single internal combustion engine (ICE) vehicles. Mixed fleets combining an EV and an ICE vehicle produce the highest average usage value, as households capture fuel savings from the EV while relying on the ICE vehicle to offset range limitations.

Fleet choices exhibit role-dependent preferences for vehicle characteristics. For example, fuel economy, driving range, and vehicle age are more important for primary vehicles, whereas size and power matter more for secondary vehicles. A one-MPG increase is valued at \$1,087 for primary vehicles compared to \$602 for secondary vehicles. In contrast, increasing vehicle size from a midsize sedan (e.g., Honda Accord) to a midsize SUV (e.g., Toyota Highlander) is valued at \$1,124 for primary vehicles but rises sharply to \$4,050 for secondary vehicles. Taken together, these patterns suggest that households assemble fleets with complementary attributes to better fulfill diverse travel needs.

Finally, I conduct counterfactual assessment of the emission outcomes to three policies: removal of EV tax credits, imposing annual EV registration fee, and a higher gasoline tax. I find that removing EV subsidies increases net emissions as the shift in high-efficiency driving dominates the complementary preference for BEVs and large utility vehicles. The abolition of tax credits leads to a reduction of 51.3% in EV market share and a 4.14 percentage point decrease in all-electric miles compared to baseline in 2022. A hypothetical fuel tax increase of 26 cents is needed to undo the emission impact.

More broadly, I find that imposing a fuel tax leads to larger changes in driving behavior, whereas the EV tax credit induces larger changes in fleet composition. This is intuitive: a purchase subsidy primarily affects vehicle ownership decisions, while a fuel tax primarily influences vehicle usage. Although my model specification excludes income effects and

is therefore neutral with respect to redistribution, the simulated policy outcomes exhibit heterogeneous distributional impacts. The fuel tax appears progressive, as it disproportionately affects households with high travel demands—typically higher-income households. In contrast, the EV registration fee is regressive, since lower-income groups tend to have more elastic demand for electric vehicles.

Ignoring fleet-level adjustments in ownership and usage biases policy evaluation. The emission rebound from removing the EV subsidy is underestimated, despite the existing incentive scheme tending to over-invest. The estimated social benefit of increasing one unit of CO₂ emissions is \$242, which is approximately 25% to 50% lower than prior estimates of abatement costs from imposing the EV subsidy; this difference mainly arises from shifts toward high-efficiency driving. Similarly, an independent model underestimates emission reductions from the gasoline tax by about 20%.

This paper contributes to the literature on the effects of environmental policies on vehicle characteristics. Previous research has mainly examined vehicle purchase decisions and corresponding gasoline demand from the perspective of individual vehicles [Knittel, 2011, Klier and Linn, 2012], and has evaluated emission outcomes of EV policies [Tal and Nicholas, 2016, Jenn et al., 2018, Muehlegger and Rapson, 2023, 2022, Remmy, 2022, Xing et al., 2021, Fournel, 2024]. A separate strand of literature focuses on fleet-level analysis, but typically considers the vehicle fleet at the aggregate, economy-wide scale [Li et al., 2009, Bhat and Sen, 2006, Mehlig et al., 2023]. In contrast, this paper analyzes fleet emission outcomes using a microfounded model of household fleet choice.

I also complement the literature on vehicle demand and utilization. Most existing studies that incorporate usage assume that utility is directly derived from the total annual miles driven [Mannering and Winston, 1985, West, 2004, Bento et al., 2009, D’Haultfœuille et al., 2014, Grigolon et al., 2018, Burlig et al., 2021, Munk-Nielsen, 2022], or model inconvenience costs as proportional to yearly mileage [Sinyashin, 2021]. In contrast, my model captures

inconvenience at trip level as the effort exerted to avoid battery depletion. My approach differs by capturing inconvenience at the trip level, modeling the effort households expend to avoid battery depletion. This approach reveals complementarity in fleet usage and flexibly highlights limitations in EV operation.

Additionally, this work relates to studies on unintended consequences of environmental policies. Most closely related is Archsmith et al. [2020], which analyzes fuel economy changes in follow-on vehicles after exogenous shifts in a household’s kept vehicle. Apart from offering a perspective on how usage potential drives fleet adjustment, my work differs from Archsmith et al. [2020] in several important ways. Most notably, my approach explicitly accounts for household trip structure and allows for the possibility that households may adapt their travel behavior in response to different fleet compositions. This framework can capture how variations in trip needs and fleet characteristics jointly determine household vehicle usage and subsequent fleet decisions. As a result, I estimate a usage-based fleet choice model, which better informs policies targeting how and how much cars are driven. More broadly, the literature shows that ignoring strategic consumer reactions can undermine policy efficiency, as seen with risk compensation effects [Peltzman, 1975], acquisition of older vehicles following driving bans [Davis, 2008], and strategic use of refunds after currency restrictions [Kim et al., 2022].

CHAPTER 2

THE INSTITUTIONAL DETAILS AND DATA

2.1 EV Market

Over the past decade, sales of electric vehicles—including both battery electric vehicles (BEVs, which run exclusively on electricity) and plug-in hybrid electric vehicles (PHEVs, which can operate on electricity for a limited range before switching to gasoline)—have grown rapidly. They produce zero tailpipe emission when they use electricity to power the motor, and their batteries are charged by plugging into an electric power source. Figure A.2 shows the overall trend in new EV sales. In the early 2010s, electric vehicles accounted for about one percent of new car sales in the U.S., but by 2024, that figure is approaching 10 percent, reflecting broader acceptance and adoption of the technology. Since 2020, BEV sales have steadily surpassed those of PHEVs, and in recent years, BEV sales have been more than triple those of PHEVs.

When modern mass-produced electric vehicles first entered the U.S. market in the early 2010s, high battery production costs prevented automakers from using batteries large enough for long-distance driving while keeping prices at a reasonable level. For example, the 2011 Nissan LEAF (BEV) offered a range of 73 miles per charge with an MSRP of \$32,780. The 2011 Chevrolet Volt (PHEV) had an all-electric range of 35 miles before switching to gasoline and was priced at \$41,000. These figures are representative of most new EV models launched during that time. Tesla was a notable exception: the 2012 Tesla Model S achieved up to 265 miles- far exceeding its counterparts- though at a higher price point of \$69,900.

The steep decline in battery costs over the past decade has enabled a dramatic expansion in the range and affordability of mainstream BEVs. In 2018, Tesla launched Model 3 (up to 310 miles) with a starting price of \$35,000 which quickly became the best-selling electric car in the United States that year—nearly an order of magnitude above any other EVs. Traditional

manufacturers caught up during 2019-2022 with popular models such as the Ford Mustang Mach-E (up to 305 miles), Volkswagen ID.4 (up to 250 miles), BMW i4 (up to 301 miles), as well as luxury models like the BMW i7 (up to 317 miles) and the Mercedes EQ series (up to 350 miles). These models are able to accommodate the majority of household trips by distance. Figure A.1 shows the advancements in the distribution of BEV range. On the other hand, due to the presence of a gas-powered engine, PHEV models are constrained in battery size, making it challenging to significantly increase their electric range. Recent PHEV models now offer 40-70 miles of electric range, which is generally practical only for daily commute on electric power. Since 2019, PHEV sales have been gradually outpaced by BEV sales, driven by improvements in battery technology and increased availability of BEV models (Figure A.2).

2.2 Data Description

My analysis uses a comprehensive dataset with the following main elements:

Household Vehicle Ownership History. The primary data source for this study is the Texas Department of Motor Vehicle vehicle registration records. The dataset includes Vehicle Identification Numbers (VINs), transaction prices, odometer readings, owner names, and address information for all vehicles registered in Texas between 2015 and 2022. Because Texas law requires residents to register their vehicles annually, the data effectively captures the complete vehicle ownership history of Texas households during this period. By matching on owner names and addresses, I construct a longitudinal dataset representing the vehicle fleets owned by Texas households each year. The analysis focuses on households owning two or fewer vehicles and excludes those with fuel types other than gasoline or electric. Additionally, households with missing or inaccurate key information—most commonly in transaction price and address fields—or whose vehicles could not be matched to supplementary vehicle attribute data are omitted to ensure completeness. After these exclusions, the final sample

comprises approximately 6 million households over the study period. I perform the analysis on a 20% random sample, around 1.1 million households.

Supplementary Vehicle Attributes. I supplement the ownership data with make and model information from VinAudit.com, Inc., a leading vehicle data and software solutions provider for the U.S. automotive market. Additional attributes are obtained by matching vehicle models with the U.S. Environmental Protection Agency (EPA) dataset.¹ The data contain fuel efficiency and EV-related attributes including MPG and MPG equivalent (MPGe) for both city and highways, electric range, electric motor power, vehicle size, etc.

Supplementary Household Demographics. I further supplement the vehicle ownership data with household demographic information from the Auto Ownership and Consumer Profiles dataset (Verisk 2024), provided by Dewey Data. This dataset compiles cross-sectional vehicle ownership linked to demographic attributes for a large national sample of U.S. households. By merging VINs, I achieve a match rate of approximately 70 percent with the Texas DMV records. The linked data provide detailed household characteristics, including income, age, household size, and residence type, etc.

Supplementary Fuel Price. I construct my instrument variable from regular-grade gasoline price at zipcode level from GasBuddy in 2018-2022. Notably, the available data covers fewer years than the household vehicle ownership history, so the sample size is smaller in IV analysis.

Household Vehicle Usage Behaviors. I use data from the 2017 and 2022 National Household Travel Survey, a cross-sectional survey that captures detailed information on household automobile ownership, vehicle miles traveled, and demographic characteristics. The NHTS includes travel diaries recording every trip undertaken during a designated survey day and represents a nationally representative sample of U.S. households. I focus on households owning two or fewer vehicles, comprising 52,692 households in 2017 and 3,295

1. <https://www.fueleconomy.gov/feg/download.shtml>

in 2022. The substantial reduction in sample sizes was due to the change in survey design and methodology. Notably, the two datasets differ variables relevant to this study: the 2017 survey provides detailed vehicle model and fuel efficiency (MPG) data, whereas the 2022 survey offers more limited information such as make, model year, body style and fuel type. To address the data limitations in the 2022 survey, missing vehicle attributes are imputed by matching households to Verisk’s vehicle ownership data, identifying the most similar households based on available vehicle features, demographic profiles and geographic context characterized by Metropolitan Statistical Area (MSA) size and urbanization level.

CHAPTER 3

MOTIVATING EVIDENCE

In this chapter, I present descriptive evidence on household vehicle fleet composition and usage pattern, and further examine the complementary relationship between EV adoption and subsequent vehicle purchases to motivate the structural analysis.

3.1 Fleet Structure

Electric vehicle adoption is closely associated with the ownership of other vehicles. In Table 3.1, I present trends in fleet ownership and the attributes of newly registered electric vehicles over time in Texas.¹ Improvements in electric range have paralleled the growth of EV adoption. However, most EV owners still maintain a mixed fleet, combining EVs and gasoline vehicles. Households with both an EV and a gasoline vehicle outnumber those with only a single EV by about four to one—much higher than the ratio for households owning two versus one gasoline vehicle. This likely reflects that the diverse functional needs of households—such as commuting, long-distance travel, and cargo hauling—are not always met by a single electric vehicle. Given the range limitations of EVs, households with some needs for longer trips may rationally retain or purchase a gasoline vehicle to fulfill those needs. This underscores the importance of understanding how EV adoption interacts with other vehicles in the household.

To assess the role of mixed fleets, I begin by examining the ownership patterns of two-car households. Figure 3.1 shows the probability of acquiring a second vehicle (in columns) conditional on the type of car already in the household fleet (in rows)—similar to a transition

1. The first panel is a "stock" concept, including all previously purchased vehicles owned at a given point in time. Households that exclusively purchase used gasoline vehicles are excluded, as less than 10 percent of EVs are adopted by such households. The second and third panels represent "flow" concepts, capturing the attributes of EVs transacted during the year. Both new and used EVs are included, which explains why the minimum range has not changed significantly despite advancements in the minimum electric range of new models (Figure A.1).

	2015	2016	2017	2018	2019	2020	2021	2022
Fleet types								
{EV} household share	0.0004	0.0004	0.0005	0.0006	0.0007	0.0008	0.0013	0.0024
{EV, EV} household share	0	0.0001	0.0001	0.0001	0.0001	0.0002	0.0004	0.0007
{EV, ICE} household share	0.0015	0.0016	0.0018	0.0023	0.003	0.0036	0.0054	0.0081
{ICE} household share	0.337	0.336	0.334	0.327	0.344	0.351	0.356	0.355
{ICE, ICE} household share	0.404	0.404	0.406	0.405	0.397	0.402	0.397	0.394
3+ car household share	0.207	0.207	0.205	0.210	0.198	0.182	0.179	0.178
no car household share	0.050	0.051	0.053	0.055	0.057	0.061	0.061	0.062
BEV attributes								
N models	10	12	14	14	19	22	29	35
Range median (mi)	75	84	218	238	264	315	326	265
Range min (mi)	50	50	62	62	50	62	62	50
Range max (mi)	265	265	310	310	373	387	405	516
Price median (\$000)	94	91	81	67	61	62	59	61
Price min (\$000)	13	10	10	14	16	20	26	35
Price max (\$000)	169	190	198	191	192	265	297	242
PHEV attributes								
N models	10	17	21	24	24	29	34	41
Range median (mi)	20	20	25	25	32	33	33	32
Range min (mi)	11	11	10	9	10	9	9	9
Range max (mi)	72	97	97	97	126	126	126	126
Price median (\$000)	40	35	34	40	34	33	43	54
Price min (\$000)	19	14	14	14	12	12	14	16
Price max (\$000)	211	185	176	279	239	220	245	211

Table 3.1: Summary statistics, registration dataset, 2015 to 2022

Notes: This table presents summary statistics for Texas DMV registration data. The first panel reports the annual stock of vehicles owned by Texas households, where each observation represents a household-year. Non-EV households that exclusively own used ICE vehicles over the data period are excluded. Shares of households without cars are calculated using American Community Survey (ACS) 1-Year Estimates. The second and third panels summarize the characteristics of newly registered electric vehicles at each point in time, including both new and used transactions. All prices are reported in 2022 USD.

matrix, except that both vehicles are held simultaneously. The figure highlights the prevailing tendency toward a "big car and small/efficient car" pairing across fuel types.² Notably, EVs are most frequently paired with large utility vehicles. Additional detail is provided in Figure A.3 in the Appendix, which presents analogous probabilities across more granular vehicle categories for households that have ever owned an electric vehicle (hereafter referred to as EV-experienced households). The figure also shows that, compared to owners of low-range BEVs, households with a high-range BEV have a lower conditional probability of choosing a small vehicle (compact cars, midsize sedan and small SUV) and a higher conditional probability of choosing a large vehicle (standard SUV and pickups).³ Figure A.4 provides additional evidence on the change in fuel economy before and after EV adoption for EV-experienced households.

This pattern could arise from two sources of correlation. First, the interdependence between high-range BEVs and low-fuel-efficiency vehicles may stem from unobserved household characteristics such as income or lifestyle. For example, high-income households are more likely to adopt high-range BEVs due to their higher price tag, while simultaneously favoring luxury designs which often sacrifice fuel efficiency or requiring larger vehicles for family needs. These factors generate spurious co-occurrence patterns.

Second, structural complementarity in preferences may drive fleet choices. Given inherent engineering trade-offs, some vehicle attributes are negatively correlated. For example, higher fuel efficiency often comes at the expense of size or horsepower. Households that value both face trade-offs when choosing each vehicle independently. A reasonable alternative is to optimize the attributes jointly by diversifying their fleets. Specifically, they may pair a fuel-efficient vehicle for daily commuting with a larger vehicle for special occasions. This likely suggests that vehicle types are not simple substitutes in fulfilling household travel demand.

2. The Large Utility category includes midsize SUVs, standard SUVs, and minivans.

3. The cutoff for high- versus low-range BEVs is 200 miles.

3.2 Causal Impact of Fleet Adjustment

I model the relationship between the fuel efficiency of the stock and the follow-on vehicle for household i at time t as follow:

$$f_{it}^{fo} = \beta_0 + \beta_f \mathbb{I}\{\text{stock EV}\} + \beta_X X_{it}^{st} + \epsilon_{it} \quad (3.1)$$

Here, f_{it}^{fo} denotes the fuel efficiency (in miles per gallon) of the follow-on vehicle, while $\mathbb{I}\{\text{stock EV}\}$ is an indicator of whether the stock vehicle is of particular fuel type.⁴ The term X_{it}^{st} is a vector of attributes for the stock vehicle, included to control for factors such as vehicle age and whether the vehicle was purchased new or used. To account for time-varying macroeconomic trends specific to each fuel type—such as surge in gasoline prices or the expansion of charging infrastructure—I include year-by-fuel-type fixed-effects in the model.⁵

To estimate the causal effect of EV adoption on subsequent vehicle fuel efficiency, the ideal experiment would randomly assign fuel types of stock vehicles to households. Since such randomization is not feasible, a primary challenge arises from endogeneity: the attributes of a household’s stock vehicle reflect underlying preferences that are also likely to affect the characteristics of their subsequent vehicle choices. To disentangle correlated preferences from true complementarity, I account for both static and time-varying preferences. First, I leverage the panel structure of household fleet histories and use household fixed effects to control for time-invariant preferences. For instance, if a household consistently prefers vehicles with high horsepower, household fixed effects will capture this persistent tendency across all their

4. The combined MPG is calculated using the city/highway weighting (55% city, 45% highway) as defined by the EPA. For BEVs, fuel economy is measured in miles per gallon equivalent (MPGe), an EPA metric that compares energy efficiency across vehicle types (1 gallon gasoline $\approx$ 33.7 kWh electricity). PHEVs have MPG and MPGe ratings for gas and electricity modes, respectively. The actual fuel economy of PHEVs depends on household driving patterns. For simplicity, I use a utility-factor-weighted (UF-weighted) average MPGe developed by the EPA and the Society of Automotive Engineers (SAE J2841). The utility factors are derived from the same travel survey data used in this study and are a function of the PHEV’s all-electric range. Generally, fuel efficiency (MPGe/MPG) reflects vehicle design (aerodynamics, weight) and powertrain, while electric range depends on efficiency and battery capacity.

5. I aggregate the fuel types into two categories: gasoline and EV (including BEV and PHEV).

vehicle choices. Similarly, if a household persistently maintains a portfolio strategy—such as pairing an EV with a large or luxury vehicle as in previous example—fixed effects will absorb this pattern as well. This approach allows me to focus on within-household changes in fuel efficiency over time, isolating the impact of EV adoption from stable household preferences.

Second, I use an instrumental variable strategy to account for unobserved time-varying household preferences. Such preferences may evolve with changes in income, work location, or household composition. For example, the arrival of a new child may simultaneously increase a household’s sensitivity to fuel costs—prompting EV adoption—and alter its subsequent vehicle choice by creating a need for a larger follow-on vehicle. The instrument leverages the gasoline price at the time when the stock vehicle was purchased. The relevance assumption requires that consumers use current gasoline price to form expectations of future prices [Anderson et al., 2013, Busse et al., 2016, Li et al., 2009]. Higher gasoline prices at the time of purchase increase the likelihood of adopting an EV, providing exogenous variation in EV adoption. The exclusion restriction requires that gasoline price fluctuations be unrelated to unobserved household preferences that jointly affect EV adoption and subsequent vehicle choice. This assumption is generally reasonable, as households are unlikely to time major life events around movements in gasoline prices.

Table 3.2 presents the regression results from Equation 3.1, estimated separately for the adoption of BEVs and PHEVs. To incorporate household fixed effect, the sample is restricted with at least two observations during the study period. Each observation corresponds to a buy-stock tuple, which requires the household to have made at least three vehicle purchases. The dependent variable is the continuous measure of MPG, and primary coefficient of interest is that on the indicator for the stock vehicle’s fuel type, $\mathbb{I}\{\text{stock EV}\}$.

In column 1, where unobserved heterogeneity is not accounted for, the results suggest that households that adopting EVs are qualitatively similar to non-adopters in terms of subsequent fuel economy. Column 2 through 4 implement two approaches to identify the

	OLS (1)	HHFE (2)	IV 1st (3)	IV 2nd (4)
<i>(a) All EV adoption</i>				
stock_EV	1.191*** (0.3976)	-7.99*** (0.5480)		-5.160 (7.254)
stock_gasprice			0.0061** (0.0031)	
F-test			16.28	
<i>(b) BEV adoption</i>				
stock_BEV	2.513** (1.018)	-19.62*** (0.5582)		-15.08** (6.416)
stock_gasprice			0.0063** (0.0031)	
F-test			27.34	
<i>(c) PHEV adoption</i>				
stock_PHEV	-1.525 (1.321)	2.05** (0.9623)		7.967 (10.984)
stock_gasprice			0.0033** (0.0014)	
F-test			4.87	
year-fuel type FE	Yes	Yes	Yes	Yes
household FE		Yes	Yes	Yes
Observations	1,434,190	1,434,190	599,442	599,442

Table 3.2: Regression result of EV adoption, continuous dependent variable

Notes: This table reports the effect of EV adoption on the MPG of the subsequent vehicle from a regression of the continuous follow-on vehicle MPG on covariates. Each observation is a buy-stock vehicle pair. Standard errors clustered by household are shown in parentheses. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively. The IV specification uses the gasoline price at the time of stock vehicle purchase.

causal effect of EV adoption. Column 2 introduces household fixed effects to control for static unobserved heterogeneity. In all cases, the estimates reverse sign compared to the ordinary least square (OLS) results, consistent with the notion that households prefer diverse fleets. This finding also aligns with our observation in Figure A.4, where the shift in subsequent fuel economy is evident only for BEV adopters.

Column 3 and 4 further address time-varying heterogeneity by using gasoline price as an instrument. Due to the limited temporal coverage of zipcode-level gas price data, only purchases made between 2018 and 2022 can be included in the IV analysis, resulting in a sample size that is reduced by about half. The first stage results (column 3) show the expected direction in all specifications, and the instrument demonstrates adequate strength in the BEV adoption case. Comparing the IV estimates in column 4 to the household fixed effects (HHFE) estimates in column 2 of panel (b), the coefficients retain the same sign but decrease in magnitude, which is consistent with the hypothesis that lifestyle changes may confound the relationship between BEV adoption and a preference for larger vehicles. For PHEV adoption, however, the IV results are subject to weak instrument problem due to the sample size.

Table 3.3 presents the regression results examining the relationship between the electric range of the stock vehicle and the fuel economy of the follow-on vehicle, considering both BEVs and PHEVs. In both column 1 and column 3, the estimates are negative, aligning with previous findings that a longer electric range leads to lower fuel efficiency in the subsequent vehicle. Quantitatively, a 100-mile increase in electric range corresponds to a 6.4 MPG decrease in the fuel economy of the follow-on vehicle.

One caveat in interpreting the estimates from Table 3.2 and Table 3.3 is that, since the dependent variable is a continuous measure of fuel economy, the fixed effects control for all prior fuel economy levels—including that of the focal EV. Given the extremely high fuel economy of BEVs and PHEVs, this may inflate the household’s baseline fuel economy,

Dependent Variables:	HHFE buy_mpg (1)	IV 1st stock_electricrange (2)	IV 2nd buy_mpg (3)
stock_electricrange	-0.0925*** (0.0020)		-0.0642*** (0.0135)
stock_gasprice		1.796*** (0.5829)	
F-test		32.46	
year-fuel type FE	Yes	Yes	Yes
household FE	Yes	Yes	Yes
Observations	1,434,190	599,442	599,442

Table 3.3: Regression result of electric range, continuous dependent variable

Notes: This table reports the effect of EV range on the MPG of the subsequent vehicle from a regression of the continuous follow-on vehicle MPG on covariates. Each observation is a buy-stock vehicle pair. Standard errors clustered by household are shown in parentheses. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively. The IV specification uses the gasoline price at the time of stock vehicle purchase.

particularly for households with shorter purchase histories. In the extreme case where only three purchases are observed (a stock car, an EV, and a follow-on vehicle), the household fixed effect is determined almost entirely by the EV’s fuel economy. As a result, even if the follow-on vehicle is a hybrid, the estimated effect will still indicate lower fuel economy, reflecting the influence of the high-EV baseline.⁶ Therefore, the original estimates can be interpreted as an upper bound on the true effect, given the influence of these extreme cases. As a robustness check, I re-estimate the model after excluding these households. The HHFE model produces estimates of similar magnitude, but the IV estimates lose statistical significance due to the reduced sample size. These results should be interpreted with caution as households with more frequent purchases may be different in unobserved aspects from those with shorter purchase histories.

The type of fleet adjustment that may raise policy concerns about the effectiveness of EV

6. Fewer than 20 percent of EV-experienced households fall into this extreme case.

incentives is when households acquire a low fuel-efficient follow-on vehicle. Table B.2 and Table B.3 in the appendix show the relationship between EV adoption and the tendency to purchase a low-efficiency vehicle, $\mathbb{I}\{\text{buy lowMPG}\}$, defined as vehicles with a combined fuel economy below 25 MPG.⁷ As before, the sign of the estimates reverses when comparing HHFE to OLS results, suggesting a higher propensity to purchase low-fuel-efficient follow-on vehicles after BEV adoption. However, the instruments lack sufficient power for the dichotomous dependent variable. Given the reduction in magnitude observed when comparing HHFE to IV estimates in the previous analysis with the continuous dependent variable, the HHFE estimates can be interpreted as an upper bound of the true effect.

The analysis suggests that the monetary gains from EV adoption (e.g., subsidies or fuel savings) may be at least partially redirected by households to cross-subsidize vehicle attributes that are typically lacking in EVs. Specifically, households are more likely to purchase an additional larger, less efficient vehicle after adopting an EV, with this tendency being stronger for high-range EVs. These findings reveal a deeper pattern: vehicle types are not simple substitutes in meeting household travel needs. Certain vehicle attributes, such as fuel efficiency and size or horsepower, are often negatively correlated, forcing households to make trade-offs. When policy or technology enhances one attribute (e.g., EVs increase fuel efficiency), households may respond by prioritizing other attributes that are negatively correlated with the improved attribute during subsequent vehicle purchases.

3.3 Fleet Usage

To assess the environmental impact of fleet adjustments and inform more effective policy decisions, it is essential to understand how electric vehicles with varying range capabilities are utilized within household fleets. Electric cars generally offer lower per-mile operating

7. Table B.1 indicates that 25 MPG sits near the dividing line between mainstream crossovers and less efficient large vehicles; large SUVs, pickups, and many luxury vehicles typically fall below this threshold.

costs than gasoline vehicles due to reduced fuel and maintenance expenses, which should encourage their adoption as primary household vehicles.⁸ However, limited range can create inconvenience from more frequent charging and the possibility of charging breaks during longer trips, potentially discouraging frequent or long-distance use. This trade-off between fuel cost savings and range limitations shapes how households deploy their EVs and influences the overall appeal of EV fleets.

In this section, I present descriptive evidence on how electric vehicle utilization has evolved alongside advancements in EV range between 2017 and 2022. The NHTS usage data does not include every available vehicle model. However, as shown in Table 3.4, the key summary statistics for model range are closely aligned with those from the Texas registration data. BEVs with less than 200 miles of range—often considered low-range models—are generally suitable for daily commuting and local driving but may be less convenient for long-distance travel. In the 2017 NHTS data, the median BEV range was 84 miles, with approximately 75 percent of BEVs classified as low-range models. By 2022, the median BEV range had increased to 326 miles, and about 75 percent of BEVs were considered high-range models. The increase in electric driving range of BEVs coincides with more annual mileage as shown in Figure A.5 in the Appendix.

From a portfolio perspective, the role of EVs has changed substantially over this period. Figure 3.2 shows the average usage rate, measured as the percentage of annual household mileage attributed to each vehicle in two-car households. Car 1 refers to the more fuel-efficient vehicle in the household, further categorized by its fuel type. Generally, two-car households tend to assign more driving to the vehicle that is more fuel efficient. On average, a gas-powered Car 1 is driven about ten percent more miles than Car 2. However, in 2017, BEVs typically served as the secondary vehicle, and was used less than Car 2 despite their cost advantage. By 2022, both BEV and PHEV saw greater utilization, with their usage

8. The U.S. Department of Energy has a tool to calculate savings from driving an EV. See <https://www.energy.gov/policy/articles/save-2200-year-driving-electric-vehicle>.

	BEV		PHEV	
	2017	2022	2017	2022
N models	11	15	12	18
Range (mi)				
median	84	326	21	32
min	60	82	6	6
max	315	405	97	53
Mileage (mi)				
median	8,623	9,000	10,054	8,935
min	4,961	4,575	5,868	4,950
max	13,038	13,928	14,614	14,250
N obs (vehicles)	472	166	465	80

Table 3.4: Summary statistics, usage dataset, 2017 and 2022

Notes: This table presents summary statistics for electric range and annual mileage of BEVs and PHEVs included in the 2017 and 2022 National Household Travel Survey. Each observation is a household-vehicle-year. The number of observations for gasoline vehicles under 5 years age are 78,285 in 2017 and 4,415 in 2022.

rates matching those of primary gasoline vehicles in the household and exceeding Car 2 by 11 percent.

To summarize, the evidence indicates that households tend to shift usage toward their more fuel-efficient vehicles as the inconvenience associated with limited electric range gradually diminishes. However, the actual effectiveness of policy remains ambiguous given both fleet adjustments and usage shift. In the next chapter, I introduce a structural model that formally analyzes how factors such as range limitations, travel patterns, and fleet preferences shape households' choices and usage of electric and gasoline vehicles.

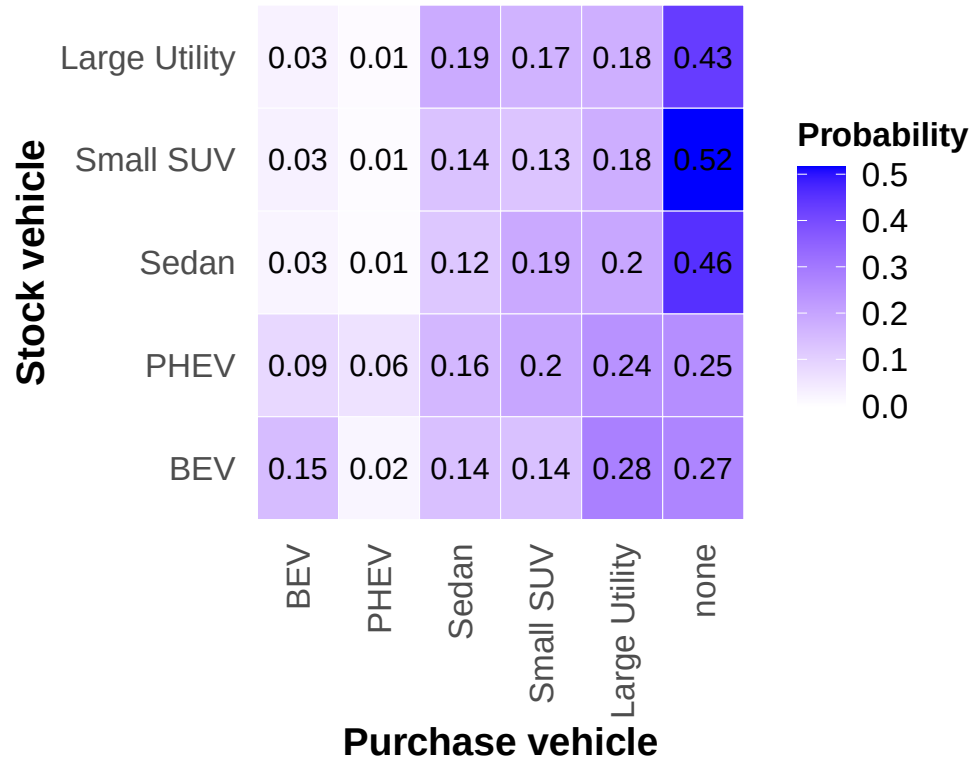


Figure 3.1: Conditional probability of second vehicle purchase by stock vehicle type

Notes: This figure shows the probability distribution of follow-on vehicle ownership (in columns) for two-car households, conditional on the first vehicle type (in rows). The Large Utility category includes midsize SUVs, standard SUVs, and minivans.

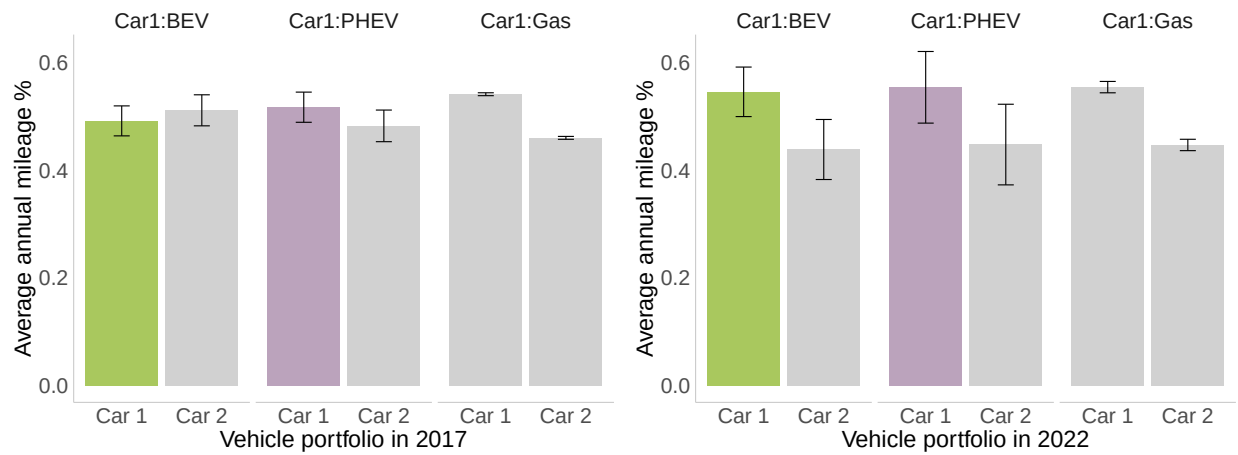


Figure 3.2: Usage rate of vehicles by fuel type in two-car households: 2017 (left panel) vs. 2022 (right panel)

Notes: This figure displays the usage rate, measured as the percentage of annual household mileage attributed to each vehicle in two-car households. Gasoline cars in the households are less than five years old. Car 1 refers to the more fuel-efficient vehicle in the household. The sample sizes are 52,692 households for 2017 and 3,295 households for 2022. Error bars represent 95% confidence intervals.

CHAPTER 4

A MODEL OF FLEET CHOICE AND USAGE

In this chapter, I present a structural model that jointly accounts for both vehicle choice and usage allocation. I incorporate the usage value of vehicle fleets following the sequential discrete choice framework of Wang [2023]. The model captures household decision-making in two sequential stages: (1) fleet composition: households first determine the number of vehicles and specific models to own (e.g., a new 2024 Volkswagen ID.4 EV with 290 miles of electric range paired with a three-year-old used 2020 Chevrolet Traverse with 5000 miles); (2) trip optimization: for each trip, household maximize travel utility by assigning vehicles based on trip-level attributes such as travel distance, fuel costs, and range limitation.

4.1 Usage Model

Setting. Vehicle usage is modeled as a multinomial choice over available travel modes, including vehicles in the household fleet and non-car alternatives such as walking, biking, or public transit. Households trade off relative convenience, fuel costs, and idiosyncratic preferences across alternatives. The utility that household i derives from using vehicle v for trip d is specified as:

$$\max_{v \in \mathcal{S}_i} u_{idv} = - \frac{\sum_q^d \text{TripMile}_q \cdot \mathbb{I}\{q \in \mathcal{D}(v)\}}{\text{Range}_v} \cdot c_{id} \cdot \mathbb{I}\{v = BEV\} + \Psi \text{FuelCost}_{dv} + \Gamma_{iv} + \Phi_v + \varepsilon_{idv} \quad (4.1)$$

where $\mathcal{S}_i$ is the portfolio of vehicles owned by the household i , and $\mathcal{D}(v)$ denotes the set of trips assigned to vehicle v on that day. All non-car alternatives (e.g., walking, transit) are grouped under the outside option. I assume EVs begin each day with a full charge.

The first term captures the inconvenience experienced when the cumulative daily miles driven by vehicle v approach or exceed its electric range. This reflects the effort households

must exert to avoid depleting the battery, encompassing factors such as the inconvenience of locating public chargers, the need for additional trip planning, and concerns about range uncertainty. The numerator represents the cumulative trip miles assigned to vehicle v up to and including trip d , and the denominator is the electric range of vehicle v . The parameter c_{id} represents the cost of recharging once the BEV’s range is depleted. It is modeled as a function of the trip attributes and home-charging accessibility:

$$c_{id} = \exp(\theta_{b1} + \theta_{b2}\mathbb{I}\{HomeCharge_i\} + \theta_{b3}\mathbb{I}\{Commute_d\} + \theta_{b4}\nu_i^{bev}) \quad (4.2)$$

where $\mathbb{I}\{HomeCharge_i\}$ is an indicator for whether the household resides in a home type conducive to easy charger installation (e.g., owner-occupied single-family homes), versus more constrained environments such as apartments or condominiums. The indicator $\mathbb{I}\{Commute_d\}$ distinguishes commute vs. non-commute trips, capturing the idea that households may be more or less sensitive to range limitations on commute trips. On the one hand, tighter schedules and limited flexibility could increase range concerns; on the other hand, the presence of convenient workplace or public charging may reduce range concerns during commutes. ν_i^{bev} captures unobserved household traits such as planning habits, risk tolerance, or latent preferences about electric vehicle usage. I further assume that PHEVs are not subject to this range penalty, as they can switch seamlessly from electric to gasoline mode once the electric range is exhausted.

The term $FuelCost_{dv}$ is the energy cost associated with trip d and depends on the vehicle type. For gasoline and conventional hybrid vehicles, fuel cost is calculated using self-reported gas prices on the day of the trip. For BEVs and for PHEVs operating in electric mode, fuel cost is based on the local electricity rates, the vehicle’s EPA-rated MPGe of the vehicle, and the energy equivalence factor $\delta = 33.7$ kWh per gallon of gasoline equivalent, consistent with EV industry standards. PHEVs are assumed to use electric power until their electric range is exhausted, after which they switch to gasoline. The usable electric range remaining

for PHEV v at trip d is denoted by $UsableRange_{dv}$, based on cumulative prior mileage in electric mode.

$$FuelCost_{dv} = \begin{cases} TripMile_d \times \frac{ElectricityRate_d \cdot \delta}{MPGe_v} & v = BEV \\ UsableRange_{dv} \times \frac{ElectricityRate_d \cdot \delta}{MPGe_v} + \\ \quad (TripMile_d - UsableRange_{dv}) \times \frac{GasPrice_d}{MPG_v} & v = PHEV \\ TripMile_d \times \frac{GasPrice_d}{MPG_v} & v = gas \end{cases} \quad (4.3)$$

The coefficient Ψ_i captures household i 's conditional sensitivity to fuel costs, given their vehicle fleet. That is, fuel cost differences matter only to the extent that vehicles in the choice set differ in operating costs. Φ_v captures homogeneous preferences for vehicle attributes including fuel and body types. The term Γ_{iv} represents household-specific preferences between the two vehicles in the fleet, where Car 1 is defined as the more fuel-efficient vehicle and Car 2 as the less fuel-efficient one. It reflects the extent to which households favor the more fuel-efficient option. Formally, I specify Γ_{iv} as a function of household demographics $\mathbf{z}_i$ (e.g., income, household size) and unobserved heterogeneity:

$$\Gamma_{iv} = \bar{\gamma}_v + \mathbf{z}_i' \gamma_r + \sigma \nu_i \quad (4.4)$$

The choice probability of household i choosing vehicle v on trip d is

$$pr_{id}(v; \Theta_i^{usage}) = \int \int \frac{\exp(u_{idv}(\nu_i^{bev}, \nu_i))}{1 + \sum_{s \in \mathcal{S}_i} \exp(u_{ids}(\nu_i^{bev}, \nu_i))} f(\nu_i^{bev}, \nu_i) d\nu_i^{bev} d\nu_i \quad (4.5)$$

and the model is estimated by maximizing the likelihood over all households and trips

$$LL = \ln \left[\prod_{i=1}^N \left\{ \int_{\Theta_i} \left(\prod_{d=1}^{\mathcal{D}(v)} pr_{id}(v; \Theta_i^{usage})^{Y_{id}} \right) f(\Theta_i^{usage}) d\Theta_i^{usage} \right\} \right] \quad (4.6)$$

Usage value. For household i and trip d , let $\mathcal{S}_i$ denote the set of vehicles owned. The ex-ante expected value of utility, prior to the realization of trip-specific shocks, is given by

$$EV_{id} = \mathbb{E}_{\varepsilon_{idv}} \left(\max_{v \in \mathcal{S}_i} u_{idv} \right) = \ln \left(1 + \sum_{v \in \mathcal{S}_i} \exp(\bar{u}_{idv}) \right) + \gamma \quad (4.7)$$

where γ is the Euler constant. The inclusive value, EV_{id} quantifies the aggregate attractiveness of all vehicles available for a single trip. Aggregating over all trips for the household yields the Expected Maximum Utility (EMU)—the ex-ante utility a household derives from optimally allocating vehicles to trips:

$$EMU_{id}(\mathcal{S}_i) = \sum_d EV_{id} = \sum_d \left(\ln \left(1 + \sum_{v \in \mathcal{S}_i} \exp(\bar{u}_{idv}) \right) + \gamma \right) \quad (4.8)$$

This model specification permits simulation of the expected utility of trips for any counterfactual vehicle fleet, independent of actual ownership. As constructed, the usage value is monotonically increasing in the utility indices $\bar{u}_{idv}$, the number of trips, and the size of the household fleet. Importantly, the model captures usage complementarities: for instance, electric vehicles typically yields greater usage value when paired with other fleet vehicles than when used alone.

4.2 Portfolio Model

Fleet compositions. Before introducing the model, I define the concept of a fleet within the portfolio framework. Let $\mathbb{S}_i$ the set of all possible combinations of vehicle types that household i can choose from, with fleet sizes of zero, one or two vehicles. Formally,

$$\mathbb{S}_i := \bigcup_{k=0}^2 \binom{\mathcal{V}}{k}_{\text{rep}}$$

where

$$\mathcal{V} = \{\text{BEV, PHEV, Compact, Sedan, Small SUV, Large Utility, Pickup}\}.$$

This set contains 36 unique combinations, including the outside option, which together represent 80% of the choices observed in the ownership data. Body types are aggregated for BEVs and PHEVs due to the limited number of models available, while gasoline vehicles are categorized by specific body types. For each household, $\mathcal{S}_i \in \mathbb{S}_i$ denotes the set of vehicles actually owned. To construct alternative fleets not owned by household i ($\mathbb{S}_i \setminus \mathcal{S}_i$), I impute these alternatives based on the choices of households with similar demographics.

Fleet choice. I model household fleet choice with a random utility model. Let $\mathcal{S}_i$ denote the set of vehicles owned by household i , and let $g \in \mathcal{S}_i$ index the individual vehicles in the fleet. Assume households can own up to two vehicles, and for tractability, the choices of the fleet vehicles are made simultaneously. The utility that household i derives from fleet $\mathcal{S}_i$ is given by:

$$V_{i\mathcal{S}_i} = \lambda(\mathcal{S}_i) + \rho \cdot EMU(\mathcal{S}_i|\mathbf{z}_i, \Theta_i^{usage}) + \sum_{g \in \mathcal{S}_i} U_{ig}(\Theta_i^{usage}) + \epsilon_{i\mathcal{S}_i} \quad (4.9)$$

$$V_{i0} = U_{i0} + \epsilon_{i0} \quad (4.10)$$

where $\lambda(\mathcal{S}_i)$ denotes fleet fixed effects that capture average attractiveness of a given composition; $EMU(\mathcal{S}_i|\mathbf{z}_i, \Theta_i^{usage})$ represents the household-specific expected utility from using fleet $\mathcal{S}_i$, estimated from the usage patterns of households with similar demographics $\mathbf{z}_i$ and the same fleet composition; $U_{ig}(\Theta_i^{usage})$ is the standard utility from the attributes of vehicle g ; and $\epsilon_{i\mathcal{S}}$ are i.i.d. Type I Extreme Value error terms.

The outside option is modeled as a function of household demographics to capture heterogeneity in access to alternative travel modes. Formally, the utility of the outside option for household i is defined as

$$U_{i0} = \mathbf{z}_i' \boldsymbol{\omega} \quad (4.11)$$

where, by slight abuse of notation, $\mathbf{z}_i$ represents the vector of demographic characteristics.

Vehicle choice. The utility a household i obtains from choosing vehicle j at the time of purchase depends on its price and attributes, specified as:

$$U_{ij}(\Theta_i^{usage}) = -\alpha_{ij}p_{ij} + x_j'\beta_{ij} \quad (4.12)$$

where the parameter vector $\mathbf{B}_{ij} = (\alpha_{ij}, \beta_{ij})'$ captures heterogeneous preferences over vehicle attributes and depends on the expected role of the vehicle within the household's fleet. The preference vector is modeled as

$$\mathbf{B}_{ij}(\Theta_i^{usage}) = \bar{B} + B_p \cdot \pi_{ij}^{primary}(\Theta_i^{usage}) + \mathbf{z}_i' B_z + \sigma \nu_i$$

where $\bar{B}$ represents average attribute preferences, B_p captures taste differentiation between primary and secondary vehicles, B_z accounts for demographic heterogeneity, and σ models unobserved household-specific taste variation.

The role-dependent attribute preference reflects that households have heterogeneous tastes for vehicle attributes conditional on the vehicle's role. While the exact role is unknown at purchase, households form expectations based on projected travel demands. The term $\pi_{ij}^{primary}$ denotes the ex-ante probability that vehicle j becomes the household's primary workhorse, estimated from demographically similar households in the usage data.

Specifically, for household $\tilde{i}$ in the usage dataset, the probability that vehicle $\tilde{j}$ serves as the primary vehicle is given by

$$\pi_{\tilde{i}\tilde{j}}^{primary} = Pr\left(\hat{s}_{\tilde{i}\tilde{j}} = \max_{v \in \mathcal{S}_{\tilde{i}}} \hat{s}_{\tilde{i}v} | \mathcal{S}_{\tilde{i}}, \mathbf{z}_{\tilde{i}}, \Theta_{\tilde{i}}^{usage}\right) = \int \mathbf{1}\left(\hat{s}_{\tilde{i}\tilde{j}}(\theta) = \max_{v \in \mathcal{S}_{\tilde{i}}} \hat{s}_{\tilde{i}v}(\theta)\right) dF_{\Theta_{\tilde{i}}^{usage}}(\theta) \quad (4.13)$$

where $\hat{s}_{\tilde{i}\tilde{j}}(\theta)$ is the distance-weighted predicted usage share:

$$\hat{s}_{ij}(\theta) = \frac{\sum_{d \in \mathcal{D}_i} pr_{idj}^{usage}(\theta) \cdot TripMile_{id}}{\sum_{d \in \mathcal{D}_i} TripMile_{id}} \quad (4.14)$$

This framework allows for the identification of vehicle roles informed directly by observed driving behavior. Consequently, households anticipate the role a vehicle is expected to play in their fleet and adjust their tastes for each attribute accordingly. This results in the effective marginal utility of attributes (e.g., size, range, MPG, etc.) varying endogenously with fleet composition and household usage—not because tastes themselves change, but because usage endowments determine which taste components are activated. At purchase, households aren’t just considering “I like fuel economy” or “I like range” in the abstract. What matters is: will this attribute matter for the car that ends up covering most of my trips? For instance, if one vehicle is expected to handle most of the driving, attributes such as fuel efficiency become more important for that vehicle; conversely, if usage is more evenly divided, the value placed on these attributes is more balanced across vehicles. Therefore, household vehicle choices reflect not vehicle technology or individual attributes, but also how those attributes fulfill usage needs across the fleet.

Estimation approach. The model estimation involves matching each household in the ownership dataset with $K = 20$ nearest neighbors in demographic space $\mathbf{z}$ who have the same fleet composition in the usage dataset. These neighbors serve as draws from the empirical distribution of usage behavior. For each household i , I simulate the expected utility and usage shares of every fleet composition in the choice set $\mathbb{S}_i$ based on travel behavior observed among its neighbors. The choice probability that household i selects fleet $\mathcal{S}_i$ integrates the logit kernel over the empirical distribution of expected usage value EMU_i and usage share π_i , as well as unobserved taste heterogeneity ν_i :

$$Pr(\mathcal{S}_i; \mathbf{B}_i) = \int \int \frac{\exp(V_i \mathcal{S}_i(EMU_i, \pi_i, \nu_i))}{\sum_{s \in \mathbb{S}_i} \exp(V_{is}(EMU_i, \pi_i, \nu_i))} f_{\Theta^{usage}}(EMU_i, \pi_i | \mathbf{z}_i) f(\nu_i) dEMU_i d\pi_i d\nu_i \quad (4.15)$$

Here, $f_{\Theta^{usage}}(EMU_i, \pi_i \mid \mathbf{z}_i)$ denotes the empirical distribution derived from the neighbors' usage data. The estimation maximizes the log-likelihood of observed choices over all households and time, accounting for taste heterogeneity $\mathbf{B}_i$ through integration:

$$LL = \ln \left[\prod_{i=1}^N \left\{ \int_{\mathbf{B}_i} \left(\prod_{t=1}^T Pr(\mathcal{S}_i; \mathbf{B}_i)^{Y_{it}} \right) f(\mathbf{B}_i) d\mathbf{B}_i \right\} \right] \quad (4.16)$$

CHAPTER 5

DEMAND ESTIMATES

5.1 Usage Model Estimates

Table 5.1 reports the estimates from the usage model in Equation 4.1. Panel (a) presents the estimated inconvenience cost of charging BEVs. All parameters have expected signs and magnitudes. In particular, households without easy access to home charging or whose vehicle's electric range is nearly depleted during commute trips face higher levels of inconvenience, with the former factor having a greater impact than the latter.

	Estimate	Std. Error
(a) BEV charging costs		
θ_{b1}	0.3394	0.0292
θ_{b2}	-3.2201	0.5236
θ_{b3}	2.1494	0.3104
θ_{b4}	0.0162	0.0030
(b) Random coefficients Γ_{iv}		
$\bar{\gamma}_{\text{Car 1}}$	1.6230	0.0127
$\gamma_{\text{Car 1} \times \text{high income}}$	-0.3769	0.0097
$\gamma_{\text{Car 1} \times \text{hhsz}}$	-0.2006	0.0044
$\sigma_{\text{Car 1}}$	0.4562	0.0398
$\bar{\gamma}_{\text{Car 2}}$	1.1119	0.0128
$\gamma_{\text{Car 2} \times \text{high income}}$	-0.2417	0.0098
$\gamma_{\text{Car 2} \times \text{hhsz}}$	-0.0851	0.0042
$\sigma_{\text{Car 2}}$	0.0183	0.0380
(c) Homogeneous parameters		
Ψ	-0.0296	0.0006
BEV	0.3442	0.0957
PHEV	0.1246	0.0495
SUV	0.3236	0.0063
Minivan	0.0937	0.0078
Pickup	0.3614	0.0107

Table 5.1: Estimation results of the usage model

To put the results in context, I normalize the charging inconvenience costs by the sensi-

tivity to fuel costs, denoted by Ψ . The baseline inconvenience cost of recharging a BEV - for households without easy home-charging access and depleting the range on non-commute trips - is estimated at \$47. When the range is depleted during commute trips, the cost increases dramatically to approximately \$407. By contrast, for households with potential access to home charging, the inconvenience costs drop significantly - down to \$16 for commute trips and a nearly negligible \$1.7 for non-commute trips. The heightened costs in risky situations, particularly for commutes without home charging, suggest the need for households to engage in planning and effort when managing BEV usage.

Panel (b) presents the estimation results for the random coefficients Γ_{iv} . The findings are consistent with Figure 3.2, which shows that households tend to use the more fuel-efficient vehicle more frequently. Households with relatively higher incomes and larger household sizes appear to use household vehicles less often, possibly due to greater access to flexible transit options or alternative modes of transportation.¹

Panel (c) presents the estimated coefficients for fuel costs and vehicle attributes. As noted earlier, these parameters should be interpreted conditionally on the vehicle fleets that households own; they do not reflect general preferences for vehicle attributes across the broader population. In particular, the coefficient on fuel cost, Ψ , captures within-fleet trade-offs. As such, its relatively small magnitude indicates households are less responsive to marginal fuel cost changes when deciding which owned vehicle to use, reflecting limited substitution opportunities within their existing fleets. This contrasts with typical discrete choice models, where fuel cost responsiveness primarily captures its influence on vehicle acquisition.

The coefficients Φ_v represent within-household, average relative utility adjustments associated with vehicle fuel and body types when households allocate usage among their owned vehicles. The interpretation of Φ_v requires caution and should always be considered in

1. High-income households are defined as those with annual incomes exceeding \$150,000 in 2022 dollars, placing them roughly in the top 25% of the household income distribution.

conjunction with the household-specific preference term Γ_{iv} . The coefficients on BEV and PHEV capture general preferences for using electrified vehicles that are independent of any range-related inconvenience. Since EVs are more likely to be the more fuel-efficient Car 1 in household fleets, the positive signs indicate that these vehicles tend to be used more frequently than gasoline vehicles, which commonly serve as Car 2 and is the baseline category in the model. This finding aligns with the pattern in Figure 3.2, where EVs with fewer range-related constraints accumulate more mileage on average than less fuel-efficient vehicles within the same household fleet.

Interpreting coefficients on vehicle body types is more nuanced. For multi-vehicle households, SUVs that happen to be the relatively more fuel-efficient vehicle in the fleet tend to be used more intensively than less fuel-efficient sedans (the baseline for body type). However, since minivans and pickups are less often categorized as the more fuel-efficient Car 1, they are generally used less frequently than sedans within the same household. Thus, household usage patterns reflect a combination of fuel efficiency preferences captured by Γ_{iv} and body-type utility adjustments expressed in Φ_v .

5.2 Usage Value

Figure 5.1 presents the empirical distribution of expected usage value for different fleet compositions across income groups. Because the sample includes limited observations of EV-owning households, the usage value for EV fleets is simulated by matching each non-EV household to demographically similar EV-owning neighbors and imputing their expected usage value with an EV. Blue points correspond to observed fleets, while orange points indicate simulated usage values.

Three key findings emerge. First, two-car fleets yield higher usage values than one-car fleets by construction. Second, fleets composed of only ICE vehicles have higher usage values than those consisting solely of EVs, both for single and double vehicle configurations.

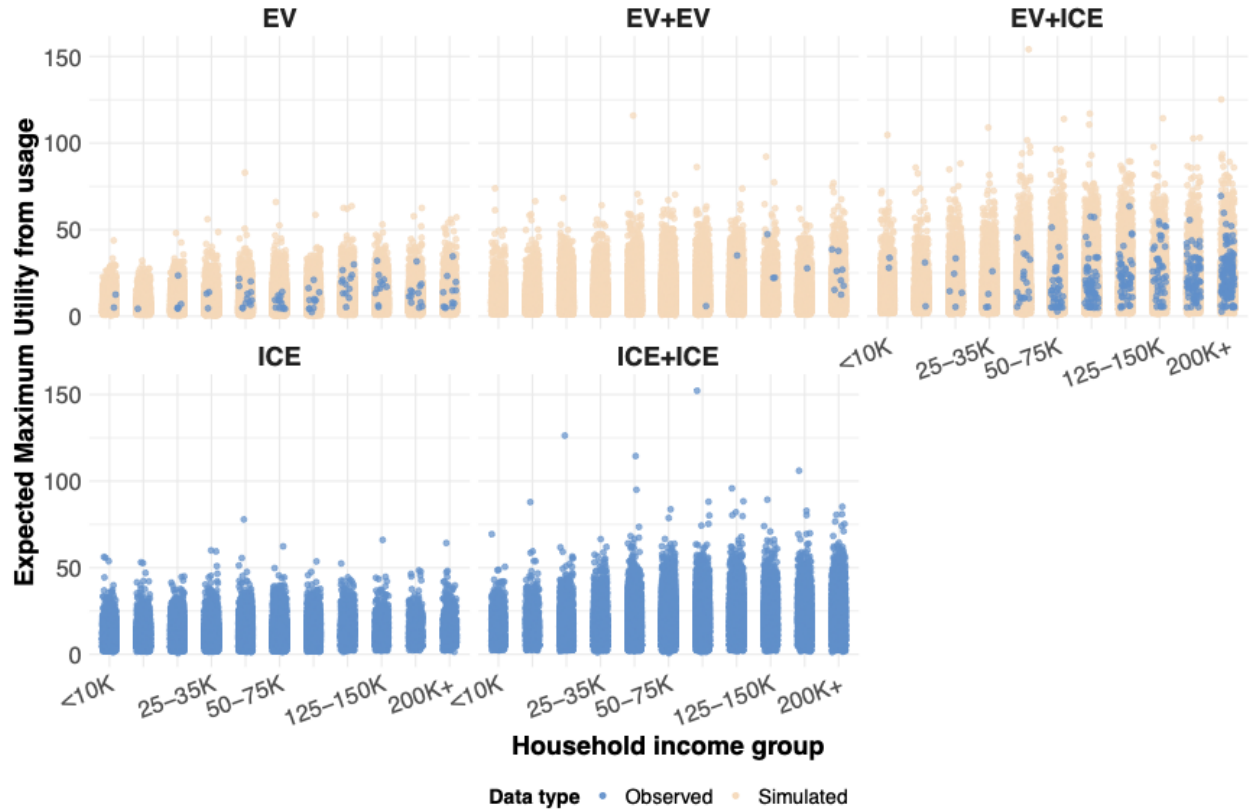


Figure 5.1: Empirical distribution of expected usage value by fleet compositions and income group

Notes: This figure displays the empirical distribution of expected usage value (EMU) across different fleet compositions and income groups. Blue points represent observed fleet configurations; orange points denote simulated usage values for EV-containing fleets, imputed for non-EV households based on matched EV-owning neighbors.

However, mixed fleets containing both an EV and an ICE vehicle deliver the highest usage values among all compositions. This outcome likely reflects the fuel savings provided by the EV alongside the ICE vehicle’s ability to address range limitations. Finally, usage value increases with income, suggesting that higher-income households travel more frequently and encounter fewer inconveniences related to charging.

Figure 5.2 illustrates the empirical distribution of $\pi^{primary}$ across two-car fleets. For EV fleets, both observed usage and simulated counterfactual usage values—generated via nearest neighbor matching—are included. Among all compositions, the pairing of a high-range BEV with an ICE vehicle results in the most distinctive assignment of primary vehicle roles. In contrast, fleets with low-range BEVs, despite comparable fuel efficiency to high-range BEVs, exhibit a more diffuse distribution of primary role probability. For instance, in households with mostly short trips, the EV may cover a larger share of mileage and produce values at the distribution’s extremes, whereas in households with longer or more frequent trips taken by the ICE vehicle, the primary role is less defined and such households fall toward the center of the distribution. These results suggest that household travel patterns endogenously determine which vehicle assumes the primary role, thereby influencing the relative importance assigned to each vehicle attribute.

5.3 Portfolio Model Estimates

Figure 5.3 presents the estimated parameters for fleet fixed effects, $\lambda(\mathcal{S}_i)$. The results are all significant and consistent with reduced-form evidence: households strongly prefer two-car fleets over single-car fleets, and this preference is especially pronounced when one vehicles is an EV. For single-car fleets, compact sedans and small SUVs are most favored, while two-car fleets are typically more attractive when one vehicle is a large utility vehicle. Finally, fleets that combine a large vehicle with a small vehicle generally exhibit higher value than fleets composed of two vehicles of the same type, indicating complementarities in household fleet

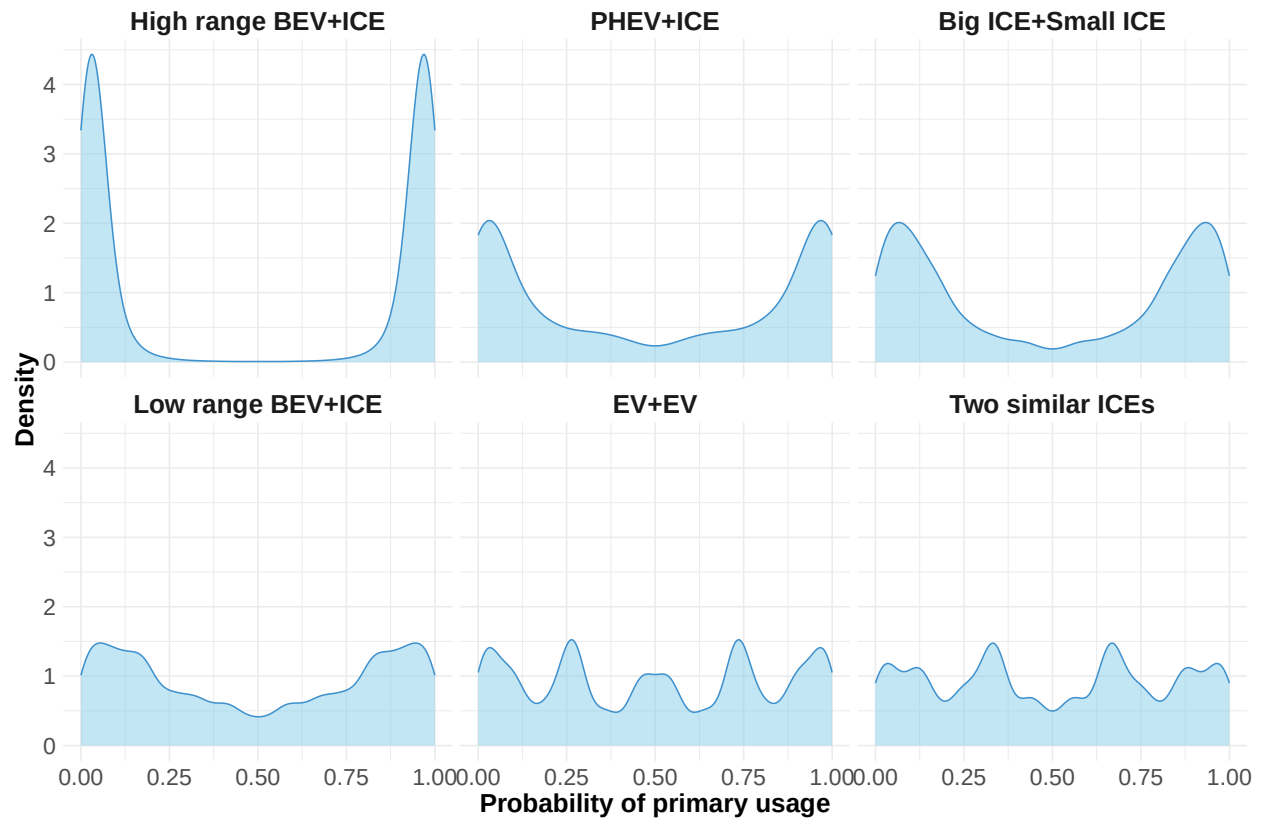


Figure 5.2: Empirical distribution of expected usage share by fleet compositions

Notes: This figure displays the empirical distribution of expected usage share $\pi^{primary}$ across different fleet compositions.

usage.

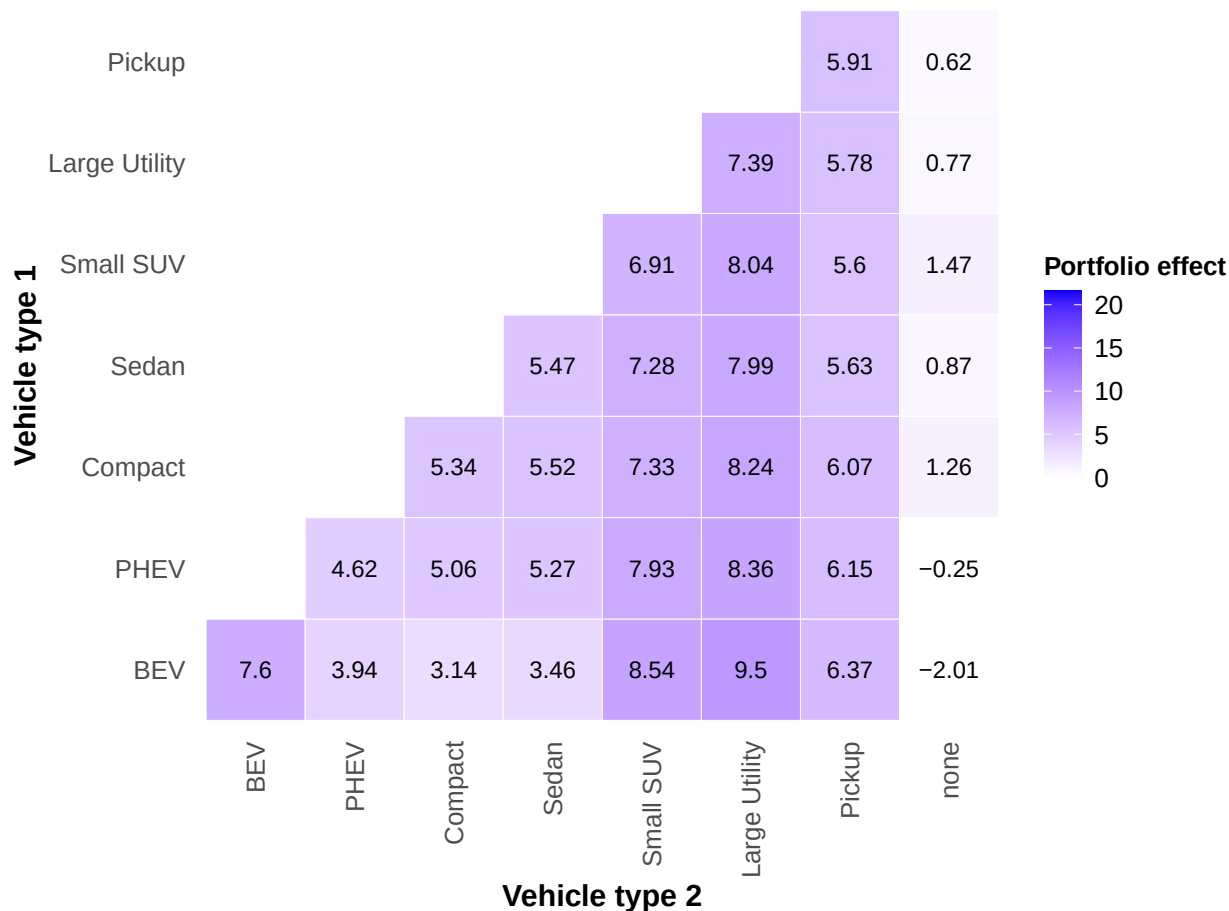


Figure 5.3: Estimated parameters for fleet fixed effects $\lambda(\mathcal{S}_i)$

Table 5.2 presents the estimation results for role-dependent attribute preferences. The estimates generally align with expectations regarding both signs and magnitudes. The average baseline own-price elasticity is -3.4 , consistent with existing literature on automobile demand estimation. The aggregate own-price elasticity for the primary vehicle is -2.8 . High-income households exhibit lower price sensitivity, with elasticity roughly half that of low-income households.

Across the board, households assign positive value to physical attributes such as fuel efficiency and power, while showing a clear preference against older vehicles. The estimates by fleet role illustrate how households value different vehicle attributes: for the primary

	Baseline		Primary	Deviations by demographic variable					Unobserved	
	Mean	Car		High income	Low income	HH Size	Child	Home Charge	Heterogeneity	
Price (\$000)	-0.0762 (0.0025)	0.0128 (0.0012)		0.0355 (0.0021)	-0.1492 (0.0037)				0.0211 (0.0002)	
MPG	0.0459 (0.0030)	0.0230 (0.0012)		0.0221 (0.0004)	-0.0314 (0.0007)				0.0060 (0.0008)	
Size (ft ³)	1.8726 (0.0402)	-1.4410 (0.0294)		0.4799 (0.0249)	-0.6378 (0.0338)	0.0485 (0.0027)	0.0182 (0.0024)		0.0035 (0.0007)	
HP-to-weight	6.4224 (0.2159)	-3.1113 (0.1935)		1.9445 (0.1960)	-3.2825 (0.2669)				0.0616 (0.0199)	
Cylinder	0.0482 (0.0031)	-0.0150 (0.0034)		-0.0137 (0.0033)	0.0109 (0.0044)				0.0017 (0.0002)	
Range (EV)	0.0990 (0.0164)	0.2072 (0.0404)		0.1682 (0.0358)	0.0535 (0.0121)			0.1204 (0.0396)	0.0772 (0.0112)	
Motor capacity (EV)	0.0560 (0.0028)	0.0294 (0.0016)		0.0077 (0.0008)	-0.0026 (0.0014)			0.0019 (0.0012)	0.0501 (0.0012)	
Vehicle age	-0.1852 (0.0504)	-0.1652 (0.0433)		-0.1988 (0.0520)	0.1025 (0.0264)				0.0522 (0.0028)	
Vehicle odometer (000 miles)	-0.0210 (0.0035)	-0.0284 (0.0042)		-0.1221 (0.0184)	0.0221 (0.0042)				0.0368 (0.0105)	

Table 5.2: Estimation results for role-dependent attribute preferences

Notes: This table displays the parameter estimation of the portfolio model. All parameters should be interpreted additively to the baseline parameter in the Mean column.

vehicle, fuel economy, driving range, and vehicle age are most important, while size and power carry less weight. In particular, the average dollar value of a one MPG increase is \$1,087 for primary vehicles and \$602 for secondary vehicles. In contrast, an increase in exterior size from a midsize sedan (e.g., Honda Accord) to a midsize SUV (e.g., Toyota Highlander) is valued at \$1,124 for primary vehicles and \$4,050 for secondary vehicles. For electric vehicles, a 100-mile increase in driving range corresponds to \$4,830 and \$1,299 for primary and secondary vehicles, respectively. The average value of vehicles that are one year younger is \$5,526 for primary and \$2,430 for secondary vehicles. Similarly, vehicles with 1,000 fewer miles on the odometer are worth \$757 and \$262 for primary and secondary vehicles, respectively.

Finally, notable heterogeneity emerges across households. High-income households show even stronger preferences aligned with the baseline estimates, except for the cylinder attribute. Larger households and those with children place greater value on vehicle size. Additionally, households with home charging installations exhibit a stronger preference for longer-range electric vehicles.

5.4 Model Fit

To evaluate the impact of including fleet usage in model prediction, the model is estimated both with and without the usage value EMU . As shown in Figure 5.4, the observed and predicted market shares of EV fleets are compared across household types. Recall that the fleet fixed effects $\lambda(\mathcal{S}_i)$ represent the average attractiveness of each fleet composition, while the usage values EMU capture household-specific preferences determined by travel demand. The model excluding EMU tends to overpredict EV adoption among low-income households and underpredict it among high-income households. By integrating usage values, model fit improves substantially. This demonstrates that the EMU term effectively captures the higher (lower) utility that high-income (low-income) households can derive from identical

fleet compositions, ensuring that the predicted adoption rates better align with observed patterns.

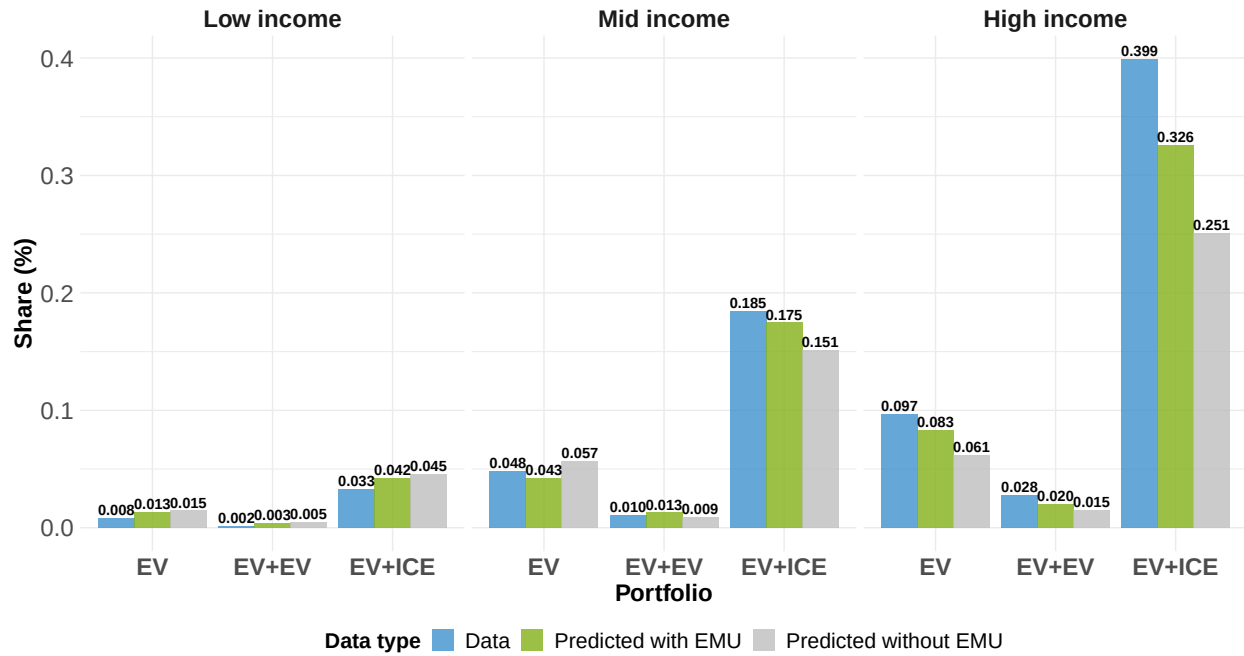


Figure 5.4: Observed and predicted market share of EV fleets

Notes: This figure shows the observed and predicted market share of EV fleets by household income group. The blue bars represent data, and the green and gray bars represent model prediction with and without *EMU*, respectively.

CHAPTER 6

COUNTERFACTUAL SIMULATION

6.1 Counterfactual Policies

In this chapter, I evaluate the effects of three environmental policy scenarios in Texas using counterfactual simulations: (1) removal of EV purchase subsidies, (2) imposition of an additional annual registration fee for EVs, and (3) an increase in gasoline taxes for ICE vehicles. The benchmark for these comparisons is the Texas market in 2022, which included a consumer tax credit of up to \$7,500. Additional details about Texas EV incentives are provided in Appendix D.

The two EV-targeted policies—the removal of the purchase subsidy and the introduction of an annual registration fee—are primarily motivated by fiscal considerations rather than explicit environmental goals (Congressional Budget Office, 2012, 2023). The \$200 registration fee, introduced in Texas in 2023, aims to compensate for declining gasoline tax revenue as EV adoption rises: unlike gasoline-powered vehicles, EVs do not contribute to state road funds through fuel taxes. The reversal of the subsidy policy, effective September 2025, also reflects concerns over its limited additional impact on emissions, as evidence suggests that many EV buyers would likely have substituted to other lower-emission vehicles even without the subsidy [Xing et al., 2021].

The third scenario—a fuel tax increase for ICE vehicles—is explicitly motivated by emission reduction objectives. It is equivalent to a carbon tax that can be seen as a Pigouvian tax that directly prices the externality. To enable meaningful comparison across policies, I calibrate the fuel tax increase to achieve a household-level CO₂ reduction equal in magnitude—but opposite in direction—to the additional emissions generated by eliminating the EV subsidy, which I estimate as 43 kg per household, or approximately 0.7% of the annual

emissions from an average U.S. passenger vehicle.¹ To reach this target, the gasoline tax is increased until household emissions fall by 43 kg, which corresponds to a consumer fuel price increase of 26 cents per gallon, representing a 7.6% rise relative to a typical 2022 gas price of \$3.43 per gallon. I assume full pass-through of all types of tax—purchase (the opposite of subsidy), registration and fuel, which is empirically plausible. In particular, Muehlegger and Rapson [2022] find the pass-through of EV subsidies in California to consumer prices to be indistinguishable from 100%. Gallagher and Muehlegger [2011] finds a pass-through of fuel taxes to consumer prices in the US of approximately 100%.

Social welfare is quantified as the net sum of consumer welfare, fiscal revenue, and the environmental externality associated with driving. Policy effects on consumer welfare are evaluated using the compensating variation formula from Small and Rosen [1981]:

$$\Delta CS = \int \int \frac{1}{\alpha_i^{primary}} \left[\ln \sum_{s \in \mathbb{S}_i} \exp(V_{is}^1) - \ln \sum_{s \in \mathbb{S}_i} \exp(V_{is}^0) \right] f_{\Theta^{usage}}(EMU_i, \pi_i | \mathbf{z}_i) f(\nu_i) dEMU_i d\pi_i d\nu_i \quad (6.1)$$

where 0 refers to the baseline scenario and 1 to the counterfactual. For simplicity, I normalize the welfare by the price coefficient for primary vehicle for each household i . Environmental impacts are estimated based on household-level CO₂ emissions, calculated from expected fleet usage. Gasoline vehicles and PHEVs in gasoline mode use fuel economy ratings to translate mileage into fuel consumption and CO₂ emissions, while BEVs and PHEVs in electric mode account for indirect emissions from electricity generation. CO₂ intensity per kWh in Texas is derived from the U.S. Energy Information Administration (EIA) state electricity profiles.² Annual EV CO₂ emissions are calculated by pairing indirect emission

1. The average annual household emission is 5.8 metric ton in the Texas data in 2022. As a fact check, according to the EPA’s Greenhouse Gas Equivalencies Calculator, a typical passenger vehicle emits 4.6 metric tons of CO₂ annually. See <https://www.epa.gov/ghgemissions/assumptions-and-references-household-carbon-footprint-calculator>.

2. EIA reports that Texas CO₂ emissions intensity for electricity generation was approximately 0.39 kg

rates with typical vehicle electricity consumption (kWh per mile) and usage estimates. To monetize the damages from emissions, a Social Cost of Carbon (SCC) value of \$56 per metric ton is used (U.S. Environmental Protection Agency, 2016).³ The estimates of SCC covers a wide range of impacts such as damages to agriculture, human health, property, reduced labor productivity, and ecosystem loss.⁴

6.2 Policy Effects on Ownership, Usage and Welfare

Table 6.1 reports the counterfactual results of imposing one policy at a time. Panel (A) quantifies the average size of the effect on vehicle purchase or fuel price. The subsidy and registration fee are measured against the purchase price, whereas the gasoline taxes are measured against the average annual fuel cost. The annual EV registration fee of \$200 was intended to compensate for the fuel tax that a comparable gasoline vehicle would pay annually. For better comparison between the two EV policies, I measure the registration fee against the vehicle purchase price. I assume the annual registration fee is discounted over 15 years with an annual discount rate of 0.05.⁵ The price effect of the registration fee is about one-third of that of the subsidy removal.

Panel (B) and (C) report the changes in vehicle composition and driving behavior in the counterfactual scenarios. An increase in emission after removing EV subsidy suggests that the emission outcome from shift in driving dominates complementary preferences for EV and

CO2 per kWh in 2022, slightly above the national average of 0.37 kg per kWh. See <https://www.eia.gov/state/print.php?sid=TX>

3. The official SCC value widely used in 2022 was about \$51 per metric ton of CO₂ (in 2007 dollars), adjusted to \$56 per ton in 2022 dollars. The 2023 SCC estimates were updated to \$190 per metric ton of CO₂ (in 2020 dollars), a substantial increase from the 2016 estimates. See <https://costofcarbon.org/e-pa-values-for-the-social-cost-of-greenhouse-gases>. I use the 2016 estimates in my main analysis to be consistent with the principles used then.

4. This paper does not measure externalities from driving apart from emission. For example, driving electricity-powered vehicles may also produce congestion, noise, etc.

5. The average annual charging cost of an EV with 10,000 miles is around \$400 assuming primarily home charging during regular time windows. The charging cost may be lower if households charge at off-peak hours. If measured otherwise, the effect size is around 50% of annual EV charging cost.

(A) Policy scenarios			
Policy instrument	(1)	(2)	(3)
Target segment	Removing purchase subsidy	Registration fee	Gasoline tax
Effect on price (%)	EV 11.72	EV 4.17	ICE 7.59

(B) Change in fleet ownership (percentage point)	
Average fleet fuel economy (MPG)	-0.61
{EV} household share	-0.05
{EV, EV} household share	-0.01
{EV, ICE} household share	-0.18
{ICE} household share	0.09
{ICE, ICE} household share	0.12
no car household share	0.07

(C) Change in driving behavior (percentage point)	
Total miles driven	-0.03
EV miles driven	-4.14
Gasoline miles driven	0.13
Gasoline consumption (gallons)	0.74

(D) Welfare effects (annual, per household)	
CO ₂ (kg)	42.98
Consumer surplus (USD)	19.92
Tax revenue (USD)	-0.64
Externality (USD)	3.22
Net benefit (+)/cost (-) per unit emission (USD)	-1.12
	0.07

Table 6.1: Counterfactual policy simulations

Notes: This table reports the counterfactual results evaluated on the 2022 data. Changes are reported in percentage points.

large utility vehicles. Column (1) and (3) allow for direct comparison as they lead to the same amount of change in emissions, although in opposite directions. Broadly, imposing a fuel tax leads to larger changes in driving behavior, whereas the EV tax credit leads to larger changes in fleet composition, measured by the average fleet fuel economy. This is reasonable, as a purchase subsidy affects vehicle ownership decisions, whereas a fuel tax influences usage.

In panel (B), removing the EV subsidy mainly shifts ownership from $\{\text{EV}, \text{ICE}\}$ and to $\{\text{ICE}\}$ or $\{\text{ICE}, \text{ICE}\}$, suggesting that most households considering the EV adoption either already have a car and are thinking about acquiring a second one, or they possess two cars and are considering replacing one with an electric model. The abolition of EV subsidy reduces EV sales by 51% compared to baseline, quantitatively similar to findings in Fournel [2024] and Muehlegger and Rapson [2022]. Comparing policy scenarios (1) and (2), imposing the EV registration fee shifts a disproportionately larger share of market share from $\{\text{EV}\}$ to $\{\text{ICE}\}$ in scenario (2) relative to scenario (1), even though subsidy removal has larger overall effects. This suggests the registration fee has a greater impact on lower-income households that own a single vehicle. Imposing a fuel tax disproportionately shifts market shares from $\{\text{ICE}, \text{ICE}\}$ towards $\{\text{EV}, \text{ICE}\}$, consistent with the fact that fuel taxes have a larger effect on households with high travel demands, who are usually higher income.

In panel (C), I report the change in driving behavior. Removing EV purchase subsidy and imposing gasoline taxes both reduce total driving, but the pathways differ. The former reduces driving primarily by cutting car ownership altogether, whereas the latter is a combination of reduced ownership but mostly a decrease in gasoline miles driven. Given the same amount of change in gasoline consumption, the fuel tax more effectively shifts driving towards the more efficient EVs than the EV subsidy does. Imposing the EV registration fee has a small but positive effect on total driving, possibly because households switching from $\{\text{EV}\}$ to ICE fleets face fewer range limitations and thus drive more.

Panel (D) reports welfare effects normalized by the number of households. All three

policies result in decreased consumer surplus and increased fiscal revenue. Both EV policies lead to higher emissions, with the EV registration fee imposing about half the increase in CO₂ compared to removing EV subsidies. The last row reports the net benefit or cost per unit of emissions. The positive numbers in column (1) and (2) indicate that increased fiscal revenue dominates, suggesting potential over-investment in EV subsidies. The estimated marginal social benefit from removing the EV subsidy is only \$242 per ton of CO₂, which is lower than prior marginal abatement cost estimates ranging from \$300 to \$500 [Fournel, 2024, Xing et al., 2021, Archsmith et al., 2015].

There are two countervailing forces that drives the marginal abatement cost of imposing an EV subsidy: the complementary preferences for large utility vehicles under the subsidy raises the cost, whereas trip optimization lowers it. If the latter dominates, the social benefit of removing EV subsidy decreases as households have already internalized the cost. My model suggests that ignoring fleet-level driving optimization underestimates emission rebounds from removing EV subsidy, despite the existing incentive scheme tending to over-invest.

The net benefit from imposing the EV registration fee is significantly lower than that from removing the EV subsidy, suggesting that the registration fee causes a proportionally larger environmental externality relative to the fiscal revenue it generates. The abatement cost of imposing a fuel tax is \$26 per ton, relatively higher than prior estimates of \$17 (in 2022 dollars) based on 2015 U.S. households data [Knittel and Sandler, 2018]. The estimated average driving elasticity with respect to fuel price is -0.04. This difference in abatement cost likely arises because households in Texas drive more, own larger, less fuel-efficient vehicles, and have fewer public transit options, leading to a less elastic fuel demand.

Panel (B) and (C) report the changes in vehicle composition and driving behavior in the counterfactual scenarios. An increase in emission after removing EV subsidy suggests that the emission outcome from shift in driving dominates complementary preferences for EV and large utility vehicles. Column (1) and (3) allow for direct comparison as they lead to the

same amount of change in emissions, although in opposite directions. Broadly, imposing a fuel tax leads to larger changes in driving behavior, whereas the EV tax credit leads to larger changes in fleet composition, measured by the average fleet fuel economy. This is reasonable, as a purchase subsidy affects vehicle ownership decisions, whereas a fuel tax influences usage.

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In panel (C), I report the change in driving behavior. Removing EV purchase subsidy and imposing gasoline taxes both reduce total driving, but the pathways differ. The former reduces driving primarily by cutting car ownership altogether, whereas the latter is a combination of reduced ownership but mostly a decrease in gasoline miles driven. Given the same amount of change in gasoline consumption, the fuel tax more effectively shifts driving towards the more efficient EVs than the EV subsidy does. Imposing the EV registration fee has a small but positive effect on total driving, possibly because households switching from $\{\text{EV}\}$ to ICE fleets face fewer range limitations and thus drive more.

Panel (D) reports welfare effects normalized by the number of households. All three policies result in decreased consumer surplus and increased fiscal revenue. Both EV policies

lead to higher emissions, with the EV registration fee imposing about half the increase in CO₂ compared to removing EV subsidies. The last row reports the net benefit or cost per unit of emissions. The positive numbers in column (1) and (2) indicate that increased fiscal revenue dominates, suggesting potential over-investment in EV subsidies. The estimated marginal social benefit from removing the EV subsidy is only \$242 per ton of CO₂, which is lower than prior marginal abatement cost estimates ranging from \$300 to \$500 [Fournel, 2024, Xing et al., 2021, Archsmith et al., 2015].

There are two countervailing forces that drives the marginal abatement cost of imposing an EV subsidy: the complementary preferences for large utility vehicles under the subsidy raises the cost, whereas trip optimization lowers it. If the latter dominates, the social benefit of removing EV subsidy decreases as households have already internalized the cost. My model suggests that ignoring fleet-level driving optimization underestimates emission rebounds from removing EV subsidy, despite the existing incentive scheme tending to over-invest.

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6.3 The Role of Complementary Preference and Usage

To assess the role of the fleet model in the above policy simulations, I re-estimate a standard random coefficient model of household vehicle demand under the assumption that households make purchase decisions independently for each vehicle. In this specification, the fleet fixed

effects $\lambda(\mathcal{S}_i)$ reduce to fixed effects based only on vehicle body types. Usage shares are fixed at observed ratios across all counterfactual fleets to calculate usage values $EMU(\mathcal{S}_i)$. Under this model, households neither optimize driving behavior across different scenarios nor consider the primary vehicle role when making purchase decisions.

Table 6.2 summarizes the main differences between the independent and fleet models. Under independent decision-making, the model undervalues {EV,ICE} fleets and thus predicts a larger loss in EV market shares. It also overestimates the uptake of large utility vehicles, since it ignores the suppression of LUV preference that occurs when fewer EVs are adopted. Both mechanisms suggest a larger emissions rebound from eliminating the EV subsidy in the independent model. However, the results show the opposite, providing direct evidence that emissions rebound from ignoring fleet-level driving optimization dominates the policy impact when the EV subsidy is abolished.

	Baseline	Removing subsidy		Registration fee		Gasoline tax	
		Ind.	Fleet	Ind.	Fleet	Ind.	Fleet
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share EV purchase	4%	-2.61	-2.01	-1.04	-0.96	1.77	1.92
Share LUV purchase	42%	0.52	0.27	0.10	0.07	-1.59	-1.47
CO ₂	5818 kg	0.68	0.74	0.37	0.34	-0.60	-0.74

Table 6.2: Policy evaluation under independent vs. fleet optimization

Notes: This table reports the counterfactual results evaluated on the 2022 data. All values except those in the baseline column are expressed in percentage points. LUV stands for large utility vehicles including standard SUV, minivan and pick-up trucks.

Similar dynamics affect changes in fleet ownership in the second policy scenario, but the bias in emission outcomes differ. As shown in Table 6.1, imposing the EV registration fee has limited effect on driving behavior, so emission outcomes are dominated by changes in market shares. The independent model therefore slightly overestimates the emission increase. The bias is smaller because the policy more strongly influences lower-income households—who are less likely to own multiple vehicles or large utility vehicles—mainly due to the relatively

modest amount of the registration fee.

The third counterfactual policy—imposing gasoline tax—illustrates the opposite influence of complementary preferences on fleet choice. On one hand, omitting the complementary preference for {EV, ICE} fleets in an independent model underestimates the attractiveness of EVs. On the other hand, it also overlooks the subsequent preference for LUVs that emerges as EV shares rise, resulting in a larger reduction in LUV shares. These two forces imply opposite prediction biases in predicted emission outcomes. However, as discussed in the previous chapter, fuel taxes stimulate more adjustments at the usage level, so fleet-level driving optimization is expected to dominate, leading the independent model to underestimate the emission emission reductions.

CHAPTER 7

DISCUSSION

This paper offers a new perspective on designing effective emission policies by analyzing demand for household vehicle fleets based on usage patterns. I estimate a role-dependent model of household fleet choice and usage, leveraging data on fleet ownership and driving behavior. A key advantage of this approach is that it incorporates trip assignment based on vehicle attributes and captures complementary preferences driven by travel demands. The findings indicate that a shift toward high-fuel-efficiency driving generally outweighs the complementary preference for high-range electric vehicles and large utility vehicles for policies impacting most households. Models that ignore the fleet perspective tend to underestimate emission policy effectiveness due to the lack of within-fleet substitution.

While I have performed counterfactual analysis on two recent EV policies and a hypothetical fuel tax increase, my framework is broadly applicable to analyzing regulations affecting multi-product household choices, such as appliances or housing, where the value of individual items depends on both their complementarity within the set and their patterns of use. These exercises could be validated through ex-post policy evaluation if and when such policies are implemented. I therefore view this paper as a foundational step toward a comprehensive framework for understanding and evaluating portfolio product choices and their policy implications.

APPENDIX A

ADDITIONAL FIGURES



Figure A.1: The distribution of BEV ranges by model year

Notes: This figure presents the distribution of electric range for BEV models available in the U.S. from model years 2011 to 2024. Red dots indicate the median range for each model year.
Data source: U.S. Environmental Protection Agency (<http://www.fueleconomy.gov/feg/>)

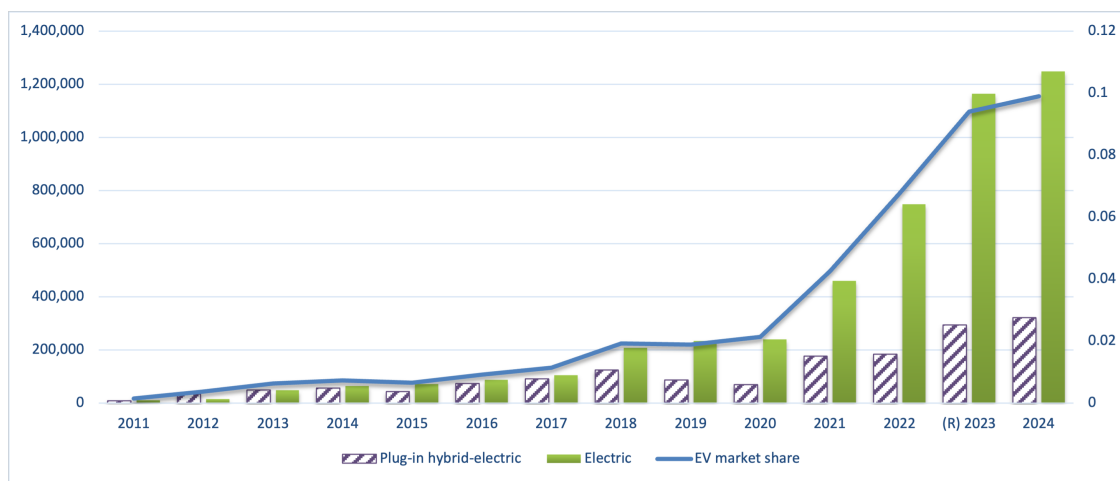


Figure A.2: EV sales trends in the U.S. over time

Notes: This figure displays annual BEV and PHEV sales in the U.S. from 2011 to 2024, along with their combined market share among new light-duty vehicle sales.

Data source: U.S. Department of Transportation Bureau of Transportation Statistics and Statista.com

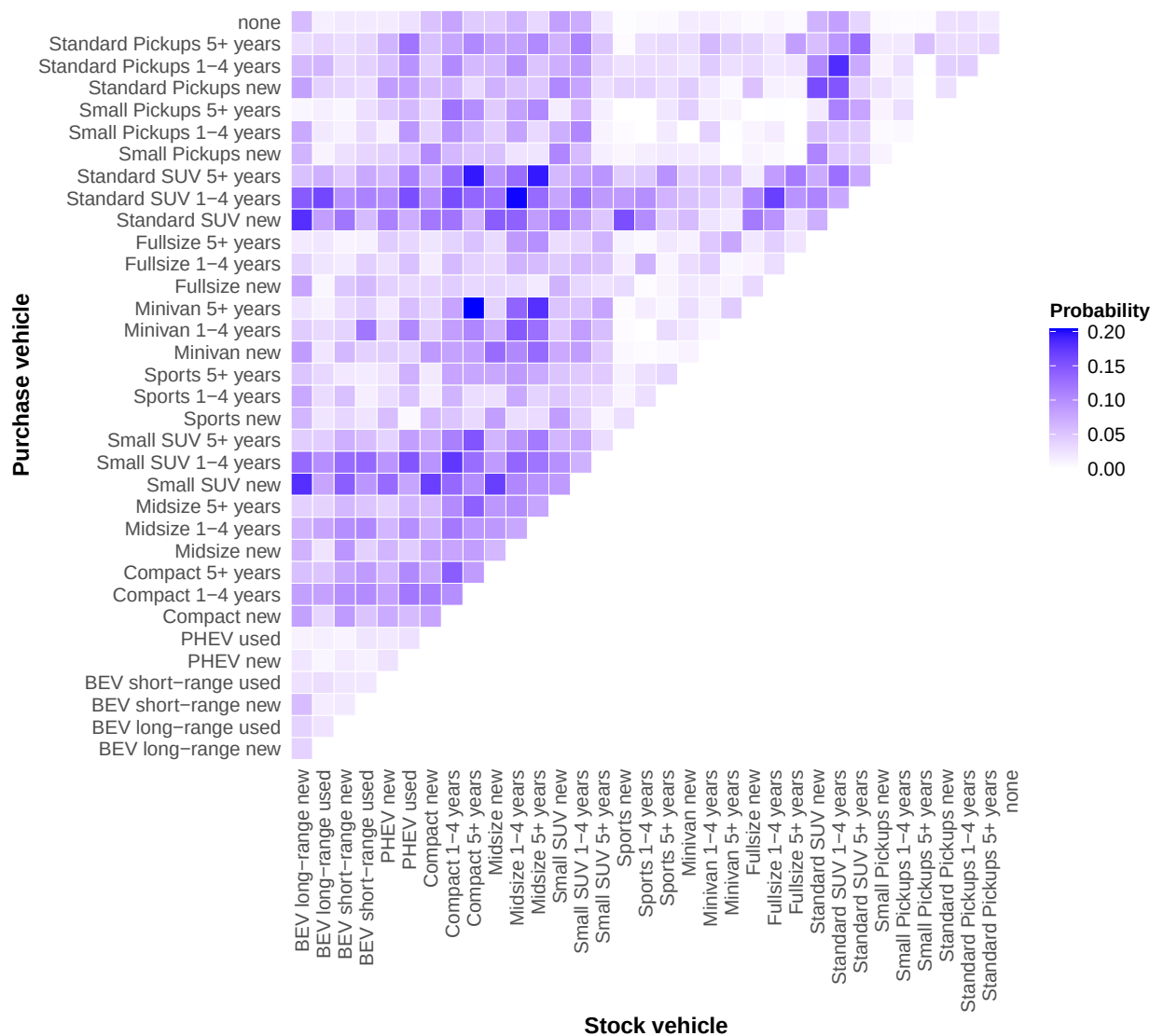


Figure A.3: Conditional distribution of fleet types for EV households

Notes: This figure shows, for EV-experienced households, the conditional probability distribution of selecting different fleet types given the stock vehicle. Each column sums to one. Vehicle types are ordered by average fuel efficiency and vehicle age; "none" indicates single-vehicle households. The cutoff between high-range and low-range BEV is 200 miles.

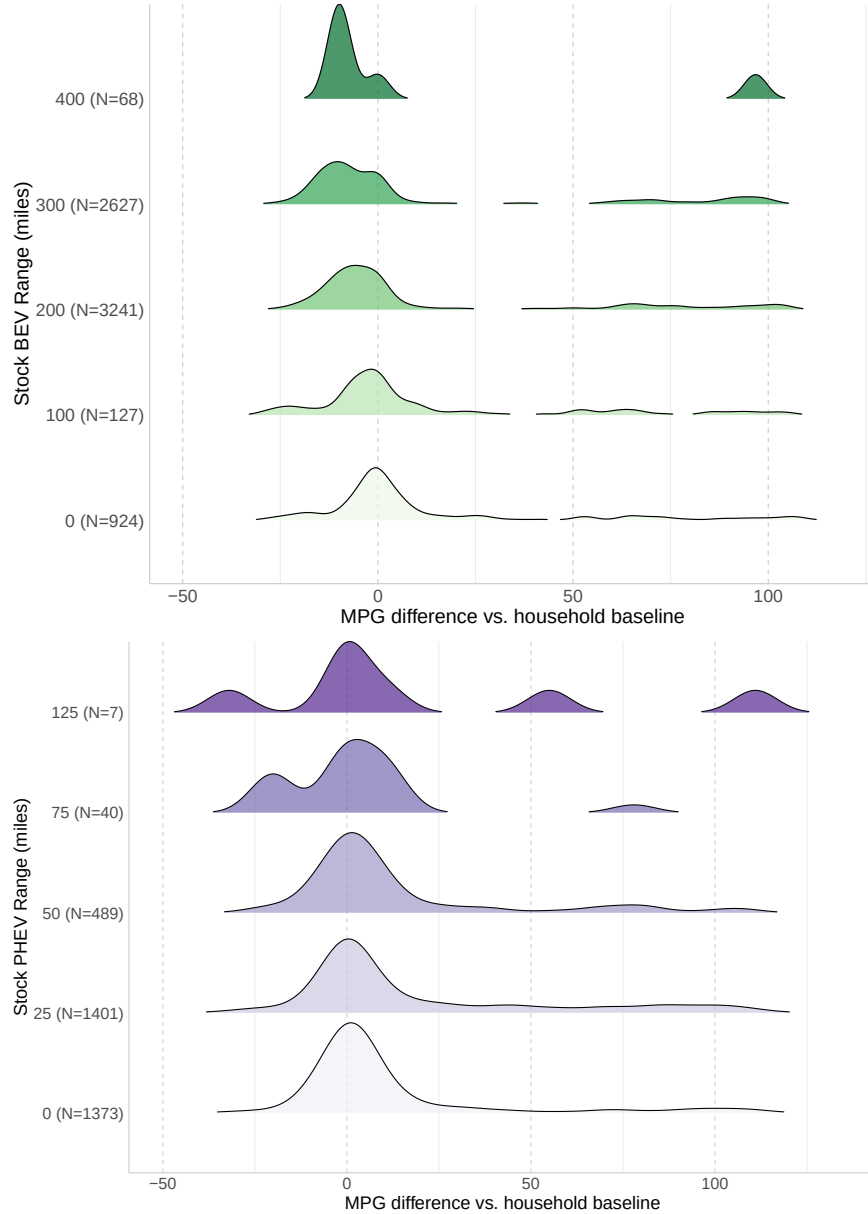


Figure A.4: Fuel economy difference distributions: post-BEV adoption (upper panel) vs. post-PHEV adoption (lower panel)

Notes: This figure shows the distribution of the difference in MPG/MPGe between households' follow-on vehicles after EV adoption and their pre-adoption average fleet MPG. The sample sizes are 6,987 for BEV households (upper panel) and 3,310 for PHEV households (lower panel). MPG/MPGe values are calculated according to EPA standards, with MPGe representing miles per gallon equivalent (1 gallon gasoline $\approx$ 33.7 kWh). The difference is computed as the post-adoption follow-on vehicle's MPG/MPGe minus the pre-adoption fleet average where the MPG of the focal EV is excluded from the analysis. For BEVs with more than 200 miles of range, the distributions is concentrated between -10 to -20 MPG. For PHEVs, the 75- and 125-miles range buckets consist exclusively of households that purchased the BMW i3 Range Extender (BMW i3 REx) which uses gasoline engine recharge the battery when depleted, rather than driving the wheels directly. Early models (2014-2016) of the BMW i3 REx had all-electric ranges of 72-81 miles. The 2017-2018 models offered 97 miles, and since the 2019 model year, the all-electric range has reached 125 miles.

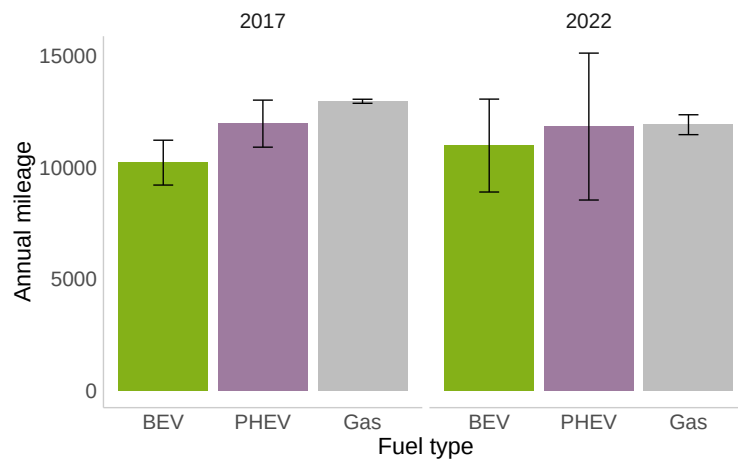


Figure A.5: Average annual mileage by vehicle fuel type

Notes: This figure represents the average annual mileage of vehicles owned by U.S. households in 2017 and 2022. Error bars indicate 95% confidence intervals. The average mileage for gasoline vehicles was 12,954 miles in 2017 and 11,905 miles in 2022, closely aligning with estimates from the Federal Highway Administration (FHWA).¹ The average BEV mileage increased by 1000 miles over the five years—even as aggregate mileage trended downward. The large confidence intervals are a result of the shrink in sample size in 2022 NHTS survey.

APPENDIX B

ADDITIONAL TABLES

Vehicle type	Fuel efficiency
BEV	100–135 MPGe
PHEV	60–100+ UF-MPGe
Conventional Hybrid Vehicle ¹	40–55 MPG
Gasoline Sedan	28–36 MPG
Gasoline small SUV	28–30 MPG
Gasoline midsize/standard SUV	22–26 MPG
Gasoline Minivan	18–24 MPG
Gasoline Pickup	17–23 MPG

Table B.1: Typical fuel efficiency by vehicle type (2015–2022)

Notes: MPGe denotes miles per gallon gasoline equivalent, and UF-MPGe denotes utility-factor-weighted miles per gallon gasoline equivalent as defined by the EPA.

1. Conventional hybrid vehicles use both a gasoline engine and an electric motor, but cannot be plugged in to recharge; instead, they generate electricity through regenerative braking and the engine to improve fuel efficiency compared to standard gasoline vehicles.

	OLS (1)	HHFE (2)	IV 1st (3)	IV 2nd (4)
<i>(a) All EV adoption</i>				
stock_EV	-0.0773*** (0.0050)	0.0655*** (0.0077)		1.938 (4.281)
stock_gasprice			0.0055 (0.0034)	
F-test			15.10	
<i>(b) BEV adoption</i>				
stock_BEV	-0.0805*** (0.0065)	0.0841*** (0.0091)		1.297 (3.453)
stock_gasprice			0.0062* (0.0036)	
F-test			20.87	
<i>(c) PHEV adoption</i>				
stock_PHEV	-0.0207* (0.0122)	-0.0079 (0.0137)		8.024 (31.99)
stock_gasprice			-0.0011 (0.0014)	
F-test			2.72	
year-fuel type FE	Yes	Yes	Yes	Yes
household FE		Yes	Yes	Yes
Observations	1,434,190	1,434,190	599,442	599,442

Table B.2: Regression result of EV adoption, discontinuous dependent variable

Notes: This table reports the effect of EV adoption on the likelihood of purchasing a subsequent vehicle with MPG below 25, based on a regression of a dichotomous indicator for low fuel efficiency on covariates. Each observation is a buy-stock vehicle pair. Standard errors clustered by household are shown in parentheses. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively. The IV specification uses the gasoline price at the time of stock vehicle purchase.

Dependent Variables:	HHFE buy_lowmpg (1)	IV 1st stock_electricrange (2)	IV 2nd buy_lowmpg (3)
stock_electricrange	0.0003*** (3.43×10^{-5})		2.61×10^{-4} * (1.50×10^{-4})
stock_gasprice		1.885* (0.9692)	
F-test		28.81	
year-fuel type FE	Yes	Yes	Yes
household FE	Yes	Yes	Yes
Observations	1,434,190	599,442	599,442

Table B.3: Regression result of electric range, discontinuous dependent variable

Notes: This table reports the effect of EV range on the likelihood of purchasing a subsequent vehicle with MPG below 25, based on a regression of a dichotomous indicator for low fuel efficiency on covariates. Each observation is a buy-stock vehicle pair. Standard errors clustered by household are shown in parentheses. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively. The IV specification uses the gasoline price at the time of stock vehicle purchase.

APPENDIX C

CONCEPTUAL FRAMEWORK

I develop a simple economic framework of utility maximization where households with diverse travel needs value multiple attributes of vehicles. This model builds on the household vehicle portfolio perspective from Archsmith et al. (2020), but makes explicit the joint maximization over multiple attributes and their interaction with household vehicle usage. The focus of the model is on a policy-relevant question: how the realization of high value in one attribute—and in particular fuel economy—of a household’s existing vehicle influences the attributes of the follow-on vehicle.

While my context is vehicles, the framework generalizes to any products with portfolio characteristics, such as spousal job choices, financial assets, or streaming subscriptions.

Suppose a household owns $j = 2$ vehicles (the model readily extends to n). To meet diverse travel needs—commuting, road trip, cargo hauling—households value multiple vehicle attributes, such as fuel economy (f_j) and alternative attributes (a_j) that are typically negatively correlated with f_j due to engineering trade-offs (e.g., horsepower, size). For simplicity, assume

$$a_j = \bar{a} - f_j \tag{C.1}$$

Utility is derived not from every vehicle, but from the combined access to these attributes in the garage. The utility function is:

$$U = \beta_f \cdot \max(f_1, f_2) + \beta_a \cdot \max(a_1, a_2) - \alpha(p_1 + p_2) - \gamma \cdot c\left(\frac{m_1}{f_1} + \frac{m_2}{f_2}\right) \tag{C.2}$$

where $\beta_f, \beta_a, \gamma > 0$, p_j is the price of vehicle j , and m_j is miles driven on vehicle j with $m_1 + m_2 = M$, the household’s total travel needs.

The term $c(\cdot)$ is a continuous, household-specific penalty reflecting monetary (e.g., fuel costs) or social (e.g., emissions) costs of fuel consumption, $\frac{m_1}{f_1} + \frac{m_2}{f_2}$. Each additional unit of fuel increases the penalty, so households have continuing incentive to maintain fleet efficiency conditional on their usage. This puts pressure against large decreases in overall household fuel economy.

Suppose the household already owns an EV (car 1) and is considering which subsequent vehicle (car 2) to purchase. The marginal utility with respect to changes in the attributes of car 2 is

$$\frac{dU}{df_2} = \frac{\partial U}{\partial f_2} + \frac{\partial U}{\partial a_2} \cdot \frac{da_2}{df_2} = \begin{cases} \gamma \cdot c'(x) \frac{m_2}{f_2^2} - \beta_a & \text{if } f_1 > f_2, a_1 < a_2 \\ \beta_f + \gamma \cdot c'(x) \frac{m_2}{f_2^2} & \text{if } f_1 < f_2, a_1 > a_2 \end{cases} \quad (\text{C.3})$$

where $x = \frac{m_1}{f_1} + \frac{m_2}{f_2}$ and $c'(\cdot) > 0$. It is standard to assume the cost penalty is convex ($c''(\cdot) > 0$), so the marginal cost of fuel consumption increases—capturing rising household, societal and regulatory costs, or decreasing returns to fuel efficiency investments. Increasing car 2's fuel efficiency (f_2) always provides utility via reduced fuel costs or penalties ($\gamma \cdot c'(x) \frac{m_2}{f_2^2} > 0$), but this marginal benefit diminishes as f_2 grows due to the $\frac{1}{f_2^2}$ term.

Equation C.3 reveals the tension between household preference β_f , β_a and cost penalty. The sign of Equation C.3 determines whether the household should emphasize a_2 (e.g., size, power) versus f_2 (fuel economy) in car 2 relative to car 1. If car 1 is already highly efficient (e.g., an EV), so $f_1 > f_2$, emphasizing the alternative attribute a_2 in car 2 is optimal when: (a) the household values a_2 (large β_a); (b) car 2 is driven relatively less (m_2 small), so fuel cost savings from improving f_2 are smaller; or (c) car 2 is already reasonably efficient (f_2 relatively high), so the marginal value of additional fuel efficiency diminishes rapidly.

Had the household chosen a hybrid for car 1, f_1 would be lower and total fuel consumption x higher. Given convexity, the marginal fuel penalty is larger, so there is more incentive to buy a moderately efficient car 2—less scope to emphasize alternative attributes, as the

household still needs to collectively satisfy an implicit efficiency target.

The model thus predicts a greater drop in car 2’s fuel economy when car 1 is highly efficient (BEV) versus less efficient (hybrid)—consistent with the concept of attribute substitution observed in empirical studies (Archsmith et al. 2020; add ref). The framework also captures that, at the intensive margin, an EV in car 1 that covers more miles (larger m_1) and leaves less of the total driving for car 2, further reducing the fuel penalty and making it more attractive to select car 2 with stronger alternative attributes (lower f_2 when negatively correlated).

Compared to independent optimization—where each vehicle is chosen in isolation and subject to the same trade-offs—the portfolio approach leverages specialization and complementarities between vehicles. This leads to diminishing marginal returns from stacking similar attributes, and the optimal attribute sets for the portfolio always nest those of the independent solution.

This framework provides an explicit account for how and under what conditions attribute substitution arises: it predicts how households adjust their fleets in response to the attributes of existing vehicles, and links substitution strength to vehicle usage and cost penalty structure. It also provides a clear policy takeaway: interventions that reduce the marginal cost of one attribute (such as EV subsidies) may indirectly encourage households to shift their budget and increase emphasis on alternative, potentially less efficient, attributes in their subsequent vehicle choices.

APPENDIX D

EV POLICY

One of the policies studied in this paper is the federal subsidy for electric vehicles, which is provided as a federal income tax credit for buyers of new EVs, including both BEVs and PHEVs.¹

The consumer tax credit for electric vehicles (EVs) is estimated to cost approximately \$15 billion over the period 2011–2031.² During the study period, the size of the federal subsidy was determined linearly by battery capacity, up to a maximum value of \$7,500. While the translation of battery capacity into electric range depends on other vehicle characteristics, all BEVs in the dataset received the full subsidy, whereas most PHEV models qualified only for a partial subsidy.³ Please refer to Appendix D for more details about the federal EV subsidy.

The subsidy scheme has gone through major changes to address concerns about efficient use of federal funds and equitable access that arose from early years of adoption. Up to 2022, the credit was subject to a manufacturer sales cap: once a manufacturer sold 200,000 qualifying vehicles in the U.S., the credit for that manufacturer began to phase out. This phase-out notably affected Tesla and General Motors vehicles between 2019 and 2022.⁴ In 2023, the Inflation Reduction Act (IRA) restructured the EV tax credit to target middle-

1. Other EV policies available in Texas but not explicitly accounted for include:

1. Texas Emission Reduction Plan (TERP) Rebate (\$2,500), which had limited impact during my data period due to its restriction to vehicles bought or leased from dealerships and intermittent funding.
2. The federal tax credit for charging equipment (up to \$1,000), which is excluded due to a lack of data on hardware and installation costs as well as changes in program availability and eligibility over time.

2. See annual fiscal spending on EV tax credits for 2011–2022 in Congressional Research Service Report IF11017 <https://sgp.fas.org/crs/misc/IF11017.pdf>, and Congressional Budget Office estimates for 2022–2031 under the Inflation Reduction Act of 2022 https://www.cbo.gov/system/files/2022-08/hr5376_IR_Act_8-3-22.pdf.

3. Notable exceptions are the Chevrolet Volt (35 to 53 miles electric range), Honda Clarity (47 miles) and Chrysler Pacifica (33 miles), all of which were eligible for the full subsidy.

4. GM models available then include Chevrolet Bolt (BEV), Bolt EUV (BEV) and Volt (PHEV).

and lower-income groups and promote domestic manufacturing. The manufacturer sales cap was removed, but new requirements were added, including vehicle price caps, income limits, and assembly and battery sourcing requirements. Eligibility for the federal EV tax credit is subject to the following requirements:

1. Income limits: eligible households must have an annual income below \$300,000 if filing jointly, and \$150,000 for single filers.
2. Price caps: eligible vehicles have MSRP below \$55,000 for Sedans and below \$80,000 for SUVs, vans, and pickup trucks.
3. Country of origin: eligible vehicles must be assembled in North America, with additional requirements for battery sourcing and critical minerals.⁵

5. See "Clean Vehicle Credits," Internal Revenue Service, accessed June 5, 2025, <https://www.irs.gov/credits-deductions/credits-for-new-clean-vehicles-purchased-in-2023-or-after>.

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