Is There a Trade-Off Between Equity and Effectiveness for Electric Vehicle Subsidies?

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Abstract

This paper considers welfare and distributional effects of US electric vehicle subsidies accounting for interactions with other climate policies. I compare subsidy scenarios using a new equilibrium model of the US new vehicles market that endogenizes vehicle entry and accounts for interactions among subsidies, zero-emission vehicle standards, and fuel economy standards. Income-based subsidies are more effective and more equitable than uniform subsidies. Accounting for interactions with other policies substantially reduces estimated efficacy and surprisingly causes all subsidies to be progressive.

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1 Introduction

Meeting global climate objectives will likely require widespread adoption of plug-in passenger vehicles (PEVs), which include all-electrics such as the Nissan Leaf and plug-in hybrids such as the Chevrolet Volt (IEAl, 2021). Two PEV policy trends have emerged. First, many countries combine vehicle subsidies with other policies to increase market penetration. Although an emissions price may efficiently address climate externalities, subsidies are far more common than emissions prices (McDonald, MacInnis, and Krosnick, 2020 and REN21, 2021).[1] Subsidies for purchasing PEVs are often combined with subsidies for charging infrastructure as well as greenhouse gas (GHG) emissions rate or fuel economy standards for all new vehicles. For example, California and 12 other states implement the zero-emission vehicle (ZEV) program that sets targets for overall market penetration. At the same time, the US Environmental Protection Agency (EPA) and Department of Transportation (DOT) set new vehicle greenhouse gas (GHG) and fuel economy standards.

The second recent trend is that many policy makers want to make subsidies more equitable. Households buying electric vehicles have incomes 2–3 times greater than typical household incomes; similar patterns exist for many other GHG-reducing consumer products such as solar photovoltaic panels (Barbose et al., 2021, Borenstein and Davis, 2016, and Truecar.com). To encourage lower-income households to purchase electric vehicles, some jurisdictions link the subsidies to income or product prices. For example, Massachusetts offers larger subsidies for relatively inexpensive PEVs, and California offers extra subsidies to low- and middle-income households buying PEVs. The US Congress has considered ways to target federal PEV subsidies to relatively low-income households.

The trends of implementing multiple policies and growing equity concerns raise the question: how cost-effective and equitable are PEV subsidies given their interactions with other policies? I define a policy as progressive (or equitable) if the welfare costs are positively correlated with consumer income.[2] I ask whether linking subsidies to household income is both more equitable and effective at increasing PEV sales. As I explain next, answering this question requires bridging literature on policy interactions with literature on incidence and entry in differentiated product markets.

Although a recent literature examines subsidies for PEVs and charging stations (e.g., Springel (forthcoming) and Li (2019)), this research has considered subsidies in isolation

[1] Combining subsidies with a GHG emissions price can be more efficient than the price alone if new technologies face market failures, such as learning spillovers and incomplete information (Acemoglu et al., 2012 and Fischer, Preonas, and Newell, 2017).

[2] A broader definition of equity could include race or other observable demographic variables, but I focus on income largely because of available data.

of overarching emissions standards and other policies. To see why welfare and distributional effects of the subsidies depend on policy interactions, consider that GHG and ZEV standards are typically set several years in advance and are therefore fixed when Congress or states choose PEV subsidies. An attribute-based policy, such as a GHG emissions rate standard and the ZEV program, introduces a shadow price for that attribute. Layering the subsidy on top of the attribute-based standard reduces the shadow price (Borenstein et al., 2019 and Perino, Ritz, and Benthem, 2019). Consequently, subsidizing PEVs does not affect PEV sales in ZEV states or average GHG emissions rates of all vehicles as long as those policies remain binding. Accounting for such policy interactions reduces estimated efficacy of subsidies at increasing PEV sales and reducing emissions.

Moreover, ZEV standards are likely to be regressive because they reduce equilibrium PEV consumer prices, and high-income households are most likely to purchase PEVs. Consequently, accounting for the interaction between the subsidy and ZEV standards makes the subsidy more progressive than if this interaction were ignored. Yet, the literature on PEV subsidies has not considered such interactions.

Turning to incidence in differentiated product markets, as I show empirically for the US market, average markups are lower for PEVs than other vehicles. By increasing PEV sales at the expense of non-PEV sales, PEV subsidies can increase deadweight loss by exacerbating pre-existing distortions. Distributional and overall welfare effects of subsidies depend on how subsidies affect equilibrium markups and how they interact with pre-existing distortions caused by market power.

A final consideration is that PEV markets are dynamic and PEV subsidies may affect entry decisions. A recent literature has considered endogenous product entry and exit (e.g., Eizenberg, 2014 and Fan and Yang, 2020), and the effectiveness and equity of subsidies depends on the entry response. In particular, subsidizing low-income consumers could cause more or less entry than a uniform subsidy, depending on entry costs, pass-through of the subsidies to equilibrium prices, and other factors. Consequently, in principle, accounting for entry could increase or decrease estimated progressivity of PEV subsidies, but literature on PEV subsidies has not considered entry.

In this paper, I use a new equilibrium model of the new vehicle market that includes interactions among subsidies, GHG standards, and ZEV standards; endogenous markups; and endogenous PEV entry that includes entry cost dynamics. In the model, each consumer chooses a vehicle that maximizes subjective utility. Consumer preference parameters vary across demographic groups defined by income, population density, age, and geographic region. The underlying data include about 1.5 million responses to a survey of new vehicle consumers between 2010 and 2018. Based on household purchasing decisions between

2010 and 2018, I find that low-income households are twice as sensitive to vehicle prices and have lower willingness to pay (WTP) for PEVs than other households. Consumers in California and other ZEV states have stronger preferences for PEVs than consumers in other states. Thus, both preferences and policies explain the variation in PEV market shares between ZEV and non-ZEV states.

Turning to the supply side of the model, manufacturers choose whether to introduce new PEVs and choose prices and fuel economy of their vehicles. I follow Leard, Linn, and Springel (2019) in modeling price and attribute choices. Modeling PEV entry is complicated by the immense set of potential entrants. Each year, a manufacturer chooses how many PEVs to introduce and their attributes. Sometimes, manufacturers use an existing vehicle architecture for a gasoline-powered vehicle and introduce a version that has a hybrid, plug-in hybrid, or electric power train. For example, in 2013, Ford introduced a plug-in hybrid version of the Fusion, which it sells alongside the gasoline and hybrid versions of the Fusion. In these cases, the versions are otherwise quite similar to one another; I use the term "sibling" to refer to vehicles that are nearly identical except for the fuel type. Other times, manufacturers introduce new vehicles that are physically distinct from existing vehicles, such as the Nissan Leaf. In these cases, manufacturers may base certain elements of the new vehicles on existing ones, but the new vehicles have different exterior styling, interior design and features, etc.

Given the immense set of feasible attributes for entrants, for tractability, in the model potential entrants include electric siblings of gasoline vehicles that do not have an electric sibling as of 2021.[3] This assumption is motivated by the fact that, excluding Tesla, in 2019, siblings accounted for 55 percent of PEV sales, and they are also a major portion of the announced post-2021 entrants. Manufacturers appear to adopt this strategy because of the cost savings of using an existing model's architecture and also for marketing purposes. Thus, aside from being computationally tractable, modeling sibling entrants likely incorporates a large share of future entrants through at least 2025, which is the period on which the policy analysis focuses.

Estimation of entry costs builds on Wollmann (2018) and introduces dynamics caused by declining battery costs and manufacturer experience with introducing new electric vehicles. A manufacturer introduces a new PEV if the ratio of expected short-run profits to entry costs exceeds an internal hurdle rate that accounts for the cost of capital, expected market dynamics, and uncertainty (short-run profits are revenue less production costs during the first year of sales). Entry costs evolve over time according to past entry decisions

[3] This paper excludes fuel-cell vehicles, such as the Toyota Mirai, because the number of vehicles of this fuel type is insufficient to estimate consumer preferences for the technology.

by the manufacturer. Estimated entry costs are higher for vehicles purchased by high-income consumers, which likely reflects their higher quality. Entry costs decrease with a manufacturer's historical entry, and equilibrium entry depends strongly on expected profits.

I validate the model along multiple dimensions. The model reproduces observed market shares, both in and out of sample. Estimated ZEV and GHG credit prices are similar to observed prices, and the model predicts entry decisions accurately.

Policy simulations include three types of subsidies that are offered in addition to current subsidies: a) uniform (continuing the status quo), b) for the two lowest income quintiles, and c) for PEVs with below-average retail prices. I also consider a feebate that combines a tax on gasoline vehicles with a subsidy to PEVs. I model the effects of these policies in 2025, with endogenous entry and exogenous stringency of ZEV and fuel economy standards. The assumption that stringency is exogenous to the subsidies is consistent with the timeline along which state and federal policy makers choose subsidies (see Section 3).

There are two main results regarding the cost-effectiveness of the subsidies. First, the income-based subsidy is at least 40 percent more effective than the others; this result is consistent with Xing, Leard, and Li (2021) and follows from the greater estimated price sensitivity of low-income consumers and the lower estimated entry costs for PEVs aimed at low-income consumers. Second, interactions among subsidies, ZEV standards, and fuel economy standards substantially reduce the efficacy of the subsidies at increasing PEV sales. Subsidies reduce ZEV credit prices without affecting total PEV sales in ZEV states.

There are two main results for the equity of the subsidies. First, the uniform subsidy is progressive, despite the fact that high-income consumers have higher PEV demand than low-income consumers. This surprising result is explained by differential subsidy incidence across vehicles. Because of differences in price sensitivity across income groups, manufacturers capture most of the subsidy for PEVs purchased by high-income consumers, but consumers capture most of the subsidy for PEVs purchased by low-income consumers. Estimated incidence is consistent with analysis of California's subsidies (Muehlegger and Rapson, 2018). Moreover, interactions with ZEV standards contribute to the progressivity of the subsidies because the lower ZEV credit prices benefit low-income households who are most likely to purchase gasoline vehicles.

The second equity result is that the income-based subsidies are more progressive than other subsidies both because they are only claimed by the lowest income groups (by construction) and also because of interactions with ZEV standards. That is, by ignoring interactions among subsidies and other policies, the literature both overstates efficacy of income-based subsidies and understates their progressivity.

The main features of this paper are a) analyzing the trade-off between equity and cost-effectiveness; and b) modeling product entry and interactions among other policies for the first time. Thus, the paper contributes to literature on electric vehicles; cost-effectiveness, equity, and incidence of environmental subsidies and taxes; policy interactions; and modeling entry in differentiated product markets.

A recent literature examines consumer demand and electric vehicle subsidies. Sheldon and Dua (2019) and Xing, Leard, and Li (2021) show that low-income households are more responsive to vehicle prices than high-income households, and income-based subsidies are more equitable and cost effective than uniform subsidies. Springel (forthcoming) employs an equilibrium model in which proximity to charging stations affects consumer demand for PEVs and charging station investment is endogenous. She finds that subsidizing charging stations is more cost effective than subsidizing PEV purchases. Remmy (2022) analyzes PEV subsidies in Germany accounting for endogenous manufacturer choices of PEV range (as a proxy for quality). The estimated cost effectiveness of the subsidies in these papers includes the effects of pre-existing distortions caused by market power, although the authors do not emphasize this point. These papers do not consider interactions among subsidies and other policies, and they do not model entry.

An expanding literature has evaluated cost-effectiveness of subsidies for GHG-reducing consumer products such as photovoltaic panels (e.g., Hughes and Podolefsky (2015), Langer and Lemoine (2018), Li (2019), and Springel (forthcoming)). Most of it (e.g., Munzel et al., 2019, Li et al., 2017, and Muehlegger and Rapson, 2018) has considered fiscal costs per ton of emissions reduction, although a few papers (e.g., Pless and Benthem, 2019) estimate welfare costs per change in product sales or emissions. I examine both fiscal cost effectiveness and welfare costs.

Considering the broader environmental policy literature, most of the literature on the equity of a policy does not consider its interactions with other policies. As noted above, subsidies affect consumer prices, whereas the ZEV program and fuel economy standards affect market shares and average fuel economy. The GHG reductions of these policies are not additive, and they may interact with one another in complex ways (Novan, 2017 and Perino, Ritz, and Benthem, 2019). Most of the literature on overlapping policies has focused on efficiency rather than equity, particularly in the context of instrument choice, overlapping jurisdictions, federalism, and local pollutants (e.g., Oates, 1999, Williams, 2012, and Ambec and Coria, 2018). Similarly, this paper considers a case of overlapping jurisdictions, and I demonstrate that the interactions substantially weaken the efficacy of the subsidies and also affect their distributional consequences.

This paper adds to the extensive literature on equity and welfare effects of fuel taxes, carbon prices, and performance standards (e.g., West, 2004 and Goulder et al., 2019). The literature on transportation climate policies has generally not considered interactions among policies. Jacobsen (2013) finds that fuel economy standards are regressive but does not consider interactions with ZEV standards, which his analysis predates.

As noted above, pass-through of the subsidies to equilibrium prices affects equity. Many studies, mostly empirical, have examined the pass-through of environmental subsidies and taxes to equilibrium prices (e.g., Lade and Bushnell (2019) and Pless and Benthem (2019)). Like this paper, most recent studies on PEV subsidies employ equilibrium models of the new vehicle market rather than reduced-form econometric analysis of the subsidies.

Finally, the paper contributes to the literature on modeling entry of new products in a differentiated product market. The use of siblings to constrain the available state space for potential entrants may have applications in other markets, where new products have many of the same characteristics as existing ones, such as offering a new high-performance version of an existing product. A recent literature (e.g., Pakes et al. (2015), Wollmann (2018), and Fan and Yang (2020)) assumes that observed entry choices constitute a Nash equilibrium, which facilitates estimating bounds on entry and exit costs. The simplifications I employ regarding unobserved entry costs allow me to identify point estimates of entry costs, which may be applicable for estimating entry costs in other industries in which firms do not simultaneously introduce multiple products that compete against one another. Durrmeyer and Samano (2017) model entry of hybrid vehicles using a similar siblings strategy to that in this paper, and Armitage and Pinter (2022) employ a static PEV entry model; unlike this paper, neither of those includes dynamics of manufacturer learning. Modeling entry is an important distinction between this paper and Reynaert (2021) as well as my previous work (Leard, Linn, and Springel (2019) and Leard, Linn, and Springel (2020)). In further contrast to the latter papers, I use data through 2018 rather than 2015, which facilitates PEV demand estimation. This paper also differs by modeling regional rather than national markets and allowing for additional consumer preference heterogeneity.

2 Data and Summary Statistics

2.1. Data

The subsection describes the construction of the main data set. The primary data source is the MaritzCX New Vehicle Customer Survey (NVCS). MaritzCX sends the survey to households that recently purchased new vehicles and sells the data to vehicle manufacturers, industry analysts, and researchers. Each year, MaritzCX collects about 200,000 responses (the response rate is about 9 percent). I use data from the 2010–2018 surveys, which include about 1.5 million responses representing about 1 percent of buyers.

Survey respondents report the transaction price of their vehicles, which excludes trade-in value and includes taxes, along with identifying information about the vehicle, such as make, model, trim, drive type (such as front-wheel drive), and power train specifications (engine size, transmission type, and fuel type). Demographics include income, age, and zip code of residence. I define 20 demographic groups that include five income groups, two age groups, and two urbanization groups based on population density. I selected these demographics because they parsimoniously explain a large share of cross-household purchase variation. The cutoffs used to define the groups are selected so that each of the 20 groups has approximately the same number of NVCS observations.[4] To facilitate modeling the ZEV standards I define three region: California, other ZEV states, and non-ZEV states.

The NVCS data have four distinguishing features: a) respondents provide information about the vehicles they purchased and their own demographics; b) the sample represents about 1 percent of all buyers; c) the data include vehicle transaction prices; and d) the data include highly detailed information about the vehicle purchased. The demographics avoid the need to impute demographics (Busse, Knittel, and Zettelmeyer, 2013), and large sample size reduces measurement error for transaction prices and vehicle choice variation across demographic groups.

The transaction prices are particularly important for estimating WTP for vehicle attributes. Manufacturers choose MSRP once each year, whereas transaction prices respond to short-term market conditions such as surprises in gasoline prices. Using MSRP can lead to biased estimates for WTP (Langer and Miller, 2013). Transaction prices differ substantially from the manufacturer's suggested retail price (MSRP), and using these rather than MSRP yields more economically plausible and precisely estimated parameter values.

The detailed vehicle information allows me to define about 1,200 unique vehicles each year, which is several times larger than the number of unique choices that can be found in most previous studies. A vehicle is defined by a unique model year, make, model, trim, fuel type, drive type, body style, and engine displacement. For example, a unique vehicle in the data is the 2018 Volkswagen Jetta SE sedan with a 1.4 liter gasoline engine and front-wheel drive. The vehicle aggregation corresponds closely to the choice set that consumers face. For example, the data distinguish all-wheel drive and front-wheel drive

[4] I use the Consumer Expenditure Survey (CEX) to weight NCVS observations to account for nonuniform response rates across demographic groups. Because of the CEX sample size, it is not possible to construct more than about 20 demographic groups. The 20 groups that include income, age, and urbanization explain a larger share of variation in vehicle attributes across households than other possible definitions.

versions and between the base and sport trims of a model. The vehicle disaggregation also aids the demand estimation (see Section 5).[5]

I supplement the MaritzCX data with new vehicle registration data and the Consumer Expenditure Survey (CEX) to obtain a regionally representative sample of households. I match the MaritzCX data with registration data by vehicle, region, and year. From the CEX, I compute the numbers of new and used vehicles purchased by year, quarter, and demographic group. The appendix explains the procedure for using the registrations and CEX data to weight MaritzCX observations and match the distributions of new registrations across vehicles, regions, and demographic groups.

I obtain vehicle attributes from Wards and EPA, which I merge to the Maritz data by vehicle and year. The merged Wards and EPA data include MSRP, fuel economy, electricity consumption per mile, horsepower, weight, wheelbase, and width.[6] I aggregate the household data by vehicle, region, demographic group, and year using the weights constructed from the registrations and CEX data. I also collect counts of public electric charging stations from the Alternative Fuels Data Center.

Vehicle and fuel prices are converted to 2018 dollars using the BLS Consumer Price Index. The final data set consists of vehicle prices and attributes for each demographic group (20 groups); vehicle (about 1,200 unique vehicles each year); region (California, other ZEV states, and non-ZEV states); and year (2010–2018).

I collect data on PEVs that have entered the market since 2018 and vehicles that manufacturers intend to introduce by 2025. For those PEVs that have already entered, I collect vehicle attributes from the same data sources as in the MaritzCX data. For vehicles that have not yet entered, I collect data from public announcements by the corresponding manufacturers. For missing values, I impute values using averages across entrants with nonmissing data.

2.2. Summary Statistics

This subsection reports summary statistics of the main dataset and some background on PEV sales. In Table 1, observations are by vehicle, demographic group, region, and year. The sample shows extensive variation in vehicle attributes. For example, the log of the ratio of horsepower to weight, which is correlated with performance, varies by about 50

[5] As is customary in the new vehicle demand literature, I do not have sufficient data to construct individual-specific choice sets. However, the data recognize situations in which manufacturers do not offer certain PEVs in certain states.

[6] For the small number of missing values for vehicle attributes, values are imputed using data from Cars.com.

percent across the 10th and 90th percentiles.

Table 1: Summary Statistics for Demand Data Set (2010–2018)

	Mean	Standard deviation	10th percentile	90th percentile
Transaction price (2018$, including subsidies)	34,411	12,518	21,924	49,434
Fuel costs (2018$) per mile	0.111	0.027	0.080	0.144
Log (horsepower / weight)	-2.82	0.21	-3.07	-2.57
Footprint (square feet)	49.9	6.7	43.9	60.2
Hybrid vehicle market share	0.021			
Plug-in hybrid vehicle market	0.007			
Electric vehicle market share	0.014			

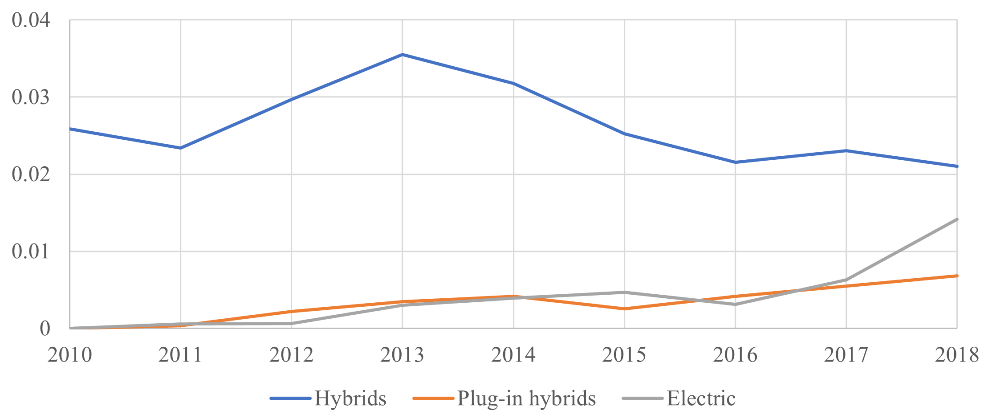
Notes: Observations are weighted by sales. The data include 647,440 observations. Footprint is the product of the vehicle's width and wheelbase.

The computational model allows prices of an individual vehicle to vary across regions. Across regions within a year, the mean absolute deviation of the transaction price is about 3 percent of the average price.

Appendix Figure A10 illustrates the variation of vehicle attributes across income groups. Individuals belonging to the highest-income group purchase vehicles with average prices about 60 percent higher than those in the lowest group. Average fuel economy is about 10 percent higher for the lowest- than the highest-income group. Horsepower and the share of light trucks in total purchases increase with income. Such extensive variation in vehicle attributes across income groups motivates the structure of the demand model, which allows preferences for vehicle attributes to vary across demographic groups.

Figure 1 shows market shares of hybrids, plug-in hybrids, and electric vehicles by year. Hybrids represent about 3 percent of sales through 2014 and decline to about 2 percent by 2018. Plug-in and electric vehicle shares increase steadily and at about the same rate as one another between 2010 and 2017. In 2018, the electric vehicle share increases relative to the plug-in hybrid share, which is largely due to the entry of the Tesla Model 3.

Figure 1: Market Shares of Hybrids, Plug-in Hybrids, and Electric Vehicles by Year



Figures 2 and 3 show variation of PEV purchasing patterns across income groups. The lowest-income group is substantially more likely to purchase a hybrid. In contrast, the probability of purchasing a plug-in hybrid or electric vehicle increases monotonically with income. A possible interpretation of this pattern is that many hybrid buyers are interested in the fuel cost savings, whereas the PEV buyers are interested in the new technology. The figure indicates one of the challenges of the demand estimation, which is to disentangle consumer demand for fuel cost savings from demand for the technology per se; for example, plug-in technology could be a status symbol, and some consumers may like being early adopters.

Figure 2: 2018 Market Shares of Hybrids, Plug-in Hybrids, and Electric Vehicles by Income Group

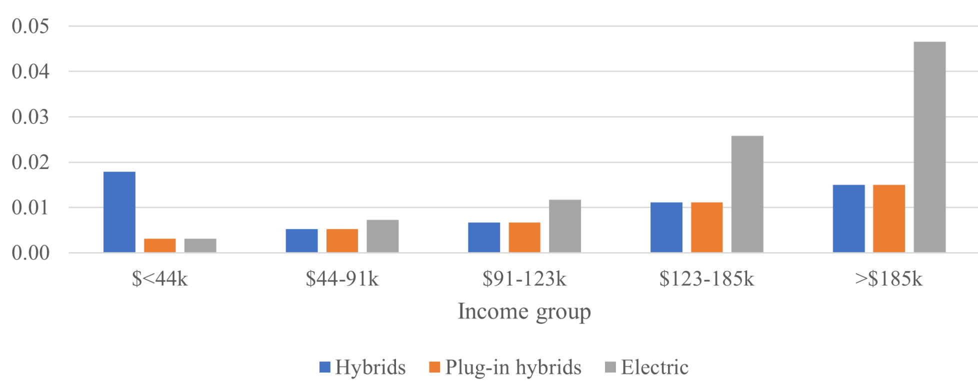
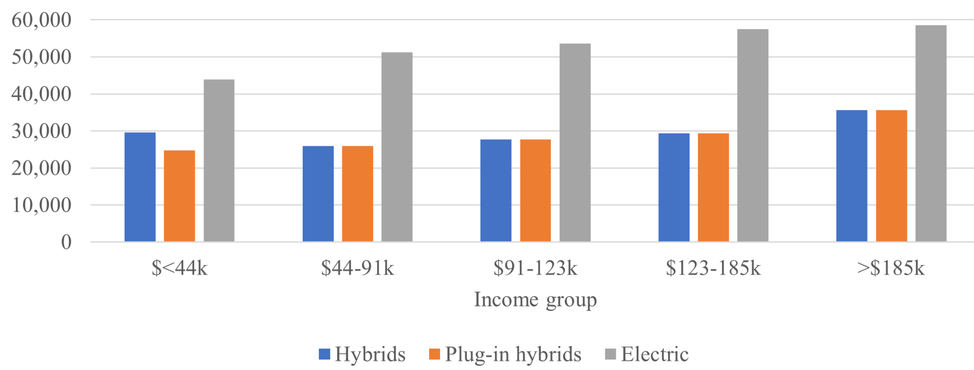


Figure 3 shows that hybrids and plug-in hybrids have lower transaction prices than electric vehicles on average. For context, the average transaction price across all vehicles is about $35,000, indicating that electric vehicles are substantially more expensive than the average, whereas hybrid and plug-in hybrid vehicles are below average. Battery costs partly explain the higher prices of electric vehicles, as they have larger battery packs. Another factor is that many electric vehicle models compete with luxury rather than midlevel vehicles and offer features common in luxury vehicles such as advanced safety technologies and automated driving features.

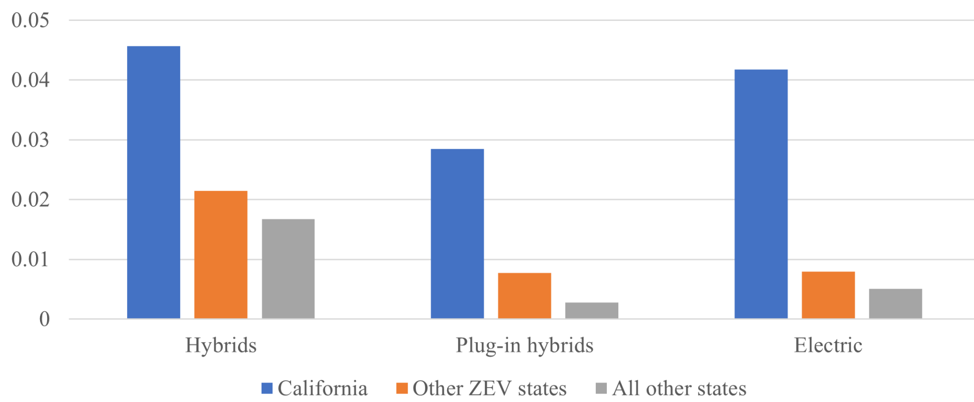
Figure 3: Transaction Prices of Hybrids, Plug-in Hybrids, and Electric Vehicles by Income Group



Note: For each income group, the figure shows the 2018 mean transaction price of the indicated fuel type.

Whereas the previous figures showed variation in vehicle attributes across fuel types, Figure 4 shows variation in hybrid and plug-in market shares across regions. The market shares of plug-in and electric vehicles are about 10 times higher in California than in non-ZEV states. Consumer preferences contribute to the regional variation. The ZEV program did not incentivize hybrid sales in 2018, and yet the share of hybrids in California is higher than in non-ZEV states. Moreover, although the ZEV programs provides the same incentives for ZEV sales in California and the other ZEV states, market shares of PEVs are still higher in California.

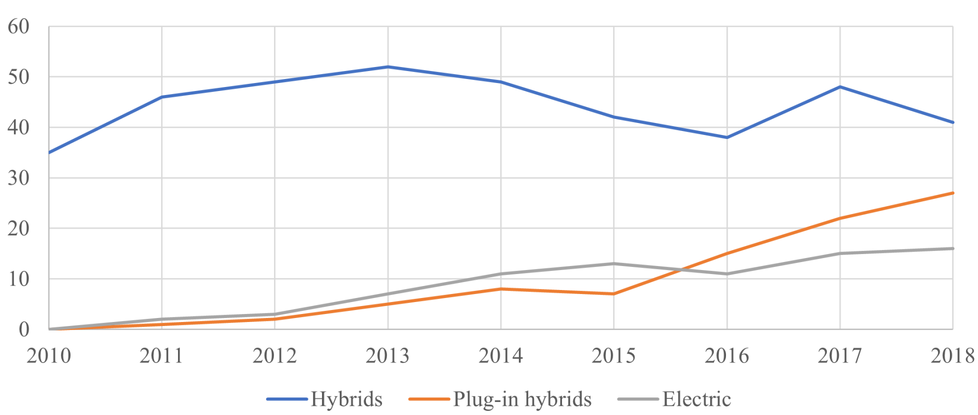
Figure 4: 2018 Market Shares of Hybrids, Plug-in Hybrids, and Electric Vehicles by Region



Notes: The figure shows the 2018 market shares of hybrid, plug-in hybrid, and electric vehicles for the indicated region. Other zero-emission vehicle (ZEV) states are Connecticut, Delaware, Maine, Maryland, Massachusetts, New Jersey, New York, Oregon, Pennsylvania, Rhode Island, Vermont, and Washington.

Figure 5 shows the increasing supply of PEVs over time. The numbers of available plug-in hybrid and electric vehicles increased steadily (some plug-in hybrids exited during the sample, such as the Toyota RAV4). By 2018, the number of plug-in hybrids was similar to that of hybrids. The number of available hybrids peaked in 2013 and declined gradually through 2018. This pattern could be explained by declining gasoline prices after 2014 (not shown) and competition between hybrids and PEVs.

Figure 5: Number of Available Hybrids, Plug-in Hybrids, and Electric Vehicles by Year



3 Policy Background

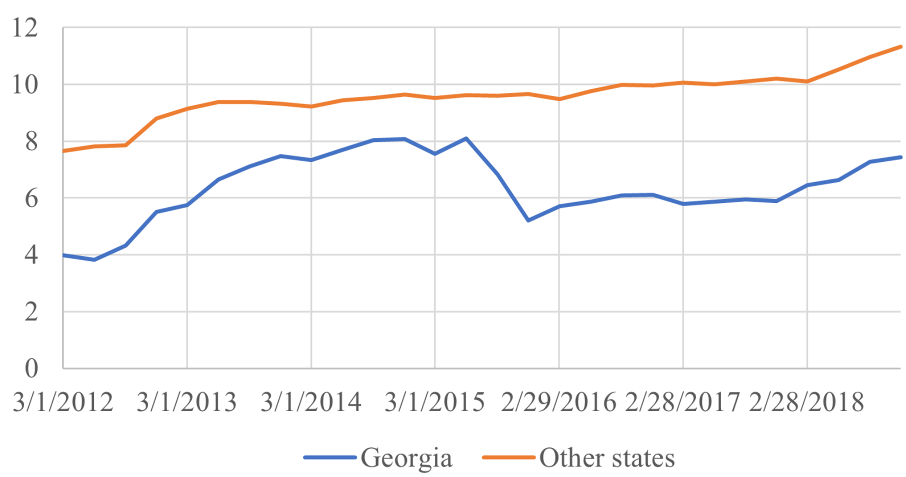
This section provides an overview of the three PEV policies analyzed in this paper: federal tax credits, the ZEV program, and federal GHG standards. It also includes a qualitative discussion of how the policies affect vehicle prices and sales, which motivates the analysis of policy interactions later in the paper.

3.1. Overview of Key Policies

Since the Nissan Leaf and Chevrolet Volt entered the US market in late 2010, the federal government has offered tax credits for PEVs that are worth up to $7,500 per vehicle. The credit is higher for PEVs with larger battery packs, and the credit begins to phase out after a manufacturer exceeds 200,000 cumulative sales. Because of this threshold, as of 2021, GM and Tesla are ineligible for the tax credit, and several other manufacturers will soon be.[7]

Figure 6 provides anecdotal if not causal evidence that subsidies have had a large effect on sales. The figure plots the logs of quarterly registrations of new electric vehicles in Georgia and other states. In July of 2015, Georgia unexpectedly eliminated a $5,000 subsidy for electric vehicles, and new registrations immediately dropped by about two-thirds; new registrations in other states were unchanged. For context, assuming that consumers capture the subsidy, the response in Georgia implies an own-price elasticity of demand equal to about -3, which is similar to estimated consumer responsiveness (e.g., Xing, Leard, and Li (2021)).

Figure 6: Log of Quarterly Electric Vehicle Registrations in Georgia and Other States



Note: Quarterly registrations of new electric vehicles are computed for Georgia and all other states combined. Georgia eliminated its electric vehicle subsidy in July 2015.

[7] Because the subsidy is a tax credit, a household must have sufficient federal tax liability to claim the credit. For leased PEVs, the manufacturer can claim the credit. In the demand estimation and policy simulations, I assume all households purchasing PEVs qualify for the full credit. This assumption is reasonable given the typical income of PEV buyers, discussed in the previous section. An equivalent assumption is that the credit is refundable. In 2021 and 2022, the US Congress considered making the credit refundable, increasing the credit, and eliminating the sales threshold.

The ZEV program requires manufacturers to achieve targets for PEV market shares. Since 1990, California has implemented the program, which has changed form several times (Leard and McConnell, 2019). Since 2012, the objective of the program has been to reduce GHG and local air pollution.

The current ZEV program is a tradable performance standard. A manufacturer earns credits for each PEV sold, and the number of credits depends on its range; an electric vehicle can earn up to four credits. Each year, a manufacturer must hold credits in proportion to its sales (the program allows banking). The credit requirement increases through 2025, when a manufacturer must have credits equal to 22 percent of its sales. For example, if a hypothetical manufacturer sells 100,000 vehicles in 2025 and each of its electric vehicles earns two credits (which corresponds to an all-electric range of 150 miles), it could comply by selling 11,000 PEVs ($11,000 * 2/100,000 = 0.22$).[8]

The EPA and Department of Transportation (DOT) jointly impose national GHG and fuel economy standards for new vehicles. In 2011, the agencies set standards through 2025 that would have roughly doubled fuel economy between 2011 and 2025. In 2020, the agencies weakened the standards by about 20 percent, and in 2021, the agencies re-tightened the standards so that they slightly exceed the levels that they had set in 2011.

Starting in 2012, for both cars and light trucks, the fuel economy and GHG requirements depend on vehicle footprint (the product of width and wheelbase, or the area defined by the four wheels). The term requirement refers to the target for a specific vehicle, and the term standard refers to the set of requirements for all vehicles. Fuel economy requirements are lower for cars than light trucks, and within the car and truck classes, requirements are lower for larger vehicles. The GHG requirements are inversely related to the fuel economy requirements because higher fuel economy implies lower GHG emissions.

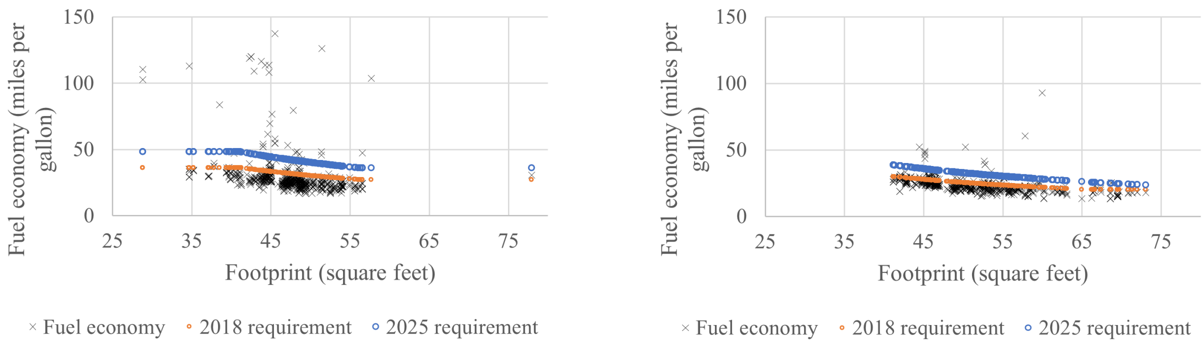
The overall GHG standard that each manufacturer faces is the sales-weighted average of the GHG requirements of its vehicles. The overall fuel economy standard for each manufacturer is the harmonic sales-weighted average of the fuel economy requirements. The agencies have set the standards so that manufactures complying with one standard are likely to be in or near compliance for the other.

To provide a sense of the stringency of the standards, Figure 7 plots actual fuel economy and fuel economy required by the 2018 and 2025 standards. Each x in the diagram indicates a unique vehicle in the data, plotting its actual 2018 fuel economy against its footprint. The

[8]Besides the credit requirement, the ZEV program sets a minimum credit requirement for electric or fuel-cell vehicles. In 2025, it is 16 percent, which refers to the ratio of credits to sales. Therefore, in the example from the text, the manufacturer would exceed the minimum requirement because its electric vehicles earn two credits per vehicle, and the credits account for 22 percent of sales. The minimum requirement does not bind in the scenarios modeled later in the paper.

orange circles indicate the 2018 fuel economy requirement for each vehicle. On average, both cars and trucks achieved the requirements. Although most cars and light trucks lie below their requirements, for both classes, a subset far exceeds them (most of those are hybrids or PEVs). The blue circles show the 2025 requirements, which are about 30 percent higher than for 2018, on average.

Figure 7: 2018 Fuel Economy, Regulatory Requirements, and Footprint



(a) Cars

(b) Light trucks

Note: For each vehicle in 2018, the figure plots fuel economy and the 2018 and 2025 fuel economy requirements against footprint.

Typically, states and the US Congress choose subsidies after fuel economy, GHG, and ZEV standards have been chosen. For example, in 2021 and 2022, Congress considered extending existing PEV subsidies through the 2020s, whereas fuel economy, GHG, and ZEV standards through 2025 or 2026 had already been chosen. Thus, between 2022 and 2025, ZEV, fuel economy, and GHG standards are exogenous to the subsidies

3.2. Framework for Policy Interactions

This subsection discusses qualitatively how PEV subsidies interact with the ZEV program and federal fuel economy and GHG standards. I consider a stylized example of a market that contains multiple firms and focus on a single firm that produces two vehicles: a ZEV (z) and a non-ZEV (n). The firm chooses prices to maximize profits subject to the ZEV standard that applies to all vehicles the manufacturer sells (that is, for simplicity, in this section, I abstract from the fact that ZEV is a regional program). The ZEV earns c_z credits, the non-ZEV earns zero ($c_n = 0$), and the credit requirement is R.

The ZEV credit market is perfectly competitive.[9] Credit demand is proportional to total

[9]It may be a strong assumption that manufacturers are credit-price takers, given that only a few manufacturers have overcomplied and been net credit sellers. I make the assumption in this section for expositional

vehicle sales, and credit supply increases with plug-in sales. The credit price, λ_Z, balances aggregate credit demand and supply. The manufacturer's profit maximization problem is

$$\max_{p_z, p_n} (p_z - mc_z + \lambda_Z(c_z - R))q_z + (p_n - mc_n + \lambda_Z(c_n - R))q_n \tag{1}$$

where p_j is the price of vehicle type j, mc_j is the marginal cost, and q_j is the vehicle's sales.

The first-order conditions for the ZEV price p_z is

$$(p_z - mc_z + \lambda_Z(c_z - R))\frac{\partial q_z}{\partial p_z} + q_z + (p_n - mc_n - \lambda_Z R)\frac{\partial q_n}{\partial p_z} = 0 \tag{2}$$

The first-order condition for the non-ZEV price is

$$(p_n - mc_n - \lambda_Z R)\frac{\partial q_n}{\partial p_n} + q_n + (p_z - mc_z + \lambda_Z(c_z - R))\frac{\partial q_z}{\partial p_n} = 0 \tag{3}$$

Because $c_j > R$, selling an additional ZEV allows the manufacturer to sell excess credits. Equation (2) shows that this effect causes the manufacturer to reduce p_z below the price it would choose if $\lambda_Z = 0$. The first-order condition for the non-ZEV price shows that the ZEV standard causes the manufacturer to increase p_n below the price it would choose if $\lambda_Z = 0$.[10]

Consider the effect of a ZEV purchase subsidy on profit-maximizing vehicle prices. The subsidy is offered to consumers who purchase ZEVs, increasing their demand for ZEVs. If hypothetically ZEV demand increases and λ_Z does not change, an excess supply of ZEV credits exists, putting downward pressure on λ_Z. According to these first-order conditions, a decrease of λ_Z causes the manufacturer to increase p_z and decrease p_n. As all other manufacturers would respond similarly, the decrease in λ_Z reduces credit supply, restoring equilibrium in the ZEV credit market.

This stylized model illustrates two points about the interaction between the subsidy and the ZEV standard. First, and not surprisingly, the subsidy benefits ZEV buyers by reducing ZEV purchase prices. Second, the subsidy benefits non-ZEV buyers by reducing the shadow price and non-ZEV markup.

Next, I turn to the interaction between a subsidy and fuel economy standard. Two assumptions simplify the discussion. First, the regulator removes the ZEV standard and replaces it with a fuel economy standard, rather than imposing both policies. Second, each vehicle's fuel economy is exogenous.

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simplicity and in the computational model for tractability.

[10] In this subsection, I assume that cross-price demand elasticities are sufficiently small that the conclusions in the text hold. This assumption is consistent with the demand estimates in Section 5.

Fuel economy credits can be traded at zero cost.[11] The equilibrium credit price is λ_M.

The fuel economy standard enters the profit maximization problem analogously to the ZEV standard in equation (1). The only difference is that the term $\lambda_Z(c_n - R))$ is replaced by the term $\lambda_M(\frac{1}{m_j} - \frac{1}{M_j})$, where m_j is the vehicle's fuel economy and M_j is the fuel economy requirement. Consequently, the first-order conditions for vehicle prices are analogous to equations (2) and (3), and the fuel economy standard affects prices of ZEVs and non-ZEVs analogously. That is, the fuel economy standard causes the manufacturer to reduce the price of the ZEV (because $m_z > M_z$) and increase the price of the non-ZEV (because $m_n < M_n$). More generally, the fuel economy standard reduces prices for vehicles whose fuel economy exceeds their requirements and vice versa.

Thus, the ZEV and fuel economy standards distort vehicle pricing decisions similarly: both cause manufacturers to reduce prices of ZEVs. Adding the subsidy raises prices of ZEVs and reduces prices of non-ZEVs, raising welfare for consumers of those vehicles.

In short, the subsidy affects credit and vehicle prices and those effects drive effictiveness and equity of the subsidy. The equilibrium model quantifies these effects.

4 Equilibrium Model

This section describes a static equilibrium model that relaxes many of the simplifying assumptions from Section 3. Consumers choose vehicles that maximize subjective utility. Vehicle prices, fuel economy, and entry are endogenous and manufacturers face both ZEV and fuel economy standards.

4.1. Demand

A market is a model year t and region r, with three regions defined in Section 2. The model year corresponds to typical production cycles, starting in October of the previous calendar year and ending in September. In the following presentation, I suppress the model year subscripts.

Each region r contains Q_{gr} consumers of demographic group g who choose a vehicle from among the J new vehicles in the market and a composite used vehicle, which repre-

[11] Recall that EPA and DOT harmonize the standards so that, based on agencies' expectations of compliance decisions, if a manufacturer complies with one program, it is likely to be close to compliance with the other. Certain technologies are credited in the EPA but not the DOT program, such as air conditioning improvements. If manufacturers use more of these credits than expected, there could be an excess supply of GHG credits. In this section and the computational model, I assume that the fuel economy standards are binding on all manufacturers, which is consistent with recent observation of the market.

sents the outside option. Each consumer i maximizes subjective utility by choosing a new or used vehicle, and utility, u_{ij}, is linear in the vehicle price and attributes:

$$u_{ij} = \alpha_{gr}\, p_{jr} + \sum_k x_{jk}\, \beta_{gkr} + \xi_{jr} + \epsilon_{ij} \tag{4}$$

where α_{gr} is the sensitivity of utility to price, x_{jk} is the value of attribute k, β_{gkr} is the sensitivity of utility for group g to attribute k in region r, ξ_{jr} is the utility from unobserved vehicle attributes, and ϵ_{ij} is an idiosyncratic preference shock. The price and attribute parameters, α_{gr} and β_{gkr}, vary across regions and demographic groups. Equation (4) distinguishes the vehicle attributes x_{jk} that are observed in the data, and the attributes that are unobserved, ξ_{jr}. Consumers' choice sets may vary across regions, for example, if manufacturers offer certain PEVs only in ZEV states.

The outside option is a composite used vehicle. Including the used vehicle option is important for the equity analysis because low-income consumers are more likely to purchase used vehicles than are high-income consumers, and the subsidies may affect used vehicle prices because new and used vehicles are imperfect substitutes for one another.

Consumer preference heterogeneity enters equation (4) via the group and region-specific parameters and the idiosyncratic error term. In contrast, the effect on utility of the unobserved attributes, ξ_{jr}, does not vary across demographic groups, although it does vary across regions. This representation of heterogeneity is similar qualitatively to a random coefficients logit model, in which preferences for certain attributes are heterogeneous across consumers, whereas preferences for unobserved attributes do not vary across consumers. An important difference between this demand model and a random coefficients logit model is that the preferences for vehicle attributes vary across observed demographic groups and regions, rather than randomly. Equation (4) links preferences explicitly to demographic groups. This enables a transparent analysis of the equity of PEV subsidies, because variation in estimated preference parameters translate directly to group-specific welfare changes.

Making the standard extreme value assumption on the error term yields an equation linking vehicle market shares and attributes:

$$ln(s_{gjr}) - ln(s_{g0r}) = \alpha_{gr}\, p_{jr} + \sum_k x_{jk}\, \beta_{gkr} + \delta_{jr} + \nu_{gjr} \tag{5}$$

where the left-hand side is the difference between the log share of purchases by group g of vehicle j in region r and the log share of the outside option. The right-hand side includes the price, observed attributes x_{jk}, vehicle–region interactions δ_{jr}, and a mean-zero error term

ν_{gjr}. The vehicle–region interactions are the sum of the mean utilities for the unobserved attributes (ξ_{jr}) and the utility of the observed attributes for the base demographic group.

4.2. Supply: Vehicle Price and Fuel Economy

This subsection and the next present the supply side of the model. Each model year t, a manufacturer first decides whether to introduce an electric vehicle and then chooses prices and fuel economy of all of its vehicles. This subsection discusses price and fuel economy choices conditional on entry choices.

Having made its entry decisions, manufacturer f chooses prices and fuel economy of each of its J_f vehicles to maximize profits. It can choose a different price in each region, but a vehicle's fuel economy cannot vary across regions. Vehicles sold in the ZEV states are subject to the ZEV standards. As in the previous section, I assume that ZEV and fuel economy credits can be traded at zero cost and that firms are price-takers in the credit markets. The Appendix provides further details about how the fuel economy and ZEV standards are modeled.

The profit maximization problem is

$$\max_{p_{jr}, m_j, T_{n(j)}} \sum_{j \in J_f} \sum_{r} \sum_{g} [(p_{jr} - mc_j) + \lambda_{Z,r}(c_{jr} - R_r) + \lambda_M(\frac{1}{m_j} - \frac{1}{M_j})] s_{jgr} Q_{gr} - F(\Delta T_{n(j)}) \quad (6)$$

where:

$$ln(mc_j) = ln(mc_{j0}) + \gamma T_{n(j)} \quad (7)$$

$$ln(m_j) = ln(m_{j0}) + T_{n(j)} \quad (8)$$

and m_j is fuel economy, mc_j is marginal cost, and $F(T_{n(j)})$ are fixed costs of choosing technology T_n for model n.

Equation (7) shows how the technology choice affects marginal costs. The technology variable $T_{n(j)}$ is scaled so that increasing it by one unit causes the log of marginal costs to increase by γ. According to equation (8), the same one-unit technology increase would raise log fuel economy by 1. In other words, adopting technology and raising fuel economy by 1 percent would increase marginal costs by approximately γ percent. The fixed cost of technology adoption, $F(\Delta T_{n(j)})$, represents the cost of redesigning and testing a vehicle with new technology. The fixed costs increase with the change in technology.

The first-order condition for vehicle price is

$$\sum_{l\in J_f}\sum_r\sum_g (p_{lr} - mc_l + \lambda_{Z,r}(c_{lr} - R_r) + \lambda_M(\frac{1}{m_l} - \frac{1}{M_l}))\frac{\partial s_{lgr}}{\partial p_{lr}} Q_{gr} + \sum_r\sum_g s_{jgr} Q_{gr} = 0 \quad (9)$$

As discussed in Section (3), an increase in the ZEV credit price causes prices of PEVs to fall and prices of other vehicles to increase (as in the previous section, this statement includes the assumption that cross-price derivatives are sufficiently small). An increase in the fuel economy credit price causes the manufacturer to raise prices of vehicles with fuel economy below their requirements. Thus, a vehicle with a large implicit ZEV or fuel economy subsidy has an equilibrium markup that is smaller than a vehicle with a smaller subsidy or tax (this comparison assumes all own and cross-price derivatives do not vary across the two vehicles). Because the subsidies I analyze have small effects on fuel economy and technology, the appendix discusses manufacturer choices of those attributes.[12]

4.3. Supply: Entry

Each model year t, prior to choosing vehicle prices, fuel economy, and technology, the manufacturer decides whether to introduce new hybrids or PEVs. Some of these, such as the Nissan Leaf, have markedly different attributes than other vehicles already in the market. Others, such as the plug-in hybrid Volvo XC90 (a large sport utility vehicle), differ from gasoline-powered vehicles primarily by their power train; the gasoline and non-gasoline vehicles otherwise look similar to one another and often have the same features, such as seating configurations. As the Introduction notes, it would be infeasible to model potential entry of entirely new types of vehicles, and I limit the set of potential entrants to include electric siblings of gasoline vehicles. Although I focus on electric vehicle sibling entry for tractability, such entry has accounted for a substantial share of total entry through 2025, which is the focus of the policy analysis in Section 6.[13]

Each potential entrant has marginal costs of production c_j^e and fixed costs of entry C_j^e. The latter includes all expenditure associated with designing, testing, and marketing.

Following industry practice and Wollmann (2018), manufacturers follow a static entry rule. Prior to entry, the manufacturer predicts the potential entrant's profits net of fixed entry costs. This prediction is based on expectations of marginal costs and mean utility

[12] Horsepower and other attributes are exogenous. This assumption is for simplicity, and it does not affect the results; outcomes of the policy simulations are nearly identical using an expanded version of the model in which horsepower is endogenous.

[13] Section 5 notes that the some PEVs are offered only in ZEV states. For tractability, I assume that when a PEV enters it is offered in the regions in which it actually appears.

ξ_{jr}, as well as the corresponding costs and mean utilities and entry decisions of all other vehicles in the market. The manufacturer can estimate ξ_{jr} using data on the corresponding gasoline sibling.

The manufacturer can introduce at most one sibling in each model year. This assumption is for computational simplicity, but it approximates the decisionmaking process during the sample period (2010–2018), which typically had about 10 entrants per year across the entire per market, and rarely did a single firm have multiple entrants in the same year and market segment.

After the firm introduces a new vehicle, it likely continues selling it for at least several years, allowing it to recover the fixed costs over multiple years. However, similar to Wollmann (2018), a manufacturer decides whether to introduce a new vehicle by calculating the ratio of entry-year profits to entry costs. The firm introduces the vehicle if this ratio exceeds an internal hurdle rate. The firm uses the initial profits rather than future profits because future profits are more uncertain and it can adjust the hurdle rate to account for the relationship between initial period profits and future profits. For example, if the firm expects consumer demand for the entrant to increase over time, this would imply a lower hurdle rate than if the firm expects demand to decline over time.[14]

A firm introduces a potential entrant to the market if the following inequality holds:

$$\frac{\pi_j^e}{\tilde{C}_j^e} \geq r \tag{10}$$

where π_j^e are the expected profits of the potential entrant and r is the internal hurdle rate. Decomposing expected entry costs into a vehicle-specific mean, C_j^e, and random error term, η_j, and rearranging the equation yields the following inequality that must hold if the firm decides to introduce the vehicle:

$$\frac{\pi_j^e}{r} \geq C_j^e + \eta_j \tag{11}$$

If the negative of the error term has a logit distribution, equation (11) implies that the probability the firm introduces the potential entrant, P_{jt} is

$$P_{jt} = \frac{1}{1 + \exp(\frac{\pi_j^e}{r} - C_j^e)} \tag{12}$$

This probability holds for each potential entrant in each model year t. Equation (12) shows

[14]In practice, firms make entry decisions several years in advance. Accounting for this lead time amounts to assuming that firms forecast profits in the entry year without error. In practice, firms can forecast costs based on contracts for batteries, other components, and labor.

that an increase in π_j^e increases the probability of actual market entry. Note that although the entry model can accommodate dynamically evolving entry costs, the entry decision is static in the sense that once the ratio of profits to entry costs crosses the hurdle rate, the vehicle enters the market.

5 Estimation

This section describes estimation of the preference parameters, marginal costs, ZEV and fuel economy credit prices, and entry costs. The section also discusses model validation.

5.1. Preference Parameters

5.1.1 Estimation Strategy

Estimation of the preference parameters is similar to Leard, Linn, and Springel (2019), except that I allow for more extensive preference heterogeneity, including allowing preferences to vary across fuel types and other attributes and across regions. The estimation consists of two steps, the first of which estimates equation (5). The key parameters are β_{gkr}—the differences in marginal utilities between each demographic group and region and the marginal utilities of the base demographic group and region (which is defined as a low-income, young, urban household located in California)—and δ_{jr}, which includes the marginal utilities of the base group and the mean utility of the unobserved attributes of vehicle j in region r.

Equation (5) can be estimated consistently by ordinary least squares (OLS) as long as the mean utility of unobserved attributes does not vary across households. Recall that this assumption is analogous to that made in random-coefficients logit models, in which the consumer-specific utility for unobserved product attributes is uncorrelated with utility for the observed product attributes. To support this assumption, I include a large set of observed physical characteristics and measures of vehicle quality, as I explain.

The price in equation (5) is the average transaction price by vehicle, region, and model year. The fuel cost and performance variables are similar to those typically used in the vehicle demand literature. Specifically, the fuel cost is the dollars per mile of driving. For gasoline and hybrid vehicles, the variable is the ratio of the regional price of gasoline to the fuel economy (miles per gallon). For electric vehicles, I use the regional price of electricity multiplied by the electricity consumption per mile. For plug-in hybrid vehicles, I assume that half of the miles are driven using gasoline and half using electricity.

Performance is the log of the ratio of the vehicle's horsepower to its weight. The variable is inversely related to the time needed to accelerate from rest to 60 miles per hour, and it is strongly correlated with other potential measures of performance, such as towing capacity.

The other attributes in x_{jkr} include footprint; dummies for a hybrid powertrain, a plug-in powertrain, all-wheel drive, a luxury brand, and the luxury trim of a model; and interactions of luxury trim with drive type and the number of engine cylinders. Footprint is the product of the vehicle's wheelbase and width, and it is a proxy for the overall size of the vehicle (it is the same variable used to compute the fuel economy requirement). The luxury brand dummy equals 1 for the high-end brands that many firms produce, such as Nissan's Infiniti brand. The luxury trim is the high-end version of a particular model, which is identified by the trim name (e.g., "Premium") and MSRP. The luxury variables and their interactions with other variables account for the fact that high-income consumers likely have stronger preferences for these vehicles and are more likely to purchase them, so firms may price them accordingly. For example, high-income groups may have higher demand than others for luxury vehicles with large engines or all-wheel drive. If these consumers are less sensitive to prices, manufacturers may charge higher markups for these vehicles.

Implicitly, this approach allows preferences to vary across demographic groups for attributes that are offered in luxury vehicles. For example, luxury brands include advanced infotainment, navigational, comfort, and safety features, and this estimation strategy allows for the possibility that preferences for those attributes vary across demographic groups. Because manufacturers price their vehicles according to expected demand, including the luxury variables reduces potential correlation between the price and error term.

The δ_{jr} correspond to vehicle-region-model year interactions. Leard, Linn, and Springel (2019) show that the preferences for the base group can be recovered in a second step that consists of regressing these estimated interaction terms on the attributes belonging to x_{jkr}.

$$\hat{\delta}_{jr} = \sum_k x_{jk} \beta_k + Z_{jr} \mu + \phi_{jr} \tag{13}$$

where Z_{jr} include attributes absent from the first step, μ is a coefficient vector, and ϕ_{jr} is a random error term. Z_{jr} includes interactions of market segment and region, number of engine cylinders and region, and drive type and region.[15] Adding these variables in the

[15] In principle, I could include the concentration of public charging stations as a utility function parameter. However, because stations vary by market, region, and year, variation is insufficient to identify the coefficient. Consequently, the estimated WTP for plug-in hybrid and electric vehicles includes WTP for charging stations. This does not affect the simulations, because the concentration of charging stations does not vary across scenarios. The conclusion discusses the assumed exogeneity of charging stations.

second step amounts to assuming that consumer preferences for them do not vary across demographic groups.[16]

Observed attributes that firms choose (X_{jk}) may be correlated with unobserved vehicle attributes.[17] For example, firms may choose a higher price for vehicles sold with a particularly popular exterior paint color. Including the same luxury variables and the interactions in X_{jk} as in the first step reduces the endogeneity concerns, because many of these unobserved attributes are correlated with luxury trims, luxury brands, drive type, and engine size, such as offering large wheels on the "Premium" trim.

To address remaining endogeneity concerns about the observed attributes, I estimate the second step by instrumental variables (IV). Because vehicle prices and fuel economy are endogenous in the supply side of the equilibrium model, I instrument for these variables using BLP-style instruments based on weight, height, and length.[18] I use these instruments because firms change them less frequently than other attributes, making them less likely to be correlated with the error term in equation (13).[19]

Finally, Z_{jr} includes interactions of the hybrid and plug-in powertrain dummies with region fixed effects. The region interactions allow preferences for these powertrains to vary across regions. Recall that the first step included only the interactions of the powertrain dummy variables with demographic group fixed effects. This setup amounts to assuming that regional preferences for each powertrain do not vary across demographic groups. For example, if California consumers have higher utility for hybrids than consumers in non-ZEV states do, that regional preference differential is constant across demographic groups. That is, $\beta_{hgr} = \beta_{hg} + \beta_{hr}$, where β_{hgr} is the marginal utility for hybrid power trains

[16] Unfortunately, the data have insufficient variation to relax this assumption. The same caveat applies to variables described in the next paragraph that are not included in the first step.

[17] The δ_{jr} control for unobserved vehicle attributes in the first step, and the endogeneity of price does not bias the first-step estimates.

[18] Specifically, the instruments include means and standard deviations of weight, height, and length for other vehicles sold by other firms in the same market segment. As noted in the previous section, performance is exogenous in the model to simplify the simulations because using a version of the model in which horsepower is endogenous yields nearly identical results for the subsidy counterfactuals in the next section. Nonetheless, firms may trade off fuel economy for performance to achieve fuel economy standards (Leard, Linn, and Springel, 2019), in which case performance could be correlated with unobserved attributes in the estimation sample. For that reason, I treat performance as endogenous in the demand estimation and I instrument for vehicle price, fuel economy, and performance using the instruments described in the text.

[19] Conlon and Gortmaker (2020) suggests using supply-side instruments to identify preference parameters in a discrete choice setting. In principle, such instruments can strengthen the first stage and reduce weak instruments bias, particularly in cases when demand-side BLP-style instruments are weak predictors of the endogenous attributes. I find that in this particular application, the BLP-style instruments are strong predictors of the endogenous attributes. Specifically, standard tests yield F-statistics of around 150, which indicates little concern for weak instruments bias. I have added supply-side instruments based on steel prices and vehicle weight (since steel is an important input to vehicle production), which does not improve the strength of the first stage or affect the parameter estimates substantially.

for group g and region r.

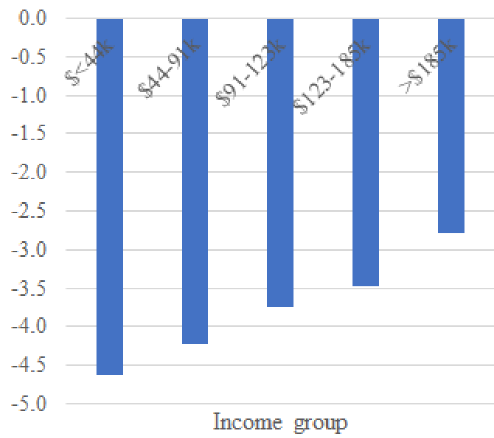
Equation (13) also includes the vehicle's electric range (which is zero for non-PEVs). Although the preference parameters do not vary over time, including range introduces demand-side consumer dynamics because range has increased over time. Consequently, the range coefficient absorbs positive trends in consumer demand that are correlated with range.

5.1.2 Estimation Results

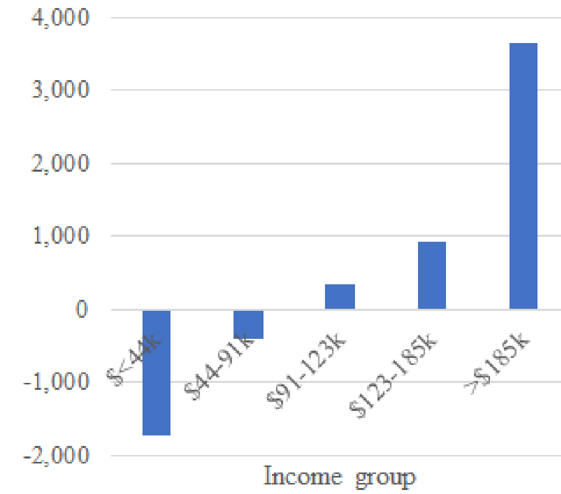
Taken together, equations (5) and (13) include almost 400 utility function parameters. Given the number of parameters, I discuss the estimation of the parameters that have the most direct relevance to the simulations considered in Section 6: the price coefficient and marginal utilities for fuel costs and powertrain type by income group and region. The appendix provides information about the other parameter estimates.

Panel A of Figure 8 shows the average own-price elasticity of demand by income group, which averages over regions, age groups, and urbanization within an income group. The magnitude of the elasticity decreases monotonically with income, and the magnitude is about 60 percent smaller for the highest group than for the lowest. Overall, the magnitudes are plausible, given the highly disaggregated data, because consumers have many closely related options. For example, if the price of the base trim of a model increases, consumers can substitute to the next-lowest trim, which may cost $1,000 more but offers additional features. Other papers using similarly disaggregated data have found large own-price elasticities (Xing, Leard, and Li, 2021).

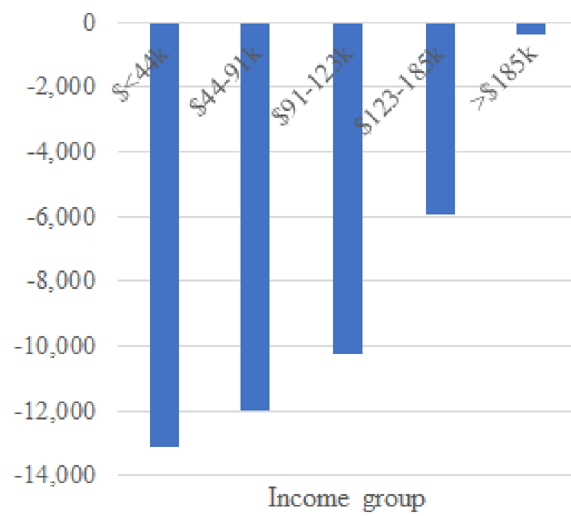
Figure 8: Own-Price Elasticity of Demand and Willingness to Pay for Hybrids and Plug-Ins by Income Group



(a) Own-price elasticity of demand



(b) Willingness to pay for hybrids, net of other attributes



(c) Willingness to pay for PEVs, net of other attributes

Notes: For each income group, Panel A shows the sales-weighted average own-price elasticity of demand. Panels B and C show the estimated WTP (2018$) for hybrids or PEVs, which include plug-in hybrid and all-electric vehicles and WTP is estimated relative to gasoline vehicles, net of WTP for fuel cost savings and other attributes.

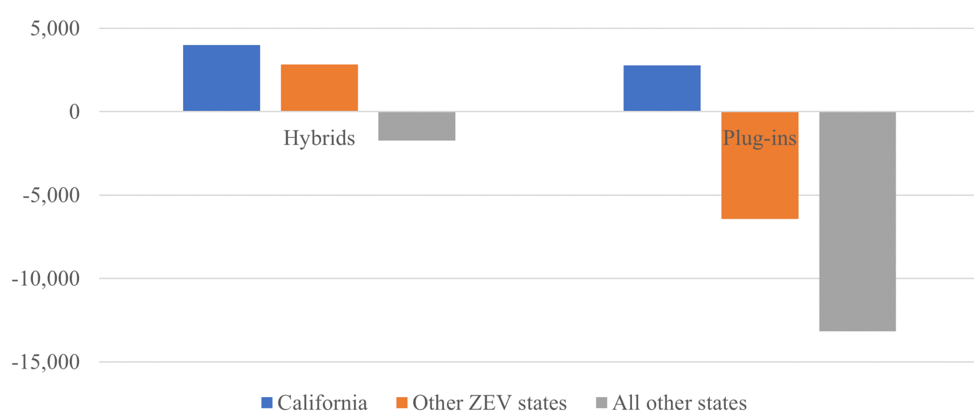
Panel B shows the WTP for hybrids relative to otherwise identical gasoline vehicles. This differential does not include the valuation of the fuel cost savings or performance of the hybrid (some hybrids have greater acceleration than gasoline siblings). Rather, the differential reflects perceptions about the technology (including range) or environmental preferences. The figure indicates that lowest-income households value the hybrid almost

$2,000 less than an otherwise identical gasoline vehicle. This estimate is comparable to the fuel cost savings of the hybrid, meaning that low-income consumers are roughly indifferent between gasoline and hybrid siblings. Highest-income households have a WTP of almost $3,500 for a hybrid. The valuations of the three middle-income groups range from modestly negative to modestly positive. The average consumer's WTP is -$73 for a hybrid, indicating that, overall, consumers compare hybrids and gasoline vehicles largely on the basis of prices, fuel costs, and performance. Higher prices and lower average performance explain the low average market share of hybrids in Figure 1)

Panel C shows that the situation is considerably different for PEVs. Although the highest-income group has approximately zero WTP for the technology, the other four income groups have large and negative WTP; the average consumer has a WTP of about -$10,000. The negative valuation could reflect range anxiety or uncertainty about the new technology. The results suggest that even if PEVs have substantially lower fuel costs and better performance than gasoline or hybrid vehicles, many consumers would still be unlikely to buy them. In other words, low purchase prices are needed to induce many consumers to purchase PEVs.

Figure 9 shows how the WTP for hybrids and PEVs varies across regions. Consumers in California have the highest WTP for both, and consumers in non-ZEV states have substantially lower WTP. The high WTP for hybrids in California is consistent with their high market share (Figure 4). This pattern suggests that many consumers in ZEV states consider PEVs to be close substitutes to gasoline vehicles.

Figure 9: Willingness to Pay for Hybrids and PEVs by Region



Notes: The figure plots WTP (2018$) not including fuel costs and other attributes.

Table 2 provides an economic interpretation of the estimated own-price elasticities and WTP for PEVs and a preview of the subsidy policy simulations considered in the next section. In the first row of column 1, I compute the change in plug-in hybrid sales caused by providing a subsidy of $1 to all plug-in hybrids purchased by households belonging to the lowest-income group (for simplicity, I assume full pass-through of the subsidy to consumers). The table reports a subsidy expenditure per additional plug-in hybrid equal to $14,172. The other cells are constructed similarly.

Table 2: Marginal Subsidy Expenditure Per Additional PEV

	Subsidy for:		
Subsidy to:	Plug-in hybrids	Electrics	Plug-in hybrids and electrics
Lowest income quintile	14,172	16,741	15,683
Second quintile	15,511	18,160	17,056
Third quintile	17,290	20,095	19,158
Fourth quintile	19,043	22,038	21,436
Highest income quintile	24,350	29,246	29,187
All income groups	17,626	22,543	21,112

Notes: The table reports the subsidy expenditure per additional vehicle sale in 2018$ per vehicle. A purchase subsidy of $1 per vehicle is offered to the type indicated in the column heading and the income group in the row heading. Changes in sales and expenditure are computed relative to a baseline scenario that includes observed subsidies, and they assume full pass-through of subsidies to prices. Calculations use vehicles in the 2018 market.

The table shows that subsidies provided to the lower-income groups increase sales at lower fiscal costs per vehicle than do subsidies to the higher-income groups. For example, the per-vehicle cost of the electric vehicle subsidy is 25 percent lower for the lowest than the highest group. This result follows from the greater price sensitivity of the lower-income groups.

Next, I discuss validation of the preference parameter estimates. Appendix Figure A11 shows scatter plots of demographic group means of observed and predicted values of vehicle attributes. The means are computed using observed and predicted sales in 2018. Because parameters are estimated using data from 2010-2018, if the true preference parameters trend over time, the observed and predicted attributes would differ from one another. The figure shows that the predicted values lie close to the 45-degree line, which supports the assumption that the preference parameters do not vary over time. This validation exercise is important because the policy counterfactuals in Section 6 use the estimated preference parameters from 2010 through 2018 to model subsidies in 2025.

Appendix Figure A12 validates further the preference parameters by evaluating the out-of-sample fit of the model. Panel A plots predicted against observed 2018 market shares by brand and class by using the 2010 market shares to predict 2018 market shares (that is, a no-change forecast). Panel B uses the estimated preference parameters to predict 2018 market shares, and comparing the two panels shows that the preference parameters yield more accurate predictions than the no-change forecast.[20] Finally, panel C uses a randomly selected 50 percent subsample of the observations used to predict parameters. The preference parameters using the subsample of demographic group, vehicle, region, year observations yields more accurate predictions than the no-change forecast in panel A.

5.2. Supply-Side Parameters Except for Entry Costs

The supply-side parameters to be estimated include the marginal costs of each vehicle (mc_{j0}), ZEV and fuel economy credit prices ($\lambda_{Z,r}$ and λ_M), the effect of technology on marginal costs in equation (7), and the fixed cost of adding fuel-saving technology ($F(\Delta T_{n(j)})$), and entry costs. This subsection discusses estimation of supply-side parameters aside from entry costs, and the next subsection discusses entry costs. The appendix discusses the estimation of the effect of technology on marginal costs and the fixed costs, all of which play a small role in the policy simulations.

5.2.1 Estimation Strategy

I use the price and fuel economy first-order conditions, equations (9) and (16), to estimate the marginal costs of each vehicle and the ZEV and fuel economy credit prices. Each model year has $2J$ equations and $J+2$ unknown variables.

I estimate the unknowns iteratively in three steps. I begin with initial guesses of the credit prices from Leard, Linn, and Springel (2019). In the first step, I use equation (9) to compute each vehicle's marginal costs. Second, the technology first-order condition defines J equations, one for each vehicle, and the two unknown credit prices. Given the marginal costs from the first step and the initial guess of the ZEV credit price, equation (16) is linear in the fuel economy credit price. Assuming that fuel economy is measured with error, I rearrange the equation and estimate the fuel economy credit price by an OLS regression. Third, given marginal costs and estimated fuel economy credit price from the second step, equation (16) is linear in the ZEV credit price. I estimate the ZEV credit price using a second OLS regression. Using the estimated marginal costs and credit prices as new guesses, I return to the first step and continue iterating until the change in estimated marginal costs and credit prices across iterations is sufficiently small.

[20]More precisely, the root mean-square error is 0.14 using preference parameters and all observations, 0.15 using preference parameters and the 50 percent subsample in Panel C, and 0.19 using the no-change forecast. The figure aggregates vehicles to brand-class because vehicle entry and exit between 2010 and 2018 makes it impossible to use the 2010 market shares to predict 2018 vehicle market shares for most vehicles sold in 2018. By comparison, there is little entry or exit of brands between 2010 and 2018.

5.2.2 Estimation Results

Table 3 summarizes the estimated marginal costs and the corresponding markups by firm for the top 10-selling firms (which account collectively for 98 percent of the market), with firms listed by decreasing total sales between 2010 and 2018. Marginal costs vary across firms in a pattern consistent with expectations. For example, Hyundai's marginal costs are about one-third lower than those of General Motors. Of the ten firms, BMW vehicles have the highest marginal costs.

Table 3: Estimated Marginal Costs and Markups by Firm

	Marginal costs (2018$)	Markup over marginal costs (2018$)	Markup over marginal costs, fuel economy shadow costs, and ZEV shadow costs (2018$)
General Motors	29,865	9,255	8,940
Toyota	26,971	8,968	8,822
Ford	27,680	8,909	8,656
Honda	23,669	8,304	8,415
Fiat Chrysler	25,648	8,891	8,405
Nissan	23,955	8,238	8,231
Hyundai	19,778	7,988	7,895
Volkswagen	28,935	9,109	8,941
Subaru	23,220	8,151	8,083
BMW	44,041	11,245	11,141

Notes: The table reports the sales-weighted marginal costs and markups by firm, in 2018$. Markup over marginal costs is the difference between the transaction price and estimated marginal costs. Markup over marginal costs, fuel economy shadow costs, and ZEV shadow costs is the difference between the transaction price and the sum of marginal costs, fuel economy shadow cost, and ZEV shadow cost. The fuel economy and ZEV shadow costs are computed using the vehicle's fuel economy and ZEV requirement for the corresponding model year and region.

The middle column of Table 3 shows the average gap between the transaction price and marginal costs. The gap varies across firms partly because of differences in the price sensitivities of the corresponding consumers. For example, BMW consumers tend to have higher income and lower estimated price sensitivity, leading to larger markups.

The rightmost column of Table 3 equals the middle column plus the ZEV and fuel economy shadow costs. The ZEV shadow cost is given by $\lambda_{Z,r}(c_{jr} - R_r)$ (see equation (6)). An electric vehicle with 350-mile range receives four credits, and the estimated shadow price, $\lambda_{Z,r}$, in 2018 is about $\$2,200$. An electric vehicle with a 350-mile range has a shadow cost of about $-\$8,200$.

The fuel economy shadow cost is proportional to the value of the additional credits that can be sold if a manufacturer increases a vehicle's fuel economy. The shadow cost is given by $\lambda_M(\frac{1}{m_j} - \frac{1}{M_j})$. The estimate of λ_M implies that increasing the average vehicle's fuel economy by 1 percent yields \$78 of additional credit market revenue. That the middle and rightmost columns in Table 3 are similar indicates that, on average, the ZEV and fuel economy standards impose small additional costs on the firms.

The averages in Table 3 mask considerable variation across vehicles. For example, in 2018, the standard deviation of the fuel economy shadow cost was nearly $\$1,000$ per vehicle. Note that the estimated ZEV and fuel economy shadow prices are similar to the estimates of these prices from Leard and McConnell (2019), who compute shadow prices based on reported credit transactions among firms.[21] The similarity helps validate the model structure and parameter estimates.

Table 4 combines the demand and marginal cost estimation and previews the importance of equilibrium markups in explaining the welfare costs of the simulated subsidies in the next section. The first row reports the sales-weighted average own-price elasticity of demand by fuel type. Plug-in hybrid consumers have a similar average own-price elasticity as gasoline vehicle consumers. Electric vehicle demand is considerably more price elastic than demand for the other fuel types.[22]

Table 4: Average Own-Price Elasticity of Demand and Markup by Fuel Type

	Gasoline	Plug-in hybrid	Electric
Own-price elasticity of demand	-3.77	-3.43	-5.27
Markup (2018$)	9,807	5,658	35

Notes: The table reports the own-price elasticity of demand and the markup, which is the difference between price and marginal costs, in 2018$; both are weighted by predicted sales. Gasoline vehicles include hybrids and flex-fuel vehicles.

The first-order condition for vehicle price (equation (9)) indicates that vehicles with more price-sensitive demand have a smaller equilibrium markup.[23] The second row of Table 4 shows markups by fuel type, where the markup is the difference between price and marginal costs. The sales-weighted average markup for electric vehicles is effectively zero, and it is much smaller than the markups for the other two fuel types. The relatively elastic demand of electric vehicles partially explains the difference in markups. The ZEV and fuel economy standards also contribute, because they effectively subsidize electric vehicle sales, which increases their sales and reduces equilibrium markups. These two policies also explain why the plug-in hybrid markup is smaller than the gasoline markup, even though plug-in hybrids and gasoline vehicles have a similar own-price elasticities

[21]Other estimates of fuel economy shadow prices, such as Jacobsen (2013) pertain to different time periods. The estimated shadow prices also appear to be the same order of magnitude as those estimated by EPA and NHTSA in their rulemaking.

[22]In Table 2, the plug-in hybrid subsidy is more cost effective than the electric vehicle subsidy, despite the fact that demand for electric vehicles is more price sensitive. Greater adverse selection for the electric vehicle subsidy explains this result.

[23]The equation shows that cross-price derivatives also affect markups. In practice, these derivatives are smaller in magnitude and vary less across fuel types than do the own-price derivatives.

of demand. Thus, demand elasticities and existing policies explain variation in markups across fuel types. If a hypothetical policy reduces gasoline vehicle sales and increases PEV sales, private welfare decreases because the policy exacerbates pre-existing distortions (that is, sales of gasoline vehicles are below private welfare-maximizing levels).

5.3. Entry Parameters

5.3.1 Estimation Strategy

Equation (12) links the probability that a potential entrant enters the market to the entrant's expected profits, costs, and the hurdle rate. The negative of the product of the hurdle rate and entry costs, rC_j^e, are decomposed into the following components:

$$-rC_j^e = C_0 + C_{d(j)} + C_{f(j)} + C_{r(j)} + C_{s(j)} + B_{b,j}\theta + L_{F,f(j)}\phi \tag{14}$$

where C_0 is a constant and $C_{d(j)}$, $C_{f(j)}$, and $C_{r(j)}$ are model, fuel type, and drive type cost shocks. The cost shocks account for the fact that costs may vary by model, fuel type, or drive type. The sibling cost shock, $C_{s(j)}$, allows for the possibility that entry costs are lower for siblings than for nonsiblings because siblings are likely to be easier to design and market.

The equation includes battery capacity, $B_{b,j}$, with coefficient θ. Conditional on fuel type, larger batteries may be more difficult to fit in the vehicle, in which case θ is negative.

In equation (14), $L_{F,f(j)}$ include counts of the number of PEV entrants for the same firm F and fuel type $f(j)$; that is, hybrid, plug-in hybrid, and electric vehicles have separate counts. The coefficient vector ϕ captures the effect of past entry on entry costs, which introduces dynamics because entry costs can evolve over time.

Substituting equation (14) into equation (12) and replacing $\frac{1}{r}$ with the coefficient ρ yields the estimating equation:

$$P_{jt} = \frac{1}{1 + \exp^{(}\pi_j^e\rho + C_0 + C_{d(j)} + C_{f(j)} + C_{r(j)} + C_{s(j)} + B_{b,j}\theta + L_{F,f(j)}\phi^{)}} \tag{15}$$

The exponential term in the denominator includes estimated profits, π_j^e; fixed effects for models, fuel type, drive type, and sibling; battery size; and counts of past entry.

Estimating equation (15) requires defining the sample of potential entrants and computing π_j^e. For each year between 2010 and 2018, the set of potential entrants includes all hybrid, plug-in hybrid, or electric vehicles that entered before 2019. The set of potential entrants changes over time. For example, Volvo introduced the plug-in hybrid XC90 in

2017, which is included among the set of potential entrants prior to 2017 but not after.

For each potential entrant, in the model year that it actually enters the market, π_j^e equals its profits (excluding entry costs) predicted by the equilibrium model. That is, I compute profits using the estimated costs and preference parameters and the predicted price and market share of the entrant.[24]

For potential entrants prior to the entry year, I predict profits assuming that the vehicle had entered the market. To estimate profits, I use the preference parameters and mean utility estimated in the year that they actually enter.[25] For each year prior to entry, I adjust marginal costs upwards using the vehicle's battery size and the difference between battery costs in the model year and the entry year according to Bloomberg NEF.

In equation (15), four main factors vary over time and explain why a vehicle enters in a particular year. First, time-varying fuel economy and ZEV standards affect an entrant's profits; tighter standards increase those profits. Second, demand for PEVs depends on fuel costs, which vary with gasoline prices. Third, battery costs decrease over time, reducing marginal costs and increasing profits. Fourth, as firms introduce more hybrids and PEVs, costs of subsequent entry diminish over time.

Table 5 shows summary statistics for the sample used for the entry parameter estimation. The average entry probability is 0.2 for the 805 observations in the sample. Average profits of a potential entrant are about $40 million, but the distribution is highly right skewed. For context, the table shows that the profits of a potential entrant represent a small share of a firm's overall profits (note that these profits include only revenue and production costs and exclude fixed costs of technology adoption). The past entry variables demonstrate considerable variation, and about half of the potential entrants are siblings. The distribution of battery sizes is highly right-skewed. For example, Tesla vehicles have battery capacity of roughly 80 kWh, which is well above the 90th percentile.

[24] Calculating profits in this manner requires the assumption that the firm observes ξ_{jr} prior to making the entry decision. This could introduce correlation between ξ_{jr} and the attributes of the potential entrant. Such correlation should not affect the preference parameter estimates because the instruments do not include attributes of hybrids or PEVs that enter during the sample.

[25] This calculation assumes that a vehicle's mean utility does not change across model years. For entrants, the estimated mean absolute deviation of the post-entry mean utility from the vehicle's mean is about 4 percent of mean utility, indicating that this is a reasonable assumption. Because I use parameters observed after entry to estimate profits, the sample includes vehicles that enter by 2018. In the simulations, I assume that entry costs of post-2018 potential entrants are drawn from the same distribution as pre-2018 entrants.

Table 5: Summary Statistics for Entry Data Set

	Mean	Standard deviation	10th percentile	90th percentile
Entry probability	0.20			
Profits (billion 2018$)	0.043	0.103	0.001	0.107
Firm's profits (billion 2018$)	9.6	6.6	1.1	18.8
Past hybrid entry	5.0	6.4	0.0	17.0
Past plug-in hybrid entry	0.3	0.7	0.0	1.0
Past EV entry	0.4	0.8	0.0	2.0
Past entry own fuel type	3.4	5.8	0.0	12.0
Sibling	0.47			
Battery size (kwh)	10.6	18.3	0.0	27.0

Notes: Past hybrid entry is a count of the number of hybrids the firm has introduced previously, and similarly for past plug-in hybrid and electric vehicle entry. Past entry of own fuel type is the firm's past entry of vehicles with the same fuel type as the potential entrant. Sibling is a dummy equal to one if the vehicle has a gasoline sibling.

5.3.2 Estimation Results

Table 6 shows the results from estimating equation (15). Column 1 reports a logistic regression that includes the variables reported in the table and model, drive type, and fuel type fixed effects. The coefficients have the expected signs and are precisely estimated (standard errors are bootstrapped and robust to heteroskedasticity). Profits and past entry have positive effects on entry, which suggests that past entry reduces costs. Being a sibling also increases the entry probability, indicating that entry costs are lower for siblings than for other vehicles. Finally, battery capacity has a negative effect on entry, which could be due to the greater complexity of incorporating a larger battery pack; this effect is independent of the effect of electric range on profits, which is included in the profits variable.

Table 6: Entry Parameter Estimation Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimated by	Logit	Logit	OLS	Probit	Logit	Logit	Logit
	Dependent variable: Entry dummy						
Profits (billion 2018$)	6.07	3.72	0.45	3.01	6.02	7.65	6.04
	(1.87)	(1.21)	(0.21)	(0.86)	(1.67)	(1.98)	(1.89)
Firm's profits (billion 2018$)							0.03
							(0.12)
Past hybrid entry	0.20		0.009	0.08			0.18
	(0.09)		(0.004)	(0.03)			(0.11)
Past plug-in hybrid entry	0.61		0.05	0.32			0.60
	(0.24)		(0.03)	(0.12)			(0.23)
Past EV entry	1.50		0.16	0.80			1.51
	(0.34)		(0.03)	(0.17)			(0.35)
Past entry own fuel type					0.32	0.47	
					(0.09)	(0.09)	
Sibling dummy	2.22		0.25	1.16	3.36	4.11	2.20
	(0.77)		(0.07)	(0.37)	(0.72)	(0.80)	(0.79)
Past entry own fuel type X sibling dummy						-0.20	
						(0.08)	
Battery size (kwh)	-0.17		-0.02	-0.09	-0.13	-0.14	-0.17
	(0.08)		(0.01)	(0.05)	(0.08)	(0.08)	(0.08)
Number of observations	770	770	805	770	770	770	770
Share of entrants predicted to enter	0.77	0.77	0.79	0.76	0.77	0.77	0.77
Share of non-entrants predicted not to enter	0.87	0.87	0.87	0.87	0.87	0.87	0.87

Notes: The table reports the estimated coefficients from equation (15). Column 1, 2, and 5–7 are estimated by logit, column 3 by OLS, and column 4 by probit. In addition to the variables reported in the table, all regressions include model fixed effects, fuel type fixed effects, and drive type fixed effects. Profits are the estimated profits of a potential entrant if it enters in a particular year.

The profits coefficient is the main coefficient of interest because of its role in the counterfactuals. To provide economic intuition for the point estimate, for each vehicle in the data, I compute profits under the assumption that it is ineligible for the federal tax credit. This reduces the predicted entry probability from 0.2 to 0.1, indicating that the tax credit explains at least half the observed entry.[26]

Coefficients on past entry and the sibling dummy are positive and statistically significant at the 1 percent level. The positive coefficients indicate that entry costs decrease with past entry, since the entry probability increases with past entry.

The remaining columns in Table 6 show alternative specifications. Column 2 shows that the past entry variables help identify the effect of profits on entry, as the coefficient declines by over one-third if these variables are omitted. Columns 3 and 4 compare results

[26] This estimate is likely a lower bound because it does not account for dynamic entry costs. Lower entry reduces the variables measuring past entry, which further reduce entry.

from estimating the equation by OLS or probit. Column 6 shows that using past entry of the same fuel type, rather than the three separate fuel type variables, does not have a large effect on the profits coefficient.

The bottom two rows of the table illustrate the performance of the entry models by reporting the shares of observations for which the model correctly predicts the outcomes. In column 1, the model correctly predicts the outcome 85 percent of the time, and it is more successful at predicting nonentry than entry. The regression models reported in the table perform similarly to one another.

Finally, as a check on the overall performance of the equilibrium model, I include the firm's profits as an explanatory variable. Implicitly, the entry model includes the assumption that firms make entry decisions vehicle by vehicle. In contrast, total firm profits could affect entry decisions, if, for example, a firm is more likely to introduce vehicles when it is relatively profitable. Column 7 shows that adding the firm's total profits as an explanatory variable does not affect the other coefficients. This suggests that omitted firm-level profits in column 1 do not affect entry.

6 Policy Counterfactuals

This section reports results from counterfactuals that include various subsidy schemes. The first subsection describes the baseline and main policy scenarios, and the remaining subsections report results.

6.1. Description of Central Baseline and Subsidy Scenarios

The central baseline and policy scenarios simulate market equilibria for the year 2025. This year is chosen to represent a year in the near future when entry could respond plausibly to a subsidy adopted in 2022, but not so far in the future that ZEV and fuel economy standards are endogenous to the subsidies.

The timing is as follows: policies are announced at the beginning of 2025; firms make entry decisions; firms choose vehicle prices, fuel economy, and technology to maximize profits; and consumers choose vehicles to maximize subjective utility. Because entry decisions are static, I simulate equilibriua for a single model year rather than estimating transitional dynamics.

The set of vehicles at the start of the simulation year includes all vehicles in 2018, PEVs that entered between 2018 and 2021, and PEVs that are expected to enter by 2025. For example, the Audi e-tron entered the US market in 2019 and is included.[27]

I characterize the set of expected entrants by collecting information from announcements by automakers. For example, the Nissan Arriya is an electric sport utility vehicle that is expected to enter the US market in 2022. The set of announced entrants includes all vehicles that manufacturers have announced will enter before 2025. I include only vehicles for which the manufacturer has indicated the battery size, all-electric range, and retail price. I fill in other vehicle attributes from the announcements or using averages from existing non-electric siblings sold by the same manufacturer.

The set of potential entrants includes all-electric siblings of existing models.[28] This definition is necessary for computational reasons, because otherwise the set of potential entrants would be essentially unlimited. Allowing for the possibility of plug-in hybrid in addition to all-electric sibling entrants would require modeling both options for each sibling and substantially increase computational time. For tractability, I assume that if an electric vehicle enters the market, the manufacturer offers the electric vehicle in all regions.

The definition of the set of potential entrants is consistent with recent entry patterns. With the obvious exception of Tesla, three-fourths of plug-in hybrids and electric vehicles introduced since 2018 have been siblings, and a majority of expected pre-2025 entrants are electric rather than plug-in hybrid.

I impute attributes of potential entrants using the averages of the attributes of the corresponding model. Based on recently announced electric vehicles, I assume a range of 350 miles and a battery pack with a capacity of 120 kilowatt hours. This range exceeds the range of nearly all electric vehicles that were available through 2018, and the assumed range of entrants allows for the likelihood that electric vehicle quality improvements over time (Remmy, 2022). Similar to the entry cost estimation, I impute the marginal costs based on the average marginal costs of the corresponding model, adjusted for the differential between the costs of an electric versus gasoline power train. This differential is computed using projected battery costs from Bloomberg NEF for 2025. Firms make entry decisions according to equation (11); implicitly, the distribution of the error term is the same in the simulation year as in the estimation sample. Entry costs are adjusted to account for observed entry between 2018 and 2025.

The simulations require inputs on total market size, fuel prices, and policies. I assume that the market size of each region and demographic group grows proportionately between

[27]In principle, I could include non-PEVs that entered after 2018 and collect data on their attributes. In practice, relatively few entered after 2018 that are not already included in the data.

[28]Potential entrants may include models that have a gasoline, hybrid, or plug-in hybrid version but not an electric version. For example, gasoline and plug-in hybrid versions of the Volvo S60 are available, but because an all-electric Volvo S60 is not yet available, that version is included among the set of potential entrants.

2018 and 2025 using aggregate sales forecasts in the Energy Information Administration Annual Energy Outlook (AEO) 2021. I also use electricity and gasoline prices from the AEO 2021. I choose the AEO 2021 rather than 2022 to avoid including the influences of the COVID pandemic.

Policy assumptions common to all scenarios include the ZEV standards for 2025 and EPA and NHTSA GHG and fuel economy standards that were finalized in 2021. As noted in the Introduction, the assumptions that ZEV, fuel economy, and GHG standards are exogenous to the subsidies is consistent with the recent timeline along which these policies have been chosen; Congress (and states) have debated vehicle subsidies after the 2025 ZEV, fuel economy, and GHG standards were chosen. The baseline scenario includes a federal tax credit of $7,500 per vehicle for the first 200,000 vehicles a manufacturer sells that is then phased out. The baseline and subsidy scenarios also includes all state subsidies that were offered in 2020.[29]

In the central subsidy scenarios, an additional $1 billion are spent on subsidies for plug-in hybrid and electric vehicles. In the first scenario, a single subsidy is provided regardless of the vehicle price or consumer's income. In the second scenario, subsidies are provided to only the two lowest-income groups, which accounted for 25 percent of PEV sales in 2018. In the third scenario, subsidies are provided only to electric vehicles with prices below the median retail price of electric vehicles sold in 2018, which accounted for 40 percent of PEV sales in 2018. In all subsidy scenarios, the subsidy is offered in addition to the federal tax credit and financed by a lump-sum tax on all new vehicle consumers.

The appendix describes the algorithm used to find the baseline and subsidy equilibria. In short, equilibrium prices and attributes are determined in an inner loop, followed by fuel economy and ZEV credit prices in a middle loop, and entry decisions in an outer loop. Market shares and profits of potential entrants are computed using the estimated demand and supply-side parameters, which includes the implicit assumption that these parameters, which were estimated using decisions observed between 2010 and 2018, do not change between 2018 and 2025. The model validation exercises discussed in Section 5 as well as results discussed in the next subsection support this assumption.

6.2. Cost Effectiveness of Subsidies without Policy Interactions

To compare with the literature and provide context for the main results that account for interactions among subsidies, fuel economy standards, and ZEV standards, first I report

[29]That is, current subsidies continue through 2025. This is a reasonable assumption, as state subsidies depend on many factors and are difficult to forecast. For consistency with estimation, regional subsidies are the average of state subsidies.

results that do not include these interactions. Table 7 shows the total sales and fiscal cost per vehicle for the baseline and three subsidies.

Table 7: Comparison of Subsidies with Exogenous ZEV and Fuel Economy Credit Prices in 2025

	Baseline	Uniform subsidy	Subsidy to two lowest income groups	Subsidy to low-price plug-in vehicles
	(1)	(2)	(3)	(4)
Plug-in vehicle sales	528,608	630,113	683,886	647,144
Fiscal cost (2018$ per vehicle)		9,857	6,428	8,432

Note: The table reports simulation outcomes in the year 2025 for the scenario in the column heading. The ZEV and fuel economy credit prices are exogenous in all scenarios. The first row reports national PEV sales. The fiscal cost is the subsidy expenditure divided by the change in PEV sales relative to the baseline scenario.

In the baseline scenario, PEVs account for about 4 percent of all vehicle sales, or about 529,000 units. This market share is similar to the Energy Information Administration's Annual Energy Outlook (AEO) 2020.[30]

The second column shows the PEV sales caused by adding a subsidy of $1,600 per vehicle for which all income groups are eligible. The subsidy increases PEV sales by about 100,000 units, which represents a 20 percent increase over the baseline level. The average fiscal cost per vehicle is about $9,900. This cost is about 5 times higher than the average subsidy amount because most of the subsidy value is claimed by consumers who would have purchased PEVs without a subsidy. The fiscal cost per vehicle is comparable to estimates in Sheldon and Dua (2019) and Xing, Leard, and Li (2021).

The third column shows that providing a subsidy of about $3,200 to the two lowest-income groups rather than all consumers reduces the fiscal cost per vehicle by about 35 percent. The larger price sensitivity of the two lowest-income groups explains why fiscal costs per vehicle are lower in this scenario.

Finally, column 4 shows that providing a $2,300 subsidy to low-price PEVs rather than

[30] The AEO 2020 is more directly comparable to the results in this paper than the AEO 2021 because the latter does not include the ZEV program and does include the final Trump administration fuel economy and GHG standards rather than the Obama administration standards (which are similar to the Biden administration standards used in the simulations). In its analysis of the Biden standards, EPA projects market shares of 8–17 percent, but those projections do not account for consumer responses to changes in attributes or vehicle prices, making it difficult to compare EPA market shares with those estimated in this paper. Through the first half of 2022, the actual PEV market share was about 5 percent. Simulating the model without entry and using the observed 2022 gasoline prices rather than the lower EIA forecasted 2025 prices and yields a market share slightly greater than 5 percent, indicating that high gasoline prices explain why the observed 2022 market share exceeds the estimated 4 percent reported in the table. The similarity of the observed 2022 market share and the simulated share using 2022 gasoline prices indicates that gasoline prices, ZEV and fuel economy standards, and PEV entry explain the market share growth between 2018 and 2022, rather than changes in consumer preferences. This similarity supports the assumption that consumer preference parameters do not vary between 2018 and 2025.

for all vehicles (column 2) reduces the fiscal cost per vehicle by about 15 percent. The per-vehicle costs are higher than the income-targeted subsidy because many consumers in the higher income groups purchase low-price PEVs. Consequently, the average consumer buying a low-price PEV is only slightly more price sensitive than the average consumer buying any PEV; that is, average price sensitivity varies more across income groups than across PEVs, causing the income-based subsidy to be substantially more cost effective than the vehicle price-based subsidy. In short, the simulations without policy interactions reproduce cost effectiveness and policy rankings in prior literature.

6.3. Cost Effectiveness of Subsidies with Policy Interactions

This subsection considers the cost effectiveness of subsidies accounting for their interactions with ZEV and fuel economy standards. Table 8 shows the results for the baseline scenario and the same three subsidy scenarios as in Table 7, with the first column showing the baseline. The table reports the fuel economy credit price in dollars per 1 percent fuel economy increase for the average vehicle in the sample. The ZEV credit price is $3,236; an electric vehicle with 200-mile range receives 2.5 credits and an implicit subsidy of about $8,000.

Table 8: Comparison of Electric Vehicle Subsidies with Policy Interactions for 2025

	Baseline	Uniform subsidy	Subsidy to two lowest income groups	Subsidy to low-price plug-in vehicles	Low-income subsidy and gasoline vehicle tax
	(1)	(2)	(3)	(4)	(5)
Subsidy amount (2018$ per vehicle)		1,838	3,779	2,589	8,045
Plug-in vehicle sales	528,608	541,803	547,409	533,715	688,540
Plug-in sales from additional entry		5,009	26,420	33,795	33,310
Private welfare (billion 2018$)	177.03	177.78	177.57	177.69	178.74
Carbon dioxide emissions (billion tons)	0.625	0.628	0.628	0.628	0.626
Fuel economy credit price (2018$ per 1% mpg increase)	77	66	65	67	51
ZEV credit price (2018$ per credit)	3,236	2,460	1,942	2,340	1,702
Fiscal cost (2018$ per vehicle)		75,482	53,745	196,749	13,129
Fiscal cost non-ZEV states (2018$ per vehicle		34,681	16,835	40,654	2,818
Welfare cost (2018$ per vehicle)		19,254	25,313	68,261	2,476

Notes: The table reports simulation outcomes for the scenario in the column heading. Results are reported for vehicles sold in 2025. Plug-in sales from additional entry refers to sales of PEVs that enter in the policy scenario and not in the baseline scenario. Private welfare is the sum of consumer welfare and manufacturer profits. Consumer welfare is the total change in equivalent variation across demographic groups and regions. Manufacturer profits are the total profits across firms. Carbon dioxide emissions are computed over the lifetimes of vehicles sold in 2025 using miles traveled and scrappage assumptions from Leard, Linn, and Springel (2019). Fiscal cost is the subsidy expenditure divided by the change in PEV sales. Fiscal cost non-ZEV states is the expenditure divided by the change in PEV sales in non-ZEV states. Welfare cost is the change in consumer welfare plus the change in manufacturer profits minus the subsidy expenditure, divided by the change in PEV sales.

Columns 2–4 show the results for each subsidy scenario. In column 2, a uniform subsidy of about $1,800 per PEV increases PEV sales by about 13,000 units and increases private welfare. Entrants account for roughly one-half of the additional PEV sales caused by the subsidies, indicating the importance of endogenizing entry. Subsidies are at least eight times more effective when the credit prices are exogenous (Table 7) than in this table. This comparison illustrates that ignoring the interaction of the subsidies with the other policies vastly overstates the cost effectiveness of the subsidies.[31]

The bottom three rows report the cost effectiveness of the uniform subsidy. I report the overall average fiscal cost and the fiscal cost in non-ZEV states. The overall average fiscal cost of the subsidy is $75,000, which is about 40 times the amount of the per-vehicle subsidy. Two reasons explain the high fiscal cost. First, for ZEV states, the subsidy reduces the ZEV credit price but does not affect sales. Second, much of the subsidy expenditure in non-ZEV states goes to consumers who would have purchased PEVs without the subsidy—that is, adverse selection. The fiscal costs in non-ZEV states are substantially lower because of the lack of interaction with the ZEV standards.

The bottom row shows welfare costs of $19,000 per additional PEV sold. The welfare costs reflect pre-existing distortions caused by the ZEV and federal standards and market power. The marginal private welfare gain of selling one additional vehicle is proportional to the vehicle's markup. The average markup of gasoline vehicles exceeds that of PEVs (see Table 4). Consequently, increasing PEV sales at the expense of gasoline vehicles reduces private welfare; that is, the subsidy exacerbates pre-existing distortions in the market.

Column 3 reports the effects of a subsidy offered to the two lowest-income groups. Total expenditure is the same as in column 2, and each vehicle receives a subsidy of about $3,800. The bottom of the table shows that the low-income subsidy has lower fiscal costs per vehicle because on average, the two lowest-income groups are twice as sensitive to vehicle prices as are the higher-income groups (see Figure 8).

Column 4 shows the results of a subsidy offered to PEVs with a retail price below $57,000, which was the median price of PEVs in 2018. This subsidy is less cost effective than the other two subsidies.

For comparison with the subsidies, I consider a feebate that imposes a tax on gasoline-powered vehicles and a subsidy to PEVs. The gasoline vehicle tax is $150 per vehicle, and the PEV subsidy is calibrated so that the feebate has the same net fiscal cost as the subsidy scenarios. Column 5 indicates that the feebate has the largest effect on PEV sales and is

[31] The overall cost effectiveness with exogenous credit prices is better than the cost effectiveness in non-ZEV states from Table 8. This result is caused by interactions between the subsidy and fuel economy standards in Table 8.

the most cost effective of the four policies. By simultaneously taxing gasoline vehicles and subsidizing PEVs, the tax revenue enables larger subsidies for a fixed fiscal cost. The ranking across scenarios of cost effectiveness in non-ZEV states is the same as the overall ranking; in both cases, the income-based subsidy and feebate are substantially more cost effective.

6.4. Cost Effectiveness of Other Scenarios

This subsection discusses results from two other scenarios: no electric vehicle entry and low battery costs. As discussed in the introduction, the literature on subsidies for GHG-reducing consumer products has largely ignored the effect of subsidies on entry. Ignoring entry could increase or decrease estimated costs of the subsidies. On the one hand, assuming no entry reduces the estimated baseline PEV market share. In turn, the lower baseline market share reduces the portion of subsidy expenditure that is claimed by consumers who would have purchased PEVs without the subsidy. On the other hand, subsidies may induce entry and increase PEV sales, and ignoring entry would underestimate the sales increase.

Table 9: Comparison of PEV Subsidies Without Entry

	Baseline	Uniform subsidy	Subsidy to two lowest income groups	Subsidy to low-price plug-in vehicles
	(1)	(2)	(3)	(4)
Plug-in vehicle sales	440,977	470,567	516,184	497,016
Fuel economy credit price (2018$ per 1% mpg increase)	85	82	78	81
ZEV credit price (2018$ per credit)	5,059	4,489	3,826	5,058
Fiscal cost (2018$ per vehicle)		33,794	13,297	17,845

Note: The table is constructed similarly to Table 8 but with no entry in the baseline or policy counterfactuals.

Table 9 reports the effects of the subsidies assuming no entry. With no entry, baseline PEV sales are substantially lower than in Table 8, which has entry: 441,000 units rather than 529,000 units. Total fiscal costs are held constant in these scenarios with and without entry. The scenarios without entry cause larger sales increases because of the lower adverse selection, meaning that ignoring entry overstates effectiveness of future subsidies.

Next, I consider the relationship between battery costs and the effectiveness of the policies. The simulations discussed earlier include battery costs predicted by Bloomberg NEF for 2025. It is widely expected that battery costs will continue falling after 2025, although considerable disagreement exists about how far. I examine scenarios that reduce battery costs by $50 per kilowatt hour between 2025 and 2030, which is representative of recent projections. These scenarios do not include entry for comparability with Table 9.

Table 10: Comparison of PEV Subsidies Using 2030 Battery Costs

	Baseline	Uniform subsidy	Subsidy to two lowest income groups	Subsidy to low-price plug-in vehicles
	(1)	(2)	(3)	(4)
Plug-in vehicle sales	637,581	641,217	667,274	631,434
Fuel economy credit price (2018$ per 1% mpg increase)	56	38	30	30
ZEV credit price (2018$ per credit)	1,648	1,172	1,106	1,374
Fiscal cost (2018$ per vehicle)		269,884	34,223	NA

Note: The table is constructed similarly to Table 9, except it reports simulations using battery cost assumptions for 2030 rather than 2025.

Reducing battery costs could increase or decrease the estimated costs of the subsidies. On the one hand, lower battery costs increase the extent of adverse selection, as baseline PEV sales are higher. On the other hand, lower battery costs could increase the marginal effects of the subsidies on PEV sales.

Column 1 of Table 10 shows the results of the baseline simulation. Relative to Table 9, reducing battery costs by 30 percent causes the PEV market share to increase from 441,000 to 638,000 units, which represents a market share increase of about 1.4 percentage points. The lower battery costs reduce the cost effectiveness of the uniform and low-income subsidy. This result demonstrates the importance of designing the subsidy to reduce the adverse selection, such as linking the subsidy to battery costs.[32]

6.5. Distributional Effects of Subsidies

This subsection discusses the distributional effects of the central subsidies that were reported in Table 8. There are several reasons the consumer welfare effects of the subsidies may vary across income groups. First, targeting the subsidies to low-income consumers or low-price vehicles is progressive by construction. Second, the subsidy is likely to cause larger consumer price reductions for vehicles purchased by low-income consumers than purchased by high-income consumers since the former group is more price-sensitive. Third, interactions with ZEV standards increases progressivity. The ZEV standards increase prices of gasoline vehicles and decrease prices of PEVs, and gasoline vehicles represent a larger share of total vehicle purchases by low-income than high-income consumers. Because the PEV subsidies reduce ZEV credit prices, the interaction with the ZEV requirement increases

[32] Because of interactions with the ZEV and fuel economy standards, the low-price subsidy reduces total PEV sales. This surprising result arises from the fact that the low-price subsidy increases sales of electric vehicles more than plug-in hybrid vehicles, and the electric vehicles receive more credits per vehicle in both programs. This result is similar to the theoretical result in Gillingham (2021), which is that over-crediting electric vehicles for compliance with the GHG standards can reduce electric vehicle sales.

progressivity. Finally, the subsidies interact with fuel economy standards. The standards tend to be progressive (Leard, Linn, and Springel, 2019), and because the PEV subsidy reduces fuel economy credit prices, this interaction makes the subsidy less progressive.[33] Thus, the first three effects cause subsidies to be progressive, whereas the last effect causes them to be regressive.

For each income group, Table 11 shows changes in consumer welfare per household for each policy case compared to the baseline. Column 1 shows that the uniform subsidy is progressive; welfare changes decrease with income. This result is somewhat surprising, given that high-income consumers are more likely to purchase PEVs and claim the subsidy than low-income consumers. However, the differential pass-through rates and policy interactions explain this result, as can be seen by a comparison of Tables 11 and 12. The latter table shows welfare changes by income group for the scenarios in which ZEV and fuel economy credit prices are exogenous (that is, for the same scenarios as those reported in Table 7). The subsidy with exogenous credit prices is more progressive than the scenario with endogenous credit prices, which means that on balance the policy interactions weaken the progressivity of the subsidy. In other words, by ignoring these interactions, previous analysis of the subsidies overstates the progressivity of the subsidies.

Note that in both tables, the sales-weighted average (pre-subsidy) price of PEVs purchased by the highest income group increases almost as much as the average subsidy. This explains why the subsidy has little effect on welfare of the highest income group in Table 12. This result contrasts with Sallee (2011), who finds less than full pass-through of the subsidy for the hybrid Toyota Prius, but the result is consistent with empirical analysis of California's PEV subsidies (Muehlegger and Rapson (2018)) and with the theoretical analysis in Pless and Benthem (2019).

[33] Jacobsen (2013) finds that fuel economy standards are regressive because of their effects on used vehicle markets. However, Leard, Linn, and Springel (2019) find that more recently the standards have been progressive. Low-income consumers undervalue fuel cost savings more than do high-income consumers, causing low-income consumers to benefit more when tighter standards cause fuel economy to increase. This effect outweighs the regresssivity caused by used vehicle price changes.

Table 11: Effects of PEV Policies by Income Group

	Uniform subsidy	Subsidy to two lowest income groups	Subsidy to low-price plug-in vehicles
	(1)	(2)	(3)
	Changes relative to baseline, 2018$ per household		
Lowest income quintile	57	117	58
Second income quintile	53	112	48
Third income quintile	38	-32	18
Fourth income quintile	23	-94	-25
Highest income quintile	-33	-296	-198

Table 12: Welfare Effects of Electric Vehicle Subsidies by Income Group with Exogenous ZEV and Fuel Economy Credit Prices

	Uniform subsidy	Subsidy to two lowest income groups	Subsidy to low-price plug-in vehicles
	(1)	(2)	(3)
	Changes relative to baseline, 2018$ per household		
Lowest income quintile	75	125	81
Second income quintile	32	89	40
Third income quintile	10	-42	22
Fourth income quintile	14	-50	26
Highest income quintile	4	-36	34

Column 2 shows that the income-based subsidy is even more progressive than the uniform subsidy because the subsidy is claimed by the two lowest income groups (by construction). Comparison of Tables 11 and 12 shows that the policy interactions strengthen the progressivity of the income-based subsidy. This result occurs because the income-based subsidy is so effective at increasing PEV sales, which creates a stronger interaction with the ZEV standards than the uniform subsidy. Recalling that this interaction strengthens the progressivity of the subsidy, I conclude that the interaction with the ZEV program contributes to the greater progressivity of the income-based subsidy. In short, the low-income subsidy has more positive welfare effects overall, and it benefits low-income consumers and harms high-income consumers.

7 Conclusion

Subsidies for PEVs will likely continue to play a major role in accelerating the transition from gasoline to plug-in passenger vehicles. To date, most PEVs have been purchased by high-income households, raising concerns about the distributional consequences of these subsidies.

This paper examines the welfare and distributional effects of subsidizing PEVs in the United States. I use a computational model that endogenizes PEV entry and accounts for interactions of subsidies with fuel economy standards and ZEV requirements. I find that subsidies directed to low-income households are more effective at raising PEV sales than those that are uniform across households or depend on retail prices. The greater price responsiveness of low-income households and variation of estimated entry costs explain this result. Moreover, combining subsidies with taxes on gasoline-powered vehicles is more effective than subsidies alone.

Interactions with ZEV and GHG standards influence the efficacy and distributional effects of the subsidies. The ZEV standards affect PEV market shares in states that comprise about one-third of the new vehicle market. For the subsidies considered in this paper, the ZEV requirements remain binding and the subsidies have little effect on PEV sales in those states. This interaction reduces their efficacy.

Interactions with the ZEV standards strengthen the progressivity of the subsidies. Intuitively, the ZEV standards are regressive because they reduce equilibrium PEV prices and high-income households are more likely to purchase PEVs. The subsidies reduce the shadow price of the standards, benefiting low-income more than high-income households. This is an important consideration for state and federal policy makers considering offering subsidies in addition to setting ZEV standards.

Throughout this paper, I have assumed that the ZEV and fuel economy standards are exogenous to subsidies. Because standards for both programs are set several years in advance, this assumption is reasonable for the short term. For example, if Congress increases PEV subsidies in 2022, the fuel economy requirements through 2026 and ZEV requirements through 2025 will not change. However, the fuel economy, GHG, and ZEV requirements for the late 2020s could adjust in response to subsidies adopted in 2022. As these requirements change in the longer term in response to subsidies, the interactions discussed herein likely attenuate. For example, if Congress increases PEV subsidies through the late 2020s, EPA and DOT could strengthen the standards for the late 2020s. Relaxing this assumption would require modeling the political economy of choosing these policies, which future research might explore.

Another assumption maintained in this paper is that charging infrastructure does not respond to the subsidies. To the extent that subsidies spur consumer demand that causes more charging station investment, my results understate the efficacy of the subsidies at boosting PEV sales, which likely would strengthen the conclusions about the cost effectiveness ranking of the subsidies I model. The distributional implications of endogenizing station entry depends on whether low-income consumer demand is more sensitive to charging station availability than is high-income consumer demand. There is little evidence about whether this is the case, which is why charging stations are exogenous in this paper; this which could be another direction for future research.

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Appendix

The Appendix contains subsections that describe the procedure for weighting the MaritzCX data, the first-order conditions for technology, details of modeling fuel economy and ZEV standards, simulation algorithm, and additional figures and tables.

Procedure for Weighting MaritzCX Data

To account for possibly nonrandom response rates across vehicles and demographic groups, I weight observations in the MaritzCX data using registrations data and the Consumer Expenditure Survey (CEX). The Appendix to Leard, Linn, and Springel (2019) explains the procedure for weighting the MaritzCX observations, which is repeated here.

I construct weights for the MaritzCX household observations in three steps. First, I compute a weight so that the total new purchases by year and demographic group matches total new purchases by year and demographic group in the CEX. Second, I adjust the household weights so that the vehicle's share of sales in total sales by year equals the corresponding share according to the registrations data. Third, I adjust the household weights so that total new vehicles obtained by year in the MaritzCX data match total vehicles obtained by year in the registrations data. After constructing these weights, I compute the total new vehicles obtained by year, vehicle, and demographic group.

Note that by taking this approach, I assume implicitly that variation in survey response rates across demographic groups is orthogonal to variation in response rates across vehicles. Reversing the order has little effect on the estimated parameters of the consumer demand model, suggesting that this is a reasonable assumption.

First-Order Condition for Technology

This subsection discusses the interpretation of the first-order condition for technology. Using equation (7) to express marginal costs as a function of technology and equation (8) to eliminate fuel economy in the objective function yields the following first-order condition for technology:

$$\begin{aligned}\sum_{l\in J_f}\sum_r\sum_g(p_{lr}-mc_l+\lambda_{Z,r}(c_{lr}-R_r)+\lambda_M(\frac{1}{m_l}-\frac{1}{M_l}))(\frac{\partial s_{lgr}}{\partial m_j}\frac{\partial m_j}{\partial T_{n(j)}}Q_{gr}\\-\sum_r\sum_g\frac{\partial mc_j}{\partial T_{n(j)}}s_{jgr}Q_{gr}-F'(\Delta T_{n(j)})=0\end{aligned} \tag{16}$$

The first-order condition for technology, equation (16), shows that the manufacturer chooses technology by balancing the benefits and costs of marginally increasing technology. Increasing technology raises demand for the vehicle because of the greater fuel economy that this enables. However, the technology adoption increases the marginal costs of producing the vehicle and causes fixed costs to increase. Note that because the marginal costs are multiplied by vehicle sales, manufacturers adopt more technology for higher-selling vehicles, which is consistent with empirical evidence (Klier, Linn, and Zhou, 2020).

Details of Modeling Fuel Economy and ZEV Standards

This subsection contains details of the assumptions used to model the fuel economy and ZEV standards. For the fuel economy standards, when a firm sells a vehicle it earns credits in proportion to the difference between the vehicle's fuel consumption rate ($\frac{1}{m_j}$) and the vehicle's fuel consumption rate requirement ($\frac{1}{M_j}$). The market for credits is perfectly competitive, and credits trade at a price λ_M.

Each firm must comply with the standards each year, and firms cannot bank or borrow credits. There is unlimited credit trading across classes and firms. I do not model standards in 2010 and 2011, and between 2012 and 2018 and for the counterfactuals, I use the DOT fuel economy requirements for the corresponding year.

The ZEV standards apply to vehicles sold in California and other ZEV states. I make a number of simplifying assumptions for tractability. Between 2010 and 2017, firms earn credits for PEVs and partial ZEVs, which are gasoline vehicles with low tailpipe emissions. In the model, firms do not earn credits for selling partial ZEVs. Although the credit rules changed in 2018, throughout the estimation and simulations I use the 2018 crediting rules. The ZEV program contains a minimum requirement for electric vehicles, but this requirement is not binding when I simulate equilibriums between 2010 and 2018. For estimation and simulation, I assume that credits can be traded freely across firms and states, which abstracts from trading restrictions introduced in 2018. All firms are subject to the ZEV requirements, although the actual program exempts certain small-volume manufacturers. Credit requirements do not depend on a firm's past compliance and firms cannot earn credits for overcompliance with the GHG standards (since 2018, California allows firms to earn such credits).

Colorado, Minnesota, Nevada, and Virginia have joined or will join the ZEV program after 2018. Because the markets defined at the regional and not the state level, these four states are considered to be non-ZEV states for purposes of modeling the counterfactual subsidies in Section 6.

Estimation of Additional Supply Parameters

This subsection discusses estimation of the elasticity of marginal costs to technology and the fixed cost function for technology. To estimate the effect of technology adoption on marginal costs, γ in equation (7), I use equation (8) to compute the change in technology between the initial model year a vehicle appears in the data and the technology in each subsequent model year. Then I regress the estimated marginal costs on vehicle fixed effects and the estimated technology. I estimate the equation by OLS, assuming that marginal costs are estimated with error. The vehicle fixed effects control for average marginal costs of each vehicle in the sample (that is, mc_{j0}in equation (7)).

The estimated technology coefficient in equation (7) is 0.31 for cars and light trucks (I allow the coefficients to differ across the two vehicle classes, but they are estimated to equal one another to two significant digits). Bootstrapping standard errors to account for the fact that the dependent variable was estimated, and clustering by model, the estimates are statistically significant at the 1 percent level. The estimates are also similar to those implied by the NHTSA model that is used to analyze the costs and emissions changes of fuel economy standards (Leard, Linn, and Springel, 2019).

Finally, I assume $F(\Delta T_{n(j)})$ is a quadratic function: $F(\Delta T_{n(j)}) = \sigma(\Delta T_{n(j)})^2$. I compute terms in equation (16) and estimate σ using an OLS regression.

The estimated fixed cost of increasing fuel economy by 1 percent is about $20 million. For an average gasoline-powered vehicle in 2018, the fixed costs imply an increase in average cost of about $100 per vehicle, which is comparable to the increase in marginal costs. The subsidies considered in this paper have small effects on technology adoption, and fixed costs vary little across scenarios.

Simulation Algorithm

The simulation algorithm begins with guesses for entry choices of all potential entrants, the ZEV credit price, fuel economy credit price, and each vehicle's fuel economy, technology level, and price. In the baseline scenario, the initial guesses for fuel economy and technology include the assumption that automakers achieve 2025 standards without trading off horsepower for fuel economy; the technology and fuel economy increases are proportional to the market-wide fuel economy change. The initial guesses of fuel economy and ZEV credit prices are adjusted from their estimated 2018 levels in proportion to the corresponding stringency increase. Based on these guesses, I compute profits of each potential entrant, and the initial entry guesses use equation (11) to predict entry.

The baseline equilibrium is found by nesting two loops and iterating until convergence.

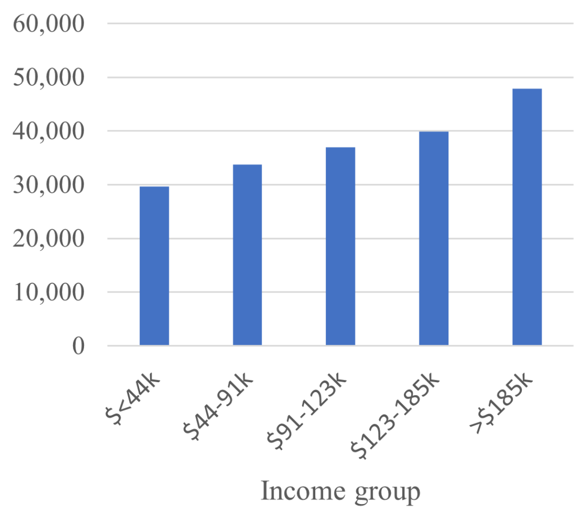
In the inner loop, given entry, vehicle price, and attribute choices of other firms, each firm chooses prices, fuel economy, and technology according to equations (9) through (16). Given these choices, I compute predicted sales-weighted ZEV credits and fuel economy and adjust the credit prices depending on whether supply or demand are in excess. Given the new credit prices, I recompute each firm's price, fuel economy, and technology choices and iterate until the market-level ZEV and fuel economy requirements are met.

The outer loop predicts entry choices of each potential entrant. Using the outcomes from the inner loop, I predict entry choices of all potential entrants, and I iterate until entry choices converge.

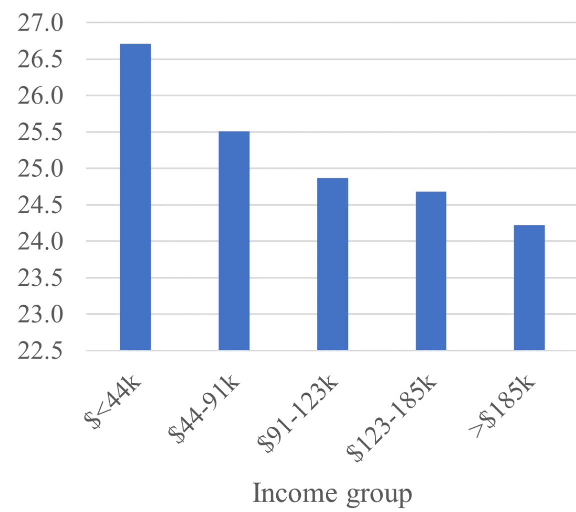
The equilibria for the subsidy scenarios are found similarly, except for an outermost loop for the fiscal cost of the subsidy. For each subsidy scenario, the initial guesses are the same as the baseline. I compute an initial guess for the per-vehicle tax subsidy by dividing the total cost of the subsidy ($1 billion) by the initial predicted sales of eligible vehicles. The inner loop is the same as for the baseline, and the entry loop constitutes the middle loop. After entry choices converge in the middle loop, for the outer loop, I compute the fiscal cost and adjust the per-vehicle subsidy accordingly. I continue iterating until convergence is achieved.

Appendix Figures and Tables

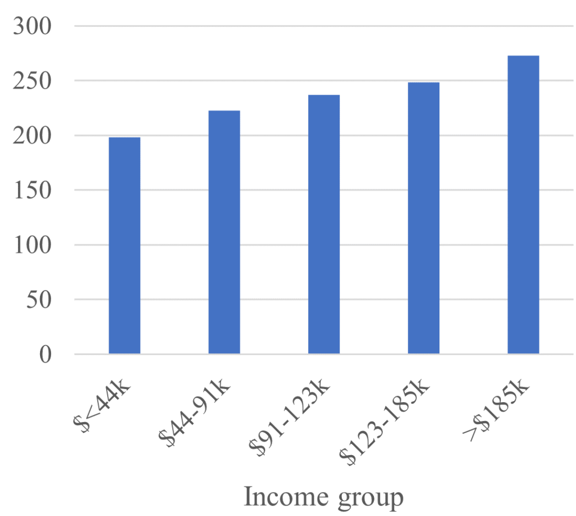
Figure A10: Mean Transaction Price, Fuel Economy, Horsepower, and Light Truck Share by Income Group



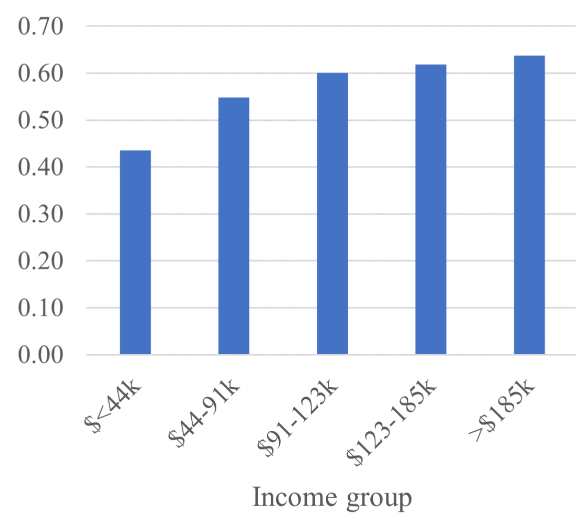
(a) Transaction price (2018 $)



(b) Fuel economy (miles per gallon)



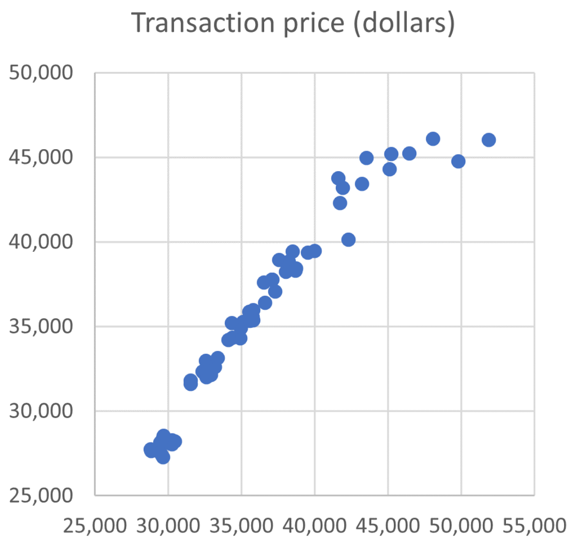
(c) Horsepower



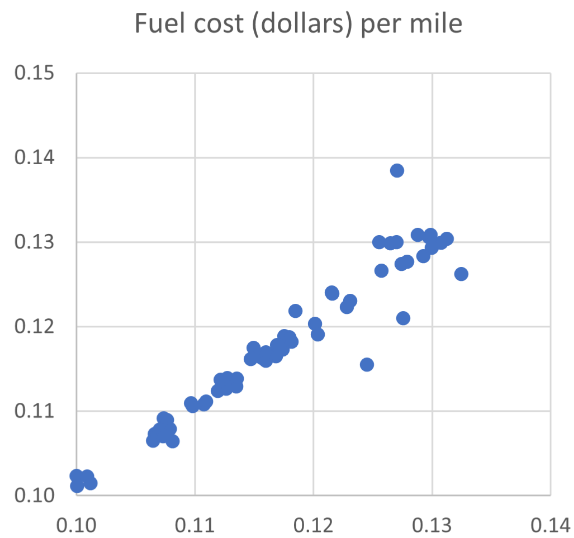
(d) Share of light trucks in total sales

Notes: For each income group, panels A through C show the sales-weighted mean of the attribute indicated in the panel title. Panel D shows the share of light trucks in total sales. The sample includes observations from 2010 through 2018.

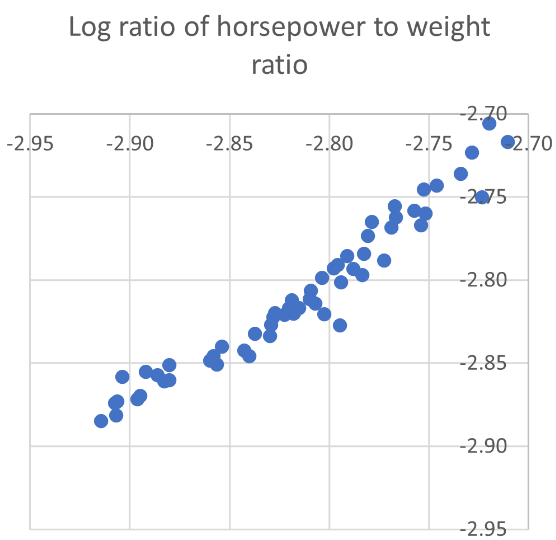
Figure A11: Comparison of Predicted and Observed Attributes by Demographic Group and Region



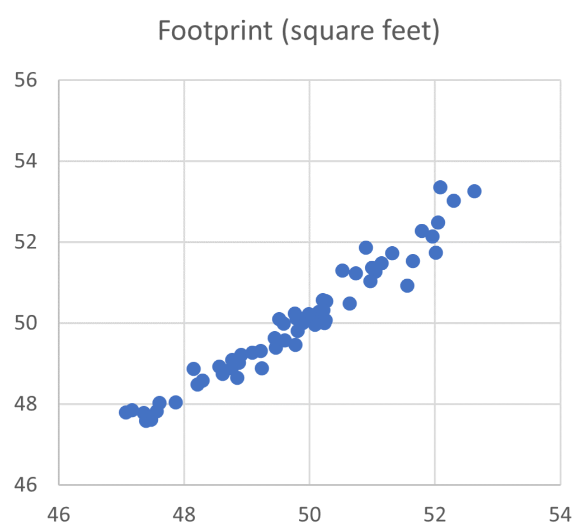
(a) Transaction price (2018 $)



(b) Fuel cost (2018 $) per mile



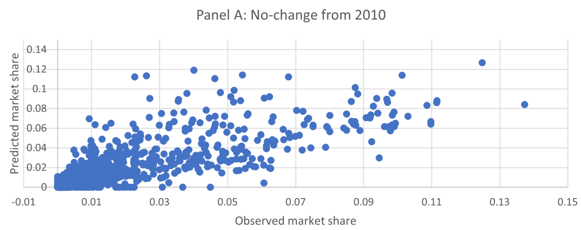
(c) Log ratio of horsepower to weight



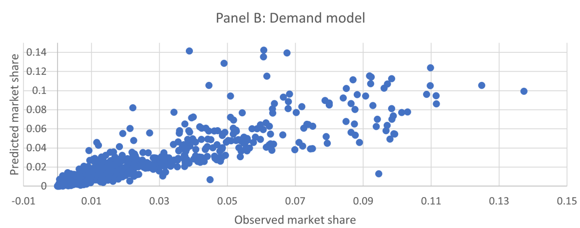
(d) Footprint (square feet)

Notes: Each panel plots the sales-weighted predicted value against the observed value in 2018. Each data point represents a unique demographic group and region. Predicted values are computed using the estimated vehicle sales from the demand model.

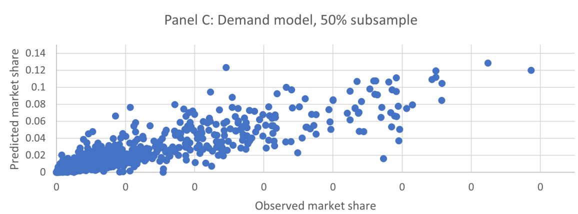
Figure A12: Comparison of Predicted and Observed 2018 Market Shares by Demographic Group, Brand, and Class: No-Change Versus Demand Model



(a) No change from 2010



(b) Demand model



(c) Demand model, 50 percent subsample

Notes: Vehicles are aggregated by brand and class. The figure plots the predicted against observed market share by aggregated vehicle and demographic group. In Panel A, the prediction is equal to the observed market share in 2010. In Panel B, the prediction is made using the demand model. In Panel C, the prediction is made using the demand model estimated on a random 50 percent subsample of vehicle by market observations.