Balancing Equity and Effectiveness for Electric Vehicle Subsidies

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Balancing Equity and Effectiveness for Electric Vehicle Subsidies

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Abstract

Subsidizing greenhouse-gas-reducing consumer products is politically popular, but recent literature on subsides ignore effects on product entry and interactions with other climate policies. This paper considers welfare and distributional effects of subsidies for electric vehicles. 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 and other policies. Income-based subsidies are more effective and more equitable than uniform subsidies. Accounting for interactions with other policies substantially reduces estimated efficacy and increases progressivity of income-based subsidies.

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1 Introduction

Meeting global climate objectives will likely require widespread adoption of "clean" consumer products that reduce greenhouse gas (GHG) emissions, such as solar photovoltaic panels and electric vehicles (EVs), which I refer to as clean products (IEA, 2021). Two policy trends have emerged for plug-in vehicles (PEVs), which include all-electric and plug-in hybrid vehicles. First, many countries adopt multiple 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).\footnote{Subsidies for purchasing PEVs are often combined with subsidies for charging infrastructure, and many countries and regions combine PEV subsidies with emissions rate or fuel economy standards for new vehicles. For example, California, New York, and many other states subsidize PEVs in addition to setting requirements for overall market penetration.} Subsidies for purchasing PEVs are often combined with subsidies for charging infrastructure, and many countries and regions combine PEV subsidies with emissions rate or fuel economy standards for new vehicles. For example, California, New York, and many other states subsidize PEVs in addition to setting requirements for overall market penetration.

The second recent trend is that many policy makers want to make clean product subsidies more equitable. Households installing photovoltaic panels or buying EVs have incomes 2–3 times greater than typical household incomes (Barbose et al., 2021, Borenstein and Davis, 2016, and Truecar.com). To encourage lower-income households to purchase clean products, 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.

These trends raise the question: how cost-effective and equitable are the subsidies given their interactions with other policies? In this paper, I ask whether linking subsidies to household income is both more equitable and effective at increasing PEV sales. As I explain next, the analysis bridges literature on policy interactions with literature on pass-through of subsidies, market power, and product entry in differentiated product markets.

At first glance, linking PEV subsidies to household income may be more effective and more equitable than offering the same subsidy level to all households. As Sheldon and Dua (2019) and Xing, Leard, and Li (2021) show, 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.

\footnote{Combining subsidies for clear technologies 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).}
However, the literature on PEV subsidies, and clean product subsidies more generally, has ignored two aspects of these markets: interactions among subsidies and other policies and new product entry. Although a few papers consider PEVs and charging investments (e.g., Springel (forthcoming) and Li (2019)), the literature has not considered the fact that many countries that subsidize PEVs–such as China, the US, and most of Europe–also impose GHG standards for all new vehicles. Moreover, in the US, California and 12 other states implement the zero-emission vehicle (ZEV) program, which sets targets for plug-in sales of vehicles sold in those states.

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). The GHG and ZEV standards are typically set several years in advance and are therefore fixed when Congress or states choose subsidy levels. 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 reducing emissions and increasing PEV sales. Moreover, interactions with other policies will also affect the overall equity of the subsidies. For example, Leard, Linn, and Springel (2019) show that GHG standards are progressive among new-vehicle consumers. Consequently, accounting for the interaction between the subsidy and standards makes the subsidy less progressive than if this interaction were ignored. Yet, the literature on plug-in subsidies, and on clean product subsidies more generally, has not considered such interactions.

In addition to policy interactions, equilibrium markups influence pass-through, welfare costs, and equity of plug-in vehicle subsidies. Low-price PEVs are more likely to be purchased by low-income consumers than high-price PEVs. Because low-income consumers are relatively responsive to equilibrium prices, pass-through of subsidies to PEV prices is likely to be lower (i.e., price increases are smaller) for low-price vehicles (Weyl and Fabinger, 2013). This mechanism strengthens progressivity of PEV subsidies. Moreover, as I show, average markups are lower for plug-in vehicles than other vehicles, and subsidizing clean products can increase deadweight loss. Although these mechanisms are present in papers using models of imperfect competition to analyze subsidies, they have not been discussed in the literature on PEV subsidies.

A recent literature has considered endogenous product entry and exit (e.g., Eizenberg, 2014 and Fan and Yang, 2020), and the effectiveness of subsidies depends on the entry response. 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.

In this paper, I define a policy as equitable if the welfare costs are uncorrelated with consumer income.\(^2\) I consider subsidies for plug-in vehicles, which include all-electric vehicles, such as the Nissan Leaf, and plug-in hybrids, such as the Chevrolet Volt.\(^3\) I use a new equilibrium model of the new vehicle market that includes interactions among subsidies, GHG standards, and ZEV standards; endogenous PEV entry; and endogenous markups.

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 region. The underlying data include about 1.5 million responses to a survey of new vehicle consumers between 2010 and 2018. An important feature of the data is that they include household demographics, which avoids the need to impute household demographics as nearly all other papers in the vehicle demand literature must do (e.g., Busse, Knittel, and Zettelmeyer, 2013). 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 plug-ins than other households. Consumers in California and other ZEV states have stronger preferences for plug-ins than consumers in other states. That is, both preferences and policy explain the variation in plug-in market shares between ZEV and non-ZEV states.

Modeling plug-in entry is complicated by the immense set of potential entrants. Each year, a manufacturer chooses how many plug-ins 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. 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, potential entrants include electric siblings of gasoline vehicles that do not have an electric sibling as of 2021. Siblings have accounted for a substantial share of the market, particularly

\(^2\)A broader definition of equity could include race or other observable demographic variables, but I focus on income largely because of data limitations.

\(^3\)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.
among legacy manufacturers. Excluding Tesla, in 2019, siblings accounted for 55 percent of plug-in vehicle 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.

Estimation of entry costs builds on Wollmann (2018). A manufacturer introduces a new plug-in 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 are dynamic and evolve according to past entry decisions 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 they depend strongly on expected short-run profits.

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 plug-in vehicles with below-average retail prices. I also consider a feebate that combines a tax on gasoline vehicles with a subsidy to plug-in vehicles. I model the effects of the subsidies over 3-5 year time horizons, during which entry is endogenous but other policies are exogenous.

There are two main results regarding the cost-effectiveness of the subsidies. First, as expected, the income-based subsidy is at least 40 percent more effective than the others; this result is consistent with Xing, Leard, and Li (2021). Second, interactions among subsidies, ZEV standards, and fuel economy standards, substantially reduces the efficacy of the subsidies at increasing plug-in vehicle sales.

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 pass-through rates 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; that is, pass-through rates are lower for those vehicles, which is consistent with analysis of California’s subsidies in Muehlegger and Rapson (2018).

The second equity result is that the income-based subsidies are more progressive than other subsidies both because they are only claimed by 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, which few others have considered; and b) modeling product entry and interactions among other policies for the first time. Thus, the paper contributes to literatures on cost-effectiveness, equity, and pass-through of environmental subsidies and taxes, overlapping policies, and modeling product entry.

Despite a vast literature on equity and welfare effects of fuel taxes, carbon prices, and performance standards (e.g., West, 2004 and Goulder et al., 2019), relatively little research addresses equity and welfare effects of subsidies for clean consumer products. An expanding literature has evaluated cost-effectiveness of subsidies for clean consumer products (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. As far as I know, Sheldon and Dua (2019) and Xing, Leard, and Li (2021) are the only existing papers to consider equity or income-based subsidies for plug-ins. Much of this literature allows for heterogeneity in price sensitivity and vehicle preferences (e.g., Li (2019) and Xing, Leard, and Li (2021)), but research has not included product entry or interactions with other policies.

As noted above, subsidies affect prices that consumers pay for products, whereas the ZEV program and fuel economy standards affect market shares and average fuel economy. The effects of these policies are not additive, and they may interact with one another in complex ways (Novan, 2017 and Perino, Ritz, and Benthem, 2019). Much 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 direct effect of the subsidy on equity.

The literature on transportation climate policies has generally not considered interactions among policies. For example, Holland et al. (2016) estimate the emissions benefits of plug-in subsidies by estimating the effects of vehicle charging on use of existing fossil-fuel-fired electricity generators. However, they do not account for interactions among the subsidies, fuel economy and GHG standards, and environmental regulations of the electricity sector; accounting for the latter would likely reduce estimated emissions caused by charging. Jacobsen (2013) finds that fuel economy standards are regressive but does not
consider interactions with ZEV standards, which his analysis predates. In contrast, I show that including the interactions has major implications for overall welfare costs and equity.

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 types of markets, where new products have many of the same characteristics as existing ones (for example, a new high-performance version). 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. Modeling entry is an important distinction between this paper, Leard, Linn, and Springel (2019), and Leard, Linn, and Springel (2020). In further contrast to those papers, I use data through 2018 rather than 2015, which is important for EV demand estimation; and I model regional markets rather than a national market.

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

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 large sample size reduces measurement error for transaction prices and vehicle choices. 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 transaction prices are particularly important for estimating WTP for vehicle attributes. Transaction prices respond to short-term market conditions such as surprises in gasoline prices, whereas manufacturers choose MSRP once each year; using MSRP can lead to biased estimates for WTP (Langer and Miller, 2013).

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. The vehicle aggregation corresponds closely to the choice set that consumers face (just as in the literature, I do not have sufficient data to construct individual-specific choice sets). For example, the data distinguish all-wheel drive and front-wheel drive versions and between the base and sport trims of a model. The vehicle disaggregation also aids the demand estimation (see Section 5).

I supplement the MaritzCX data with data from IHS and the Consumer Expenditure Survey (CEX) to obtain a regionally representative sample of households. 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. I match the MaritzCX data with IHS data on new registrations 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 IHS and CEX data to weight MaritzCX observations and match the distributions of new registrations across vehicles, regions, and

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4I 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.
demographic groups.

I obtain vehicle attributes from Wards and EPA, which I merge to the Maritz data by vehicle and year. The Wards and EPA data include transaction price, fuel economy, electricity consumption per mile, horsepower, weight, wheelbase, width, and MSRP. I aggregate the household data by vehicle, region, demographic group, and year using the weights constructed from IHS and CEX. 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 supplement the data with plug-ins that have entered the market since 2018 and vehicles that manufacturers intend to introduce by 2023. For those 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 data used for the computational model estimation and simulations and some background on plug-in sales over time and across demographic groups. In Table 1, observations are by vehicle, demographic group, region, and year, and the sample shows extensive variation in vehicle attributes.

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5For the small number of missing values for vehicle attributes, values are imputed using data from Cars.com.
Table 1: Summary Statistics for Demand Data Set (2010–2018)

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

Notes: Observations are weighted by sales. The data include 647,440 observations.

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 EVs by year. Hybrids represent about 3 percent of sales through 2014 and decline to about 2 percent by 2018. Plug-in and EV shares increase steadily and at about the same rate as one another between 2010 and 2017. In 2018, the EV 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 plug-in 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 EV increases by income. A possible interpretation of this pattern is that many hybrid buyers are interested in the fuel cost savings, whereas the plug-in 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 EVs on average. For context, the average transaction price across all vehicles is about $35,000, indicating that EVs 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 EVs, as they have larger battery packs. Another factor is that many EV models compete with luxury rather than midlevel vehicles and offer features common in luxury vehicles such as advanced safety technologies and automated driving features.
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-ins and EVs are about 10 times higher in California than in non-ZEV states. The ZEV program may explain this difference, but the figure indicates that consumer preferences also play a role. The ZEV program does not incentivize hybrid sales, 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 plug-ins are still higher in California.

Figure 5 shows the increasing supply of plug-ins over time. The numbers of available plug-in hybrids and EVs increased steadily (some plug-in hybrids have exited, such as the...
RAV4). By 2018, the number of plug-ins 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 plug-ins.

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 plug-in 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 plug-ins that are worth up to $7,500 per vehicle. The credit is higher for plug-ins 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.6

Because the subsidy is a tax credit, a household must have sufficient federal tax liability to claim the credit. For a lease, the manufacturer can claim the credit. In the demand estimation and policy simulations, I assume all households purchasing EVs qualify for the full credit. This assumption is reasonable given the typical income of EV buyers, discussed in the previous section. An equivalent assumption is that the credit is refundable. In 2021, Congress considered making the credit refundable, increasing the credit, and eliminating the sales threshold.
Figure 6 provides anecdotal evidence that subsidies have had a large effect on sales. The figure plots the logs of quarterly registrations of new EVs in Georgia and other states. In July of 2015, Georgia unexpectedly eliminated a $5,000 subsidy for EVs, and new registrations immediately dropped by about two-thirds; new registrations in other states were unchanged. Of course, this difference does not establish causality, but for context and 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)).

The ZEV program requires manufacturers to achieve targets for plug-in market shares. Since 1990, California has implemented the program, which has changed form several times (see Leard and McConnell (2019) for an overview of the program). 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 plug-in sold, which depends on its range; an EV can earn up to four credits. Each year, a manufacturer must hold credits in proportion to its total sales. The credit requirement increases through 2025, when a manufacturer must have credits equal to 22 percent of its vehicle sales. For example, if a hypothetical manufacturer sells 100,000 vehicles in 2025 and each of its EVs earns two credits (which corresponds to an all-electric range of 150 miles), it could comply by selling 11,000 plug-ins ($11,000 \times 2 / 100,000 = 0.22$).\footnote{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}
The EPA and Department of Transportation (DOT) jointly impose national standards for new vehicles. The EPA sets standards for GHG emissions, and DOT sets standards for fuel economy. 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 area defined by the four wheels; I use the term requirement to refer to the target for a specific vehicle and the term standard to refer 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.

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 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 plug-ins). The blue circles show the 2025 requirements, which are about 30 percent higher than for 2018, on average.

\[ \text{example from the text, the manufacturer would exceed the minimum requirement because its EVs earn two credits per vehicle and so the credits account for 22 percent of sales. This constraint does not bind in the scenarios modeled later in the paper.} \]
3.2. Framework for Policy Interactions

This subsection discusses qualitatively how plug-in vehicle 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.\(^8\) Credit demand is proportional to total vehicle sales, and credit supply increases with plug-in sales. The credit price, $\lambda_Z$, balances aggregate credit demand and aggregate credit supply. The manufacturer’s profit maximization problem is

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

$$\left( p_z - mc_z + \lambda_Z (c_z - R) \right) \frac{\partial q_z}{\partial p_z} + q_z + \left( p_n - mc_n - \lambda_Z R \right) \frac{\partial q_n}{\partial p_z} = 0$$  \hspace{1cm} (2)$$

\(^8\)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 simplicity and in the computational model for tractability.
The first-order condition for the non-ZEV price is

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

(3)

Because \(c_j > R\), the ZEV is implicitly subsidized, meaning that selling an additional unit allows the manufacturer to sell excess credits. Equation (2) shows that this subsidy 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 introduces an implicit tax on the non-ZEV, causing the manufacturer to increase \(p_n\) below the price it would choose if \(\lambda_Z = 0\).

Consider the effect of a subsidy to ZEV purchases on profit-maximizing vehicle prices. The subsidy is offered to consumers who purchase ZEVs, increasing their demand for ZEVs. If ZEV demand increases and \(\lambda_Z\) does not change, an excess supply of ZEV credits exists, causing \(\lambda_Z\) to decrease. According to these first-order conditions, a decrease of \(\lambda_Z\) causes the manufacturer to increase \(p_z\) and decrease \(p_n\). As all other manufacturers would respond similarly, the decrease in \(\lambda_Z\) 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 vehicle prices. Second, the subsidy benefits non-ZEV buyers by reducing the prices of those vehicles. Consequently, consumer welfare changes depend on price changes for the ZEV and non-ZEV consumers.

Next, I turn to the interaction between a subsidy and fuel economy standard. I make two assumptions to simplify the discussion, which are relaxed in the next section. 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.

Fuel economy credits can be traded at zero cost.\(^{10}\) The equilibrium credit price is \(\lambda_M\).

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

\(^9\)In this discussion, I assume that cross-price demand elasticities are sufficiently small that they can be ignored. This assumption is consistent with the demand estimates.

\(^{10}\)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.
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 ($m_j$) 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 vehicles with high fuel economy and reduces prices of other vehicles, raising welfare for consumers of those vehicles.

Leard, Linn, and Springel (2019) analyze the effect of fuel economy standards on income groups and find that the standards impose larger costs on high-income groups than low-income groups. Section 3 showed that a subsidy reduces the fuel economy credit price. Consequently, the results in Leard, Linn, and Springel (2019) imply that the interaction of the subsidy with the standards disproportionately benefits high-income consumers. Likewise, the subsidy reduces the ZEV credit price, which benefits consumers of non-ZEVs. Thus overall equity of a subsidy depends on these policy interactions.

4 Equilibrium Model

This section describes an equilibrium model that relaxes many of the assumptions from Section 3. In the model, vehicle prices, fuel economy, and entry are endogenous and manufacturers face both ZEV and fuel economy standards. Consumers are differentiated by demographic groups.

4.1. Demand

A market is a model year $t$ and region $r$, with three regions: California, other ZEV states, and non-ZEV states (regions are defined to facilitate modeling the ZEV program). 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 represents 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:
\[ u_{ij} = \alpha_{gr} p_{jr} + \sum_k x_{jk} \beta_{gkr} + \xi_{jr} + \epsilon_{ij} \]  

(4)

where \( \alpha_{gr} \) is the sensitivity of utility to price, \( x_{jkr} \) is the value of attribute \( k \) in region \( r \), \( \beta_{gkr} \) is the sensitivity of utility for group \( g \) to attribute \( k \) in region \( r \), \( \xi_{jr} \) is the utility from unobserved vehicle attributes, and \( \epsilon_{ij} \) is an idiosyncratic preference shock. Note that the price and attribute parameters, \( \alpha_{gr} \) and \( \beta_{gkr} \), vary across regions and demographic groups. Equation (4) distinguishes between the vehicle attributes \( x_{jk} \) that are observed in the data, and the attributes that are unobserved, \( \xi_{jr} \).

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, \( \xi_{jr} \), 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 and other observed 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 plug-in subsidies, because variation in estimated preference parameters translate directly to welfare changes across groups.

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

\[ \ln(s_{gjr}) - \ln(s_{g0r}) = \alpha_{gr} p_{jr} + \sum_k x_{jk} \beta_{gkr} + \delta_{jr} + \nu_{gjr} \]  

(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 market share of the outside option. The right-hand side includes the price, observed attributes \( x_{jk} \), vehicle–region interactions \( \delta_{jr} \), and a mean-zero error term \( \nu_{gjr} \). Note that the vehicle–region interactions are the sum of the mean utilities for the unobserved attributes (\( \xi_{jr} \)) and the utility of the observed attributes for the base demographic group.
4.2. Supply: Vehicle Price and Fuel Economy Choices

This subsection and the next present the supply side of the model. Each model year \( t \), a manufacturer first decides whether to introduce one or more new plug-ins and then chooses prices and fuel economy of all of its vehicles. I discuss 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 profit maximization problem is

\[
\max_{p_{jr}, m_{jr}, T_{n(j)}} \sum_{j \in J_f} \sum_r \sum_g [(p_{jr} - m_{cj}) + \lambda_{Z,r}(c_{jr} - R_r) + \lambda_M(\frac{1}{m_j} - \frac{1}{M_j})]s_{jgr}Q_{gr} - F(T_{n(j)}) \tag{6}
\]

where:

\[
\ln(m_{cj}) = \ln(m_{cj0}) + \gamma T_{n(j)} \tag{7}
\]

\[
\ln(m_j) = \ln(m_{j0}) + T_{n(j)} \tag{8}
\]

where \( m_j \) is fuel economy, \( m_{cj} \) 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 \( \gamma \). 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 \( \gamma \) percent.

The first-order condition for vehicle price is

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

As discussed in Section (3), an increase in the ZEV credit price causes prices of plug-ins to fall and prices of other vehicles to increase. An increase in the fuel economy credit price causes the manufacturer to raise (reduce) prices of vehicles with fuel economy below
(above) 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. Compared to an equilibrium without a subsidy, if a subsidy marginally increases ZEV sales and reduces non-ZEV sales, profits decrease because of the different markups (i.e., assuming changes in markups are small).

Because the subsidies I analyze have small effects on fuel economy and technology, the appendix discusses manufacturer choices of those attributes. Note that 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.

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 plug-ins. 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, so I limit modeling to siblings.

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.

Prior to entry, the manufacturer has perfect foresight about the potential entrant’s profits net of fixed entry costs: that is, no uncertainty exists regarding its marginal costs and mean utility $\xi_{jr}$, as well as the corresponding costs and mean utilities and entry decisions of all other vehicles in the market. Supporting this assumption is that the manufacturer can estimate $\xi_{jr}$ using data on the corresponding gasoline sibling.\footnote{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.}

The manufacturer can introduce at most one sibling in each model year. This assumption is for computational simplicity, but it reasonably approximates the decisionmaking process during the period for which I have data (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 profits during the entry year to entry costs. The firm introduces the plug-in 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.

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

\[
\frac{\pi_j^e}{C_j^e} \geq r
\]  \hspace{1cm} (10)

where \(\pi_j^e\) 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, \(\eta_j\), and rearranging the equation yields the following inequality that must hold if the firm decides to introduce the vehicle:

\[
\frac{\pi_j^e}{r} \geq C_j^e + \eta_j
\]  \hspace{1cm} (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

\[
P_{jt} = \frac{1}{1 + \exp\left(\frac{\pi_j^e}{r} - C_j^e\right)}
\]  \hspace{1cm} (12)

This probability holds for each potential entrant in each model year \(t\). Equation (12) shows that an increase in \(\pi_j^e\) increases the probability of actual market entry.

5 Estimation

This section describes estimation of the preference parameters, marginal costs, ZEV and fuel economy credit prices, and entry costs.
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 stages, the first of which includes estimation of equation (5). The key parameters to be estimated are $\beta_{gkr}$—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 $\delta_{jr}$, 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. Note 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 EVs, I use the regional price of electricity multiplied by the electricity consumption per mile. For plug-in hybrid EVs, 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, the number of engine cylinders, 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, some demographic groups may have higher demand than others for luxury vehicles with large engines or all-wheel drive. 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.

I estimate \( \delta_{jr} \) by including a full set of vehicle-region-model year interactions. Leard, Linn, and Springel (2019) show that the preferences for the base group can be recovered in a second stage that consists of regressing these estimated fixed effects on the attributes belonging to \( x_{jkr} \).

\[
\hat{\delta}_{jr} = \sum_k x_{jk} \beta_k + Z_{jr} \mu + \phi_{jr}
\]

where \( Z_{jr} \) include attributes absent from the first stage, \( \mu \) is a coefficient vector, and \( \phi_{jr} \) 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. Adding these variables in the second stage amounts to assuming that consumer preferences for them do not vary across demographic groups.\(^{12}\)

Observed attributes that firms choose (\( X_{jk} \)) may be correlated with unobserved vehicle attributes.\(^{13}\) 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 stage 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 stage 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.\(^{14}\) I use these instruments

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\(^{12}\)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 stage.

\(^{13}\)The \( \delta_{jr} \) control for unobserved vehicle attributes in the first stage, and the endogeneity of price does not bias the first-stage estimates.

\(^{14}\)Specifically, the instruments include means and standard deviations of weight, height, and length for
because firms change them less frequently than other attributes, making them less likely to be correlated with the error term in equation (13).

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 stage 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 $\beta_{hgr}$ is the marginal utility for hybrid power trains for group $g$ and region $r$. Equation (13) also includes the vehicle’s electric range (which is zero for non-plug-in vehicles).

### 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 steadily 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).

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

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 for hybrids or plug-in vehicles, where plug-ins include plug-in hybrid and all-electric vehicles and WTP is estimated relative to gasoline vehicles.

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 2.5 times more than higher-income households.
$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 fuel
costs and performance.

Panel C shows that the situation is considerably different for plug-ins. 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, uncertainty about the new
technology, and perceptions about the technology. The results suggest that even if plug-ins
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, large subsidies are
needed to induce many consumers to purchase plug-ins.\footnote{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-ins and EVs includes WTP for charging stations. This does not
affect the simulations, because the concentration of charging stations does not vary across scenarios.}

Figure 9 shows how the WTP for hybrids and plug-ins 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 plug-ins to be close substitutes to gasoline vehicles.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Figure9.png}
\caption{Willingness to Pay for Hybrids and Plug-Ins by Region}
\end{figure}

Table 2 provides an economic interpretation of the estimated own-price elasticities and

\footnote{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-ins and EVs includes WTP for charging stations. This does not affect the simulations, because the concentration of charging stations does not vary across scenarios.}
WTP for plug-in vehicles 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 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 equal to
$14,172. The other cells are constructed similarly.

Table 2: Marginal Subsidy Expenditure Per Additional Plug-in Vehicle

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

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 plug-in 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 is almost 50 percent lower for the lowest than the highest
group. This result follows from the greater price sensitivity of the lower-income groups.

5.2. Supply Parameters Except for Entry Costs

The supply-side parameters to be estimated include the marginal costs of each vehicle
\((m_{c,j0})\), ZEV and fuel economy credit prices \((\lambda_{Z,r} \text{ and } \lambda_{M})\), the effect of technology on
marginal costs in equation (7), the fixed cost of adding fuel-saving technology \((F(T_{n(j)}))\),
and entry costs. This subsection discusses estimation of all supply-side parameters aside
from entry costs, and the next subsection discusses entry costs.

5.2.1 Estimation Strategy

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. 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 an 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 across iterations is sufficiently small.

5.2.2 Estimation Results

The appendix discuss estimates of the elasticity of marginal costs to technology and technology fixed cost function parameter. Here, I focus on the estimated marginal costs and shadow prices.

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

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>General Motors</td>
<td>29,865</td>
<td>9,255</td>
<td>8,940</td>
</tr>
<tr>
<td>Toyota</td>
<td>26,971</td>
<td>8,968</td>
<td>8,822</td>
</tr>
<tr>
<td>Ford</td>
<td>27,680</td>
<td>8,909</td>
<td>8,656</td>
</tr>
<tr>
<td>Honda</td>
<td>23,669</td>
<td>8,304</td>
<td>8,415</td>
</tr>
<tr>
<td>Fiat Chrysler</td>
<td>25,648</td>
<td>8,891</td>
<td>8,405</td>
</tr>
<tr>
<td>Nissan</td>
<td>23,955</td>
<td>8,238</td>
<td>8,231</td>
</tr>
<tr>
<td>Hyundai</td>
<td>19,778</td>
<td>7,988</td>
<td>7,895</td>
</tr>
<tr>
<td>Volkswagen</td>
<td>28,935</td>
<td>9,109</td>
<td>8,941</td>
</tr>
<tr>
<td>Subaru</td>
<td>23,220</td>
<td>8,151</td>
<td>8,083</td>
</tr>
<tr>
<td>BMW</td>
<td>44,041</td>
<td>11,245</td>
<td>11,141</td>
</tr>
</tbody>
</table>

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 difference between the transaction price and marginal costs. The difference varies across firms 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 $\lambda_{Z,r}(c_j - R_r)$. An EV with 350-mile range receives four credits, and the estimated shadow price, $\lambda_{Z,r}$, in 2018 is about $2,200, so an EV with a 350-mile range has a shadow cost of about $-8,200.

The fuel economy shadow cost is proportional 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 $\lambda_M\left(\frac{1}{M_j} - \frac{1}{M'_j}\right)$, which is derived from the first-order condition for vehicle price. The estimate of $\lambda_M$ implies that increasing the average vehicle’s fuel economy by 1 percent yields $78 of additional revenue. That the middle and rightmost columns in Table 3 are similar indicates that, on average, the ZEV and fuel economy standards impose a small additional cost 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 $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 across firms.

Table 4 combines the demand and marginal cost estimation and previews the importance of pre-existing distortions caused by market power and other policies 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. Demand for plug-in hybrids has a similar average elasticity as gasoline vehicles (which include hybrid and flex-fuel, in addition to gasoline). Demand for EVs is considerably more price elastic than demand for the other fuel types.

<table>
<thead>
<tr>
<th>Table 4: Average Own-Price Elasticity of Demand and Markup by Fuel Type</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Own-price elasticity of demand</strong></td>
</tr>
<tr>
<td><strong>Gasoline</strong></td>
</tr>
<tr>
<td><strong>Markup (2018$)</strong></td>
</tr>
</tbody>
</table>

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. The second row of Table 4 shows markups by fuel type, where the markup is the difference between price and marginal costs. The average markup for EVs is effectively zero, and it is much smaller than the markups for the other two fuel types. The relatively elastic demand of EVs partially explains the difference in markups, but the ZEV and fuel economy standards also contribute, because they effectively subsidize EV sales. 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 of demand. Thus, demand elasticities and existing policies explain variation in markups across policies. In turn, the markup variation indicates that a hypothetical subsidy that marginally shifts sales from gasoline to plug-in hybrid or EVs would reduce manufacturer profits (again, assuming changes in markups are small), which previews results in the next section.

5.3. Entry Parameters

5.3.1 Estimation Strategy

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

$$-rC^e_j = C_0 + C_{d(j)} + C_{f(j)} + C_{r(j)} + C_{s(j)} + B_{b(j)}\theta + L_{F,f(j)}\phi$$  (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.

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

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

I arrive at an estimating equation by substituting equation (14) into equation (12) and replacing $\frac{1}{r}$ with the coefficient $\rho$:

---

16The 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.
\[
P_{jt} = \frac{1}{1 + \exp(\pi_j^e \theta + C_0 + C_{d(j)} + C_{f(j)} + C_{r(j)} + C_{s(j)} + B_{b,j} \theta + L_{F,f(j)} \phi)}
\]  

The estimation includes estimated profits, \(\pi_j^e\); 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 \(\pi_j^e\). For each year between 2010 and 2018, the set of potential entrants includes all the hybrid, plug-in hybrid, or electric siblings of a gasoline vehicle without an existing sibling and that entered before 2019. Note that 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, \(\pi_j^e\) 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.

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.\(^{17}\) 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 plug-ins 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 plug-ins, 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). The past entry variables demonstrate considerable variation, and about half of the potential entrants are siblings. The distribution of battery sizes is highly

\(^{17}\)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.
right-skewed; for example Tesla vehicles have battery capacity of roughly 80 kWh, which is well above the 90th percentile.

Table 5: Summary Statistics for Entry Data Set

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

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 EV 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 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

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

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.\(^\text{18}\)

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 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.

\(^{18}\)This estimate is likely a lower bound because it does not account for dynamics; lower entry reduces the variables measuring past entry, which further reduce entry.
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 the variables included in column 1 control for firm-level profit shocks that 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 latter two 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 reflect a period in which subsidies could plausibly affect entry but during which ZEV and fuel economy standards are exogenous.

The timing is as follows: policies are announced at the beginning of the year; firms make entry decisions; firms choose vehicle prices, fuel economy, and technology to maximize profits; and consumers choose vehicles to maximize subjective utility.

The set of vehicles at the start of the simulation year includes all vehicles in 2018, plug-ins that entered between 2018 and 2021, and plug-ins that are expected to enter by 2025. For example, the Audi e-tron entered the US market in 2019 and is included.\textsuperscript{19}

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\textsuperscript{19}In principle, I could include non-plug-ins 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.
for which the manufacturer has indicated the likely battery size, all-electric range, and retail price. I fill in other vehicle attributes from the announcements or using averages from existing siblings sold by the same manufacturer.

The set of potential entrants includes all-electric siblings of existing models that do not already have an electric sibling. 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 rather than all-electric sibling entrants would require modeling both options for each sibling and substantially increase computational time.

The definition of the set of potential entrants is consistent with recent entry patterns. With the obvious exception of Tesla, three-fourths of plug-ins and EVs introduced since 2018 have been siblings, and a majority of expected 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 EVs, I assume a range of 350 miles and a battery pack with a capacity of 120 kilowatt hours. 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.

The simulations require inputs on total market size, fuel prices, and policies. The total market size across regions and demographic groups is taken from the Energy Information Administration Annual Energy Outlook (AEO) 2021. I assume that the market size of each region and demographic group grows proportionately between 2018 and 2025. I also use electricity and gasoline prices from the AEO 2021.

Policy assumptions include the ZEV standards for 2025 and EPA and NHTSA GHG and fuel economy standards that were finalized in 2022. 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 also includes all state subsidies that were offered in 2020.

The data set and assumptions are the same for the central subsidy scenarios, except that an additional $1 billion are spent on subsidies for plug-ins and EVs. In the first

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20 Potential entrants may include models that include 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 no all-electric Volvo S60 is yet available, that version is included among the set of potential entrants.

21 That is, current subsidies continue through 2025. This is a reasonable assumption, as state subsidies depend on many factors and are difficult to forecast.
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 plug-in sales in 2018. In the third scenario, subsidies are provided only to EVs with prices below the median retail price of EVs sold in 2018, which accounted for 40 percent of plug-in sales in 2018. For comparison with the subsidies, I consider a feebate that imposes a tax on gasoline-powered vehicles and a subsidy to plug-ins. The gasoline vehicle tax is $150 per vehicle, and the plug-in subsidy is calibrated so that the feebate has the same net fiscal cost as the three other subsidy scenarios.

In all four scenarios, the subsidy is offered in addition to the tax credit and financed by a lump-sum tax on all new vehicle consumers. The appendix describes the algorithm used to find the new equilibriums.

6.2. Cost Effectiveness of Central Subsidy Scenarios

In presenting the results, I first discuss cost effectiveness and then consider distributional effects; this subsection discusses cost effectiveness of the central subsidy scenarios. Table 7 shows the results for the baseline scenario and three subsidy scenarios, with the first column showing the baseline. In the baseline scenario, plug-ins 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. 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 EV with 200-mile range receives 2.5 credits and an implicit subsidy of about $8,000.

22 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. The Biden administration has strengthened the standards for model years 2023–2026. In its analysis of the 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.
Table 7: Entry Parameter Estimation Results

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

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 plug-ins 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 plug-in sales. Welfare cost is the change in consumer welfare plus the change in manufacturer profits minus the subsidy expenditure, divided by the change in plug-in sales.

Columns 2–4 show the results for each subsidy scenario. In column 2, a uniform subsidy of about $1,800 per plug-in increases plug-in sales by about 13,000 units and increases private welfare. Entrants account for roughly one-half of the additional plug-in sales caused by the subsidies, indicating the importance of endogenizing entry.

The bottom two rows report the cost-effectiveness of the uniform subsidy. The 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 plug-ins without the subsidy—that is, adverse selection.

The bottom row shows welfare costs of $19,000 per additional plug-in. 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 gasoline vehicle exceeds that of selling one additional plug-in (see Table 4). Consequently, increasing sales of plug-ins at the expense of gasoline vehicles reduces private welfare.

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 subsidy is about twice the uniform subsidy in column 2, and the sales increase is about 40 percent larger than in column 2. 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). The greater effectiveness of the income-based subsidy than the uniform subsidy is consistent with Sheldon and Dua (2019) and Xing, Leard, and Li (2021).

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

Column 5 indicates that the feebate has the largest effect on plug-in sales and is the most cost-effective of the four policies because by simultaneously taxing gasoline vehicles and subsidizing plug-ins, the tax revenue enables larger subsidies for a fixed fiscal cost.

6.3. Cost Effectiveness of Other Scenarios

This subsection discusses results from three other scenarios: exogenous ZEV and fuel economy credit prices; no electric vehicle entry; and low battery costs. To illustrate the role of policy interactions in determining the subsidies’ welfare costs, I consider scenarios in which the fuel economy and ZEV shadow prices are exogenous. Table 8 shows the aggregate outcomes to compare with Table 7.

Table 8: Comparison of Subsidies with Exogenous ZEV and Fuel Economy Credit Prices

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

Note: The table is constructed similarly to Table 7, except that the ZEV and fuel economy credit prices are exogenous in the baseline and subsidy scenarios.

Subsidies are at least eight times more effective in these scenarios than in those where the credit prices were endogenous. This comparison illustrates that ignoring the interaction of the subsidies with the other policies vastly overstates the cost-effectiveness of the subsidies.

As discussed in the introduction, the literature on green product subsidies 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 estimated future market shares of plug-ins in the baseline that does not include the additional subsidies. In turn, lower baseline market shares reduces the share of subsidy expenditure that is claimed by consumers who would have purchased plug-ins without the subsidy. On the other hand, subsidies may induce entry and increase plug-in sales, and ignoring entry would underestimate the sales increase. Table 7 reports the effects of the subsidies assuming no
entry and the set of vehicles in the market includes only those that belonged to the market in 2018, entrants between 2018 and 2021, and announced entrants.

Table 9: Comparison of Plug-In Subsidies Without Entry

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>Uniform subsidy</th>
<th>Subsidy to two lowest income groups</th>
<th>Subsidy to low-price plug-in vehicles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plug-in vehicle sales</td>
<td>440,977</td>
<td>470,567</td>
<td>516,184</td>
<td>497,016</td>
</tr>
<tr>
<td>Fuel economy credit price (2018$ per 1% mpg increase)</td>
<td>85</td>
<td>82</td>
<td>78</td>
<td>81</td>
</tr>
<tr>
<td>ZEV credit price (2018$ per credit)</td>
<td>5,059</td>
<td>4,489</td>
<td>3,826</td>
<td>5,958</td>
</tr>
<tr>
<td>Fiscal cost (2018$ per vehicle)</td>
<td>33,794</td>
<td>33,794</td>
<td>13,297</td>
<td>17,845</td>
</tr>
</tbody>
</table>

Note: The table is constructed similarly to Table 7 but with no entry in the baseline or policy counterfactuals.

With no entry, baseline plug-in sales are substantially lower than in Table 9, which has entry: 441,000 units rather than 529,000 units. Because fiscal costs are held constant in these scenarios with and without entry, in the scenarios without entry, a lower proportion of the subsidy goes to consumers who purchase plug-ins in the baseline scenario. The lower adverse selection reduces the average fiscal costs per plug-in, particularly for the uniform and retail price-based subsidies. That is, the lower adverse selection outweighs the absence of the entry response. Consequently, ignoring entry overstates effectiveness of the 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 Plug-In Subsidies Using 2030 Battery Costs

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

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
plug-in sales are higher. On the other hand, lower battery costs could increase the marginal effects of the subsidies on plug-in 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 plug-in 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 targeting the subsidy to reduce the adverse selection.²³

6.4. Distributional Effects of Subsidies

This subsection discusses the distributional effects of the central subsidies. 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, pass-through of the subsidy to equilibrium plug-in vehicle prices is likely to be greater for vehicles purchased by high-income consumers than purchased by low-income consumers since the demand of the former group is less sensitive to prices (Weyl and Fabinger, 2013). The greater pass-through for vehicles purchased by high-income consumers increases progressivity of the subsidy. Third, interactions with ZEV standards increases progressivity. The ZEV standards increase prices of gasoline vehicles and decrease prices of plug-in vehicles, and gasoline vehicles represent a larger share of total vehicle purchases by low-income than high-income consumers. Because the plug-in vehicle subsidies reduce ZEV credit prices, the interaction with the ZEV requirement increases progressivity. Finally, the subsidies interact with fuel economy standards. The standards tend to be progressive (Leard, Linn, and Springel, 2019), and because the plug-in vehicle subsidy reduces fuel economy credit prices, this interaction makes the subsidy less progressive. 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 plug-in vehicles and claim the subsidy than low-income consumers. However, the differential pass-through rates and

²³Because of interactions with the ZEV and fuel economy standards, the low-price subsidy reduces total plug-in vehicle sales. This surprising result arises from the fact that 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.
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 8. 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, average pass-through is nearly complete for vehicles purchased by the highest income group, meaning that the sales-weighted average price of plug-in vehicles 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), who show that full pass-through is possible in imperfectly competitive markets given sufficient curvature of demand curves; this condition is satisfied for the highest income group.

Table 11: Effects of Plug-In Policies by Income Group

<table>
<thead>
<tr>
<th>Uniform subsidy</th>
<th>Subsidy to two lowest income groups</th>
<th>Subsidy to low-price plug-in vehicles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Changes relative to baseline, 2018$ per household</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lowest income quintile</td>
<td>57</td>
<td>117</td>
</tr>
<tr>
<td>Second income quintile</td>
<td>53</td>
<td>112</td>
</tr>
<tr>
<td>Third income quintile</td>
<td>38</td>
<td>-32</td>
</tr>
<tr>
<td>Fourth income quintile</td>
<td>23</td>
<td>-94</td>
</tr>
<tr>
<td>Highest income quintile</td>
<td>-33</td>
<td>-296</td>
</tr>
</tbody>
</table>
Table 12: Welfare Effects of EV Subsidies by Income Group with Exogenous ZEV and Fuel Economy Credit Prices

<table>
<thead>
<tr>
<th></th>
<th>Uniform subsidy</th>
<th>Subsidy to two lowest income groups</th>
<th>Subsidy to low-price plug-in vehicles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lowest income quintile</td>
<td>75</td>
<td>125</td>
<td>81</td>
</tr>
<tr>
<td>Second income quintile</td>
<td>32</td>
<td>89</td>
<td>40</td>
</tr>
<tr>
<td>Third income quintile</td>
<td>10</td>
<td>-42</td>
<td>22</td>
</tr>
<tr>
<td>Fourth income quintile</td>
<td>14</td>
<td>-50</td>
<td>26</td>
</tr>
<tr>
<td>Highest income quintile</td>
<td>4</td>
<td>-36</td>
<td>34</td>
</tr>
</tbody>
</table>

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 also 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 plug-in vehicle sales, which creates a stronger interaction with the ZEV standards than the uniform subsidy. Recalling that this interaction strengthens the progressivity of the subsidy shows, 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 plug-ins will likely continue to play a major role in accelerating the transition from gasoline to electric passenger vehicles. To date, most plug-ins 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 plug-ins in the United States. I use a computational model that endogenizes plug-in 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 plug-in sales than those that are uniform across households or depend on retail prices. The greater price responsiveness of low-income households explains this result. Moreover, combining subsidies with taxes on gasoline-powered vehicles is more effective than subsidies alone.
Interactions with ZEV requirements and GHG standards influence the efficacy and distributional effects of the subsidies. The ZEV requirements affect plug-in 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 plug-in sales in those states. This reduces their efficacy. Interactions with the ZEV standards strengthens the progressivity of the subsidies. Intuitively, the standards are regressive, and the subsidies effectively reduce the shadow price of the standards, benefiting low-income more than high-income households. This is an important consideration for policy makers considering offering subsidies in addition to PEV standards, such as in California and other ZEV states.

Throughout this paper, I have assumed that the ZEV and fuel economy requirements are exogenous to subsidies. Because requirements for both programs are set several years in advance, this assumption is reasonable for the short term. For example, if Congress increases the 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 may attenuate. For example, if the plug-in subsidies reduce the fuel economy shadow price, EPA and DOT could strengthen the standards for the late 2020s, which would increase the shadow price. Relaxing this assumption would require modeling the political economy of choosing these policies, which future research might explore.
References


Appendix

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 data from IHS Markit 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 IHS 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 IHS 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:

\[
\sum_{l \in J} \sum_{r} \sum_{g} (p_{lr} - mc_{l} + \lambda_{Z,r}(c_{lr} - R_{r}) + \lambda_{M}(\frac{1}{m_{l}} - \frac{1}{M_{l}})) \left( \frac{\partial s_{lgr}}{\partial m_{j}} \frac{\partial m_{j}}{\partial T_{n(j)}} \right) Q_{gr} - \sum_{r} \sum_{g} \frac{\partial mc_{j}}{\partial T_{n(j)}} s_{lgr} Q_{gr} - F'(T_{n(j)}) = 0
\]

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).

Estimation of Additional Supply Parameters

This section 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, $\gamma$ 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 $F(T_{n(j)})$ is a quadratic function: $F(T_{n(j)}) = \sigma T_{n(j)}^2$. I compute terms in equation (16) and estimate $\sigma$ 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

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.