# Emissions Standards and Electric Vehicle Targets for Passenger Vehicles

Joshua Linn*

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**Abstract**

This paper analyzes welfare and distributional effects of nested US policies affecting plug-in vehicles: state-level zero-emission vehicle (ZEV) standards and national fuel economy and greenhouse gas (GHG) standards for passenger vehicles. I use a computational model of the passenger vehicle market that endogenizes manufacturer choices of prices, technology, fuel economy, and horsepower and incorporates the timing of regulatory decisions and pre-existing distortions caused by market power and consumer undervaluation of fuel economy. Ignoring the influence of the 2022 ZEV standards on fuel economy and GHG standards, ZEV standards would appear to impose high costs without reducing emissions. However, accounting for such influence reveals that ZEV standards reduced GHG emissions at modest costs.

*University of Maryland and Resources for the Future. Email: linn@umd.edu. I am grateful to the Alfred P. Sloan Foundation and Smith Richardson Foundation for funding this research. Kevin Ankney provided excellent research assistance on the data construction and Benjamin Leard and Katalin Springel collaborated in creating a prior version of the equilibrium model. I thank Raphael Calel, Carolyn Fischer, Art Fraas, John Graham, Mark Jacobsen, and participants at the Association for Public Policy Analysis and Management Fall Research Conference and the American Economic Association Annual Meetings for helpful comments.

# 1 Introduction

In the United States, state-level electric vehicle targets are nested within federal fuel economy and greenhouse gas (GHG) standards. Since the 1970s, the US Department of Transportation (DOT) has regulated fuel economy of new passenger vehicles, and since 2011, the US Environmental Protection Agency (EPA) has regulated their GHG emissions. Current EPA and DOT standards apply to vehicles sold through 2026. California also implements the zero-emission vehicle (ZEV) program, which essentially sets a minimum plug-in vehicle market share and which 14 other states—mostly in the northeast and mid-Atlantic—have adopted. ZEV standards apply to vehicles sold through 2025, and California recently required that all new vehicles be plug-in or fuel cell by 2035. The program covers one-third of all new vehicle sales in the US and nearly three-fourths of plug-in sales; it is likely to continue coexisting with federal standards and play a major role in the expected transition from gasoline to electric vehicles.

According to standard theory of nested policies, it appears inefficient for states to adopt ZEV standards given federal GHG and fuel economy standards. The GHG standards determine the average emissions rate of new vehicles. Compared to a hypothetical with national GHG standards but no ZEV standards, the ZEV standards force more plug-in vehicles into the market. As long as federal standards remain binding, the additional plug-ins do not affect the average GHG emissions rate of new vehicles. The situation is a form of emissions leakage for the ZEV program, because emissions reductions in ZEV states are offset by increases in other states, leaving the national total unchanged. The ZEV standards increase the total cost of achieving the federal GHG standards by imposing an additional constraint on manufacturers.[1] In short, the situation appears to be an example of the inefficiency of overlapping regulations that share the objective of reducing GHG emissions (Tinbergen, 1952).[2]

Despite the prominence of the ZEV program and its role in accelerating the transition from gasoline to electric vehicles, economics literature on it is sparse. This paper challenges the standard view of its inefficiency by considering the timing of regulatory decisions and incorporating pre-existing distortions caused by market power and consumer undervalua-

[1] When assessing compliance, EPA does not include GHG emissions from electricity generation to charge EV batteries. Ignoring these emissions means that tighter ZEV standards can *increase* GHG emissions after accounting for electricity emissions (Jenn, Azevedo, and Michalek, 2016).

[2] The ZEV standards are also motivated by reducing local air pollution. Holland et al. (2016) find that EVs in California reduce local air pollution compared to typical gasoline-powered vehicles, and Fowlie, Knittel, and Wolfram (2012) argue that tailpipe standards for nitrogen oxides are inefficiently weak. ZEV standards may not be the efficient policy to reduce local air pollution from passenger vehicles, because (among other reasons) they regulate only new vehicles (Gruenspecht, 1982).

tion of fuel economy. The paper provides the first retrospective estimates of the welfare and distributional effects of the ZEV program and illustrates the importance of accounting for pre-existing distortions and the timing of the regulatory process.

The standard view of overlapping regulations is overly simplified in this context for two reasons. First, California chooses ZEV standards before EPA and DOT set federal GHG and fuel economy standards. For example, in 2011, California set targets for 2012–2025, ten years before EPA and DOT set final standards for 2025.[3] Moreover, EPA and DOT consider ZEV standards to be part of the baseline against which they evaluate benefits and costs of changing standards. Consequently, tighter ZEV standards reduce the incremental costs of EPA and DOT standards, which could cause them to be stricter.[4]

The second reason this view is overly simplified is that it ignores market failures of imperfect competition and consumer behavior. The new vehicle market contains differentiated products and is fairly concentrated; the seven top-selling manufacturers account for about 90 percent of sales. Equilibrium markups over marginal costs depend on consumer price sensitivity, and markups may vary between plug-in and gasoline vehicles. Because ZEV, fuel economy, and GHG standards affect market shares and equilibrium markups, in principle, ZEV standards could increase private welfare by reducing distortions in gasoline and plug-in vehicle sales caused by market power. Thus, the standard view does not incorporate economics of regulating differentiated product markets that contain distortions caused by market power (Weyl and Fabinger, 2013).

Moreover, consumers may choose fewer plug-ins than is privately optimal. If consumers choose between two hypothetical vehicles that are identical except that one has lower fuel costs, “undervaluation“ refers to a situation in which consumers are willing to pay less than $1 for a dollar of future fuel cost savings. Literature has focused on estimating undervaluation for gasoline vehicles, finding mixed evidence (e.g., Busse, Knittel, and Zettelmeyer (2013) and Gillingham, Houde, and Benthem (2021)). Undervaluation (that is, an internality) provides manufacturers too little incentive to increase fuel economy and offer plug-ins (which have lower fuel costs than gasoline vehicles), and fuel economy standards can be more cost-effective than a carbon price if the undervaluation is sufficiently high (Allcott and Greenstone, 2012). By extension, if undervaluation for plug-ins is sufficiently high, ZEV standards could increase private welfare.[5]

[3] More specifically, in 2012, EPA adopted GHG standards through 2025. However, federal law prevents DOT from setting standards so far in advance. Partly because of changes in the executive branch's political party, the two agencies set standards for 2025 vehicles on four occasions: 2012, 2016, 2020, and 2021.

[4] More specifically, ZEV standards reduce incremental costs more than they reduce the incremental benefits of EPA and DOT standards.

[5] Demand spillovers strengthen this argument, such that consumer adoption of plug-ins in one period raises consumer demand for them in subsequent periods because of learning or network externalities with

In this context, I ask three questions: a) given pre-existing distortions, how ZEV and fuel economy standards affect social welfare; b) whether tighter ZEV standards cause EPA and DOT to tighten federal standards; and c) what the distribution of costs and benefits of ZEV standards are across manufacturers and demographic groups. To answer these questions, I employ an equilibrium model of the new vehicle market designed to endogenize the key margins along which manufacturer and consumer choices may respond to the policies. I estimate all supply and demand parameters from observed choices and simulate counterfactual policy scenarios to answer these questions.

I explain next how the model used in this paper builds on recent literature and meets these requirements. Consumers are assigned to mutually exclusive regions and demographic groups according to income, age, and urbanization. Consumers choose vehicles to maximize subjective utility, and preference parameters vary freely across demographic groups.

Vehicle manufacturers maximize profits by adopting fuel-saving technology and choosing fuel economy, horsepower, and prices subject to ZEV and federal standards. Modeling these choices follows Whitefoot, Fowlie, and Skerlos (2017), Leard, Linn, and Springel (2023), and Reynaert (2021). Specifically, fuel-saving technology allows the manufacturer to increase fuel economy without reducing horsepower. For example, the manufacturer can replace a six-speed transmission with a seven-speed transmission that allows the engine to operate more efficiently. The manufacturer incurs a sunk cost of technology adoption to redesign and test the vehicle before beginning production; technology adoption increases marginal costs of producing the vehicle. The manufacturer can also retune the engine to trade off horsepower (and performance) for fuel economy, as in Whitefoot, Fowlie, and Skerlos (2017).

All model parameters are estimated based on observed consumer and manufacturer choices between 2010 and 2018. Demand estimation accounts for the endogeneity of vehicle prices, fuel economy, and horsepower, and I report substantial preference variation across demographic groups and regions. Consumers in ZEV states and high-income groups have relatively high willingness to pay for plug-ins. On average, consumers are willing to pay about $0.35 for $1 of fuel cost savings, indicating a substantial degree of undervaluation on average. After conditioning on income and region, I do not find evidence that undervaluation differs between gasoline and plug-in vehicles. This undervaluation causes manufacturers to invest less in raising fuel economy than is privately optimal (that

charging stations (Springel, 2021). This argument is strengthened further if tighter ZEV standards reduce plug-in costs because of learning-by-doing in battery or vehicle production. In principle, tighter ZEV standards would increase sales of electric vehicles, reducing both battery costs via learning by doing and the cost of achieving federal standards.

is, even putting aside the GHG externality).

Estimated marginal and sunk costs of technology adoption rationalize observed choices. The estimated effect of technology adoption on marginal costs implies that by the early 2010s, manufacturers had exhausted many low-cost fuel-saving opportunities. The fixed costs are plausible, implying sunk costs of $15 million for a 10 percent efficiency improvement.

I use the equilibrium model and estimated parameters to simulate a set of counterfactuals that analyze ZEV and federal standards in isolation and then the interactions of the two policies. Considering the ZEV standards first, I find that tightening them while holding fixed the stringency of the fuel economy and GHG standards increased plug-in sales at average welfare costs of at least $15,000 per vehicle. These costs increase with ZEV stringency because the standards exacerbate pre-existing distortions. Per-vehicle costs of ZEV standards are lower in scenarios with stringent fuel economy standards because those raise the costs of gasoline vehicles relative to plug-ins, reducing incremental costs of ZEV standards (Leard and McConnell (2020) demonstrate this theoretical possibility). This result highlights the importance of endogenous markups and pre-existing distortions in evaluating overlapping policies.

Turning to the welfare effects of stricter fuel economy standards, the standards tightened by 15 percent between 2016 and 2022. The tighter standards increased social welfare by $18 billion for vehicles produced in 2022. Fuel cost savings account for most of the welfare gains, which is consistent with ex ante predictions by EPA and NHTSA. I estimate smaller welfare gains than the agencies predicted largely because of higher estimated technology costs and forgone horsepower improvements (which the agencies ignore).[6]

Next, I ask whether ZEV standards cause EPA and DOT to adopt stricter standards.[7] The 2016 standards represent the baseline, and I estimate the effect of the ZEV standards on the welfare gains of 2022 standards relative to 2016 standards. Tightening ZEV standards increases welfare gains of 2022 fuel economy standards by $13 billion. Consequently,

[6]Leard, Linn, and Springel (2023) estimate welfare effects of 2012–2022 standards, rather than 2016–2022. As the text explains, there are some differences in model structure and parameter estimates between that paper and this one, but the model used in this paper yields similar welfare estimates for the 2012–2022 standards.

[7]As I discuss in Section 3, EPA and DOT may set standards based on multiple factors besides estimated social welfare, and it is not possible to assess definitively whether tighter ZEV standards cause tighter fuel economy and GHG standards. However, the higher the welfare gains of a particular level of standards (relative to a fixed baseline level), the more likely it is that EPA and DOT adopt those standards. Consequently, I focus on whether tighter ZEV standards cause larger welfare gains for tighter fuel economy and GHG standards. If the answer is yes, I conclude that tighter ZEV standards increase the likelihood that EPA and DOT adopt stricter standards. To simplify exposition, I write that tighter ZEV standards cause tighter fuel economy and GHG standards if they increase the net benefits of adopting more stringent fuel economy and GHG standards.

tighter ZEV standards reduce GHG emissions after accounting for the effects of the tighter ZEV standards on the fuel economy and GHG standards. Accounting for this effect implies modest welfare costs of the ZEV standards. For example, if tighter ZEV standards caused EPA and DOT to tighten fuel economy stringency by 15 percent, ZEV standards reduced emissions by \$50–\$100 per metric ton of $CO_2$. This range is comparable to the social cost of carbon (IWG, 2021) and lower than estimated costs of plug-in subsidies (e.g., Xing, Leard, and Li (2021)). Moreover, tightening ZEV standards increases social welfare after accounting for the greater stringency of tighter fuel economy and GHG standards, contradicting the standard view of overlapping regulations.

Finally, I assess the distributional effects of the policies across income groups. Both ZEV and fuel economy standards have small effects on manufacturer profits; consumers incur most of the costs of ZEV standards and receive most of the benefits of fuel economy standards. Similar to Leard, Linn, and Springel (2023), standards are progressive primarily because they reduce performance and higher-income households have relatively high valuation of performance.

Because high-income groups are more likely to buy plug-ins, and ZEV standards reduce equilibrium plug-in prices, ZEV standards are regressive. However, when considering the ZEV and fuel economy standards jointly, overall, the two policies are progressive. That is, for the range of policies considered, the progressivity of the fuel economy and GHG standards outweighs the regressivity of the ZEV standards.

Thus, I find that pre-existing distortions cause high costs of ZEV standards (due to market power) and low costs of fuel economy standards (due to consumer undervaluation). Accounting for the effect of ZEV standards on the stringency of fuel economy standards reduces the ZEV costs per emissions reduction.

This paper contributes to the literatures on passenger vehicle policies and more broadly to the literatures on regulating imperfectly competitive markets and overlapping policies. Armitage and Pinter (2022) compare the welfare effects of ZEV standards with a hypothetical feebate that simultaneously taxes gasoline vehicles and subsidizes plug-ins. Rather than comparing those policies, I estimate welfare effects of ZEV standards relative to no standards, which is relevant to states considering adopting California's 2035 standards. To my knowledge, this paper reports the first retrospective estimates of the welfare effects of ZEV standards.

The modeling in this paper builds on Leard, Linn, and Springel (2023), who estimate the welfare effects of the 2022 fuel economy standards at a fixed stringency of ZEV standards. From a modeling perspective, the main differences are that I endogenize both ZEV and fuel economy credit prices and model regional rather than national markets. Moreover, I allow preference parameters to vary across demographic groups for a more extensive set of vehicle attributes. Linn (2022) evaluates interactions among electric vehicle subsidies and ZEV and fuel economy standards; in this paper, subsidies are exogenous. Regarding the computational model, the main difference between this paper and Linn (2022) is that in this paper, fuel-saving technology and horsepower are endogenous.

The estimation of sunk costs of technology adoption builds on recent efforts to estimate sunk costs associated with improving product quality or introducing new products (e.g., Blonigen, Knittel, and Soderbery (2017) and Wollmann (2018)). Similar to other papers in this literature, estimated sunk costs rationalize observed technology choices.

Finally, the paper contributes to literature on the distributional and welfare effects of overlapping policies, including overlapping jurisdictions. Much of the literature focuses on instrument choice and emissions leakage across jurisdictions in homogeneous product markets (e.g., Fowlie, Reguant, and Ryan (2015)). In contrast, the ZEV program is more similar to a technology policy nested within a broader GHG policy, such as states in the US choosing renewable portfolio standards given the possibility of federal GHG policy for the electricity sector (Sovacool, 2008) or European countries subsidizing renewable energy sources given the European Union Emissions Trading System (Schafer (2019) and Landis and Heindl (2019)).

# 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) for 2010–2018. MaritzCX sends the survey to households that recently purchased new vehicles and sells the data to vehicle manufacturers, industry analysts, and researchers (the data are the same as in Linn (2022)). Each year, MaritzCX collects about 200,000 responses, with a response rate of 9 percent. The data include 1.5 million responses representing 1 percent of buyers.

Respondents report the transaction price of a vehicle, which excludes trade-in value and includes taxes, along with identifying information: model, trim, drive type (such as front-wheel drive), and power train specifications (engine size, transmission type, and fuel type). Respondents also report demographics, such as income, age, and zip code of residence.

The survey data are unusual among data sets used for demand estimation in that they include a large sample, transaction rather than retail prices, and household demographics.

Transaction prices differ substantially from the manufacturer's suggested retail price (MSRP). Manufacturers typically set MSRP up to one year in advance at the national level. Transaction prices may respond to short-term and regional variation in market conditions, such as gasoline price shocks (Langer and Miller, 2013). In the NVCS data, the average absolute difference between the transaction price and MSRP is about 10 percent and is correlated with income and region. Much of the vehicle demand literature (e.g., Busse, Knittel, and Zettelmeyer (2013)) imputes household demographics using data from the US Population Census (or similar sources), which assumes that new vehicle buyers are drawn randomly from an area, such as a Census tract. However, new vehicle buyers may have substantially different demographics from the overall population in an area.

I weight the NVCS observations using data from the Consumer Expenditure Survey (CEX) and registrations data. The appendix explains the weighting procedure designed to match the weighted distributions of sample responses to the CEX and registrations data distributions across vehicles, regions, and demographic groups. I define 20 demographic groups that include five income groups, two age groups, and two urbanization groups based on population density. These demographic groups parsimoniously explain a large share of cross-household purchase variation. Because of the CEX sample size, it is not possible to construct more than about 20 demographic groups. Three regions are defined to facilitate modeling the ZEV standards: California, other ZEV states, and non-ZEV states.

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 studies. A vehicle is defined by a unique model year, make, model, trim, fuel type, drive type, body style, and engine displacement, such as the 2018 Cadillac CT6 Luxury trim sedan with a 2-liter gasoline engine and rear-wheel drive. The vehicle aggregation corresponds closely to the choice set that consumers face. For example, the data distinguish between all-wheel and front-wheel drive versions and the base and premium trims of a model.

I obtain vehicle attributes from Wards and EPA, which I merge to the Maritz data by vehicle and year. The combined Wards and EPA data include MSRP, fuel economy, electricity consumption per mile, horsepower, weight, wheelbase, and width. I aggregate the household data by vehicle, region, demographic group, and year using the weights constructed from registrations and CEX data.

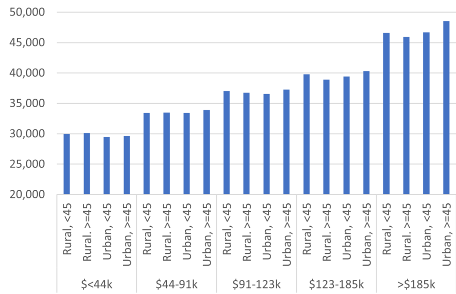
Fuel prices are from the EIA State Energy Data System. Vehicle and fuel prices are converted to 2018 dollars using the BLS Consumer Price Index. The final data set consists of vehicle prices and attributes for each demographic group (20 groups); vehicle (about 1,200 unique vehicles each year); region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

and year (2010–2018).

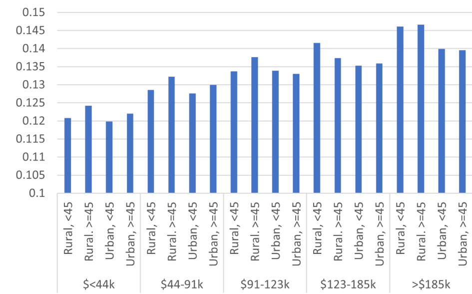
## 2.2. Summary Statistics

This subsection reports summary statistics of the main dataset and some background on plug-in sales. Figure 1 shows means of vehicle prices and attributes by demographic group. Appendix Table A1 provides numerical values of the means and standard deviations of the continuous variables.

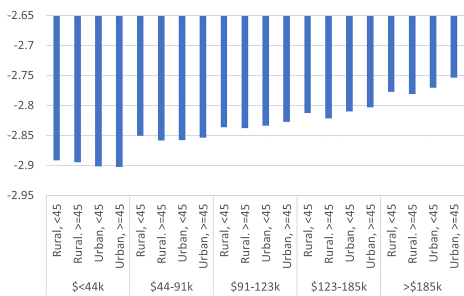
Figure 1: Means of Vehicle Attributes by Demographic Group



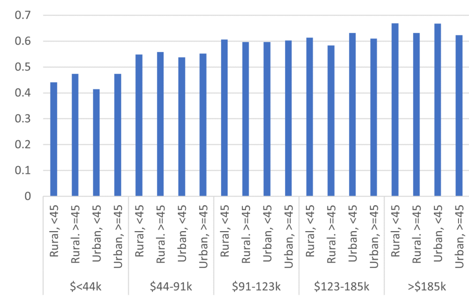

(a) Transaction price (2018$)



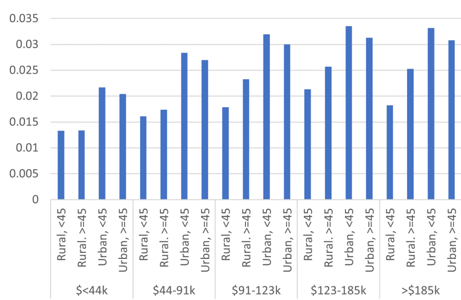

(b) Fuel costs (2018$ per mile)



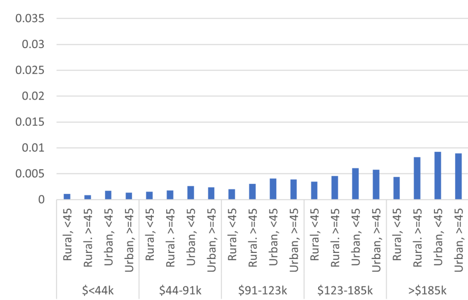

(c) Log (horsepower / weight)



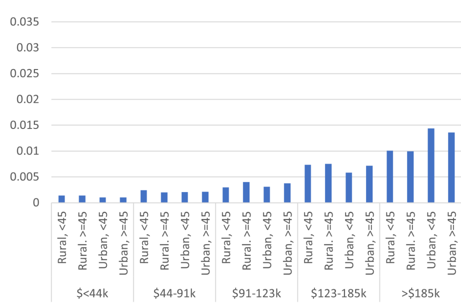

(d) Share of light trucks in total purchases



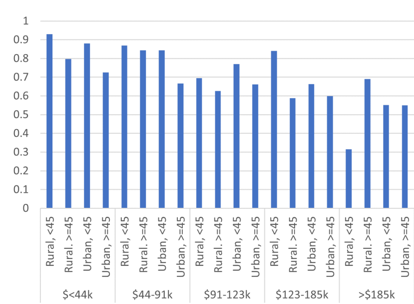

(e) Share of hybrids in total purchases




(f) Share of plug-in hybrids in total purchases




(g) Share of electrics in total purchases




(h) Share of used vehicles in total purchases

Notes: The figure shows the purchases-weighted mean attribute or market share for each demographic group. The sample includes all vehicles purchased, 2010–2018. Panel (c) shows the log of the ratio of the vehicle's horsepower to weight (pounds).

Average purchase prices vary more by income than by age and urbanization (panel (a)). The average household in the highest income group purchases vehicles that are about twice as expensive as vehicles purchased by the average household in the lowest income group. Within income groups, typically, average prices vary by a few percent across age or urbanization groups.

Fuel costs increase with income because high-income households tend to choose vehicles with relatively low fuel economy. Urban households obtain vehicles that have 2–4 percent lower fuel costs, which is explained by higher fuel economy.

The log of the ratio of horsepower and weight is the measure of performance used in this paper. This is a commonly used metric (Greene et al., 2018) and strongly correlated with the time needed to accelerate from rest to 60 miles per hour. Average performance increases by about 10 percent across the income groups, and, particularly among the higher-income groups, urban consumers typically buy higher-performance vehicles than do rural consumers.

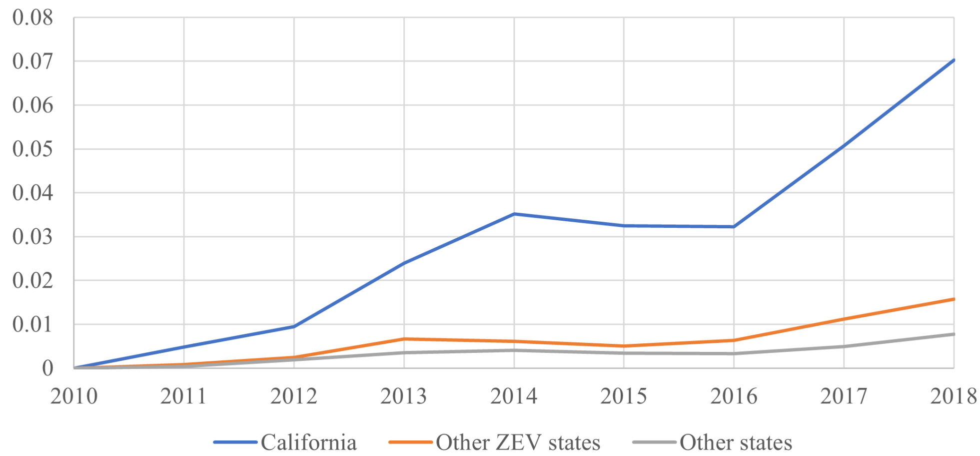
Rural households are more likely to obtain light trucks than are urban households, and the share of light trucks does not vary much across income groups. Income is correlated positively with shares of hybrid, plug-in hybrid, and electric vehicles. Urban consumers are more likely to obtain these power train types than are rural consumers.

Panel (h) shows that low-income consumers are more likely than high-income consumers to purchase used rather than new vehicles. Conditional on income, young and rural households are more likely to purchase used rather than new vehicles, which has implications for the distribution of welfare effects of ZEV and fuel economy standards across these demographic groups.

Thus, Figure 1 shows that sales-weighted vehicle attributes vary considerably across demographic groups. Overall, variation across income groups is greater than for age and urbanization groups, although shares of non-gasoline power trains vary considerably across urbanization and age groups. This extensive variation motivates the structure of the vehicle demand model, which allows consumer preferences to vary across groups.

Figure 2 shows how the combined market share of hybrids, plug-ins, and electrics varies over time and across regions. In all regions, it increased throughout the period, rising to a peak of about 7 percent for California, 2 percent for other ZEV states, and 1 percent in all other states.

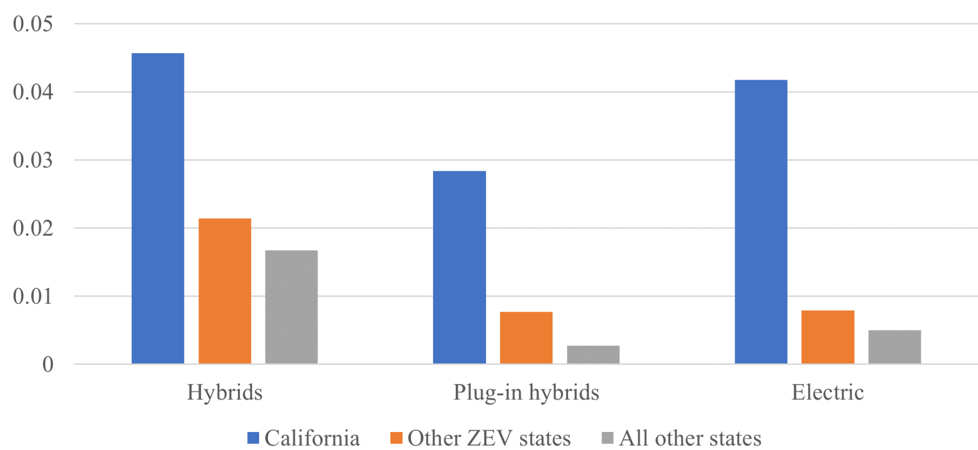
Figure 2: Combined Market Share of Plug-In Hybrids and Electric Vehicles by Region and Year




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

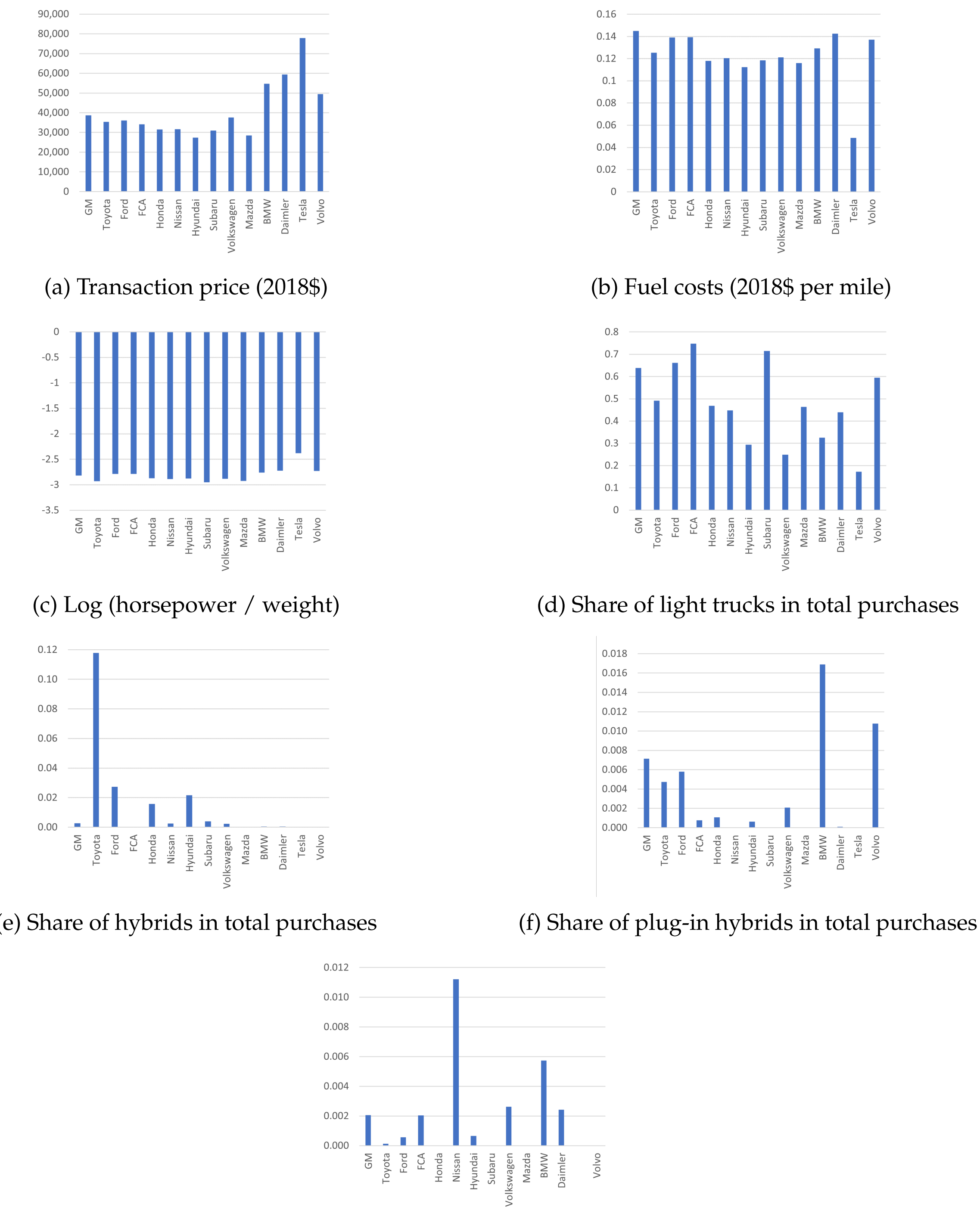
Figure 3 provides further detail on the regional variation of power train technologies. Market shares of hybrids, plug-ins, and electrics are higher in California. Note that in 2018, the ZEV program incentivized plug-ins and electrics but not hybrids, which indicates that consumer demand plays a role in the regional variation of 2018 market shares.

Figure 3: 2018 Market Shares of Hybrids, Plug-in Hybrids, and Electric Vehicles by Region




Turning to the supply side of the market, Figure 4 shows means of vehicle prices and attributes by firm. Appendix Table A2 provides numerical values of the means and standard deviations of the continuous variables.

Figure 4: Means of Vehicle Attributes by Firm




(a) Transaction price (2018$)

(b) Fuel costs (2018$ per mile)

(c) Log (horsepower / weight)

(d) Share of light trucks in total purchases

(e) Share of hybrids in total purchases

(f) Share of plug-in hybrids in total purchases

(g) Share of electrics in total purchases

Notes: The figure shows the purchases-weighted mean attribute or market share for each firm. The sample includes all vehicles purchased 2010–2018. Panel (g) omits Tesla, which has an electric vehicle market share of 1.

The figure indicates that manufacturers sell different types of vehicles. BMW, Mercedes, and Tesla sell expensive cars that have high performance (and low fuel costs, in the case of Tesla). Manufacturers also vary in their specialization in selling light trucks rather than cars; the light truck share for General Motors, Ford, Fiat-Chrysler, and Volvo are substantially higher than that of other manufacturers.

The extent to which the manufacturers sell hybrids, plug-ins, or electrics is also heterogenous (note that Tesla is not shown in panel (g) because it sells only electrics and has a market share of 1). The hybrid market share for Toyota is several times higher than that of any other company, but Toyota is not among the leading firms selling plug-ins or electrics. In contrast, Nissan has a high market share of electrics (primarily the Leaf) but sells few hybrids and no plug-ins. BMW is the only firm with relatively high shares of both both plug-ins and electrics. Given the technology variation across manufacturers, when modeling manufacturer responses to fuel economy and ZEV standards, it is important to allow for the possibility that they choose different compliance strategies.

# 3 Policy Framework

The first subsection provides background on the ZEV program and fuel economy and GHG standards. The second subsection contains a simple framework to explain how ZEV standards affect welfare costs of the fuel economy and GHG standards.

## 3.1. Policy Background

The ZEV program aims to reduce GHG emissions and improve local air quality. It requires manufacturers to achieve targets for plug-in market shares via a tradable performance standard (see Leard and McConnell (2019) for an overview of the program).

To approximate variation in electricity consumption across plug-ins, each plug-in earns manufacturer credits proportional to its all-electric range. For example, the 2022 Nissan Leaf, with a range of 149 miles, earns 1.99 credits, whereas the Tesla Model 3 (272-mile range) earns 3.22 credits (both calculations use the base rather than extended-range versions of the vehicles). Each year, a manufacturer must hold credits in proportion to its sales in California and other states participating in the program.

The credit requirement increases through 2025, when a manufacturer must have credits equal to 22 percent of its sales. That is, the ZEV program determines the ratio of credits to sales but not the market share of plug-ins. For example, a hypothetical manufacturer selling plug-ins that each earn 2 credits could meet the 22 percent requirement if those vehicles account for 11 percent of its sales. A different manufacturer selling plug-ins that each earn

1 credit could meet the 22 percent requirement if those vehicles account for 22 percent of its sales. Because vehicles are credited in accordance with their range, manufacturers can comply by increasing the range or sales of their plug-ins.[8]

In 2022, California set ZEV requirements for 2026–2035. Other states will decide whether to adopt them. Because many ZEV states have similar long-term objectives of transitioning from gasoline to electric vehicles, likely at least some of them will indeed follow suit; some non-ZEV states may adopt them as well.

The EPA sets standards for passenger vehicle GHG emissions, and DOT sets standards for fuel economy. For both cars and light trucks, the fuel economy and GHG requirements depend on the footprint (the area defined by the four wheels). In this paper, "requirement" refers to the target for a specific vehicle, and "standard" refers to the set of requirements for all vehicles. The GHG requirements, in grams of CO2 per mile, are more strict for cars than light trucks and for smaller than larger vehicles. Fuel economy is related inversely with GHG emissions for gasoline vehicles, and DOT sets stricter fuel economy requirements for cars than light trucks and smaller than larger vehicles.

The EPA GHG standard for each manufacturer is the sales-weighted average GHG requirement of its vehicles. Because GHG requirements depend on class (car or light truck) and footprint, manufacturers selling more cars and more small vehicles must achieve lower average GHG emissions rates than other manufacturers.

The DOT fuel economy standard is the harmonic sales-weighted average of the fuel economy requirements. The agencies coordinate the standards so that manufacturers complying with one standard are likely to be in or near compliance for the other.[9]

The stringency of the standards has fluctuated during the Obama, Trump, and Biden administrations. In 2011, the Obama administration set standards that would have roughly doubled fuel economy for 2011–2025. In 2020, the Trump administration weakened the 2021–2026 standards. For example, the Trump 2025 standards were about 15 percent weaker; that is, the average CO2 emissions rate in 2025 would have been about 15 percent higher. In 2021, the Biden administration retightened the standards; the standards in 2026 are about 25 percent stricter than the Trump standards would have been (and about 11 percent more stringent than the Obama standards would have been in 2025).

Thus, vehicle manufacturers have faced uncertainty over how quickly the standards are

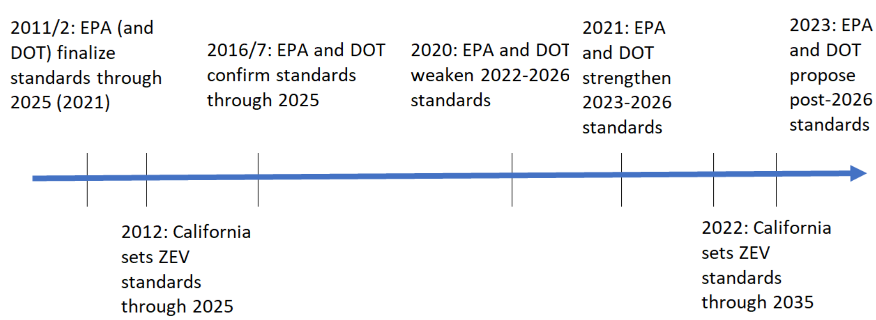
[8]The ZEV program also sets a minimum credit requirement for electric or fuel-cell vehicles. In 2025, it is 16 percent, which refers to the ratio of credits to sales. This constraint does not bind in the scenarios modeled in Section 6.

[9]The EPA has different crediting rules than DOT for plug-ins and recognizes credits for certain technologies that do not directly reduce gasoline consumption but reduce GHG emissions, such as air conditioning improvements. In contrast, DOT crediting reflects the agency's legal mandate to reduce liquid fuel consumption; it does not credit technologies that reduce only GHG emissions.

tightening. Litigation has followed the standards set by each administration, adding to this uncertainty. The Biden standards cover 2023–2026, and the administration is likely to set post-2026 standards by 2024. Given the 2024 presidential election and the litigation over the standards and more broadly over EPA's ability to regulate GHGs under the Clean Air Act, considerable uncertainty remains over future standards. In contrast, the major source of uncertainty for ZEV standards has been whether EPA continues to provide the waiver under the Clean Air Act that California needs to set the standards.

Figure 5 summarizes the recent developments regarding the ZEV and fuel economy standards. The figure indicates how the ZEV standards have been set first, particularly considering that the 2025 standards were changed twice after they were announced in 2012.

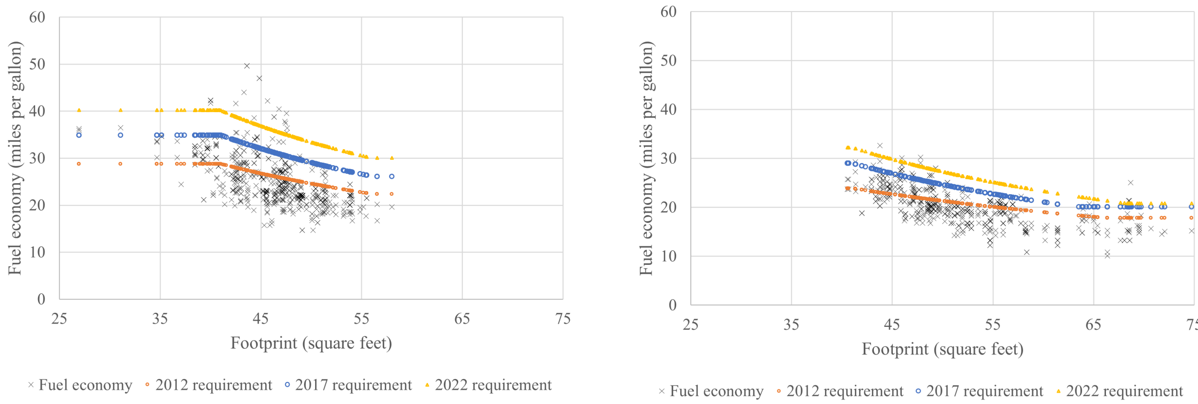
Figure 5: Timeline of Major ZEV, GHG Emissions, and Fuel Economy Program Events




In the policy simulations in this paper, I analyze the GHG and fuel economy standards between 2012 and 2022. Figure 6 plots the actual fuel economy of vehicles sold in 2012 and the fuel economy required by the 2012, 2017, and 2022 standards. Each x in the diagram indicates a unique vehicle, plotting its actual 2012 fuel economy against its footprint. Trucks tend to have larger footprint and lower fuel economy than cars.[10]

[10] In 2012, the Nissan Leaf was an outlier and achieved about 100 miles per gallon; it is omitted from the figure to show the variation across mainstream vehicles more clearly. The EPA calculates fuel economy equivalent for electrics that converts electricity consumption to an energy-equivalent liquid fuel consumption. To evaluate compliance with the GHG standards, the EPA uses tailpipe emissions of CO2 and not the equivalent fuel economy.

Figure 6: 2018 Fuel Economy, Regulatory Requirements, and Footprint




(a) Cars (b) Light trucks

Notes: For each vehicle in 2018, the figure plots fuel economy and its requirements in 2012, 2017, and 2022 against footprint (the product of wheelbase and width, in square feet).

The orange circles in the figure indicate the 2012 fuel economy requirement for each vehicle. On average, both cars and trucks achieved the requirements in 2012. The blue and yellow circles show the 2017 and 2022 requirements, respectively. The figure shows the preferential treatment for light trucks, conditional on footprint. For example, a light truck with a footprint of 45 square feet has a 2017 fuel economy requirement of 30 miles per gallon, whereas a car with the same footprint must achieve 36 miles per gallon. The sales-weighted average requirements increased by about 18 percent between 2012 and 2017 and about 13 percent between 2017 and 2022. Thus, the rate of increase slowed somewhat in the latter subperiod, largely because of shifts of sales from cars to light trucks and from smaller to larger vehicles. Overall, the standards increased by about one-third during the 10-year period.

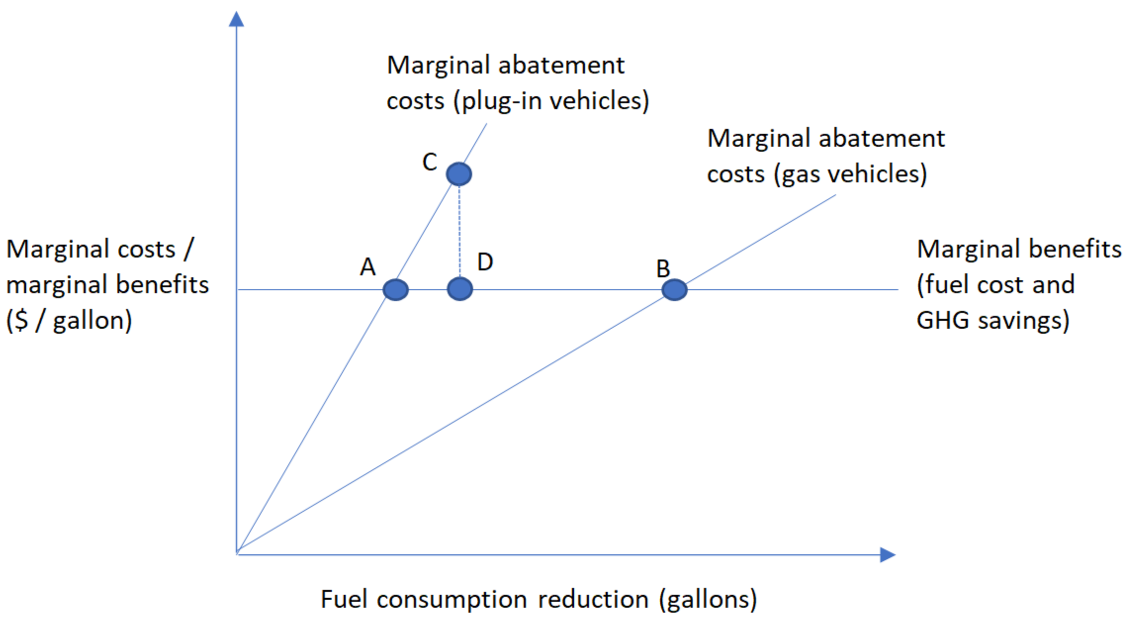
## 3.2. Effect of ZEV Standards on Fuel Economy Standards

As the introduction notes, when choosing levels of standards, EPA and DOT analyze a range of stringencies. Presidential executive orders and the Office of Management and Budget direct agencies to choose standards that maximize social welfare, but the agencies may consider effects of standards that cannot be quantified. Consequently, if tighter ZEV standards increase the net benefits for stricter more than weaker federal standards, it is more likely but not certain that agencies adopt stricter standards. For ease of exposition throughout this paper, I assume the agencies choose welfare-maximizing standards conditional on ZEV standards.

This subsection provides a stylized representation of the ZEV and federal standards. Simplifying assumptions are made to facilitate exposition, most of which are relaxed in the computational model. I suppose ZEV states choose a minimum ZEV market share and the federal government sets fuel economy standards conditional on the ZEV standard. This timing assumption is consistent with recent patterns depicted in Figure 5.

Figure 7 shows a schematic representation of the costs and benefits of tightening fuel economy standards relative to a baseline level. In year $t$, California is considering adopting ZEV standards for year $s > t$. After California decides, EPA and DOT choose standards for year $s$. The figure depicts marginal costs and benefits against the fuel consumption reduction in time $s$, relative to a scenario in which the agencies choose the same standards for years $t$ and $s$. As none of the policies affect fuels' carbon content, the fuel consumption reduction on the horizontal axis is proportional to the GHG benefits.

Figure 7: Schematic Representation of Marginal Benefits and Marginal Costs of Fuel Economy Standards




Notes: The horizontal axis measures fuel consumption reduction in year $s > t$ in gallons relative to existing policy at time $t$. The vertical axis is the marginal benefits and costs of reducing fuel consumption in dollars per gallon. The horizontal line is the marginal benefit of reducing fuel consumption, which includes fuel cost savings and GHG emissions reductions. The upward-sloping lines are the marginal abatement costs of reducing consumption from gasoline or electric vehicles. Points A and B equate marginal benefits and marginal abatement costs. Point C represents a ZEV standard that causes a larger market share of plug-ins than the level that equates marginal costs and marginal benefits.

As the Appendix explains, the marginal benefits of reducing fuel consumption are approximately constant, which is shown by the horizontal line parallel to the axis. The marginal abatement cost curve for gasoline vehicles represents the costs of making them more efficient. Moving to the right along the curve, manufacturers are installing increasingly less cost-effective technologies, which causes the curve to be upward sloping.

The marginal abatement cost curve for plug-ins represents the cost of increasing their sales by either adjusting vehicle prices or introducing new plug-ins to the market. The curve lies above the gasoline curve because, given the battery costs and consumer preferences during the 2010s (the period of analysis), it was less costly to reduce gasoline vehicle emissions rates than to increase plug-in sales. For simplicity, I assume that the two cost curves are separable, so that reducing fuel consumption from gasoline vehicles does not affect the plug-in curve.

With no ZEV standard, the EPA and DOT maximize social welfare by choosing standards such that marginal benefits of reducing fuel consumption equal marginal costs for gasoline and electric vehicles. Points A and B in the diagram indicate these optimal points.[11]

Suppose instead that California sets a ZEV standard before DOT and EPA select fuel economy and GHG standards. The ZEV standard stipulates a plug-in market share, which causes the fuel consumption reduction indicated by point C in the diagram. Taking the ZEV standard as exogenous, the agencies maximize social welfare by choosing standards such that marginal benefits equal marginal costs for gasoline vehicles, which occurs at point B. Consequently, fuel economy standards are more stringent and fuel consumption is lower than in the no-ZEV scenario (the fuel economy standards determine the average fuel consumption rate across gasoline and plug-in vehicles). Social welfare is lower relative to the no-ZEV scenario, since marginal costs exceed marginal benefits for the plug-ins. Nonetheless, the ZEV standards reduce total emissions.

The diagram also indicates how the incremental cost of the ZEV standard depends on the level of the fuel economy standard. Suppose that DOT and EPA choose fuel economy standards before California chooses the ZEV standard. In the diagram, the triangle ACD is the incremental cost of the ZEV standard. The higher the fuel economy standard, the smaller the area of this triangle. Intuitively, a higher fuel economy standard raises the costs of producing gasoline vehicles, which reduces the incremental cost of converting a gasoline to a plug-in power train.

This discussion includes a number of simplifications. First, in practice, manufacturers maximize profits across multiple products, and consumers have heterogeneous preferences

[11] In practice, the agencies simulate a range of standards and compare welfare effects across scenarios. This approach should reveal the welfare-maximizing level of standards as long as they consider a sufficiently broad range.

for fuel economy and other vehicle attributes. Second, EPA overcredits plug-in vehicles, which reduces the GHG benefits of tighter GHG standards. Third, marginal cost curves for gasoline and plug-in vehicles interact with one another, such that adopting stricter ZEV standards may affect the marginal cost curve for gasoline vehicles. Fourth, the ZEV program credits vehicles based on their fuel type and electric range, rather than setting a minimum market share. Finally, the agencies choose multiple parameters rather than a single fuel consumption rate to define the standards. Because of these simplifications, tighter ZEV standards do not necessarily reduce emissions; they could also cause social welfare to increase, depending on pre-existing distortions (see Appendix for additional discussion on these simplifications).

Notwithstanding the simplifications, the framework illustrates why tighter ZEV standards may cause tighter fuel economy and GHG standards. The remainder of the paper considers whether this situation has held in practice.

# 4 Equilibrium Model

This section describes an equilibrium model that relaxes many of the assumptions from Section 3. Each consumer chooses the new or used vehicle that maximizes subjective utility. Manufacturers maximize profits by choosing prices, fuel economy, and horsepower, subject to fuel economy and ZEV standards.

## 4.1. Demand

Because the demand side of the model is the same as Linn (2022), this subsection describes the main features of the model and the Appendix provides details. A market is a model-year $t$ and region $r$. Each region and model year contains $Q_{grt}$ consumers of demographic group $g$ who choose a vehicle from among the $J_{rt}$ new vehicles in the market and a composite used vehicle, which represents the outside option. Consumer $i$ maximizes subjective utility by choosing a new or used vehicle, and utility, $u_{ijrt}$, is linear in the vehicle price and attributes:

$$u_{ijtr} = \alpha_{gr}\, p_{jrt} + \sum_k x_{jkt}\, \beta_{gkr} + \xi_{jrt} + \epsilon_{ijrt} \tag{1}$$

where $\alpha_{gr}$ is the sensitivity of utility to price, $p_{jrt}$ is the price, $x_{jkt}$ is the level of attribute $k$ in model-year $t$, $\beta_{gkr}$ is the sensitivity of utility for group $g$ to attribute $k$, $\xi_{jrt}$ is the utility from unobserved vehicle attributes, and $\epsilon_{ij}$ is an idiosyncratic preference shock. Equation

(1) distinguishes between the vehicle attributes, $x_{jkt}$, observed in the data and the attributes that are unobserved, $\xi_{jrt}$.

The price and attribute parameters, $\alpha_{gr}$ and $\beta_{gkr}$, vary across regions and demographic groups. This is an important feature of the demand model because $\alpha_{gr}$ is the marginal utility of income, which can vary with income of the demographic group. Both sets of parameters determine willingness to pay for each attribute, which can also vary by demographic group.

Thus, consumer preference heterogeneity enters equation (1) via the group- and region-specific parameters and the idiosyncratic error term. In contrast, the effect on utility of the unobserved attributes does not vary by demographic group, although it does vary by region. This representation of heterogeneity is similar qualitatively to a random coefficients logit model, in which preferences for certain attributes are heterogeneous across consumers but preferences for unobserved attributes are not.

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. Linking preferences explicitly to demographic groups illustrates transparently the link between parameter estimates and distributional effects of the policies. On the other hand, equation (1) implies that conditional on observed vehicle attributes and the idiosyncratic error term, utility does not vary by demographic groups. In other words, the observed attributes absorb all preference variation across demographic groups. This is analogous to the assumption in a random coefficients setting.

Making the standard extreme value assumption on the error term in equation (1) yields an equation linking vehicle market shares and attributes:

$$ln(s_{gjrt}) - ln(s_{g0rt}) = \alpha_{gr}\, p_{jrt} + \sum_k x_{jkt}\, \beta_{gkr} + \delta_{jrt} + \nu_{gjrt} \tag{2}$$

where the left-hand side is the difference between the log share of purchases by group $g$ of vehicle $j$ and the log market share of the outside option. The right-hand side includes the price, observed attributes $x_{jkt}$, vehicle–region–year interactions $\delta_{jrt}$, and a mean-zero error term $\nu_{gjrt}$ that reflects measurement error of the dependent variable. The vehicle–region–year interactions are the sum of the mean utilities for the unobserved attributes ($\xi_{jrt}$) and the utility of the observed attributes for the base demographic group.

## 4.2. Supply

This subsection outlines the supply side of the model, focusing on the intuition provided by the first-order conditions for the firm's profit maximization. The Appendix contains additional details.

Each manufacturer faces a fuel economy standard that sets a minimum level for the harmonic average fuel economy of its vehicles and a ZEV standard for vehicles sold in California and other ZEV states. Fuel economy and ZEV standards are implemented as tradable credit standards: manufacturers that exceed the standards can sell credits to those that fall short.[12] Manufacturers also face GHG standards, and I assume that they are nonbinding if manufacturers are in compliance with fuel economy standards.

The supply side is static, and each time period represents five years and contains two stages. The first stage occurs instantaneously, when the manufacturer redesigns the vehicle and chooses technology, fuel economy, and horsepower. The second stage lasts for the remainder of the five-year period. This structure approximates typical vehicle design cycles that occur every five years.[13]

I discuss the second stage before the first stage. In the second stage, the manufacturer has already chosen technology, horsepower, and fuel economy. The manufacturer can choose the vehicle's price for each model year $t$ and region $r$.[14]

Consider the manufacturer's second-stage optimization problem for choosing the prices of its vehicles subject to ZEV and fuel economy standards. For each market, the manufacturer chooses $p_{jrt}$ to maximize profits

$$\max_{p_{jrt}} \sum_{j \in J_f} \sum_{rt} \sum_{g} [(p_{jrt} - mc_j) + \lambda_{Z,rt}(c_{jrt} - R_{rt}) + \lambda_M(\frac{1}{m_j} - \frac{1}{M_{jt}})] s_{jgrt} Q_{grt} \tag{3}$$

where $mc_j$ is marginal costs, $\lambda_{Z,rt}$ is the ZEV credit price, $c_{jrt}$ is the number of credits the vehicle earns, $R_{rt}$ is the credit requirement, $\lambda_M$ is the fuel economy credit price, $m_j$ is fuel economy, $M_{jt}$ is the vehicle's fuel economy requirement, and $s_{jgrt}$ is the market share. The profit maximization expression includes the assumptions that fuel economy and ZEV credit markets are competitive and that all firms face the same credit prices.[15]

The Appendix shows that the profit-maximization problem (3) yields first-order con-

[12] Modeling a fuel economy standard is equivalent to modeling a GHG standard without offcycle credits or a fuel consumption rate standard.

[13] Manufacturers typically stagger redesigns across their vehicles. The supply side of the model assumes that all redesigns occur concurrently, which simplifies the modeling.

[14] In practice, a manufacturer chooses a single MSRP for each vehicle and year, and it does not vary across regions within a year. However, new vehicle dealers can offer incentives and negotiate final transaction prices; Section 2 noted the differences between transaction prices and MSRP in the data. Effectively, the model characterizes the combined profits of manufacturers and dealers, and I abstract from arrangements among manufacturers and dealers that aim to address double marginalization, investments in dealership quality, and other considerations.

[15] The first assumption is for tractability, avoiding the need to estimate a shadow price of each regulation for each firm.

ditions for prices that link the equilibrium markups to own- and cross-price demand elasticities and the shadow prices caused by the ZEV and fuel economy standards. For example, the less sensitive demand is to the product's price, the larger the markup.

Compared to the hypothetical in which credit prices are zero, the ZEV credit price reduces the marginal cost of selling the plug-in, and raises the marginal cost of selling the gasoline vehicle. Given parameter estimates in the next section, this reduces equilibrium prices of plug-ins and increases equilibrium prices of gasoline vehicles.

Similarly, the fuel economy credit price causes the manufacturer to raise prices of vehicles with fuel economy below their requirements. Thus, a vehicle with a large implicit ZEV or fuel economy subsidy has a small equilibrium markup.

During the redesign stage, the manufacturer chooses the vehicle's fuel-saving technology, horsepower, and fuel economy. Building on Knittel (2011), fuel economy is a function of horsepower $(h_{jt})$, weight $(w_{jt})$, and technology $(T_{n(jt)})$):

$$ln(m_{jt}) = ln(m_{j0}) + \gamma_h ln(h_{jt}) + \gamma_w ln(w_{jt}) + T_{n(jt)} \tag{4}$$

where $\gamma_h$ and $\gamma_w$ are coefficients, and the technology varies by model $n$ and model year. Holding fixed horsepower and weight, adopting energy-saving technology raises $T_{n(jt)}$ and increases fuel economy proportionately. For example, the manufacturer can install a stop-start ignition, which turns off the engine when the vehicle is stopped for a prolonged time and restarts it when the driver releases the brake pedal. Such technology adoption causes $T_{n(jt)}$ to increase. The technology variable is scaled: increasing it by 0.01 units raises log fuel economy by 0.01, or approximately 1 percent.

According to equation (4), holding fixed the level of technology, the manufacturer can trade off weight and horsepower for fuel economy. Specifically, the manufacturer can retune the engine and increase fuel economy while simultaneously reducing horsepower. The coefficient $\gamma_h$ is the elasticity of fuel economy to horsepower. Conditional on both, heavier vehicles have lower fuel economy, and the coefficient $\gamma_m$ is the elasticity of fuel economy to weight.

Adopting fuel-saving technology affects the manufacturer's costs in two ways. First, the vehicle must be redesigned and tested to ensure that it functions properly. For example, installing a turbocharger increases the overall power train efficiency, but it may be necessary to reconfigure the vehicle to make room for the turbocharger and associated components. After installing technology, the manufacturer must test that the vehicle operates properly. Such redesign and testing constitutes a sunk cost, $F(\Delta T_{n(jt)})$, that the manufacturer incurs before it begins producing the redesigned vehicle. It increases with the absolute change of technology; in general, a large technology increase requires multiple new fuel-saving technologies, more extensive redesign, and additional testing.

Technology adoption also affects costs by raising the vehicle's marginal costs, $mc_{lt}(T_{n(jt)})$. Installing fuel-saving technology increases materials and labor costs. For example, to add a turbocharger, the manufacturer must purchase and install it (which could increase production costs). Adopting technology may involve installing new parts, such as the turbocharger example, or swapping existing parts. For example, the manufacturer could replace a 5-speed with a 6-speed automatic transmission. In this example, marginal costs increase by the cost of the higher-speed transmission net of the removed lower-speed transmission.

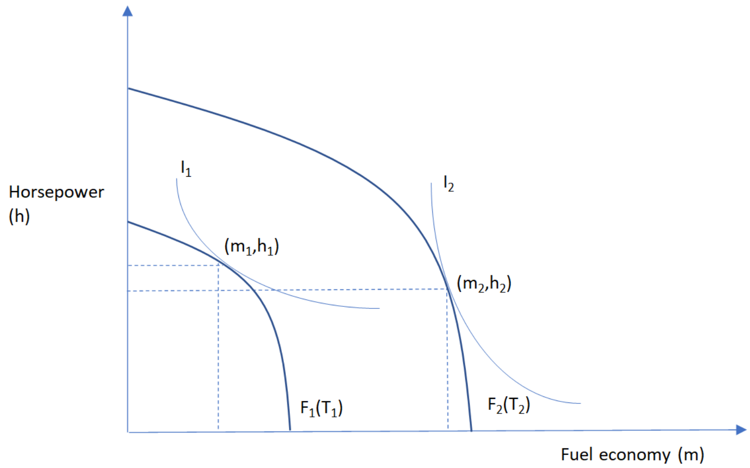
Equation (5) shows how the technology choice affects marginal costs.

$$ln(mc_j) = ln(mc_{j0}) + \gamma_T T_{n(j)} \tag{5}$$

The technology variable $T_{n(j)}$ is scaled: increasing it by one unit causes the log of marginal costs to increase by $\gamma_T$. According to equation (4), this increase would also raise log fuel economy by 1. In other words, adopting technology and raising fuel economy by 1 percent would increase marginal costs by approximately $\gamma_T$ percent.

The technology and attribute choice can be illustrated by conceiving of the horsepower frontier. For a representative vehicle, Figure 8 shows the maximum level of horsepower that the manufacturer can choose, given the vehicle's technology and fuel economy. For a given level of technology, the manufacturer faces a tradeoff between horsepower and fuel economy: it can increase horsepower by reducing fuel economy. According to equation (4), the parameter $\gamma_h$ describes this tradeoff. Moving along frontier $F$ does not affect the vehicle's costs.

Figure 8: Schematic Representation of Technology, Fuel Economy, and Horsepower Choices




The figure plots a vehicle's horsepower (h) against its fuel economy (m). The two curves labeled "F" are the frontier of feasible levels of horsepower and fuel economy given technology T. The curves labeled I represent isoprofit lines, and the points (m,h) are the profit-maximizing choices of horsepower and fuel economy, which are the points of tangency between the F and I curves. Curves and points labeled with a 1 subscript correspond to choices made with a low level of fuel economy standard, and points and curves labeled with a 2 subscript correspond to choices made with a high level of fuel economy standard.

The figure also shows that adopting technology causes the frontier to shift away from the origin. Technology adoption allows the manufacturer to increase horsepower without sacrificing fuel economy but also incurs sunk costs and raises marginal costs.

The manufacturer's optimization problem in the redesign stage is the following:

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

where $F(\Delta T_{n(j)})$ are sunk costs of choosing technology $T_n$ for model $n$. Note that in the optimization (6), the vehicle prices are implicit functions of horsepower, fuel economy, and technology. Marginal costs are a function of technology according to equation (5). Because fuel economy is a function of horsepower and technology according to equation (4), the optimization is over horsepower and technology.

Figure 8 shows isoprofit lines; the slope depends on the consumer's marginal willingness to pay for horsepower relative to fuel economy, which is the ratio of the derivative of the market share with respect to the attribute and the derivative of the market share with respect to the price. A higher marginal willingness to pay for horsepower implies a flatter isoprofit line.

The level of technology determines the position of the frontier of feasible values of horsepower and fuel economy. Lin and Linn (forthcoming) show that the manufacturer chooses the level of horsepower along the frontier such that the frontier and isoprofit lines are tangent.[16] Consequently, a hypothetical gasoline price increase raises the marginal willingness to pay for fuel economy, causing the isoprofit line to become steeper and the manufacturer to choose a higher level of fuel economy. The shadow price from the fuel economy standard affects the manufacturer's choice of fuel economy similarly to the increase in consumer demand for it. Intuitively, the shadow price raises the benefit to the manufacturer of trading off horsepower for fuel economy because doing so increases the revenue from selling credits.

The fuel economy shadow price also causes the manufacturer to adopt more technology. Thus, the shadow price causes an outward shift of the frontier and movement along the frontier, which Klier and Linn (2016) document has been caused by both the US fuel economy standards and the European CO2 standards for passenger vehicles.

The model allows for the possibility that each manufacturer chooses a unique compliance strategy for the ZEV and fuel economy standards. For example, a manufacturer that offers only unpopular plug-ins may decide to purchase credits rather than reduce prices to boost sales of those vehicles. A different manufacturer whose consumers have high preferences for horsepower is less likely to trade off horsepower for fuel economy; instead, it may adopt more technology or purchase fuel economy credits.

# 5 Estimation

This section describes estimation of the preference parameters and supply-side parameters that include marginal costs, technology adoption costs, and the tradeoff between fuel economy and horsepower.

## 5.1. Preference Parameters

### 5.1.1 Estimation Strategy

Estimation of the preference parameters is similar to Linn (2022). I estimate parameters in two stages, beginning with equation (2), which links market shares to vehicle attributes. The coefficients on the vehicle attributes, $\beta_{gkr}$, are the differences in marginal utilities between each demographic group and region and the marginal utilities of the

[16] They analyze a single product monopolist rather than a multiproduct firm. The cross-price demand elasticities estimated in the next section are sufficiently small that the intuition from their analysis applies to this case.

base demographic group and region (which is defined as a low-income, young, urban household in California). The equation includes interactions of vehicle, region, and year ($\delta_{jrt}$). These interactions are the sum of the marginal utilities of the base group and region and the mean utility of the unobserved attributes of vehicle $j$ in region $r$ and year $t$ (Leard, Linn, and Springel, 2019).

The price in equation (2) is the average transaction price by vehicle, region, and model year. The price does not vary across demographic groups, which implies no price discrimination by group. The equation includes fuel costs, measured as 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 electrics, I use the regional price of electricity multiplied by the electricity consumption per mile. For plug-ins, I assume that half of the miles are driven using gasoline and half using electricity and compute fuel costs per mile as the average of the gasoline and electric fuel costs per mile (the assumption is broadly consistent with charging data from voltstats.net). Performance is the log of the ratio of horsepower to weight.

The other attributes in $x_{jkrt}$ include footprint; dummies for a hybrid power train, a plug-in power train, all-wheel drive, a luxury brand, and the luxury trim of a model; and interactions of luxury trim with drive type and the number of engine cylinders. Footprint is the product of 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. The luxury trim is the high-end version of a particular model, which is identified by the trim name (e.g., "Premium") and MSRP.

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. For example, some members of the low-income group may have high demand for luxury trims, which would affect the parameter estimate.

Estimating equation (2) by ordinary least squares (OLS) yields consistent parameter estimates if the price and attributes are not correlated with the error term after partialing out the vehicle-region-year intercepts. For example, consider a hypothetical vehicle sold under a luxury brand that has many high-end attributes, such as advanced safety features. If high-income consumers are more likely to purchase it and also have lower price sensitivity of demand than other consumers, the manufacturer is likely to charge a high markup. Absent any controls for luxury brand or high-end features, this would cause the price in equation (2) to correlate with the error term. That is, including controls for luxury brands and trims reduces the correlation between price and the error term and the concerns that parameter estimates from OLS are biased.

I estimate $\delta_{jrt}$ 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 $x_{jkrt}$.

$$\hat{\delta}_{jrt} = \sum_{k} x_{jkt}\, \beta_{kr} + Z_{jrt}\, \mu + \phi_{jrt} \tag{7}$$

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. Unfortunately, the data have insufficient variation to relax this assumption.

Observed attributes that firms choose ($X_{jkt}$) may be correlated with unobserved vehicle attributes.[17] For example, firms may choose a higher price for vehicles sold with a particularly popular exterior paint color. Including the same luxury variables and the interactions in $X_{jkt}$ 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.

To address remaining endogeneity concerns about the observed attributes, I estimate the second stage by instrumental variables (IVs). Because prices, fuel economy, and horsepower are endogenous in the supply side of the equilibrium model, I instrument for these variables using BLP-style instruments that include means and standard deviations of weight, height, and length for other vehicles sold by other firms in the same market segment. I use these instruments because firms change them less frequently than other attributes, making them less likely to be correlated with the error term in equation (7).[18]

Finally, $Z_{jr}$ includes interactions of the hybrid and plug-in power train dummies with region fixed effects. The region interactions allow preferences for these power trains to

[17]The $\delta_{jrt}$ control for unobserved vehicle attributes in the first stage. The endogeneity of price does not bias the first-stage estimates if the vehicle attributes and fixed effects control for cross-group preference heterogeneity.

[18]Conlon and Gortmaker (2020) suggest using cost shifters to identify demand coefficients because these instruments can strengthen the first stage and reduce weak instruments bias. I find that the BLP-style instruments are strong predictors of the endogenous attributes, with first-stage F-statistics of around 150, which indicates little concern for weak instruments bias. I have added supply-side instruments based on steel prices and vehicle weight (as steel is an important input to vehicle production), which does not improve the strength of the first stage or the parameter estimates substantially.

vary across regions. Recall that the first stage included the interactions of the power train dummy variables with demographic group fixed effects. This setup amounts to assuming that regional preferences for each power train 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 (7) also includes the vehicle's electric range, which is zero for non-plug-ins.

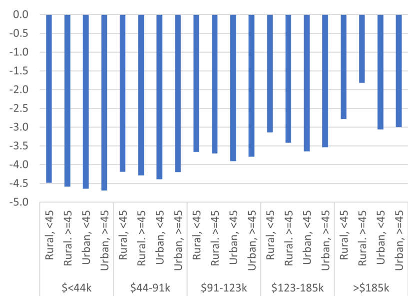
### 5.1.2 Estimation Results

Equations (2) and (7) include hundreds of parameters. I focus on the estimates of the main parameters relevant to the simulations in the next section: price sensitivity and willingness to pay for fuel economy, horsepower, and fuel type. The Appendix discusses validation of the demand side of the model and the other parameter estimates.

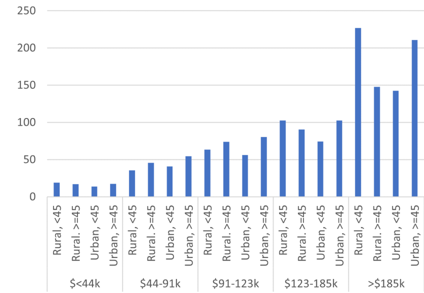
Panel (a) of Figure 9 shows the estimated own-price elasticity of demand by demographic group.[19] Its magnitude generally decreases with income, meaning that low-income groups tend to respond more to price changes than high-income groups do. Urban consumers tend to be more price sensitive than rural consumers are, although those differences are smaller than differences across income groups.

[19] Estimates are the same as those reported in Linn (2022), which uses the same data and estimation strategy.

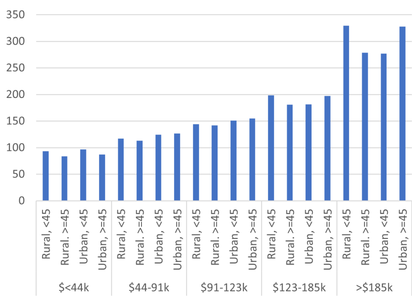
Figure 9: Own-Price Elasticity of Demand and Willingness to Pay for Fuel Economy and Horsepower by Demographic Group



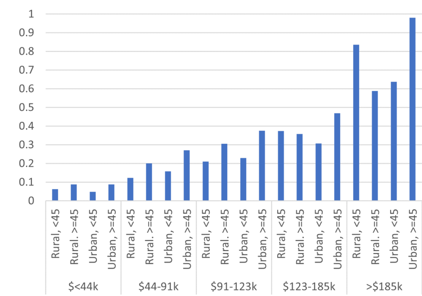

(a) Own-price elasticity of demand




(b) Willingness to pay for 1 percent fuel economy increase




(c) Willingness to pay for 1 percent horsepower increase




(d) Valuation ratio

Notes: Each panel shows estimation results by demographic group. Panel (a) reports the own-price elasticity of demand. Panels (b) and (c) report willingness to pay for a 1 percent fuel economy and horsepower increase. Panel (d) reports the valuation ratio, which is the willingness to pay for a 1 percent fuel economy increase divided by the present discounted value of the associated fuel cost savings.

Panel (b) shows the estimated willingness to pay for a 1 percent fuel economy increase, which depends on the estimated price sensitivity parameter and the coefficient on fuel costs. Willingness to pay increases with income, and the highest income group is willing to pay about 10 times as much as the lowest income group for a 1 percent fuel economy increase. Part of that difference may reflect variation across income groups in average interest rates and expected miles traveled; low-income groups tend to pay higher interest rates, and hence have higher discount rates, and drive their vehicles fewer miles. Both factors reduce willingness to pay.[20]

To investigate that possibility, Panel (d) reports the valuation ratio, which is the willingness to pay for a 1 percent fuel economy increase divided by the present discounted value of the associated fuel cost savings. To calculate those savings, I compute the annual

[20]The demand model imposes the restriction that, conditional on demographic group, the valuation ratio does not differ between gasoline and plug-in vehicles. I estimated versions of the model that relax this assumption and did not find evidence that the valuation ratio differs across fuel types, although the estimates are noisy.

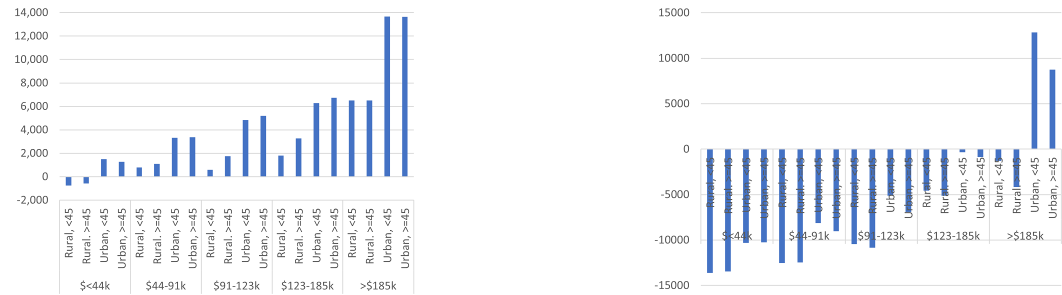
fuel costs of a gasoline vehicle with the sample-average fuel economy, which equals the per-mile fuel costs multiplied by the expected miles traveled each year the vehicle is in operation. Expected miles traveled are estimated as in (Leard, Linn, and Springel, 2023) and account for variation across demographic groups in how much they drive. I compute the present discounted value using average borrowing rates by demographic group from the Survey of Consumer Finances. Although the valuation ratios account for variation across demographic groups in borrowing rates and miles traveled, in practice, it is minor compared to the variation in willingness to pay for fuel economy (i.e., the numerator of the valuation ratio), and the valuation ratio in Panel (d) exhibits a similar pattern across demographic groups as the willingness to pay in Panel (b).

Consumer responses to gasoline prices help identify the fuel cost coefficients. These responses explain much of the cross-group variation in willingness to pay for fuel cost savings and valuation ratios. Specifically, in the estimation sample, an increase in gasoline prices causes larger substitution toward smaller engines or hybrid power trains among high-income households.

Panel (c) shows the willingness to pay for a 1 percent horsepower increase. Demand for horsepower increases across income groups in a pattern that is broadly similar to the demand for fuel economy. Thus, the figure indicates that demand for fuel economy and horsepower are strongly correlated across demographic groups.

Figure 10 shows estimated willingness to pay for hybrid and plug-in power trains by demographic group. It is calculated net of the observed attributes, meaning that the vertical axis is what consumers are willing to pay for the power train itself, independent of associated fuel cost savings and differences in performance or other attributes between hybrid and other vehicles. Consequently, willingness to pay may include the value of driving an environmentally friendly vehicle and any real or perceived disutility, such as range anxiety. Panel (a) shows that, overall, consumers have a somewhat positive valuation of hybrids that increases with income. Note that hybrids have lower fuel costs, higher prices, and lower performance than otherwise comparable gasoline vehicles (after controlling for model and trim level). The higher prices and lower performance outweigh the lower fuel costs and higher willingness to pay for the hybrid power train, which explains why hybrids have such small market shares.

Figure 10: Willingness to Pay for Hybrid and Plug-In Power Trains



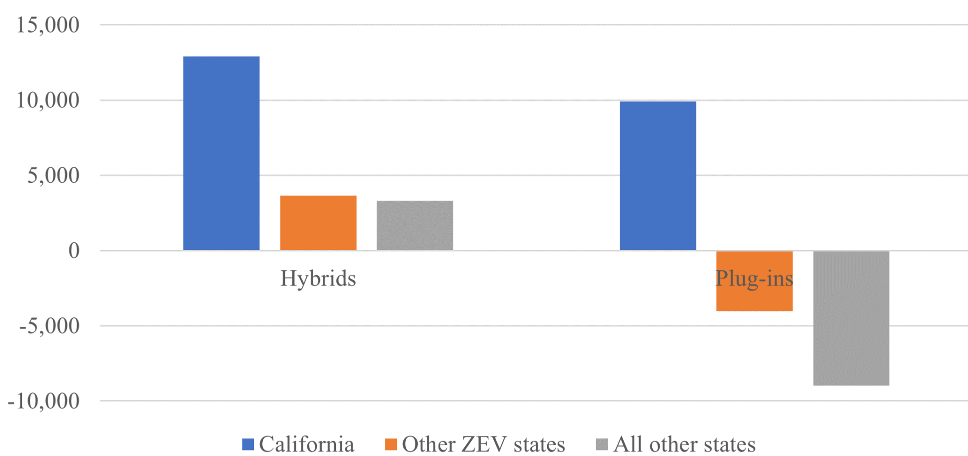

(a) Willingness to pay for hybrid power train (b) Willingness to pay for plug-in power train

Notes: Panel (a) shows willingness to pay for hybrid power trains, and Panel (b) shows willingness to pay for plug-in power trains by demographic group; it is calculated net of other attributes included in equation (2).

Panel (b) shows the willingness to pay for a plug-in power train. As with hybrids, this is calculated net of other attributes. It increases across income groups and is substantially higher for the top income groups. The positive correlation between willingness to pay and income is consistent with the relatively high likelihood that high-income consumers purchase plug-ins (see Figure 1).

Figure 11 shows variation in willingness to pay for hybrid and plug-in vehicles by region. For both types of power train, consumers in California have a higher willingness to pay than consumers in other regions.

Figure 11: Willingness to Pay for Hybrids and Plug-Ins by Region




Notes: The figure shows willingness to pay for hybrid and plug-in power trains by region. Willingness to pay is calculated net of other attributes included in equation (2).

## 5.2. Supply-Side Parameters

This subsection discusses the strategy for estimating supply-side parameters and presents the estimates.

### 5.2.1 Estimation Strategy

Supply-side parameters include the tradeoff between fuel economy and horsepower, marginal costs of each vehicle, shadow prices of fuel economy and ZEV credits, and sunk and marginal costs of adopting fuel-saving technology. Equation (4) is the basis for estimating the tradeoff between fuel economy and horsepower. Fuel economy is measured with error, which yields the following estimation equation

$$ln(m_{jt}) = \gamma_h ln(h_{jt}) + \eta_{vt} + \mu_{jt} \tag{8}$$

The dependent variable is the log of fuel economy by vehicle and year, and the first independent variable is the log of horsepower. $\eta_{vt}$ is the interaction of model year with make, model, trim, fuel type, drive type, and body style; that is, the interactions include all variables that identify a vehicle except for engine displacement. Consequently, the horsepower coefficient is identified by within-vehicle variation in horsepower and fuel economy across vehicles that have different engines. For example, if a manufacturer offers a pickup truck with an option for a 6- or 8-cylinder engine, the fuel economy and horsepower variation helps identify the horsepower coefficient.[21]

I use the price and technology first-order conditions to estimate the marginal costs of each vehicle and the ZEV and fuel economy credit prices (see the Appendix for the equations). Each model year has $2J$ equations and $J + 2$ unknown variables, and I estimate the unknowns iteratively in two steps. I begin with initial guesses of the credit prices from Leard, Linn, and Springel (2019). In the first step, I use the price first-order condition to compute each vehicle's marginal costs. Second, the technology first-order condition defines $J$ equations, one for each vehicle, and contains two unknown credit prices. Given the marginal costs from the first step, equation (10) is linear in the fuel economy and ZEV credit prices. Assuming again that fuel economy is measured with error, I rearrange the equation and estimate the fuel economy and ZEV credit prices by OLS. 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.

[21] Equation (4) includes weight, whereas equation (8) includes $\eta_{vt}$. Because weight does not vary within a model-trim-body style, it is colinear with $\eta_{vt}$ and can be omitted from the estimation without affecting other parameter estimates.

According to equation (5), adopting fuel-saving technology causes the log of marginal costs to increase by $\gamma_T$. Because the level of technology is unobserved, for all vehicles I normalize it to equal zero in the year they are first observed in the market. Technology adoption for each vehicle is estimated relative to this starting point; I use equation (4) to compute the change in technology between the initial model year a vehicle appears in the data and each subsequent model year. Then I regress the estimated marginal costs on estimated technology. I estimate the equation by OLS, assuming that marginal costs are estimated with error. The regression includes vehicle fixed effects, which control for average marginal costs of each vehicle in the sample (that is, $mc_{j0}$ in equation (5)). The coefficient $\gamma$ is identified by fuel-saving technology adoption that causes marginal costs to increase over time, using only within-vehicle variation to identify the coefficient.

Finally, I assume $F(\Delta T_{n(j)})$ is a quadratic function: $F(\Delta T_{n(j)}) = \sigma(\Delta T_{n(j)})^2$. Given the estimated marginal costs and credit prices, the technology first-order condition is a linear function of $\sigma T$, and I estimate $\sigma$ using an OLS regression. The parameter is identified by variation in the profitability of adopting fuel-saving technology and the imputed adoption. For example, gasoline prices decreased between 2014 and 2015, which reduces the profitability of adopting fuel-saving technology because of the lower consumer demand for fuel economy. The resulting slowdown in adoption between 2014 and 2015 compared to other years identifies the coefficient. Thus, the coefficient rationalizes the observed technology adoption, given variation in its expected profitability.

### 5.2.2 Estimation Results

This subsection presents supply-side parameter estimates and discusses validation of the supply side of the model. The top panel of Table 1 reports the coefficient on log horsepower in equation (8), which is the tradeoff between fuel horsepower and fuel economy. The estimates indicate an elasticity of fuel economy to horsepower of about $-0.56$ for cars and $-0.69$ for light trucks. These elasticities are larger than those estimated in Knittel (2011), which use earlier data. The increase in the elasticity is consistent with recent analysis by EPA that uses power train simulation tools and finds that changes in engine technology over time mean that manufacturers do not have to sacrifice as much horsepower to increase fuel economy.

Table 1: Estimated Fuel Economy-Horsepower Tradeoff and Marginal Cost Function

| | Dependent variable is log fuel economy | |
|---|---|---|
| | Cars | Light trucks |
| Log horsepower | -0.554 | -0.687 |
| | (0.040) | (0.056) |
| N | 5,863 | 5,801 |
| R-squared | 0.986 | 0.949 |
| | **Dependent variable is log marginal costs** | |
| | Cars | Light trucks |
| Fuel-saving technology | 0.539 | 0.589 |
| | (0.107) | (0.105) |
| N | 5,845 | 5,785 |
| R-squared | 0.863 | 0.735 |
| Change in marginal costs per mpg | 716 | 999 |
| | (140) | (161) |

Notes: The top panel reports estimates of the horsepower coefficient in equation (8). Observations are by vehicle and model year. The first column includes cars and the second column includes light trucks. The regressions also include interactions of model year, model trim, fuel type, drive type, and body style. Bootstrapped standard errors are in parentheses. The second panel reports estimates of the fuel-saving technology coefficient in equation (5), separately for cars and light trucks. Both regressions include vehicle fixed effects, and bootstrapped standard errors are in parentheses. The bottom two rows report the average change in marginal costs caused by adopting fuel-saving technology and increasing fuel economy by one mile per gallon. The calculation uses the estimated technology coefficient and the average ratio of marginal costs to fuel economy.

The bottom panel of Table 1 shows the estimated change in log marginal costs caused by increasing the level of fuel-saving technology by one unit. The point estimates are similar for cars and light trucks. To provide context for the magnitudes, the bottom row shows the change in marginal costs caused by adopting enough fuel-saving technology to increase fuel economy by 1 mile per gallon. The estimates are two times higher than in Leard, Linn, and Springel (2019), likely because I am using data through 2018 rather than 2015. To explain why, I define the cost-effectiveness of fuel-saving technology as the change in fuel economy per dollar of cost increase. Manufacturers adopt the most cost-effective technologies first, causing estimated costs to be relatively low using data for 2010–2015. Costs increase over time as manufacturers adopt increasingly less cost-effective technologies. Consequently, using more recent data likely explains the larger estimated coefficients.

As described, I estimate the coefficient in the sunk cost function using observed technology adoption and changes in the profitability of such adoption. The coefficient itself is positive and precisely estimated (statistically significant at the 1 percent level), but its interpretation is not obvious from the technology first-order condition. To provide a clearer interpretation, Table 2 compares the change in marginal costs and average sunk costs associated with adopting fuel-saving technology and increasing fuel economy by 1, 5, or 10 percent. The average sunk costs are computed as the total sunk costs divided by the sales of the model over the five years following technology adoption. The table reports the average of these sunk costs across models in the estimation sample, along with standard deviation and median in parentheses and curly brackets, respectively.

Table 2: Estimated Changes in Marginal and Sunk Costs from Adopting Fuel-Saving Technology

| | Percent change in fuel economy | | |
|---|---|---|---|
| | 1 | 5 | 10 |
| Marginal costs | 153.25 | 759.86 | 1504.33 |
| | (65.23) | (323.50) | (640.68) |
| | {142.02} | {703.82} | {1393.70} |
| Average sunk costs | 3.34 | 83.41 | 333.62 |
| | (30.21) | (755.36) | (3021.45) |
| | {1.15} | {28.87} | {115.47} |

Notes: Each cell reports the mean with standard deviation in parentheses and median in curly brackets. Each row reports the changes in costs caused by the percentage fuel economy change indicated in the column heading. Average sunk costs are the sunk costs divided by vehicle sales over a five-year period.

The top rows show that marginal costs increase roughly linearly with the percent fuel economy increase. In contrast, average sunk costs are a convex function of the fuel economy change. Average sunk costs are smaller than the change in marginal costs for small fuel economy changes, but they increase more quickly with the fuel economy change than do the marginal costs. In other words, the sunk costs of technology adoption become increasingly important, in terms of profitability, as the magnitude of the fuel economy change increases.

Table 3 summarizes the results of the supply-side estimation by showing average marginal costs, ZEV and fuel economy net credit costs, and markups by firm. The first column shows the average marginal costs, which vary across firms in accordance with their specialization in luxury vehicles or light trucks rather than cars. On average, Hyundai sells the least costly vehicles and Tesla the most expensive, with BMW, Daimler, and Volvo also selling relatively expensive vehicles.

Table 3: Estimated 2018 Marginal Costs, Net Credit Costs, and Markups

| Firm | Mariginal costs ($ / vehicle) | ZEV standard net credit cost ($ / vehicle) | Fuel economy standard net credit cost ($ / vehicle) | Percentage markup |
|---|---|---|---|---|
| General Motors | 27,597 | -29 | 2,173 | 27 |
| Toyota | 22,958 | 33 | 1,972 | 29 |
| Ford | 25,558 | 18 | 2,250 | 27 |
| Fiat Chrysler | 21,741 | 26 | 3,483 | 28 |
| Honda | 20,015 | 41 | -2 | 31 |
| Nissan | 20,602 | 23 | 1,467 | 30 |
| Hyundai | 15,783 | 20 | 1,404 | 34 |
| Subaru | 19,352 | 52 | 1,119 | 28 |
| Volkswagen | 23,253 | 43 | 2,341 | 28 |
| Mazda | 18,236 | 46 | 1,034 | 30 |
| BMW | 36,281 | -14 | 1,444 | 24 |
| Daimler | 39,380 | 41 | 2,414 | 22 |
| Tesla | 81,562 | -5,980 | -35,451 | 37 |
| Volvo | 41,753 | 35 | 545 | 20 |

Notes: The table shows the sales-weighted mean markup, marginal costs, net credit cost of the ZEV standard, net credit cost of the fuel economy standard, and percentage markup using observations from 2018. Markup is the difference between the transaction price and the sum of marginal costs, ZEV net credit cost, and fuel economy net credit cost. Net credit costs are computed according to equation (9) with estimated shadow prices.

The second column shows the average net credit cost of the ZEV standard in 2018. According to equation (9), the ZEV net credit cost is the credit price multiplied by the difference between the vehicle's credits and the standard. Except for Tesla, net credit costs are small relative to marginal costs because manufacturers were typically close to compliance (i.e., sales-weighted credits approximately equal the sales-weighted requirement). The average subsidy for Tesla indicates the magnitude of the implicit subsidy for electrics, as Tesla only sells electrics. Tesla receives an average implicit subsidy of $6,000 per vehicle, which represents the value of the credits Tesla is able to sell for each vehicle it produces. The estimated credit price is similar to Leard and McConnell (2019), who calculate credit prices from reported transactions.

The third column shows the average fuel economy standard net credit cost. It is positive for most manufacturers because, on average, their fuel economy is below the level required by the standards. This is consistent with manufacturers having overcomplied with the standards in the early and mid-2010s, when they accumulated excess credits, and then undercomplying and using some of the excess credits in the late 2010s.

The final column in the table shows the percentage markup including the ZEV and fuel economy net credit costs. The variation across manufacturers reflects several effects. On the one hand, high-end vehicles tend to be purchased by high-income consumers who have relatively low own-price sensitivity (see Figure 9), which causes large markups for luxury vehicles. On the other hand, such vehicles typically have fuel economy below their requirement and (except for Tesla vehicles) are unlikely to be plug-ins, which reduces the equilibrium markup net of credit costs. These factors cause BMW and Daimler to have relatively low markups, even though they specialize in high-end vehicles. They also explain why Tesla has such a high average markup, as well as Hyundai, which sells less expensive vehicles but also has relatively low net credit costs because its vehicles achieve high fuel economy.

# 6 Policy Simulations

This section analyzes welfare effects of ZEV and fuel economy standards in isolation and then assesses whether tighter ZEV standards cause tightening fuel economy standards. The first subsection describes the scenarios, and the following subsections report the results.

## 6.1. Scenario Descriptions

I compare welfare estimates across policies that are defined by the stringency of the ZEV and fuel economy standards. The ZEV standard is the share of credits in total sales across ZEV states. For tractability, the policy is implemented as a tradable performance standard with a competitive credit trading market, and all firms take the common credit price as exogenous to their actions. ZEV credits can be traded across states, which the program allowed until 2018. All scenarios use the credit rules that California adopted in 2018.

As Section 3 notes, EPA sets GHG emissions standards, and DOT sets fuel economy standards. I model the latter, implicitly assuming that when manufacturers comply with these, they also comply with the GHG standards. Supporting this assumption is that EPA provides manufacturers greater flexibility to earn and trade credits than does DOT. For tractability, I abstract from credit trading restrictions in the DOT program, and I assume that the credit market is competitive.[22]

[22] The DOT credit trading restrictions appear to be binding for some firms, as indicated by some manufacturers' lobbying Congress to loosen them. However, including credit trading restrictions substantially increases simulation times. Also, if trading restrictions are imposed in the model, some firms, such as Jaguar-Land Rover, can only comply with implausibly large technology adoption or horsepower reductions. Note that some firms wanting the trading restrictions loosened is consistent with the modeling assumption that the DOT rather than EPA standards have been binding.

Because the computational model is static, I simulate the steady state of each counterfactual. Specifically, at the beginning of 2018, California and DOT announce the policies; manufacturers can comply by adopting fuel-saving technology or trading off horsepower for fuel economy in the first stage (i.e., 2018) and adjusting prices of any of their vehicles in the second stage (2018–2022). Each vehicle has starting values for fuel economy, horsepower, and technology level corresponding to the observed 2018 levels. This setup approximates a situation in which policy makers announce policies and allow manufacturers five years to comply. Implicitly, I assume that parameters do not change between 2018 and 2022 and that the 2018 data year represents a steady state that repeats for 2018–2022.[23]

The simulations include all vehicles in the market in 2018 and plug-ins that entered the market between 2018 and 2022. For the post-2018 entrants, I impute attributes using the same data sources that were used to construct attributes for vehicles in the 2010–2018 data. I calibrate the mean utilities in equation (1) using averages for plug-ins sold by the same manufacturer.[24] This definition of the set of vehicles in the market amounts to assuming that policies do not affect entry and exit. This is the same assumption EPA and DOT make in their cost–benefit analysis of the national standards, facilitating comparison with their results. While this may be a strong assumption, relaxing it would require endogenizing both entry and exit, which lies beyond the scope of this paper.

Other assumptions include energy prices and the total market size by region and demographic group. Electricity and gasoline prices vary by region and are the average prices observed in 2018. Market size equals the observed 2018 values. I use the 2018 rather than observed 2021 or 2022 values of these variables to avoid modeling the effects of COVID on the new vehicles market.[25]

Finally, I compute fuel costs and CO2 emissions over the vehicles' lifetimes using assumptions on miles traveled and scrappage from Leard, Linn, and Springel (2019). I assume a 10 percent rebound effect, meaning that a 10 percent reduction in the vehicle's per-mile fuel costs causes a 1 percent increase in miles traveled. This is similar to the approach EPA takes to estimating fuel costs and emissions, which assumes that the policies do not

[23] An alternative approach would be to use observed 2018–2022 data, but this would include the influences of the COVID pandemic.

[24] In principle, I could similarly add gasoline-powered vehicles that entered the market after 2018. Whereas plug-ins have typically had roughly similar market shares—and hence mean utilities—to one another soon after their entry, market shares of entering gasoline vehicles vary by substantially more. Consequently, using the mean utilities of other gasoline vehicles to impute the mean utilities of gasoline entrants likely would introduce considerable measurement error.

[25] I have simulated scenarios that use observed vehicle sales and fuel prices from 2021. The results, available upon request, are broadly similar to those reported in the text. In particular, they indicate that the 2022 standards increased social welfare, tighter ZEV standards justify tighter fuel economy standards, and ZEV standards are regressive.

affect scrappage and that they affect miles traveled according to the rebound assumption. A departure from their approach is that I include estimated emissions associated with battery charging. I use regional emissions rates consistent with Palmer et al. (2017).

The appendix summarizes the algorithm for finding the equilibrium in each scenario. In short, I make initial guesses for credit prices, vehicle prices, fuel economy, and horsepower. An inner loop characterizes the second stage of manufacturers' profit maximization, in which they choose vehicle prices to maximize profits. This loop is nested in a middle loop in which manufacturers choose fuel economy, horsepower, and technology. An outer loop adjusts the ZEV and fuel economy credit prices until convergence is achieved.

## 6.2. Welfare Effects of ZEV Standards

This subsection considers the welfare effects of the ZEV program. I simulate four levels of standards: 4, 10, 12, and 14.5 percent, which are the levels for 2018–2022. The timing is such that prior to the first stage in 2018, California chooses a ZEV standard. The DOT chooses the 2016 stringency. I choose the 2016 stringency because it represents the level of stringency after the first phase of tightening standards during the Obama administration.

Table 4 shows summary statistics from four policy scenarios. Each column reports results of a separate simulation that includes the ZEV requirement and fuel economy standards indicated in the first two rows. Each vehicle has starting values of fuel economy, horsepower, and technology equal to the observed 2018 levels. Consequently, manufacturers can adopt fuel-saving technology above 2018 levels. Because most manufacturers had average fuel economy in 2018 that was better than required by the 2016 standards, manufacturers can also reduce fuel economy and increase horsepower compared to the 2018 levels.

Table 4: Annual Welfare Effects of ZEV Standards

| | | | | |
|---|---|---|---|---|
| ZEV requirement (percent) | 4 | 10 | 12 | 14.5 |
| Stringency of fuel economy standards | 2016 | 2016 | 2016 | 2016 |
| | | Panel A: Credit prices | | |
| ZEV ($/credit) | 0 | 2,202 | 3,045 | 3,800 |
| Fuel economy ($/1% mpg improvement) | 134 | 134 | 131 | 127 |
| | | Panel B: Private welfare | | |
| Consumer welfare (billion $) | 543 | 542 | 537 | 534 |
| Profits (billion $) | 124 | 124 | 124 | 125 |
| Subsidy expenditure (billion $) | 2.3 | 2.7 | 3.0 | 3.3 |
| | | Panel C: CO2 emissions and damages | | |
| Emissions (million metric tons) | 704 | 702 | 706 | 708 |
| Damages (billion $) | 132 | 132 | 132 | 133 |
| | | Panel D: Plug-in sales and market share | | |
| Sales | 315,978 | 349,008 | 371,682 | 402,744 |
| Market share | 0.022 | 0.024 | 0.026 | 0.028 |
| | | Panel E: Social welfare | | |
| Total welfare (billion $) | 532.0 | 531.6 | 525.5 | 522.4 |

Notes: The ZEV requirement is the share of ZEV credits in total sales across ZEV states, expressed as a percent. The stringency of fuel economy standards uses the footprint functions from the indicated year. The fuel economy credit price is the value of a 1 percent fuel economy improvement for a single vehicle, holding fixed all market shares. Consumer welfare includes welfare changes caused by changes in vehicle prices, fuel economy, and horsepower using the present discounted value of fuel costs over the vehicle's lifetime. Total welfare is the sum of consumer welfare and profits, net of subsidy expenditure and CO2 damages.

The ZEV and fuel economy credit prices are in panel (a). The ZEV credit price increases from $0 to $3,800 across the four scenarios; the highest price translates to an implicit subsidy of about $7,500 for a vehicle with a 100-mile range, such as the Nissan Leaf. The fuel economy credit price decreases from $134 to $127; the latter means that if the manufacturer adopts technology and raises fuel economy by 1 percent, it earns $127 in additional credit revenue for selling one more unit of that vehicle (this credit price is calculated holding fixed vehicle prices and sales of all other vehicles). The fuel economy credit price decreases as the ZEV stringency increases because tighter ZEV standards increase the plug-in market share and reduce the incremental average fuel economy improvement needed to achieve the 2016 standards. In other words, tighter ZEV standards increase the supply of fuel economy credits, causing the credit price to decrease.

Panel (b) shows consumer welfare, manufacturer profits, and subsidy expenditure.[26] Tightening the ZEV standard increases the implicit subsidy for plug-ins and the implicit tax for gasoline vehicles. On average, manufacturer profits are unchanged.[27] The price changes distort consumer choices and reduce their welfare by almost $10 billion comparing the 4 and 14.5 percent scenarios.

Panel (c) shows that tighter ZEV standards sometimes reduce and sometimes increase GHG emissions. The federal standards affect total GHG emissions rates, and these results reflect two opposing interactions between ZEV and federal standards. On the one hand, because the federal standards do not include emissions from electricity generation, plug-ins are overcredited relative to their actual emissions. Consequently, increasing plug-in sales without changing the federal standards raises emissions (Jenn, Azevedo, and Michalek, 2016). On the other hand, plug-ins are more likely to be cars than light trucks, and cars are subject to higher fuel economy (lower emissions) requirements (see Figure 6). Tighter ZEV standards increase the share of cars in total sales, and this effect leads to lower emissions. The table shows that in some cases, the latter effect dominates.

Panels (d) and (e) report plug-in sales and social welfare.[28] Welfare decreases by about $9 billion when the ZEV standards are increased from 4 to 14.5 percent. Tighter ZEV standards increase ZEV sales at an average private welfare cost of at least $15,000 per vehicle.

In the model, the marginal cost of a plug-in is about $10,000 higher than the cost of an otherwise comparable gasoline vehicle. The welfare costs are higher than this cost differential because of pre-existing market power distortions. For each vehicle in the model, the markup is approximately equal to the marginal change in private welfare caused by marginally increasing its sales. In each simulation, the average markup for gasoline vehicles is about $5,000 higher than that of plug-ins. This means a larger deadweight loss is associated with reducing gasoline than plug-in vehicle sales. Consequently, because tighter ZEV standards shift sales from gasoline to plug-in vehicles, private welfare decreases.

Per-vehicle costs of ZEV standards are closer to $5,000 when fuel economy standards are more stringent, as reported in the next subsection, because the tighter standards increase costs and prices of gasoline vehicles. This reduces the incremental costs of ZEV standards,

[26]The bottom row of panel (b) shows the subsidy expenditure for plug-ins. As discussed in the main text, the tighter fuel economy standards cause higher plug-in sales, raising subsidy expenditure. Consumer welfare includes subsidies, and I assume these are financed by lump-sum taxes.

[27]Profits increase slightly when the ZEV standard increases from 12 to 14.5 percent. Manufacturers more than fully pass through the program costs.

[28]Social welfare includes consumer welfare, manufacturer profits, and GHG costs (subsidies are represented as transfers financed by lump-sum consumer taxes). It does not include energy security benefits, which recent EPA and DOT rulemaking have estimated to be small relative to the costs and benefits that are included.

which is consistent with Figure 7 and the theoretical analysis of interactions among ZEV and fuel economy standards in Leard and McConnell (2020).

In summary, the table indicates that if fuel economy standards are exogenous to ZEV standards, the latter impose high average welfare costs per additional vehicle, which is explained by pre-existing distortions caused by market power.

### 6.3. Welfare Effects of 2022 Fuel Economy Standards

This subsection reports estimates of the welfare effects of the 2022 fuel economy standards, using the 2016 fuel economy and 2022 ZEV standards as the baseline. Table 5 shows summary statistics from two policy scenarios and is organized the same as Table 4. For both scenarios, the ZEV standards equal their 2022 levels, and the columns report welfare results for varying levels of fuel economy standards under the assumption that California and ZEV states committed to the actual 2022 standards prior to the choice of fuel economy standards. That is, the structure of the scenarios is consistent with the timing of the regulations, in which California chooses ZEV standards before DOT chooses GHG and fuel economy standards.

Table 5: Annual Welfare Effects of Fuel Economy Standards

| | | |
|---|---|---|
| ZEV requirement (percent) | 14.5 | 14.5 |
| Stringency of fuel economy standards | 2016 | 2022 |
| | Panel A: Credit prices | |
| ZEV ($/credit) | 3,800 | 0 |
| Fuel economy ($/1% mpg improvement) | 127 | 305 |
| | Panel B: Private welfare | |
| Consumer welfare (billion $) | 534 | 545 |
| Profits (billion $) | 125 | 121 |
| Subsidy expenditure (billion $) | 3 | 6 |
| | Panel C: CO2 emissions and damages | |
| Emissions (million metric tons) | 708 | 636 |
| Damages (billion $) | 133 | 119 |
| | Panel D: Plug-in sales and market share | |
| Sales | 402,744 | 844,051 |
| Market share | 0.028 | 0.058 |
| | Panel E: Social welfare | |
| Total welfare (billion $) | 523 | 541 |

Notes: The ZEV requirement is the share of ZEV credits in total sales across ZEV states, expressed as a percent. The stringency of fuel economy standards uses the footprint functions from the indicated year. The fuel economy credit price is the value of a 1 percent fuel economy improvement for a single vehicle, holding fixed all market shares. Consumer welfare includes welfare changes caused by changes in vehicle prices, fuel economy, and horsepower using the present discounted value of fuel costs over the vehicle's lifetime. Total welfare is the sum of consumer welfare and profits, net of subsidy expenditure and CO2 damages.

Panel (a) reports the ZEV and fuel economy credit prices. The ZEV credit price is $3,800 in column 1 (2016 standards), meaning that an electric vehicle with a 100-mile range receives an implicit subsidy of about $6,000. The fuel economy credit price is $127 per 1 percent fuel economy improvement.

Panel (b) shows the private welfare and subsidy expenditures for each scenario. Tightening the fuel economy standards from 2016 to 2022 levels raises consumer welfare because of undervaluation. From a manufacturer's standpoint, the benefit of increasing fuel economy depends on the fuel economy credit price and consumer willingness to pay for fuel economy. The costs include the marginal and sunk costs of raising fuel economy (see equation (10)). Because consumers undervalue fuel economy on average, if its credit price is zero, manufacturers offer less than is privately optimal to consumers. By extension, increasing the credit price above zero closes the gap between the market equilibrium level of fuel economy and the private optimum. The first row of panel (b) shows that tightening the standards from 2016 to 2022 levels increases the credit price and private consumer welfare.[29]

Although the tighter standards raise consumer welfare, they reduce manufacturer profits by causing more fuel economy adoption, which raises marginal and sunk costs of the vehicles. In equilibrium, manufacturers are unable to pass through all of these costs to consumers, causing profits to decrease.

Panel (c) shows the CO2 emissions and climate damages the emissions cause. Recall that these emissions are calculated over the lifetimes of the vehicles sold in the year 2022. Compared to the 2016 standards, the 2022 standards reduce emissions by about 10 percent.

As equation (9) shows, increasing the fuel economy credit price raises the implicit subsidy to vehicles with fuel economy greater than their requirements. The subsidy is particularly large for plug-ins, whose fuel economy equivalent far exceeds their requirements, and panel (d) shows that tighter standards increase their market share. Compared to the 2016 standards, the 2022 standards more than double plug-in sales.

Note that this plug-in market share is almost exactly equal to that observed for the first half of 2022. This similarity further validates the estimated preference parameters and other parameters, as these were estimated using observed vehicle choices and attributes between 2010 and 2018.[30]

Panel (e) shows that the 2022 standards increase annual welfare by $18 billion, compared to the 2016 standards. I estimate smaller welfare gains than EPA and DOT anticipated. The difference appears to be explained partly by higher technology costs and forgone horsepower improvements (which EPA and DOT do not include). However, a similarity with the EPA and DOT analysis is that fuel cost savings account for most of the welfare gains of the tighter standards.[31]

The 2022 fuel economy standards reduces the ZEV credit price to zero, meaning that the ZEV standard provides no additional incentive to sell ZEVs. Comparing the 2016 and 2022 standards shows that the fuel economy credit price more than doubles, which causes more

[29] Leard, Linn, and Zhou (forthcoming) find that marginally tightening fuel economy standards does not affect consumer welfare. They estimate a higher valuation ratio than in this paper, which explains the differing results.

[30] I use 2018 rather than 2022 fuel prices in these scenarios. Using 2022 fuel prices has a small effect on plug-in market shares because higher fuel prices raise demand for plug-ins, which reduces ZEV and fuel economy credit prices and dampens the effect of fuel prices on market shares.

[31] Note that EPA and DOT include energy security, refueling time, and a few other welfare categories not included in this paper. However, the omitted categories represent small benefits and costs relative to the included categories.

technology adoption and a greater shift from horsepower to fuel economy (see Figure 8).

## 6.4. Interactions Between ZEV and Fuel Economy Standards

To illustrate the interactions between ZEV and fuel economy standards, this subsection compares scenarios across which the two standards vary. Table 6 focuses on the 2016 and 2022 standards. The first column shows a 10 percent ZEV requirement, which is binding for the 2016 but not 2022 standards. That is the minimum level shown in the table because the ZEV requirements are nonbinding for both 2016 and 2022 standards at lower levels. The 2016 and 2022 standards correspond to a hypothetical in which California sets ZEV standards in 2018 and expects that DOT will then set standards for 2022. Comparing the 2016 and 2022 levels of the standards amounts to assuming that in 2018, DOT decide to either maintain the 2016 standards through 2022 or tighten standards. This timing and the choice set are consistent with the timeline in Figure 5.

Table 6: Annual Social Welfare and Emissions by Level of ZEV: 2016 and 2022 Fuel Economy Standards

| | | ZEV standard (percent) | | | |
|---|---|---|---|---|---|
| | | 10 | 12 | 17 | 22 |
| | | Panel A: Social welfare (billion $) | | | |
| Stringency of fuel economy standards | 2016 | 532 | 525 | 518 | 514 |
| | 2022 | 541 | 540 | 538 | 536 |
| | | Panel B: CO2 emissions (million metric tons) | | | |
| Stringency of fuel economy standards | 2016 | 702 | 706 | 710 | 710 |
| | 2022 | 636 | 637 | 638 | 641 |
| | | Panel C: Cost effectiveness of 2022 fuel economy standards | | | |
| Social welfare gains of 2022 standards (billion $) | | 9.0 | 15.0 | 20.0 | 22.0 |
| Cost effectiveness of 2022 standards ($ / metric ton) | | -89 | -166 | -228 | -269 |

Notes: The table reports annual total welfare in billions of dollars for the ZEV standard in the column heading and the fuel economy standard in the row heading. Welfare is computed as in Table 5. Social welfare gains of 2022 standards are the difference between social welfare for the 2016 and 2022 standards for the level of ZEV standard in the column heading. Social welfare is computed as in Table 5. Cost-effectiveness of the 2022 standards is the change in private welfare divided by the change in emissions.

In panel (a), the row headings indicate the level of fuel economy standard, and the column headings indicate the level of the ZEV standard. Tightening ZEV standards could reduce GHG emissions if doing so causes DOT to tighten GHG and fuel economy standards. Evaluating this hypothesis amounts to a differences-in-differences comparison: how do the net benefits of tighter standards vary with the level of the ZEV standard? Panel (c) facilitates this comparison by reporting the net benefits of 2022 relative to 2016 standards for each level of the ZEV standard.

The bottom row of the table accounts for differences in emissions across the simulations by computing cost-effectiveness as the change in private welfare divided by the change in emissions. Negative numbers indicate that the tighter standards increase private welfare and reduce emissions.

The results indicate that if DOT assumes a 10 percent ZEV requirement in the baseline, adopting the 2022 standards would increase social welfare by about $9 billion. As the ZEV requirement increases from 10 to 22 percent moving across the table, the welfare gains of the 2022 standards increase from $9 billion to $22 billion. Thus, tighter ZEV standards strengthen the case for DOT to tighten fuel economy standards. Although not shown, the results are the same qualitatively if I use the 2012 rather than the 2016 standards as the baseline.

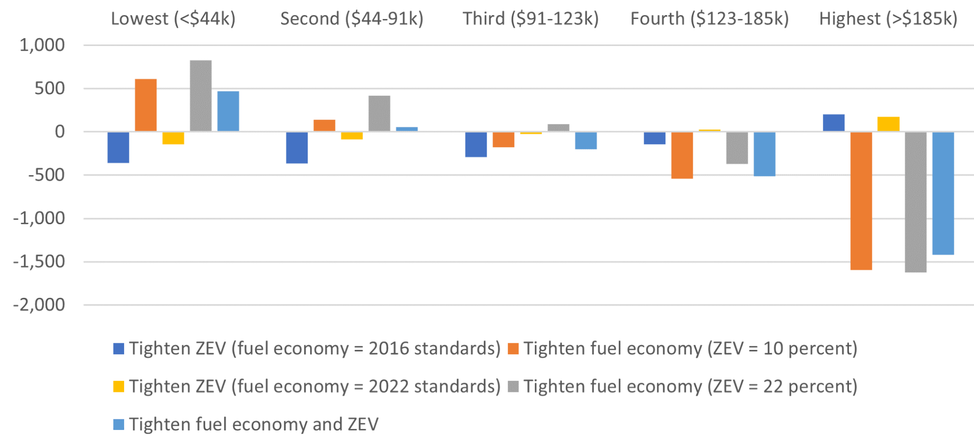
Each row shows that tighter ZEV standards reduce social welfare and increase GHG emissions, holding fixed the fuel economy standards. However, Table 6 shows that tighter ZEV standards reduce GHG emissions at moderate welfare costs after accounting for their effect on the stringency of the fuel economy standards. If tightening ZEV standards from 10 to 12, 17, or 22 percent causes DOT to adopt 2022 rather than 2016 standards, that will reduce emissions at a cost of $50–$100 per metric ton of CO2. This estimate is smaller than estimated costs of plug-in subsidies (e.g., (Xing, Leard, and Li, 2021)) and the same order of magnitude as the estimated social cost of carbon IWG (2021).[32]

## 6.5. Distributional Effects of ZEV and Fuel Economy standards

This subsection discusses the distribution of consumer welfare changes across demographic groups and regions. Figure 12 illustrates the welfare effects of ZEV and fuel economy standards by income group. Each bar shows the change in average welfare per household caused by the policy change indicated in the legend. In the figure, tightening ZEV indicates an increase of the credit requirement from 10 to 22 percent, and tightening fuel economy indicates an increase of the standards from 2016 to 2022 levels. For example, the blue bars show the effect of raising the ZEV standard to 22 percent while holding the fuel economy standards at 2016 levels (the changes correspond to the leftmost and rightmost columns of Table 6).

[32]Conclusions about the effects of ZEV standards on DOT standards are similar if I simulate counterfactuals assuming either 20 percent higher or lower gasoline prices (results available upon request), indicating that recent gasoline price fluctations are unlikely to affect the main results.

Figure 12: Welfare Effects of ZEV and Fuel Economy Standards by Income Group




Notes: Each bar shows the change in average welfare per household for the policy change indicated in the legend. The dark blue bars are the welfare changes caused by tightening ZEV from 10 to 22 percent with fuel economy standards at 2016 levels. The orange bars are the welfare changes caused by tightening fuel economy standards from 2016 to 2022 levels with ZEV at 10 percent. The yellow bars are welfare changes caused by tightening ZEV from 10 to 22 percent with fuel economy standards at 2022 levels. The gray bars are the welfare changes caused by tightening fuel economy standards from 2016 to 2022 levels with ZEV at 22 percent. The light blue bars are the welfare changes caused by tightening fuel economy standards from 2016 to 2022 levels and ZEV from 10 to 22 percent.

The dark blue and yellow bars show that tightening ZEV while holding fuel economy at 2016 or 2022 levels is regressive. Tightening ZEV from 10 to 22 percent causes the prices of gasoline vehicles to increase 1 percent and prices of plug-ins to decrease 1 percent. Because low-income consumers are more likely to buy gasoline than high-income consumers are, the higher gasoline vehicle prices harm the welfare of low-income consumers more. Likewise, high-income consumers benefit more from the lower prices of plug-ins. Consequently, tightening ZEV standards without simultaneously changing fuel economy standards is regressive.

In contrast, the fuel economy standards are progressive. The orange and gray bars show that tightening them while holding fixed the ZEV standards benefits low-income consumers more. Leard, Linn, and Springel (2023) find similar progressivity of the standards, using a national (rather than regional) version of the model, and they show that the progressivity arises from the horsepower reductions that tighter standards cause (high-income households have relatively high willingness to pay for horsepower).[33] The combination

[33]Undervaluation causes manufacturers to increase the fuel economy of vehicles purchased by low-income consumers less than that of vehicles purchased by high-income consumers. This effect tends to make the standards regressive, as high-income consumers experience larger fuel economy gains, but this effect is outweighed by the horsepower effect discussed in the text. These results account for the increase in used vehicle prices caused by tighter standards. Low-income consumers are more likely to purchase used vehicles (see Figure 1), so the price increases have a larger adverse welfare effect on them. Jacobsen (2013) finds a

of tighter ZEV standards and tighter fuel economy standards is progressive because, for the scenarios considered, the progressivity of the fuel economy standards outweighs the regressvity of the ZEV standards.

# 7 Conclusion

California sets ZEV standards that essentially mandate a minimum market share for plug-in or fuel-cell vehicles. Fourteen other states have adopted these standards. The ZEV standards are nested within federal fuel economy and GHG standards, and this situation is likely to persist at least into the 2030s during the anticipated transition from gasoline to plug-in (or fuel-cell) passenger vehicles.

This paper analyzes interactions among the ZEV and federal standards. I show conceptually that because California chooses ZEV standards before EPA and DOT choose GHG and fuel economy standards, tighter ZEV standards may induce EPA and DOT to strengthen federal standards.

Pre-existing distortions arising from market power and consumer choices complicate the welfare analysis of these policies. I use a new version of a computational model of the new vehicle market to estimate welfare effects of ZEV and federal standards on their own and investigate interactions among the policies. The modeling is capable of illustrating the implications of pre-existing distortions.

The paper contains four main results. First, tightening ZEV standards while holding fixed fuel economy and GHG standards caused plug-in sales to increase at high average welfare costs per vehicle, particularly when fuel economy standards are not stringent. The high welfare costs arise from pre-existing distortions from market power. This result is consistent with the traditional view of the inefficiency of overlapping regulations.

Second, tightening fuel economy standards from 2016 to 2022 stringency substantially increased social welfare, largely by addressing consumer undervaluation of fuel cost savings. These two results underscore the importance of including pre-existing market failures.

Third, tighter ZEV standards increased the net benefits of tighter fuel economy standards. Consequently, adopting stricter ZEV standards should cause EPA and DOT to adopt more stringent GHG and fuel economy standards. This result indicates that tightening ZEV standards through 2035 may induce EPA and DOT to adopt tighter fuel economy and GHG standards for the late 2020s and 2030s; in fact, this effect may partly explain California's

similar effect on used vehicle prices, but in Figure 12, this effect is dominated by the horsepower effects discussed in the text.

decision to pursue aggressive standards though 2035.

Across the range of scenarios I consider, tightening ZEV standards reduced GHG emissions by \$50–\$100 per metric ton of CO2 after accounting for the tighter fuel economy standards. These costs are lower than estimated costs of plug-in subsidies and the social cost of carbon. The combination of tighter ZEV standards and tighter fuel economy standards yields higher social welfare than weaker ZEV and fuel economy standards. Finally, the combination of tighter ZEV standards and tighter fuel economy and GHG standards is progressive across income groups.

The results have two additional policy implications. First, the United States could adopt a national ZEV standard, either as part of the EPA GHG program or enacted by Congress. If the national ZEV standard coexists with the EPA and DOT GHG and fuel economy standards, it would have similar implications as the California ZEV standard analyzed in this paper. Specifically, setting tighter national ZEV standards could support tighter overall fuel economy and GHG standards.

The second implication is that tighter ZEV standards could increase social welfare after accounting for effects on fuel economy and GHG standards. In this paper, consumer demand is static: consumer choices in one time period do not affect demand in subsequent periods. This may be a strong assumption for plug-ins, particularly given the importance of consumer learning about new products and network dynamics for charging stations. That is, omitting dynamics likely understates the benefits of ZEV standards. EPA and DOT do not include such dynamics, which could cause them to set standards that are weaker than socially optimal; tighter ZEV standards could increase social welfare by preventing this. Future work may incorporate consumer dynamics by taking advantage of recent increase in plug-in entry and sales.

An important caveat to this analysis is that the model does not include plug-in entry or long-term dynamics of using ZEV standards to stimulate plug-in sales. Armitage and Pinter (2022) and Linn (2022) endogenize plug-in entry, but both papers also take fuel economy and performance to be exogenous, which is inappropriate for the large changes in fuel economy standards modeled in this paper. Endogenizing entry would likely reduce estimated costs of ZEV standards and strengthen the conclusion that tighter ZEV standards cause stronger fuel economy and GHG standards. Including consumer dynamics, such as learning-by-using, would also likely strengthen the case that tighter ZEV standards cause stronger fuel economy and GHG standards, reducing emissions at modest (or even negative) costs.

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# 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 registrations and Consumer Expenditure Survey (CEX) data. 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 that in the CEX. Second, I adjust the household weights so that the vehicle's share of sales in total sales by year equals the corresponding share according to the registrations data. Third, I adjust the household weights so that total new vehicles obtained by year in the MaritzCX data match that in the registrations data. After constructing these weights, I compute the total new vehicles obtained by year, vehicle, and demographic group.

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

## Overview of DOT and EPA Models

DOT and EPA use computational models to estimate benefits and costs of their standards. The models recognize vehicles at a highly disaggregated level, approximately at the same level as the vehicles defined in Section 2. The sales of each vehicle are taken as exogenous and based on projections by the Energy Information Administration and other sources. To comply with tighter standards, manufacturers can adopt fuel-saving technology for gasoline-powered vehicles. In addition, they can increase the market share of plug-ins and electrics by converting vehicles with gasoline engines to vehicles with plug-in hybrid or electric powertrains. The market share increases because gasoline vehicles are converted and not because manufacturers adjust prices to increase sales.

Manufacturers minimize costs of complying with standards, and the marginal costs of improving fuel economy increases with the level of improvement. Both costs and fuel economy improvements are estimated relative to a base year that includes the most recent data available to the agencies.[34]

[34]This discussion abstracts from some of the details of the agencies' models. For example, they account

The marginal benefits of raising fuel economy are (approximately) constant. The benefits of a marginal change in fuel consumption rate include the GHG reduction and the fuel cost savings. The GHG reduction is proportional to the carbon content of the fuel, the number of miles the vehicles are driven over their lifetimes, and the social cost of CO2. The marginal fuel cost savings are proportional to the number of miles the vehicles are driven over their lifetimes and gasoline prices. According to the agencies' computational models, all of these factors are constant (or approximately so) over the range of fuel consumption rates they consider. That is, a reasonable assumption is that the marginal benefits are approximately constant.

The agencies estimate benefits and costs of particular standards relative to the baseline, which usually reflects no change from existing regulation. For example, in 2021, the EPA and DOT estimated benefits and costs of setting more stringent standards than in 2020. To do so, the agencies simulate their models assuming the no-change level of standards and that manufacturers minimize the cost of achieving that. Importantly, the agencies assume that manufacturers are complying with the ZEV standard in the no-change case. They compare the model output in the baseline scenario with the output in multiple alternative scenarios that vary the stringency of the standards and hold all else equal.

The main text discusses an approximation to the models the agencies use in which marginal abatement costs of plug-in and gasoline vehicles are separable from one another. In other words, by assumption, converting to a plug-in does not affect the marginal cost curve for gasoline vehicles. This is a simplification because the conversion would cause the marginal cost curve for gasoline vehicles to rotate to the left because it decreases the opportunities to reduce consumption at the remaining gasoline vehicles. This causes the intersection point in the figure, B, to shift left along the marginal benefits curve.

## Supply

This subsection contains the first-order conditions for the firm's choice of vehicle price, technology, and horsepower (see main text for explanation of the notation). For each market, the following first-order condition for price holds:

for interactions among specific power train technologies, and the EPA allows for adopting technologies that reduce GHG emissions without affecting fuel consumption. Also, technology costs decline over time because of learning and anticipated declines in battery costs. Nonetheless, the agencies show that the marginal costs of increasing fuel economy rise with the level of the increase.

$$\sum_{l\in J_f}\sum_{rt}\sum_{g}[p_{lrt}-mc_{lt}+\lambda_{Z,rt}(c_{lrt}-R_{rt})+\lambda_{M,t}(\frac{1}{m_{lt}}-\frac{1}{M_{lt}})]\frac{\partial s_{lgrt}}{\partial p_{lrt}}Q_{grt}+\sum_{rt}\sum_{g}s_{jgrt}Q_{grt}=0 \tag{9}$$

If the shadow prices equal zero, the equation simplifies to the familiar first-order condition for a multiproduct firm. The equilibrium price depends on the own and cross-price derivatives.

Using equation (5) to express marginal costs as a function of $T_{n(j)}$ and equation (4) to express fuel economy as a function of $h_j$ and $T_{n(j)}$ yields the following first-order condition for technology:

$$\begin{aligned}\sum_{l\in J_f}\sum_{rt}\sum_{g}[p_{lr}-mc_{l}+\lambda_{Z,r}(c_{lr}-R_{r})+\lambda_{M}(\frac{1}{m_{l}}-\frac{1}{M_{l}})](\frac{\partial s_{lgr}}{\partial m_j}\frac{\partial m_j}{\partial T_{n(j)}}+\frac{\partial s_{lgr}}{\partial p_{jrt}}\frac{\partial p_{jrt}}{\partial T_{n(j)}})Q_{gr}+\\ \sum_{rt}\sum_{g}s_{jgrt}Q_{grt}[\frac{\partial p_{lgr}}{\partial T_{n(j)}}+\frac{\partial p_{lgr}}{\partial m_j}\frac{\partial m_j}{\partial T_{n(j)}}]-\sum_{rt}\sum_{g}\frac{\partial mc_j}{\partial T_{n(j)}}s_{jgr}Q_{gr}-F'(T_{n(j)})=0\end{aligned} \tag{10}$$

Equation (10) 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. The term on the first line of equation (10) captures this effect. However, the technology adoption increases the marginal costs of producing the vehicle and causes fixed costs to increase. The second line of the equation captures the two cost effects. 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).

The first-order condition for horsepower is the following:

$$\begin{aligned}\sum_{l\in J_f}\sum_{rt}\sum_{g}[p_{lr}-mc_{l}+\lambda_{Z,r}(c_{lr}-R_{r})+\lambda_{M}(\frac{1}{m_{l}}-\frac{1}{M_{l}})](\frac{\partial s_{lgr}}{\partial h_j}+\frac{\partial s_{lgr}}{\partial m_j}\frac{\partial m_j}{\partial h_j}+\frac{\partial s_{lgr}}{\partial p_{jrt}}\frac{\partial p_{jrt}}{\partial h_j})Q_{gr}\\ +\sum_{rt}\sum_{g}s_{jgrt}Q_{grt}[\frac{\partial p_{lgr}}{\partial h_j}+\frac{\partial p_{lgr}}{\partial m_j}\frac{\partial h_j}{\partial h_j}]=0\end{aligned} \tag{11}$$

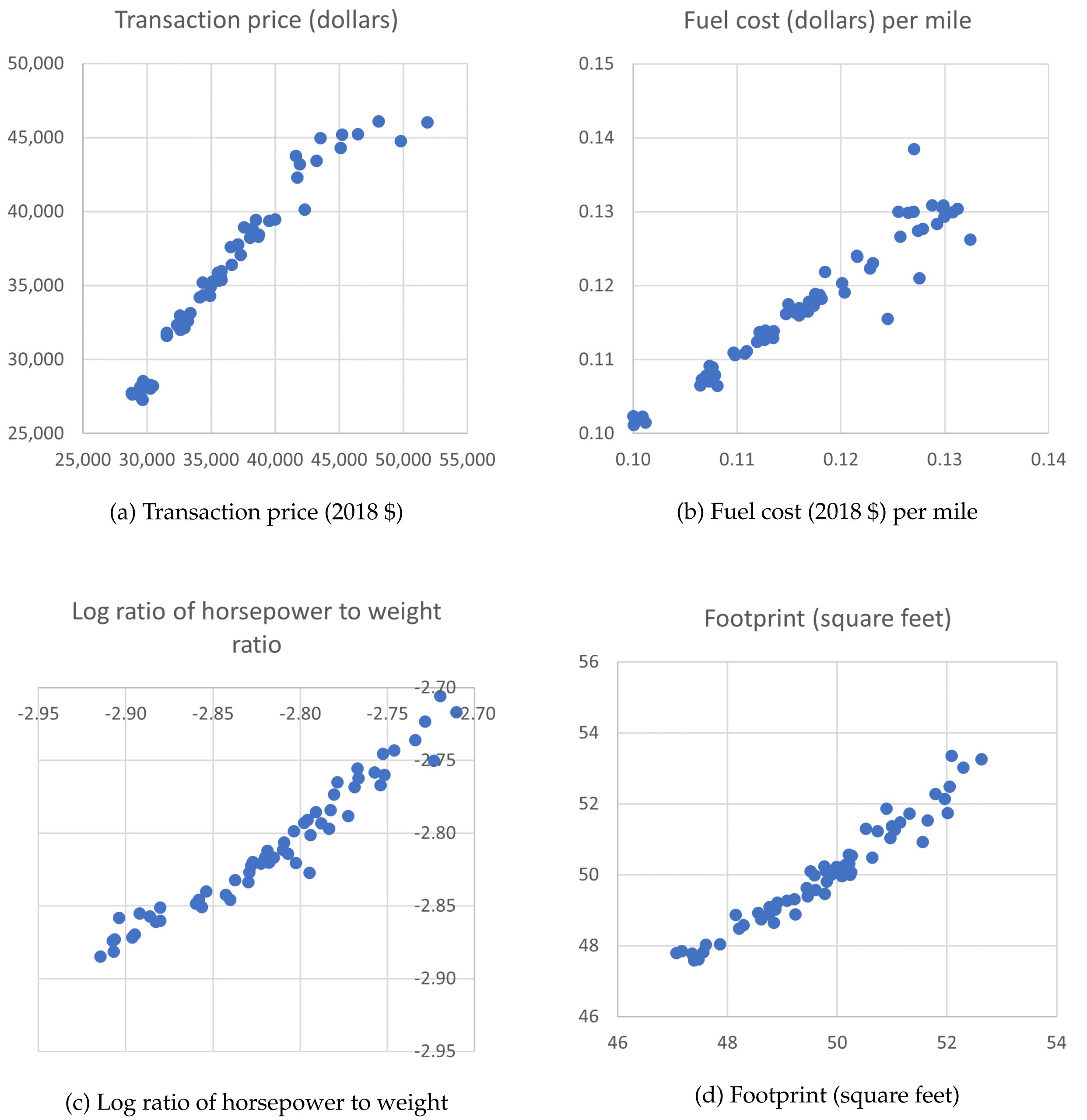
In equation (11), the term in square brackets is the same as the term in square brackets in the price first-order condition, and this term can be interpreted as the equilibrium markup including the shadow costs of the ZEV and fuel economy standards. Given this markup, equation (11) shows that equilibrium value of horsepower balances the sensitivity of market share to horsepower, the sensitivity of market share to fuel economy, and the tradeoff between horsepower and fuel economy. For example, suppose a vehicle's market share is highly sensitive to horsepower, which would imply a high marginal willingness to pay for horsepower.[35] Assuming that the second derivative of market share for fuel economy is negative (which is consistent with estimates reported in the next section), a higher sensitivity to horsepower implies that the manufacturer chooses a low level of fuel economy. This can be seen in Figure 7, in which a higher sensitivity of market share to horsepower implies a shallower isoprofit curve (note that the diagram abstracts from cross-vehicle terms in the first-order condition).

### Validation of the Demand Side of the Model

Because the demand side of the model is the same as in Linn (2022), this subsection adapts the discussion of the demand model validation from that paper. Appendix Figure A13 shows scatter plots of demographic group means of observed and predicted values of vehicle attributes. The means are computed using observed and predicted sales in 2018. Because parameters are estimated using data for 2010–2018, if the true preference parameters trend over time, the observed and predicted attributes would differ. The figure shows that the predicted values lie close to the 45-degree line, which supports the assumption that the preference parameters do not vary over time. This validation exercise is important because the policy counterfactuals in Section 6 use the estimated preference parameters from 2010–2018 to model subsidies in 2022.

[35]The marginal willingness to pay can be defined as the ratio of the derivative of the market share for horsepower and the derivative of market share for price.

Figure A13: Comparison of Predicted and Observed Attributes by Demographic Group and Region




(a) Transaction price (2018 $)

(b) Fuel cost (2018 $) per mile

(c) Log ratio of horsepower to weight

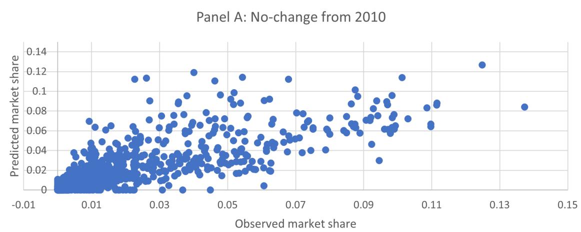
(d) Footprint (square feet)

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

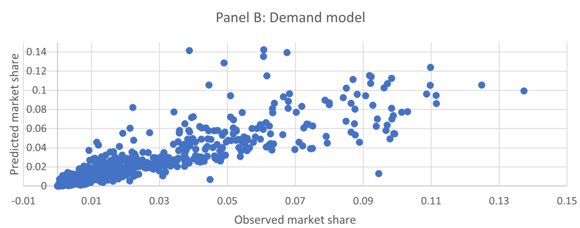
Appendix Figure A14 validates further the preference parameters by evaluating the out-of-sample fit of the model. Panel A plots predicted against observed 2018 market shares by brand and class by using the 2010 market shares to predict 2018 (that is, a no-change forecast). Panel B uses the estimated preference parameters to predict 2018 market shares.

Comparing the two panels shows that the preference parameters yield more accurate predictions than the no-change forecast.[36] Finally, panel C uses a randomly selected 50 percent subsample of the observations used to predict parameters. The preference parameters using the subsample of demographic group, vehicle, region, year observations yields more accurate predictions than the no-change forecast in panel A.

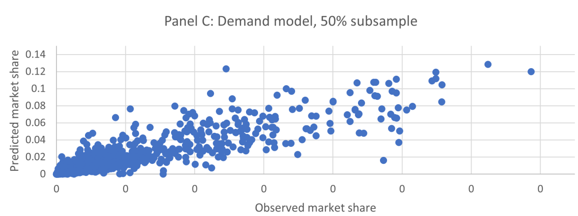
Figure A14: Comparison of Predicted and Observed 2018 Market Shares by Demographic Group, Brand, and Class: No-Change Versus Demand Model




(a) No change from 2010




(b) Demand model




(c) Demand model, 50 percent subsample

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

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

## Simulation Algorithm

For each simulation, the equilibrium is found by nesting second-stage price choices within first-stage horsepower and technology choices and iterating until both fuel economy and ZEV standards are met. The algorithm begins with an initial guess of equilibrium ZEV and fuel economy shadow prices, vehicle prices, horsepower, and technology. For the scenario with the 2016 fuel economy and ZEV standards (column 1 of Table 5), I use the estimated shadow prices and observed vehicle prices and attributes for 2018. For the other scenarios, for initial values, I use the simulated equilibrium values for a similar scenario. For example, for the scenario with 2016 fuel economy standards and ZEV standards of 12 percent, for initial guesses, I use the simulated equilibrium values of the scenario with 2016 fuel economy standards and ZEV standards of 14.5 percent.

In the inner loop, given credit prices and the horsepower and technology of each vehicle, each firm chooses the prices of its vehicles according to equation (9). I iterate through each firm and region until the vector of prices for the entire market converges to a specified tolerance (for example, that the maximum price change across all vehicles does not exceed 0.1 percent).

After the inner loop converges, the algorithm computes the profit-maximizing levels of horsepower and technology according to equations (11) and (10). I use equations (5) and (4) to compute marginal costs and fuel economy. After horsepower, technology, and vehicle prices converge, I compute the difference between credits and requirements for the fuel economy and ZEV standards. I adjust the fuel economy and ZEV credit prices in accordance with the discrepancy between credits and requirements and iterate until the credits are sufficiently close to requirements (within 0.1 percent).

## Additional Figures and Tables

Table A1: Vehicle Attributes by Demographic Group

| Income (2014 $) | Age group | Transaction price (2018 $) | Fuel costs (2018$ per mile) | Log (horsepower / weight) | Share of trucks in total purchases | Share of hybrids in total purchases | Share of plug-in hybrids in total purchases | Share of electrics in total purchases |
|---|---|---|---|---|---|---|---|---|
| | | | | | Panel A: Rural | | | |
| < 44k | < 45 | 29,965 | 0.12 | -2.89 | 0.44 | 0.013 | 0.001 | 0.001 |
| | | (8,930) | (0.04) | (0.18) | | | | |
| 44k - 91k | < 45 | 33,451 | 0.13 | -2.85 | 0.55 | 0.016 | 0.002 | 0.002 |
| | | (9,685) | (0.04) | (0.19) | | | | |
| 91k - 123k | < 45 | 37,020 | 0.13 | -2.84 | 0.61 | 0.018 | 0.002 | 0.003 |
| | | (11,337) | (0.04) | (0.19) | | | | |
| 123k - 185k | < 45 | 39,798 | 0.04 | 0.20 | 0.61 | 0.021 | 0.003 | 0.007 |
| | | (12,944) | (0.05) | (0.20) | | | | |
| > 185k | < 45 | 46,611 | 0.15 | -2.78 | 0.67 | 0.018 | 0.004 | 0.010 |
| | | (14,563) | (0.05) | (0.20) | | | | |
| < 44k | >= 45 | 30,129 | 0.12 | -2.89 | 0.47 | 0.013 | 0.001 | 0.001 |
| | | (8,644) | (0.04) | (0.18) | | | | |
| 44k - 91k | >= 45 | 33,510 | 0.13 | -2.86 | 0.56 | 0.017 | 0.002 | 0.002 |
| | | (9,583) | (0.05) | (0.19) | | | | |
| 91k - 123k | >= 45 | 36,771 | 0.14 | -2.84 | 0.60 | 0.023 | 0.003 | 0.004 |
| | | (11,288) | (0.05) | (0.20) | | | | |
| 123k - 185k | >= 45 | 38,899 | 0.14 | -2.82 | 0.58 | 0.026 | 0.005 | 0.008 |
| | | (12,416) | (0.05) | (0.19) | | | | |
| > 185k | >= 45 | 45,906 | 0.15 | -2.78 | 0.63 | 0.025 | 0.008 | 0.010 |
| | | (15,752) | (0.05) | (0.21) | | | | |
| | | | | | Panel B: Urban | | | |
| < 44k | < 45 | 29,482 | 0.12 | -2.90 | 0.41 | 0.022 | 0.002 | 0.001 |
| | | (8,270) | (0.04) | (0.19) | | | | |
| 44k - 91k | < 45 | 33,419 | 0.13 | -2.86 | 0.54 | 0.028 | 0.003 | 0.002 |
| | | (9,622) | (0.04) | (0.20) | | | | |
| 91k - 123k | < 45 | 36,555 | 0.13 | -2.83 | 0.60 | 0.032 | 0.004 | 0.003 |
| | | (11,002) | (0.04) | (0.20) | | | | |
| 123k - 185k | < 45 | 39,415 | 0.14 | -2.81 | 0.63 | 0.034 | 0.006 | 0.006 |
| | | (12,367) | (0.05) | (0.21) | | | | |
| > 185k | < 45 | 46,674 | 0.14 | -2.77 | 0.67 | 0.033 | 0.009 | 0.014 |
| | | (15,954) | (0.05) | (0.21) | | | | |
| < 44k | >= 45 | 29,629 | 0.12 | -2.90 | 0.44 | 0.020 | 0.001 | 0.001 |
| | | (8,219) | (0.04) | (0.18) | | | | |
| 44k - 91k | >= 45 | 33,906 | 0.13 | -2.85 | 0.55 | 0.027 | 0.002 | 0.002 |
| | | (10,104) | (0.04) | (0.20) | | | | |
| 91k - 123k | >= 45 | 37,295 | 0.13 | -2.83 | 0.60 | 0.030 | 0.004 | 0.004 |
| | | (11,889) | (0.05) | (0.21) | | | | |
| 123k - 185k | >= 45 | 40,299 | 0.14 | -2.80 | 0.61 | 0.031 | 0.006 | 0.007 |
| | | (13,447) | (0.05) | (0.21) | | | | |
| > 185k | >= 45 | 48,552 | 0.14 | -2.75 | 0.62 | 0.031 | 0.009 | 0.014 |
| | | (17,291) | (0.05) | (0.22) | | | | |

Notes: The table shows the purchases-weighted mean attribute or market share for each demographic group, with standard deviations in parentheses. The sample includes all vehicles purchased 2010–2018.

Table A2: Vehicle Attributes by Firm

| Firm | Transaction price (2018 $) | Fuel costs (2018$ per mile) | Log (horsepower / weight) | Share of trucks in total purchases | Share of hybrids in total purchases | Share of plug-in hybrids in total purchases | Share of electrics in total purchases |
|---|---|---|---|---|---|---|---|
| General Motors | 38,619 | 0.15 | -2.82 | 0.64 | 0.003 | 0.007 | 0.002 |
| | (13,648) | (0.06) | (0.23) | | | | |
| Toyota | 35,378 | 0.13 | -2.93 | 0.49 | 0.118 | 0.005 | 0.000 |
| | (11,258) | (0.04) | (0.22) | | | | |
| Ford | 36,128 | 0.14 | -2.78 | 0.66 | 0.027 | 0.006 | 0.001 |
| | (10,050) | (0.05) | (0.20) | | | | |
| Fiat Chrysler | 34,076 | 0.14 | -2.79 | 0.75 | 0.000 | 0.001 | 0.002 |
| | (7,755) | (0.04) | (0.19) | | | | |
| Honda | 31,558 | 0.12 | -2.87 | 0.47 | 0.016 | 0.001 | 0.000 |
| | (8,193) | (0.03) | (0.13) | | | | |
| Nissan | 31,650 | 0.12 | -2.88 | 0.45 | 0.003 | 0.000 | 0.011 |
| | (10,487) | (0.04) | (0.20) | | | | |
| Hyundai | 27,338 | 0.11 | -2.88 | 0.29 | 0.022 | 0.001 | 0.001 |
| | (6,283) | (0.03) | (0.15) | | | | |
| Subaru | 30,926 | 0.12 | -2.95 | 0.72 | 0.004 | 0.000 | 0.000 |
| | (4,237) | (0.03) | (0.14) | | | | |
| Volkswagen | 37,604 | 0.12 | -2.88 | 0.25 | 0.002 | 0.002 | 0.003 |
| | (15,440) | (0.03) | (0.17) | | | | |
| Mazda | 28,430 | 0.12 | -2.93 | 0.46 | 0.000 | 0.000 | 0.000 |
| | (5,435) | (0.03) | (0.09) | | | | |
| BMW | 54,675 | 0.13 | -2.76 | 0.325 | 0.001 | 0.017 | 0.006 |
| | (15,962) | (0.04) | (0.20) | | | | |
| Daimler | 59,350 | 0.14 | -2.73 | 0.439 | 0.001 | 0.000 | 0.002 |
| | (16,107) | (0.04) | (0.20) | | | | |
| Tesla | 77,893 | 0.05 | -2.38 | 0.173 | 0.000 | 0.000 | 1.000 |
| | (15,635) | (0.01) | (0.14) | | | | |
| Volvo | 49,517 | 0.14 | -2.73 | 0.594 | 0.000 | 0.011 | 0.000 |
| | (7,905) | (0.04) | (0.12) | | | | |

Notes: Notes: The table shows the purchases-weighted mean attribute or market share for each firm, with standard deviations in parentheses. The sample includes all vehicles purchased 2010–2018.