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Abstract

We apply a simple methodology to estimate own- and cross-price elasticities of new passenger vehicle demand based on household-level survey data. Our methodology combines own-price elasticity estimates with diversion fractions constructed from second-choice data. We obtain a set of elasticities that are relevant for policy analysis, including an aggregate market elasticity, a matrix of car and light truck elasticities, and a matrix of gasoline and electric vehicle (EV) elasticities. Our results have implications for evaluating incidence of fuel economy and greenhouse gas standards for passenger vehicles and policies for increasing EV adoption.

1 Introduction

Estimating consumer demand for products has numerous applications for economic analysis, including assessing mergers, identifying pricing strategies, and estimating costs and benefits of regulations. In this paper, we apply a general methodology for estimating own- and cross-price elasticities of consumer demand based on survey data. We apply the methodology to estimate elasticities for passenger vehicle demand based on a survey of new vehicle buyers. Our estimates yield a set of plausible nameplate-level own- and cross-price elasticities and aggregated elasticities that are relevant for current passenger vehicle regulations, including Corporate Average Fuel Economy (CAFE) and greenhouse gas (GHG) standards for passenger vehicles and policies for increasing the adoption of electric vehicles (EVs). In particular, we estimate the aggregate market-price elasticity of new vehicle demand, own- and cross-price elasticities at the car-light truck level, and own- and cross-price elasticities at the gasoline-EV level. Our approach is computationally simple, making it

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widely accessible, and our application informs current design of policies for reducing GHG emissions in the transportation sector.

Our approach builds on the methodology used by Bordley (1993), which centers on constructing diversion fractions using market-level data and micro-level second-choice data to estimate price elasticities. Leard (2022) expands this approach to estimate substitution patterns between new and used vehicles. We further develop this methodology to allow for flexible definition of vehicle category based on attributes. In particular, we expand the vehicle category of analysis to obtain elasticity estimates at the aggregated body style and fuel type levels. Furthermore, our approach disaggregates consumers by income group, thus accounting for consumer heterogeneity in all of our price elasticity estimates. Our methodology differs from other studies that use second-choice data in the vehicle demand estimation literature because it does not require estimating complex models of demand with random coefficients, such as in Berry et al. (2004) or Grieco et al. (2023).

We obtain plausible estimates on various price elasticities of interest. Our estimates for the market-price elasticity for new vehicles show considerable heterogeneity across consumer income groups, ranging from -0.2 for the highest income group to -0.84 for the lowest. The average is -0.5 , which is similar in magnitude to the parameter value used by the Environmental Protection Agency (EPA) and the National Highway Traffic Safety Administration (NHTSA) in their final regulatory impact analysis of the 2024–2026 fuel economy and GHG standards (NHTSA 2022). In terms of category elasticities, we find that car and EV buyers are more price sensitive than light truck and gasoline vehicle buyers.

Using the estimated cross-price elasticities along with sales data, we simulate sales changes for gasoline vehicles in response to price drops in EVs and calculate the average fuel economy of vehicles that would have been purchased absent the EV price change. Similar to prior studies such as Xing et al. (2021) and Muehlegger and Rapson (2023), we find that new EVs replace relatively fuel-efficient vehicles that have an average fuel economy that is 4 miles per gallon greater than that of the fuel economy a typically purchased new gasoline vehicle. However, we find evidence that this replacement fuel economy is likely to converge to the fleet-wide average as more electric sport utility vehicles (SUVs) and pickup trucks enter the market.

We organize the rest of this paper as follows. In Section 2, we briefly describe the data, highlighting the key role of the second-choice data in the estimation. In Section 3, we outline our estimation strategy, which shows that vehicle substitution patterns depend on the relevant diversion fractions. We then present our empirical results in Section 4. In Section 5, we show the results from an application of our model to analyze the fuel economy of vehicles being replaced by EVs. We then discuss the policy implications of our results in Section 6 and make concluding remarks in Section 7.

2 Data

The primary data source that we use for estimation is the 2018 wave of the New Vehicle Customer Survey (NVCS) administered by InMoment (formerly called MaritzCX). These are household-level survey data with a sample of nearly 250,000 U.S. households. The 2018 wave includes surveys of households that purchased or leased a new vehicle in the fourth quarter of 2017 through the third quarter of 2018. The data provide detailed vehicle information, including including firm, make, model, fuel type, and body style identifiers, financing, purchase prices, and engine characteristics including the number of cylinders. The data also include self-reported household income groups (e.g., \$85,000–\$100,000). The survey data represent about 1–2% of national new vehicle transactions during the sampled time period.

The survey aims to create a nationally representative sample of new vehicle transactions and samples households until vehicle model-level sampling quotas are met; quotas are based on a database of national registrations. However, this sampling method does not guarantee a perfect representation of the entire universe of households buying or leasing vehicles. Furthermore, due to constraints imposed by the sampling methodology, a select number of luxury brands are not sampled in certain states.¹ We address these data concerns in a few ways. First, we aggregate the sample by household income group and analyze the data across the income groups. Our investigation of the data illustrates plausible purchase and lease patterns across households, providing some assurance of the data quality and alleviating the first concern.² Second, we aggregate the sample to the national level and do not formulate the model at the brand or state level. Third, we use survey weights provided by InMoment to weight the data in all of our estimation, elasticity, and simulation calculations. The survey weights represent monthly nameplate-level national sales derived from IHS Automotive registration data, which InMoment uses during the sampling process to send surveys out to new vehicle owners and lessees.³

¹InMoment does not sample BMW, Jaguar-Land Rover, Mercedes Benz, MINI, Porsche, Smart, and Tesla purchase or lease transactions in the following states: Alaska, Arizona, California, Hawaii, Illinois, Kansas, Maryland, Montana, Nevada, New Hampshire, New York, Oregon, Pennsylvania, South Dakota, and Washington.

²Leard et al. (2023) use NVCS data from 2010 to 2018 and provide further analysis of how representative the data are of the universe of new vehicle transactions.

³We use the national sales weights when aggregating nameplate counts. To weight the counts, we first aggregate counts by make-model-fuel type-body style and compute a market share for each vehicle combination. We also aggregate the value of the weight variable across all months of the data by the same vehicle identifiers and compute a weight share for each nameplate, which represents nationally representative market shares for the sample period. We then compute the final weight for each nameplate as the ratio of the two shares. For example, if we observe 2 percent of survey observations as a Ford F-150, but the aggregated weight variable has the market share at 3 percent, then the final weight for Ford-150's is $0.03/0.02 = 1.5$. In other words, we count each Ford F-150 in the survey data as 1.5 sales. We can then aggregate the weighted sales to the demographic group at the nameplate level.

The NVCS data also include information about vehicles they considered besides the one they purchased or leased, including the model that was most seriously considered, but did not end up buying or leasing. The survey allows respondents to provide details on the seriously considered vehicle, including make, model, fuel type, body style, and the desire to acquire it new or used. From these responses, we are able to define a nameplate for roughly two-thirds of respondents.⁴ Following convention in the literature (Berry et al. 2004), we denote these data as second-choice data, as they represent plausible second choices that would have been chosen had the purchased or leased vehicle not been available. From these data, we are able to construct diversion fractions, as described in Bordley (1993). We do so for purchased and leased vehicles in the data. For example, among the respondents in the \$55,000–\$85,000 income group who purchased or leased a Ford F-150, 9 percent of them reported a Toyota Tacoma as their second choice.

We merge the NVCS data with vehicle characteristics from Wards Automotive. These data include fuel economy (miles per gallon), horsepower, weight, and size and also drive type (e.g., all-wheel drive) as a discrete characteristic. After merging, we aggregate the vehicle characteristics data to the nameplate level, which is a unique make-model-fuel type-body style combination (e.g., Honda Accord gasoline sedan), by taking averages of vehicle characteristics, including non-price characteristics from Wards and transaction prices reported by respondents in the NVCS. We assign a single average transaction price for each vehicle nameplate in the data.

To incorporate household preference heterogeneity in our model, we use self-reported annual household income data to create five approximately evenly distributed income groups and produce a survey sales count for each nameplate by income group. The income groups are less than \$55,000, \$55,000–\$85,000, \$85,000–\$125,000, \$125,000–\$200,000, and over \$200,000. The survey sales count represents the number of households in each income group that bought or leased a particular type of vehicle nameplate. For example, 319 surveyed households with reported incomes under \$55,000 purchased or leased a Chevrolet Malibu, and only 88 survey households with reported incomes of \$125,000–\$200,000 did so.⁵

We use the survey data to construct an average purchase price for each vehicle nameplate by observed income group combination.⁶ To address a tiny number of observations with unrealistically

⁴The remaining one-third of respondents reported insufficient information for us to identify a vehicle at the nameplate level, e.g., some provided only make information.

⁵In 2018, the Chevrolet Malibu was considered an affordable, entry-level new sedan. In our data, its average purchase price is \$24,857, which is much lower than the overall average purchase price paid for a vehicle (see Table 1). Therefore, this vehicle was especially popular among budget-constrained, low-income households.

⁶When constructing our price data, we do not account for state or federal incentive programs, such as tax credits for EVs. In particular, we omit EV tax credits because we do not observe whether households claimed the credits or the pass-through rate. Therefore, we base our methodology for estimating elasticities on transaction cost variation and do not exploit other sources of price variation.

low reported purchase prices, when computing the averages we exclude prices that are less than \$10,000.

2.1 Summary statistics

Table 1 summarizes the key variables in our data by household income groups. All calculations except household counts are done using the weights, as explained in the previous subsection.

The first four rows show the means of vehicle characteristics. Price is the mean of the average transaction price of all nameplates within an income group. Gallons per mile is computed as 1 divided by the city/highway average fuel economy rating.⁷ Horsepower/weight is a vehicle’s horsepower divided by its weight, denoted in hp/pounds. This variable is highly correlated with a vehicle’s 0–60 miles per hour acceleration time and represents its engine performance (Leard et al. 2023). Footprint is wheelbase multiplied by its width, measured in thousand square inches, and represents a vehicle’s size.⁸ The statistics in the table show that high-income households tend to purchase more expensive, larger vehicles with greater acceleration.

The rows with first- and second-choice information show the share of each vehicle type in the survey, where electric includes both electric and plug-in hybrid vehicles. The electric share increases in income group, accounting for 6 percent of the highest-income households. This reflects that many EV models are much more expensive than the average new vehicle (e.g., most Tesla models). The market share of plug-in hybrid and battery EVs is 2 percent, which is representative of the national market sales share for EVs in 2018. Furthermore, the share of a used car as the second choice steadily decreases by income group. The overall average is 9 percent – slightly higher than the frequency reported in Leard (2022), which uses 2013 data. Finally, the last row provides a sense of the household income distribution, with the middle group comprising about a quarter of households in the survey.

2.2 Second-choice data statistics

An advantage of the NVCS data is its second-choice information, which is a key empirical component of our estimation strategy. These second-choice vehicles are realistic candidates for households that respond to a price increase. Bordley (1993) and Leard (2022) assume that second-choice vehicles would be purchased in this way, and we adopt a similar assumption. Table 2 shows that households’ first and second choices are closely related in terms of price and vehicle segments across all income groups.⁹ The first row is the correlation coefficient between the transaction price of the first-

⁷We include gallons per mile in the model instead of miles per gallon because a vehicle’s fuel costs are proportional to gallons per mile.

⁸This variable approximately equals the rectangular surface area between where a vehicle’s wheels touch the ground.

⁹We use our constructed weights for all calculations in this table.

choice vehicle and the average transaction price of all second-choice vehicles with that same first choice. For example, the lowest-income group has a correlation coefficient of 0.79, which suggests a strong and positive relationship between average prices of first- and second-choice vehicles. The remaining rows show the shares of households that had a second choice of the same body style/fuel type as their first choice (e.g., among the lowest-income group purchasing a pickup truck, 87 percent had another pickup as their second choice). This table shows consistency in household preferences between their first and second choice with respect to relevant vehicle attributes, and provides justification for our assumption that second choices represent plausible substitution patterns for households.

3 Estimation Strategy

The estimation strategy for obtaining own- and cross-price elasticities of demand builds on Bordley (1993) and Leard (2022). Bordley (1993) states that own- and cross-price elasticities can be obtained from two empirical components:

1. How much share a product loses when its own price increases.
2. The fraction of that lost share diverted to various other products.

The first statistic is defined by an own-price elasticity of demand. Bordley (1993) denotes the second statistic as the diversion fraction. We use household-level data to estimate both statistics for the entire set of new vehicles sold in the United States in 2018.

3.1 Own-price elasticities

The first step is to estimate nameplate-level own-price demand elasticities. We do so separately by income group using instrumental variables.¹⁰ This yields a set of own-price elasticities by vehicle nameplate and income group. We then aggregate these elasticities to nameplate level (e.g., Toyota Prius hybrid sedan) and category level (e.g., EV) following the methodology outlined next.

3.1.1 Nameplate own-price elasticity

We estimate the nameplate-level own-price elasticity of new vehicle sales using a log-log specification. We assume that the natural log of nameplate j sales counts purchased by income group g ,

¹⁰The survey data include other demographics, such as age of respondent, which would allow us to disaggregate the model over a broader set of household characteristics. We chose to organize the model by income group only as a way to capture relevant consumer heterogeneity (i.e., it is typical for vehicle demand models to show price responsiveness as a function of household income) yet maintain a large enough sample in each group to estimate own-price elasticities accurately. Further disaggregation would pose a problem of fewer sales observations per demographic group, which would make it more challenging to estimate a plausible set of own-price elasticities.

denoted by q_{gj} , is a linear function of the natural log of the average transaction price for vehicle j . We control for a series of continuous nonprice vehicle attributes, including gallons per mile, performance measured as the ratio of horsepower to weight, and size measured by footprint. We include a control variable for the average model year of each vehicle and the number of cylinders and dummy variables for all-wheel and rear-wheel drive.. We also include fixed effects for body style (e.g., pickup truck) by fuel type (e.g., hybrid) and firm. The estimation equation is

$$\ln(q_{gj}) = \beta_g \ln(p_j) + \theta X_j + \epsilon_{gj}. \quad (1)$$

The coefficient of interest is β_g , which represents the average own-price elasticity of demand for new vehicles for income group g . This is interpreted as the percentage change in household group g purchases of vehicle j due to a 1 percent increase in the price of vehicle j . To address concerns about price endogeneity, we instrument for the log of transaction price following Berry et al. (1995) and Train and Winston (2007), using the sums of gallons per mile, horsepower divided by weight, and footprint of other vehicles sold by the same manufacturer, the sum of the continuous characteristics of other vehicles sold by other manufacturers in the same body style category, and squared values of each sum.

We can aggregate these elasticity estimates to the nameplate level using the following formula:

$$\varepsilon_j = \frac{d \ln q_j}{d \ln p_j} = \frac{dq_j p_j}{dp_j q_j}, \quad (2)$$

where $q_j = \sum_g q_{gj}$. Substituting the definition of the group-specific elasticity $\beta_g = \frac{d \ln q_{gj}}{d \ln p_j} = \frac{dq_{gj} p_j}{dp_j q_{gj}}$ and canceling terms yields

$$\varepsilon_j = \sum_g \beta_g \frac{q_{gj}}{\sum_g q_{gj}}. \quad (3)$$

This elasticity is interpreted as the percentage change in total sales of vehicle j (across all groups of consumers) due to a 1 percent increase in the price of vehicle j .

Given the functional form assumption in equation (1), we define a household-group specific elasticity as

$$\varepsilon_{gj} = \frac{d \ln q_{gj}}{d \ln p_j} = \beta_g. \quad (4)$$

3.1.2 Category own-price elasticity

Our methodology yields closed-form solutions of vehicle category elasticities. Vehicle category c can represent any subset of nameplates, such as body style segment (e.g., all light trucks) or fuel type by body style category (e.g., all hybrid cars). We define ε_c as the percentage change in vehicle category c sales, in response to a 1 percent increase in the price of every vehicle in category c :

$$\varepsilon_c = \sum_{j \in C} \frac{d \sum_{k \in C} \sum_g q_{gk}}{dp_j} \frac{p_j}{\sum_{k \in C} \sum_g q_{gk}}. \quad (5)$$

This can be rearranged as

$$\varepsilon_c = \sum_{j \in C} \left(\sum_{k \in C} \sum_g \frac{dq_{gk}}{dp_j} \right) \frac{p_j}{\sum_{k \in C} \sum_g q_{gk}}. \quad (6)$$

Define $\delta_{gj'c'}$ as the percentage of vehicle j sales for household group g going to purchases of vehicles in categories other than c in response to a vehicle j price increase. Then $1 - \delta_{gj'c'}$ defines the fraction of sales going to other vehicles in category c in response to a price increase, and the following identity holds:

$$\sum_{k \neq j, k \in C} \frac{dq_{gk}}{dp_j} = -(1 - \delta_{gj'c'}) \frac{dq_{gj}}{dp_j}. \quad (7)$$

Rearranging yields

$$\sum_{k \in C} \frac{dq_{gk}}{dp_j} = \delta_{gj'c'} \frac{dq_{gj}}{dp_j}. \quad (8)$$

Substituting (8) into (6) yields

$$\varepsilon_c = \sum_{j \in C} \left(\sum_g \delta_{gj'c'} \frac{dq_{gj}}{dp_j} \right) \frac{p_j}{\sum_{k \in C} \sum_g q_{gk}}. \quad (9)$$

Define the nameplate own-price elasticity of demand for household group g as

$$\varepsilon_{gj} = \frac{dq_{gj}}{dp_j} \frac{p_j}{q_{gj}} = \beta_g. \quad (10)$$

Rearranging yields

$$\beta_g q_{gj} = \frac{dq_{gj}}{dp_j} p_j. \quad (11)$$

Substituting (11) into (9) yields

$$\varepsilon_c = \sum_{j \in C} \sum_g \delta_{gj} \beta_g \frac{q_{gj}}{\sum_{k \in C} \sum_g q_{gk}}. \quad (12)$$

The vehicle category own-price elasticity is a sales-weighted average of diversion fractions multiplied by nameplate-level own-price elasticities. The weights are equal to the fraction of vehicle sales in each household group.

3.2 Cross-price elasticities

To estimate cross-price elasticities at the nameplate level, we combine the estimates of the nameplate own-price elasticities with second-choice data that represent diversion fractions. Cross-price elasticities are identified by two features: the degree to which sales of a vehicle falls in response to a price increase and the degree to which these lost sales are diverted to other products. The first statistic is derived from estimates of own-price elasticities. The second statistic is defined according to diversion fractions. We use the second-choice data to calculate diversion fractions (see Sections 2 and 2.2).

3.2.1 Nameplate cross-price elasticity

We can derive vehicle cross-price elasticities based on the estimated own-price elasticities and diversion fractions. Define the nameplate cross-price elasticity as

$$\varepsilon_{jk} = \frac{d \ln q_k}{d \ln p_j} = \sum_g \frac{dq_{gk}}{dp_j} \frac{p_j}{q_k}. \quad (13)$$

This cross-price elasticity is interpreted as the percentage change in vehicle k sales due to a 1 percent increase in the price of vehicle j . Define δ_{gjk} as the fraction of households in group g that switch to vehicle k as a result of a vehicle j price increase. Mathematically, this is equivalent to

$$\frac{dq_{gk}}{dp_j} = -\delta_{gjk} \frac{dq_{gj}}{dp_j}. \quad (14)$$

Substituting equation (14) into (13) yields

$$\varepsilon_{jk} = \sum_g -\delta_{gjk} \frac{dq_{gj}}{dp_j} \frac{p_j}{q_k}. \quad (15)$$

Substituting the definition of group g average own-price elasticity $\beta_g = \frac{dq_{gj}}{dp_j} \frac{p_j}{q_{gj}}$ gives

$$\varepsilon_{jk} = \sum_g -\delta_{gjk} \beta_g \frac{q_{gj}}{q_k}. \quad (16)$$

3.2.2 Vehicle category cross-price elasticity

Define ε_{cd} as the percentage change in vehicle category c sales in response to a 1 percent increase in the price of every vehicle in category d :

$$\varepsilon_{cd} = \sum_{j \in D} \frac{d \sum_{k \in C} \sum_g q_{gk}}{dp_j} \frac{p_j}{\sum_{k \in C} \sum_g q_{gk}}. \quad (17)$$

This can be rearranged as

$$\varepsilon_{cd} = \sum_{j \in D} \left(\sum_{k \in C} \sum_g \frac{dq_{gk}}{dp_j} \right) \frac{p_j}{\sum_{k \in C} \sum_g q_{gk}}. \quad (18)$$

Define δ_{gjc} as the fraction of vehicle j sales for household group g going to purchases of vehicles in category c in response to a vehicle j price increase, where vehicle j is in category d (and not in category c). Then, for household group g ,

$$\sum_{k \in C} \frac{dq_{gk}}{dp_j} = -\delta_{gjc} \frac{dq_{gj}}{dp_j}. \quad (19)$$

Substituting (19) into (18) yields

$$\varepsilon_{cd} = \sum_{j \in D} \left(\sum_g -\delta_{gjc} \frac{dq_{gj}}{dp_j} \right) \frac{p_j}{\sum_{k \in C} \sum_g q_{gk}}. \quad (20)$$

Substituting the definition for the nameplate-level own-price elasticity (11) into (20) yields

$$\varepsilon_{cd} = - \sum_{j \in D} \sum_g \delta_{gjc} \beta_g \frac{q_{gj}}{\sum_{k \in C} \sum_g q_{gk}}. \quad (21)$$

This equation appears similar to (12) but has three key differences. The first is that the summation for j is across vehicles in category d , not c . The second is that the diversion fraction δ_{gjc} represents sales diverted from vehicle j , which is in category d , to vehicles in a different category c . The third is that the last term, which represented a weight in (12) now does not add up to 1, because vehicle j is not in category c .

4 Estimation results

4.1 Nameplate own-price elasticities

We present estimates of own-price elasticities in Table 3. The dependent variable in each specification is the natural log of sales counts. Columns (1)–(5) report estimates using ordinary least squares (OLS), and columns (6)–(10) report instrumental variables (IV) results. Each column includes observations for a specific household income group.¹¹ For example, column (7) reports IV results for the \$55,000–\$85,000 group.

We include a set of vehicle attributes in each model, including the natural log of purchase price, the inverse of fuel economy denoted as gallons per mile, performance as measured by horsepower divided by weight, and vehicle size as measured by footprint.¹² All coefficients are estimated with the expected sign. Households prefer to purchase vehicles that have a lower price, lower driving costs, better performance, and larger size.

The coefficient of interest is the natural log of vehicle price, which is interpreted as a demand elasticity. For a given income group, the magnitude of the estimate is larger for the IV specification, suggesting some degree of price endogeneity in the OLS specifications. The average own-price elasticity across all income groups for the IV specifications is -4.85 , which falls within the range of model-level demand elasticities in Berry et al. (1995) and is similar to the average own-price elasticity in Leard et al. (2023) and Leard (2022).

¹¹For simplicity, we estimate the elasticities using only observed sales by each income group. This set up allows for a simple log-log IV estimation approach, but creates an uneven sample size across the groups. Our approach could result in selection bias from ignoring zero sales observations. However, we believe this bias is minimal for several reasons. First, the set of vehicles appearing in each estimation equation has a large overlap, with only about a 15 percent difference in the number of unique nameplates observed with positive sales (comparing the lowest-income group to the highest). Second, selection bias caused by treating zero sales observations as the outside option in demand modeling typically causes estimated elasticities to be biased toward zero (Gandhi et al. 2023). Our estimates imply elasticities in the range of those from the literature (e.g., Berry et al. (1995)). Finally, the group with the fewest positive sales observations (lowest income) has the largest elasticity magnitude, contrary to what we would expect if bias was substantial.

¹²For plug-in hybrid and battery EVs in the sample, we use the EPA fuel economy miles per gallon equivalent rating to create an equivalent gallons per mile value. For example, the Tesla Model X has a miles per gallon equivalent rating of 93, which converts to a gallons per mile of 0.01.

For both OLS and IV specifications, the magnitude of the coefficient is smaller in magnitude for higher-income groups. This is intuitive because higher-income households tend to be less price sensitive, a pattern that is consistent with new vehicle demand modeling literature (Petrin 2002; Train and Winston 2007; Beresteanu and Li 2011). The lowest group has an own-price elasticity of around -6 , whereas the highest group has a demand elasticity of -2.7 .

In Figure 1, we plot average nameplate-level own-price elasticities and purchase prices. Our model yields a plausible relationship between the two where more expensive vehicles tend to be purchased by consumers that are less price sensitive (Berry et al. 1995; Beresteanu and Li 2011). For example, vehicles with an average purchase price of \$20,000 have an own-price elasticity of demand of about -5.5 , while vehicles with an average purchase price of \$60,000 have an own-price elasticity of about -4 .

4.2 Selected nameplate own- and cross-price elasticities

Table 4 presents substitution patterns from our estimated elasticities for a selected group of nameplates shown in the first column.¹³ The next three columns show their average sales, price, and own-price elasticities. The demand for less expensive vehicles tends to be more price sensitive, which is consistent with Figure 1. More expensive options, such as the Tesla Models S and X have lower own-price elasticities. The remaining columns show, respectively, the best and second-best substitutes for each vehicle and their cross-price elasticities. Specifically, for each nameplate in the first column, we define its best substitute as the one with the largest cross-price elasticity out of all nameplates in our sample. Similarly, its second best substitute has the second-largest cross-price elasticity. Thus, the best substitute for the Honda Civic (Gas-Car) is the Kia Forte5 (Gas-Car), and the second best substitute is the Hyundai Veloster (Gas-Car).

The substitution patterns in Table 4 are intuitive. Both substitutes are of the same fuel type-body style category for most of the selected nameplates. This shows that household preferences are stable within a category, which is consistent with Table 2. This pattern is highlighted for the battery EVs. Despite the relatively few model offerings and sales, all of them have other battery EVs as their best substitute. Additionally, the alternatives of the same fuel type-body style category tend to have vehicles with prices similar to the original vehicle. For example, for the Tesla Model X (BEV-SUV), the best and second-best substitutes are the Tesla Model S (BEV-Car) and Land Rover Range Rover (Gas-SUV), respectively; both are luxury models priced over \$90,000.

¹³We chose these vehicles because they represent a diverse mix of fuel types and body styles. They also have some of the highest sales in their respective categories and display significant price variation.

4.3 Category elasticities

To draw policy implications from our estimates, we aggregate the price elasticities using equations (12) and (21). We present aggregated price elasticities in Table 5 along with their standard errors. Panel A shows elasticities aggregated to the new-vehicle market level and across all income groups. We see an expected pattern across the income distribution. Low-income households have a larger market-price elasticity of demand, with the lowest group having an elasticity of -0.84 and the highest income group an elasticity of -0.2 . Low-income households are more price sensitive with a larger own-price elasticity of demand relative to high-income households (see Table 3) and more likely to leave the new vehicle market in response to a new vehicle price increase, as indicated by their diversion fractions (see Table 1). Together, this yields a realistic pattern for the elasticities across the income distribution.

The average market-price elasticity of new vehicle demand is -0.5 , which is smaller to the estimate in McCarthy (1996) and larger than that in Leard (2022); a key reason for this has to do with the correlation between own-price elasticities and diversion fractions. Low-income households tend to be more sensitive to changes in nameplate prices and more frequently state that they would leave the new vehicle market altogether if their chosen vehicle was not available. This positive correlation leads to a larger aggregate elasticity, as it is essentially the product of the two statistics summed across vehicles and households.

Panel B of Table 5 shows elasticities aggregated to the car and light truck level, where light truck includes SUVs, pickup trucks, and vans. The diagonal of the panel represents own-price elasticities, and the off-diagonals represent cross-price elasticities. The column names denote the vehicle type that has all of its options increase in price by 1 percent, and the row names represent the percentage change in sales of a vehicle type. For example, the bottom left estimate of 0.51 represents the cross-price elasticity interpreted as the percentage change in sales of all new light trucks as a result of a 1 percent increase in the price of all new cars. The magnitudes of the elasticities are in line with expectations, with the own-price elasticities being larger than the market-level price elasticities reported in Panel A. Car buyers tend to be much more price sensitive, because many car models represent entry level-options for households that want to buy a new vehicle.

Panel C of Table 5 reports elasticities aggregated to two fuel types: gasoline and electric. Gasoline includes gasoline and hybrid vehicles, and electric includes plug-in hybrid and battery EVs. The own-price elasticity of demand for all new gasoline vehicles is -0.53 , which is only slightly larger in magnitude than our estimate of the aggregate new vehicle market price elasticity because gasoline vehicles represent a large share of the new vehicle market in the sample. Our estimate of the cross-price elasticities is of particular interest. Specifically, we find that a one percent increase in the price of all

new electric cars leads to a 0.03 percent increase in sales of gasoline cars. This is three times as large as the baseline assumption in Holland et al. (2021), which relies on estimates from Xing et al. (2021) that uses 2014 data. This difference could be due to several factors, including that our estimates are based on a different methodology with more recent data.

5 EV replacement

To illustrate an application of our estimated elasticities, we analyze how households substitute between gasoline vehicles and EVs. Several recent studies have suggested that EVs replace relatively fuel-efficient gasoline vehicles (Muehlegger and Rapson 2023; Xing et al. 2021). In other words, households would have bought a vehicle with high fuel economy had EVs not been available. This substitution pattern reduces the environmental benefits of EVs, which are defined relative to the fuel use of a counterfactual replacement gasoline vehicle. Our cross-price elasticity estimates and data allow us to calculate how households substitute among vehicles in response to a price change, which is a type of measurement of what EVs are replacing. This measurement is especially relevant because the prices of EVs are expected to fall over time due to declining battery costs and product entry.

We use our estimated nameplate-level cross-price elasticities along with data on sales to simulate sales changes for gas and hybrid vehicles in response to a 1 percent reduction in plug-in hybrid EV and battery EV prices. We then multiply these sales changes by fuel economy ratings to calculate the simulated average fuel economy of vehicles that would have been purchased without the EV price change.

Table 6 shows the results along with their standard errors. The last row shows that the average fuel economy among all gasoline and hybrid vehicles is 25.9 miles per gallon, which serves as a comparison for the average among vehicles that EVs are replacing. The remaining rows show the average fuel economy of replacement vehicles. For the full sample, it is 30.2, which is about 4 miles per gallon higher than the comparison average. Therefore, the increased EV sales are pulling from vehicles with relatively high fuel economy. This simulated replacement fuel economy sits between differences reported in Xing et al. (2021) and Muehlegger and Rapson (2023), which also find that EVs replace relatively fuel-efficient vehicles.

We calculate the average fuel economy of gasoline and hybrid vehicles being replaced with alternative samples to see how the results vary depending on vehicle attributes. The Tesla Model 3 was the best-selling EV in 2018 and represented a relatively affordable option for going electric. Prior studies used data before the entry of the Model 3, which included many expensive EV models. Restricting the sample to include only the Tesla Model 3 reduces the replacement vehicle fuel economy average to about 28 miles per gallon, which is about 2 miles per gallon higher than the comparison

average. This difference is substantially less than that found in prior studies, suggesting that the EV market has been moving toward replacing more vehicles with average fuel economy.

Another distinct feature of the EV market in 2018 was the lack of available options for SUVs and pickup trucks: only a few SUVs and no pickups were for sale. However, this is quickly changing, as many new electric SUV and pickup models enter the market, such as the Ford F-150 Lightning. We explore whether body style availability plays a role in the fuel economy of replacement vehicles by restricting the sample to electric SUVs only.¹⁴ For this sample, we simulate the replacement vehicle fuel economy average to be about 25 miles per gallon, which is slightly less than the comparison average. This reflects how households sort based on body style: those deciding to buy an electric SUV would have likely otherwise purchased a gasoline or hybrid SUV that is relatively fuel inefficient. Therefore, as more electric SUVs and pickup trucks enter the market, we can expect the average fuel economy of replacement vehicles to converge to the comparison average.

6 Policy implications

We draw several policy implications based on our estimates. First, based on the results in Panel A of Table 5, new vehicle price increases due to tightening CAFE and GHG standards are likely to lead to disproportionately more low-income households leaving the new vehicle market. This raises vehicle affordability concerns, which have been highlighted by the EPA (EPA 2016). This implication also motivates federal agencies to model effects of CAFE and GHG standards across the income distribution to assess these concerns.

Second, our results provide a new estimate for a key input in the federal agencies analysis of CAFE and GHG standards. Our estimate for the aggregate new vehicle own-price elasticity of demand of -0.5 is larger than the assumed new vehicle sales elasticity of -0.4 used in the final RIA of the 2024–2026 fuel economy and GHG standards (NHTSA 2022). Our estimate, however, is interpreted as a demand elasticity rather than a policy elasticity, where the latter accounts for market equilibrium adjustments as a result of a new vehicle price increase (Jacobsen et al. 2021). In particular, increasing new vehicle prices causes household demand for new vehicles to fall and demand for used vehicles to increase, which raises used vehicle prices. This price adjustment leads to an increase in the demand for new vehicles, which dampens the direct effect of the new vehicle price increase. Therefore, the implied equilibrium policy elasticity is generally smaller than the demand elasticity. Jacobsen et al. (2021) argue that a policy elasticity is the more appropriate application for evaluating the sales impacts of the standards and find that policy elasticities are roughly half as large as the assumed demand elasticity.

¹⁴Specifically, this sample includes all vehicles that are classified as an SUV and a plug-in hybrid or battery EV.

Half of our estimated demand elasticity would be moderately smaller than what the agencies assume in their central case.

Third, the results have implications for compliance costs of federal fuel economy and GHG standards. Panel B of Table 5 shows that cars have almost a twice as large an own-price elasticity relative to light trucks. Leard et al. (2023) find that pass-through of costs associated with fuel economy and GHG standard requirements is related to price-sensitivity: the more price sensitive a consumer group, the more expensive it is to raise prices because of a fuel economy increase. Therefore, our results suggest that it will be more costly for manufacturers to pass through the cost increase of the same fuel-economy technology adoption applied to cars versus light trucks. This has potentially significant implications for the incidence of the standards across manufacturers, given that traditionally certain manufacturers tend to sell disproportionately more cars than light trucks.

Fourth, the results have implications for the interaction of CAFE and GHG standards with the used vehicle market. The federal agencies model how the standards interact with the used vehicle market using a used vehicle scrappage adjustment model. The underlying theory is that new vehicle buyers respond to higher new vehicle prices due to tightening standards by substituting to used vehicles. The increase in used vehicle demand increases used vehicle prices and reduces the rate at which used vehicles are scrapped, which is known as the Gruenspecht effect (Gruenspecht 1982). The literature has shown that this effect erodes gasoline savings and emissions reductions due to the standards (Jacobsen and van Benthem 2015). This effect could be different across vehicle types, namely cars and light trucks. The literature on vehicle scrappage has identified that light trucks tend to last longer and be scrapped less often than cars (Lu 2006; Greene and Leard 2023). They also typically are less fuel efficient and emit more carbon dioxide per mile, implying that changes in the rate at which used light trucks are scrapped could have significant effects on the emissions reductions due to the standards. The elasticities in Panel B of Table 5 suggest that light truck buyers are less likely than car buyers to leave the new vehicle market in response to a 1 percent price increase; this is indicated by a relatively small own-price elasticity and a relatively large cross-price elasticity appearing in the light truck column of Panel B. Therefore, increases in new light truck prices may result in a smaller Gruenspecht effect as fewer light truck buyers leave the new car market due to tightening standards.

Fifth, the results have implications for policy analysis of programs that ban the sale of gasoline vehicles, such as California Air Resources Board's Advanced Clean Cars II rule, which requires all new vehicles sold in the state to be zero-emissions by 2035. The welfare cost of such programs depends on the degree of substitution between electric and gasoline vehicles. If these two are poor substitutes, a gasoline ban may result in large deadweight loss as EV adoption begins too early (Holland et al. 2021). In general, Holland et al. (2021) show that the effectiveness of gasoline vehicle bans is likely sensitive

to gasoline-electric cross-price elasticities. The larger this estimate, the better substitutes EVs are to gasoline vehicles. Holland et al. (2021) show that as EVs and gasoline vehicles become better substitutes, a ban on new gasoline vehicle sales leads to a smaller deadweight loss. Our cross-price elasticity estimate of 0.03 is larger than the benchmark value of 0.01 assumed in Holland et al. (2021), suggesting that the deadweight loss from banning gasoline vehicles is smaller than what those authors find. However, they show that the deadweight loss is large relative to the environmental benefits of EV adoption as long as the cross-price elasticity remains in the range of 0.01 to 1.¹⁵ Nonetheless, optimal policy design can benefit from correct and up-to-date estimates of the underlying structural parameters.

7 Conclusion

Our methodology and estimation results have several caveats. The first is that we calculate our diversion fractions using survey responses that may not reflect how consumers substitute among vehicles in response to price changes. Based on our exploratory analysis of the data (e.g., Table 2) and our elasticity estimates, however, it seems plausible that these data reveal useful information about household substitution patterns. Nevertheless, the analysis could be improved by using data in a survey with a more direct question for what vehicles households would consider if their purchased vehicle were more or less expensive.

Second, our simulation analysis of EV substitution is based on data from 2018. Since 2018, the new EV sales share has significantly increased.¹⁶ Our analysis suggests that EVs have become better substitutes for gasoline vehicles relative to when manufacturers began selling EVs. We expect this trend to continue as manufacturers introduce many new EV models. Repeating this analysis with recent sales and diversion fraction data would reveal whether this trend has continued and valuable information about how EV substitution has evolved over time.

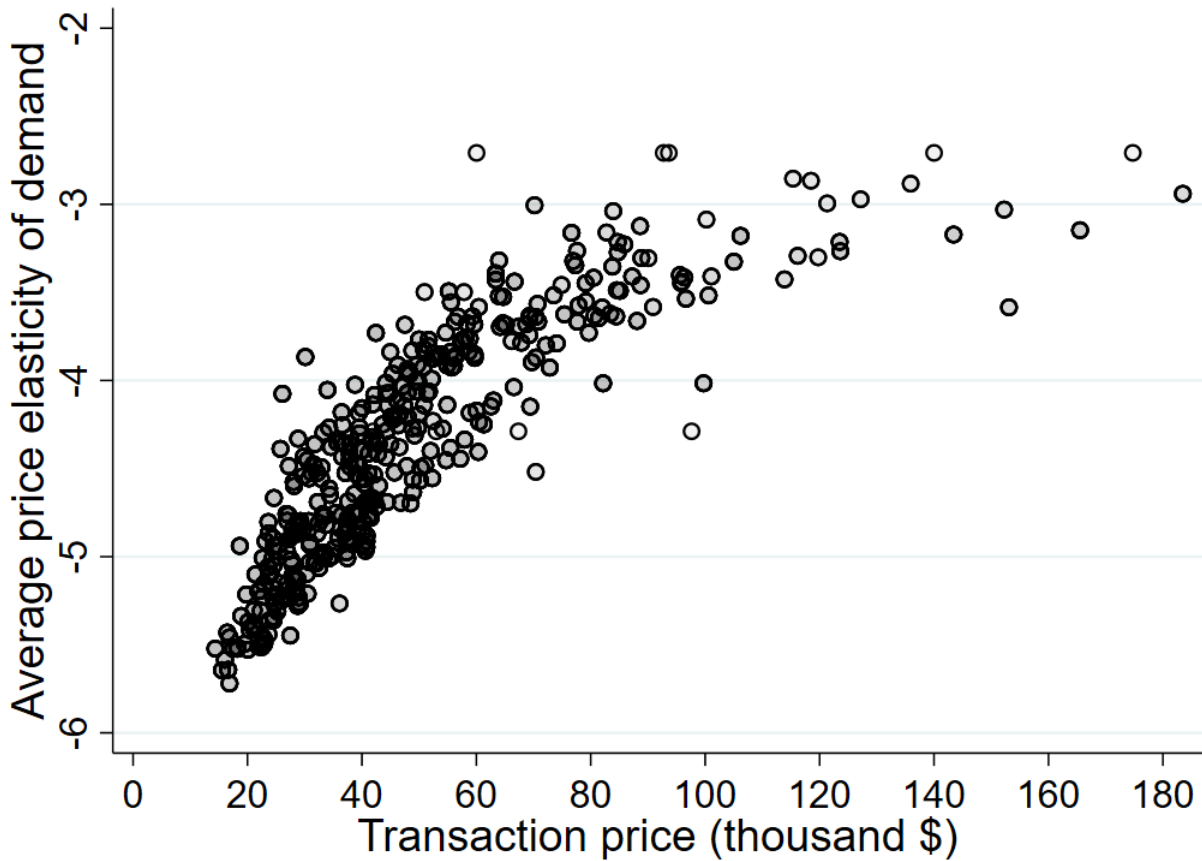
Nevertheless, our methodology produces plausible own- and cross-price elasticities of new vehicle demand that can be used as inputs for simulation models, such as those for estimating the costs and benefits of CAFE and GHG standards and policies for increasing EV sales. The computational simplicity of our methodology makes it straightforward for policy analysts to apply it to evaluating current and future regulations.

¹⁵Table 2 and Figure 2 in Holland et al. (2021) illustrate this point by showing the optimal policy as a function of the cross-price elasticity.

¹⁶The new EV market share was 7.1 percent in January 2023. For more details, see <https://insideevs.com/news/657660/us-electric-car-sales-january2023/>.

8 Figures and Tables

Figure 1: The relationship between implied average own-price elasticities of demand and average transaction prices



Notes: This graph shows the relationship between the average own-price elasticity of demand and the average transaction price. Each circle represents a unique make-model-fuel type-body style combination in our dataset. The own-price elasticity is a weighted average across all income groups.

Table 1: Summary Statistics

| Income group | < 55k | 55–85k | 85–125k | 125–200k | > 200k | All |
|-----------------------|--------|--------|---------|----------|--------|---------|
| Price (\$) | 29,198 | 32,648 | 35,207 | 38,362 | 47,751 | 35,094 |
| Gallons per mile | 0.038 | 0.04 | 0.041 | 0.042 | 0.042 | 0.04 |
| Horsepower/weight | 0.057 | 0.059 | 0.061 | 0.063 | 0.066 | 0.06 |
| Footprint | 8.01 | 8.27 | 8.39 | 8.46 | 8.57 | 8.3 |
| First choice SUV | 0.44 | 0.50 | 0.52 | 0.53 | 0.56 | 0.5 |
| First choice pickup | 0.11 | 0.15 | 0.15 | 0.13 | 0.09 | 0.13 |
| First choice electric | 0.00 | 0.01 | 0.02 | 0.03 | 0.06 | 0.02 |
| Second choice used | 0.13 | 0.10 | 0.09 | 0.08 | 0.07 | 0.09 |
| Household count | 42,403 | 40,910 | 48,039 | 42,899 | 30,300 | 204,551 |

Notes: This table shows summary statistics of key variables by income group, which we weight by sales counts. Price is defined as the average purchase price for each vehicle make-model-fuel type-body style combination. Gallons per mile is computed as 1 divided by the city/highway average fuel economy rating. Horsepower/weight is a vehicle’s horsepower divided by its weight, measured in hp/lb. Footprint is a vehicle’s wheelbase multiplied by its width, measured in thousand square inches. The rows with first choice and second-choice information show the share of each vehicle type in the survey, where electric includes both electric and plug-in hybrid vehicles.

Table 2: First- and Second-Choice Comparisons

| Attribute correlation | < 55k | 55–85k | 85–125k | 125–200k | > 200k | All |
|-----------------------|-------|--------|---------|----------|--------|------|
| Price | 0.79 | 0.81 | 0.83 | 0.85 | 0.87 | 0.86 |
| Car | 0.75 | 0.76 | 0.8 | 0.81 | 0.81 | 0.77 |
| Pickup | 0.87 | 0.89 | 0.91 | 0.92 | 0.92 | 0.9 |
| SUV/Van | 0.82 | 0.86 | 0.87 | 0.86 | 0.86 | 0.85 |
| Electric | 0.58 | 0.63 | 0.65 | 0.69 | 0.71 | 0.68 |
| Gasoline | 0.99 | 1.00 | 0.99 | 0.99 | 0.99 | 0.99 |

Notes: This table shows comparisons between the first and second choices by income group with weighted sales counts. Price correlation for a given income group is the correlation coefficient between the transaction price of the first-choice vehicle and the average transaction price of all second-choice vehicles with that same first choice. The remaining rows show the shares of households with a second choice of the same body style/fuel type as their first choice; for example, among households with an annual income less than or equal to \$55,000 that purchased a pickup truck, 87 percent of them had a pickup as their second choice. The electric attribute includes both plug-in hybrid and battery electric vehicles.

Table 3: Nameplate Own-Price Elasticity Estimates

| | | Dependent Variable: Ln(Sales) | | | | | | | | | |
|-------------------|--|-------------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Specification | | OLS | | | | | IV | | | | |
| Income group | | < 55k | 55–85k | 85–125k | 125–200k | > 200k | < 55k | 55–85k | 85–125k | 125–200k | > 200k |
| Ln(Price) | | −4.26 (0.53) | −3.46 (0.46) | −2.87 (0.41) | −1.97 (0.39) | −0.53 (0.38) | −5.96 (1.38) | −5.00 (1.42) | −4.98 (1.64) | −4.29 (1.79) | −2.71 (1.73) |
| Gallons per mile | | −103.6 (19.81) | −76.81 (18.90) | −68.24 (19.50) | −58.00 (17.46) | −37.19 (16.21) | −94.62 (21.96) | −68.89 (21.10) | −59.45 (22.56) | −35.96 (26.55) | −18.40 (24.92) |
| Horsepower/weight | | 20.13 (7.25) | 23.00 (7.44) | 19.38 (6.63) | 10.45 (6.27) | 7.116 (6.85) | 35.94 (13.32) | 37.25 (14.17) | 40.16 (16.87) | 33.82 (19.31) | 28.58 (18.49) |
| Footprint | | 0.51 (0.167) | 0.73 (0.149) | 0.79 (0.150) | 0.58 (0.140) | 0.61 (0.158) | 0.81 (0.286) | 1.01 (0.304) | 1.18 (0.344) | 0.96 (0.332) | 0.96 (0.34) |
| Model year | | 0.71 (0.37) | 0.82 (0.37) | 1.11 (0.31) | 1.35 (0.33) | 1.04 (0.32) | 0.83 (0.37) | 0.89 (0.37) | 1.25 (0.33) | 1.53 (0.35) | 1.19 (0.33) |
| Constant | | −1,388 (754.9) | −1,613 (740.1) | −2,204 (616.8) | −2,696 (665.7) | −2,091 (645.2) | −1,608 (750.9) | −1,750 (737.4) | −2,466 (660.5) | −3,054 (696.3) | −2,381 (666.9) |
| Observations | | 344 | 376 | 394 | 403 | 404 | 344 | 376 | 394 | 403 | 404 |
| R-squared | | 0.68 | 0.62 | 0.61 | 0.52 | 0.42 | 0.66 | 0.61 | 0.58 | 0.48 | 0.37 |

Notes: The dependent variable in each specification is the natural log of weighted sales counts. We define the weighted sales variable as the number of weighted observations of each unique vehicle make-model-fuel type-body style combination by income group. Weights are constructed based on InMoment weights representing national monthly model-level registrations. Each column in this table represents a separate set of estimates by income group. Columns (1)–(5) include results using OLS and columns (6)–(10) show results using instrumental variables. The variable Ln(Price) is the natural log of average transaction price, implying that the coefficient estimate for this variable is interpreted as the average own-price elasticity of demand with respect to price. Gallons per mile is computed as 1 divided by the city/highway average fuel economy rating. Horsepower/weight is a vehicle’s horsepower divided by its weight, measured in hp/lb. Footprint is a vehicle’s wheelbase multiplied by its width, measured in thousand square inches. For the models in columns (6)–(10), we treat the natural log of transaction price as endogenous and calculate instruments as the sums of cost per mile, horsepower/weight, and footprint of other vehicles sold by the same manufacturer, the sum of the continuous characteristics of other vehicles sold by other manufacturers in the same body style category, and the squares of each sum. Coefficient estimates for models for the lowest-income group (households that report an annual income less than or equal to \$55,000) appear in columns (1) and (6). Standard errors are clustered by vehicle model nameplate (e.g., Honda Accord) and reported in parentheses.

Table 4: Own- and Cross-Price Elasticities for Selected Nameplates

| Vehicle | Sales | Price (\$) | Own | Best substitute | Cross | Second best substitute | Cross |
|------------------------------|-------|------------|-------|------------------------------|-------|----------------------------------|-------|
| Honda Civic (Gas-Car) | 5,382 | 23,691 | -5.16 | Kia Forte5 (Gas-Car) | 1.72 | Hyundai Veloster (Gas-Car) | 1.65 |
| Toyota Camry (Gas-Car) | 4,628 | 26,969 | -5.28 | Honda Accord (Gas-Car) | 1.50 | Chevy Impala (Gas-Car) | 1.32 |
| Honda CR-V (Gas-SUV) | 5,631 | 30,508 | -4.87 | Toyota RAV4 (Gas-SUV) | 1.29 | Toyota RAV4 (Hybrid-SUV) | 1.16 |
| Toyota RAV4 (Gas-SUV) | 5,319 | 30,514 | -5.32 | Honda CR-V (Gas-SUV) | 1.17 | Subaru Forester (Gas-SUV) | 0.66 |
| Ford F-150 (Gas-Pickup) | 5,864 | 40,789 | -5.00 | Chevy Silverado (Gas-Pickup) | 2.11 | Toyota Tundra (Gas-Pickup) | 1.81 |
| Chevy Silverado (Gas-Pickup) | 5,370 | 40,623 | -5.04 | Ford F-150 (Gas-Pickup) | 2.05 | GMC Sierra (Gas-Pickup) | 1.85 |
| Tesla Model 3 (BEV-Car) | 1,117 | 56,096 | -3.73 | Chevy Bolt (BEV-Car) | 3.92 | Nissan Leaf (BEV-Car) | 1.31 |
| Tesla Model S (BEV-Car) | 344 | 95,581 | -2.96 | Chevy Bolt (BEV-Car) | 0.35 | BMW 540 Series (Gas-Car) | 0.28 |
| Chevy Bolt (BEV-Car) | 304 | 36,449 | -3.96 | Nissan Leaf (BEV-Car) | 1.73 | Tesla Model 3 (BEV-Car) | 0.35 |
| Tesla Model X (BEV-SUV) | 290 | 105,015 | -2.94 | Tesla Model S (BEV-Car) | 0.33 | Land Rover Range Rover (Gas-SUV) | 0.16 |
| Toyota Prius Prime (PH-Car) | 409 | 30,741 | -4.47 | Chevy Volt (PH-Car) | 0.99 | Honda Clarity (PH-Car) | 0.63 |
| Chevy Volt (PH-Car) | 275 | 34,590 | -4.41 | Honda Clarity (PH-Car) | 0.63 | Toyota Prius Prime (PH-Car) | 0.56 |

Notes: This table shows average own-price elasticities for a selected sample of nameplates and the average cross-price elasticities of their best and second-best substitutes. For the vehicles in the first column, their best substitutes are the ones with the largest cross-price elasticity out of all the vehicles in our sample. Similarly, their second-best substitutes are those with the second-largest cross-price elasticity. Own-price elasticities reported in the Own column are interpreted as the percentage change in sales of a nameplate in response to a 1 percent increase in its price. Each cross-price elasticity reported in the Cross columns is interpreted as the percentage change in sales of the substitute vehicle in response to a 1 percent increase in the price of the nameplate defined in the first column. These elasticities are calculated based on own-price elasticity estimates presented in Table 3, diversion fraction data, and equations (4) and (16). These are averages across all income groups. Specifically, we apply our estimates and data to equations (4) and (16) by income group and vehicle, then take averages across income groups for each vehicle. The terms in parentheses indicate the fuel type-body style combination. BEV and PH stand for battery electric and plug-in hybrid fuel types, respectively.

Table 5: Aggregate Price Elasticities

Panel A: New vehicle market price elasticity

| Income group | Aggregate elasticity |
|--------------|----------------------|
| < 55k | -0.84 (0.11) |
| 55-85k | -0.48 (0.06) |
| 85-125k | -0.41 (0.04) |
| 125-200k | -0.32 (0.03) |
| > 200k | -0.20 (0.02) |
| Average | -0.50 (0.03) |

Panel B: Car-light truck elasticity matrix

| Class | Car | Light Truck |
|-------------|-----------------|-----------------|
| Car | -1.60 (0.17) | 0.82 (0.06) |
| Light truck | 0.51 (0.05) | -0.85 (0.07) |

Panel C: Gasoline-electric elasticity matrix

| Fuel type | Gasoline | Electric |
|-----------|-----------------|-----------------|
| Gasoline | -0.53 (0.03) | 0.03 (0.01) |
| Electric | 1.71 (0.16) | -1.91 (0.41) |

Notes: This table presents price elasticities aggregated to certain vehicle classification levels. Panel A shows elasticities aggregated to the entire new vehicle market for each income group along with their standard errors. These elasticities are defined as the percentage change in new vehicle sales as a result of a 1 percent increase in all new vehicle prices. We compute these elasticities with own-price elasticity estimates from Table 3, diversion fraction data, and equation (12). In Panels B and C, columns represent changes in prices of a particular vehicle type and rows represent changes in sales of a type. The category Light truck in Panel B includes all SUVs, pickup trucks, and vans, and the category Electric in Panel C includes both plug-in hybrid electric vehicles and battery electric vehicles. The own-price elasticities along the diagonals are the percentage change in sales of a vehicle type in response to a 1 percent increase in the price of all vehicles that share that same type. The cross-price elasticities along the off diagonals represent the percentage change in sales of a vehicle type indicated by a row name of the matrix in response to a 1 percent change in the price of all vehicles that share the same type indicated by a column name of the matrix. We compute these elasticities with own-price elasticity estimates from Table 3, diversion fraction data, and equations (12) and (21). We bootstrap standard errors with 200 random draws, which we report in parentheses.

Table 6: Average Fuel Economy of EV Replacement Vehicles

| Sample | Average fuel economy |
|---|----------------------|
| Full sample | 30.2 (0.84) |
| Battery EVs only | 27.3 (0.80) |
| Plug-in hybrid EVs only | 33.1 (1.45) |
| Exclude Tesla Model 3 | 31.0 (1.05) |
| Tesla Model 3 only | 28.0 (1.38) |
| Sport utility EVs only | 24.8 (0.57) |
| Average fuel economy of gasoline vehicles | 25.9 |

Notes: This table reports the simulated sales-weighted average fuel economy of gasoline and hybrid vehicles that would have been purchased had prices of all EVs been 1 percent higher. Each row besides the bottom represents subsets of the sample of EVs. The row titled “Battery EVs only,” for example, excludes plug-in hybrid EVs. We bootstrap standard errors with 200 random draws, which we report in parentheses below each corresponding estimate.

References

- (2016). Examining the affordability impacts of light-duty vehicle greenhouse gas emission standards. Technical report, Environmental Protection Agency.
- Beresteanu, A. and S. Li (2011). Gasoline prices, government support, and the demand for hybrid vehicles in the united states. *International Economic Review* 52(1), 161–182.
- Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica* 63(4), 841–890.
- Berry, S., J. Levinsohn, and A. Pakes (2004). Differentiated products demand systems from a combination of micro and macro data: The new car market. *Journal of Political Economy* 112(1), 68–105.
- Bordley, R. F. (1993). Estimating automotive elasticities from segment elasticities and first choice/second choice data. *The Review of Economics and Statistics* 75(3), 455–462.
- Gandhi, A., Z. Lu, and X. Shi (2023). Estimating demand for differentiated products with zeroes in market share data. *Working paper*.
- Greene, D. L. and B. Leard (2023). Statistical estimation of trends in scrappage and survival of u.s. light-duty vehicles. *Howard H. Baker Jr. Center for Public Policy*.
- Grieco, P. L. E., C. Murry, and A. Yurukoglu (2023). The evolution of market power in the us automobile industry. *Working paper*.
- Gruenspecht, H. K. (1982). Differentiated regulation: The case of auto emissions standards. *American Economic Review* 72(2), 328–331.
- Holland, S. P., M. Erin, and Y. Andrew (2021). The electric vehicle transition and the economics of banning gasoline vehicles. *American Economic Journal: Economic Policy* 13(3), 316–44.
- Jacobsen, M. R., M. R. Beach, C. Cowell, and J. Fletcher (2021). The effects of new-vehicle price changes on new- and used-vehicle markets and scrappage. *Environmental Protection Agency*.
- Jacobsen, M. R. and A. A. van Benthem (2015). Vehicle scrappage and gasoline policy. *American Economic Review* 105(3), 1312–38.
- Leard, B. (2022). Estimating consumer substitution between new and used passenger vehicles. *Journal of the Association of Environmental and Resource Economists* 1(9), 27–49.
- Leard, B., J. Linn, and K. Springel (2023). Vehicle attribute tradeoffs and the distributional effects of us fuel economy and greenhouse gas emissions standards. *Resources for the Future Working Paper*.
- Leard, B., J. Linn, and C. Zhou (2023). How much do consumers value fuel economy and performance? evidence from technology adoption. *The Review of Economics and Statistics* 105(1), 158–174.
- Lu, S. (2006). Vehicle survivability and travel mileage schedules. *NHTSA Technical Report*, 1–37.
- McCarthy, P. S. (1996). Market price and income elasticities of new vehicles demand. *The Review of Economics and Statistics* 78(3), 543–547.
- Muehlegger, E. J. and D. S. Rapson (2023). Correcting estimates of electric vehicle emissions abatement: Implications for climate policy. *Journal of the Association of Environmental and Resource Economists* 10(1).

- NHTSA (2022). Final regulatory impact analysis: Final rulemaking for model years 2024-2026 light-duty vehicle corporate average fuel economy standards. Technical report.
- Petrin, A. (2002). Quantifying the benefits of new products: The case of the minivan. *Journal of Political Economy* 110(4), 705–729.
- Train, K. E. and C. Winston (2007). Vehicle choice behavior and the declining market share of U.S. automakers. *International Economic Review* 48, 1469–1496.
- Xing, J., B. Leard, and S. Li (2021). What does an electric vehicle replace? *Journal of Environmental Economics and Management* 107, 1–33.

