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Estimating Consumer Substitution Between New and Used Passenger Vehicles

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Abstract

Recent literature has shown the importance of modeling consumer demand for assessing the effects of new passenger vehicle fuel economy and greenhouse gas emissions standards. A relevant feature of demand for making this assessment is how vehicle buyers substitute between new vehicles and other options, such as a used vehicle. In this paper, I estimate this substitution using market-level and second choice data. I estimate a long run market-price elasticity of demand for new vehicles equal to -0.34. I then explore the implications of this elasticity for assessing the welfare effects of 2021-2026 SAFE Vehicles Rule. The simulation results show that applying the estimated elasticity significantly reduces the net benefits of the rule.

Keywords: Passenger vehicle demand, second choice data, substitution, fuel economy and greenhouse gas emissions standards
JEL codes: C51, C54, L91, Q48

1 Introduction

Since the enactment of corporate average fuel economy (CAFE) standards for new passenger vehicles in the 1970s and the creation of federal greenhouse gas (GHG) standards in the 2000s, policy makers have been interested in the effects of the standards on vehicle sales. The automobile sector currently employs about 2.5 percent of the labor force, so any significant shock to new vehicle demand has substantial effects on jobs in the United States. Furthermore, research has shown that assessing the social costs and benefits of the standards requires measuring how households substitute between buying new vehicles and other options, such as purchasing a used vehicle. The standards are a type of differentiated regulation, where new vehicles are subject to the standards while used vehicles are not.

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Gruenspecht (1982) finds that since fuel economy standards increase new vehicle prices, new vehicle sales fall and households substitute to used vehicles, thereby slowing used vehicle scrappage.

This substitution can undo the intended effects of the standards, since used vehicles tend to have lower fuel economy and greater per mile oil consumption than new vehicles. The magnitude of this effect depends on several key factors, including how new vehicle buyers substitute between new and used vehicles and the relationship between used vehicle prices and scrappage (Bento et al. 2018; Jacobsen and van Benthem 2015). Furthermore, this substitution has implications for other features of costs and benefits of the standards, including traffic accident costs. The standards, by altering new vehicle prices, cause a change in the number of new vehicles sold and a shift in the amount of vehicle miles traveled (VMT) by used vehicles. Since new vehicles are generally safer than used vehicles, this shift in VMT can alter accident costs due to changes in the standards.

Recent literature has made substantial progress on identifying the effect of the standards on used vehicle scrappage (Jacobsen and van Benthem 2015; Bento et al. 2017). But less is known about the willingness of new vehicle buyers to leave the new vehicle market, which, for the purposes of analyzing changes to fuel economy and greenhouse gas standards, is denoted as the new vehicle sales elasticity or the market-price elasticity of demand for new vehicles. One paper exploring this issue is Bordley (1993), which uses time-series data and survey data from new vehicle buyers to estimate 40,000 model-level cross-price elasticities. The study finds a market-price elasticity of demand equal to -1. The market-price elasticity is estimated using a panel regression of nameplate-level vehicle sales on vehicle prices. This methodology has several drawbacks: nameplate-level vehicle prices are endogenous (Berry et al. 1995), and this type of regression does not control for aggregate unobservable characteristics that influence aggregate new vehicle sales, such as unemployment. Therefore, this methodology likely produces biased estimates for how new vehicle buyers substitute between new and used vehicles.

McCarthy (1996) is another study that estimates a market-price elasticity of new vehicle demand, using a cross-section of household survey data from 1989. The estimate is derived from parameter estimates of a multinomial logit model. Therefore, the substitution patterns in this model are determined by proportional substitution inherent in a logit model. The logit assumption implies a high willingness of new vehicle buyers to leave the new vehicle market, since the market share for the outside option to not purchase a vehicle is around 90 percent. As a result, using a logit specification likely leads to a biased estimate of the market-price elasticity of demand.

Dou and Linn (2020) directly estimate the effect of the standards on new vehicle sales using recent increases in the level of the standards, finding that tightening standards lowered new vehicle sales relative to used vehicle sales. They back out an implied short-run new vehicle sales elasticity equal to -1.5 based on assumptions about manufacturer compliance behavior and technology costs.

In contrast to prior literature, I present estimates of substitution patterns for vehicle buyers obtained from unique second choice data that includes the option for new vehicle buyers to select a used vehicle as their second choice. I then infer the implications of these substitution patterns for evaluating fuel economy and GHG emissions standards.

The policy relevance of this issue has grown with recent revisions to the standards. In 2008, the Obama administration passed legislation to double the stringency of the standards by 2025, which would have required 5 percent annual year-over-year increases in fuel economy between 2020 and 2025. In 2020, however, the Trump administration rolled back the Obama standards by finalizing the Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule, which requires annual year-over-year fuel economy increases of 1.5 percent through 2026. A recent analysis of the rollback proposal completed by the Environmental Protection Agency (EPA) and the National Highway Traffic Safety Administration (NHTSA) finds that the rollback will lead to less VMT in older, less safe vehicles, preventing a significant number of vehicle accident costs (EPA 2020). This feature of the analysis is partly driven by the inclusion of a new vehicle sales elasticity response: the agencies find that the rollback increases new vehicle sales as new vehicles become cheaper, which causes households to shift their VMT from older vehicles to new vehicles. The size of this shift is directly related to the assumed market-price elasticity of demand for new vehicles.

I estimate a long run market-price elasticity of demand for new vehicles equal to -0.34. This is a smaller elasticity than the one assumed by the agencies in their final regulatory impact analysis of the SAFE Vehicles Rule (EPA 2020). To assess how the elasticity changes the cost-benefit analysis calculation, I run the VOLPE model – the model that the agencies use to perform cost-benefit analysis of changes to the standards – with the estimated elasticity and compare outcomes. The model runs show that applying the estimated market-price elasticity significantly reduces the net benefits of the rollback. For the EPA GHG program with a 7 percent discount rate, net benefits fall from around 6 billion to nearly zero.

The remaining sections of the paper are organized in the following manner. In Section 2, I derive a method for estimating the market-price elasticity of demand for new vehicles. In Section 3, I present data and elasticity estimation results. I then apply the estimated elasticity to simulate the effect of the 2021-2026 SAFE Vehicles Rule in Section 4. I make concluding remarks in Section 5.

2 Model Development

In this section, I develop a method for estimating substitution patterns between new vehicles and used vehicles. My methodology builds on the approach developed in Bordley (1993), which also relies on second choice data. A key difference that distinguishes my approach from Bordley (1993) is that I use second choice data on the decision to purchase any new vehicle versus purchasing a used vehicle.

I index new vehicles by j and I denote new vehicle j's price and sales by p_j and q_j, respectively. The market has J distinct new vehicles available for purchase. I define the market price elasticity of demand to equal the percentage change in new vehicle sales in response to a one percent change in the price of every new vehicle. This elasticity is written as

$$\varepsilon_{market-price} = \sum_{j=1}^{J} \frac{d \sum_{k=1}^{J} q_k}{dp_j} \frac{p_j}{\sum_{k=1}^{J} q_k}. \tag{1}$$

This elasticity is equal to sum of the change in total new vehicle sales due to a change in the price of vehicle j multiplied by the ratio of vehicle j's price and new vehicle sales. The inner summation can be expanded to the following:

$$\varepsilon_{market-price} = \sum_{j=1}^{J} \left(\sum_{k=1}^{J} \frac{dq_k}{dp_j} \right) \frac{p_j}{\sum_{k=1}^{J} q_k}. \tag{2}$$

Bordley (1993) states that product elasticities are deducible from two statistics:

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) defines the second statistic as the diversion fraction. I denote new vehicle j's diversion fraction as δ_j, which is equal to the percentage of vehicle j lost sales that go to alternatives of new vehicles, i.e., used vehicles. Given this definition, $1 - \delta_j$ represents the percentage of sales of vehicle j that are diverted to other new vehicles when vehicle j's price increases. This definition for $1 - \delta_j$ implies an identity between changes in sales of vehicle j and the sum of changes in all other new vehicles:

$$\sum_{k \neq j}^{J} \frac{dq_k}{dp_j} = -(1 - \delta_j) \frac{dq_j}{dp_j}. \tag{3}$$

This equation can be rearranged so that the sum of sales changes for all vehicles appear on the left hand side:

$$\sum_{k=1}^{J} \frac{dq_k}{dp_j} = \delta_j \frac{dq_j}{dp_j}. \tag{4}$$

Substituting equation (4) into equation (2) yields

$$\varepsilon_{market-price} = \sum_{j=1}^{J} \delta_j \frac{dq_j}{dp_j} \frac{p_j}{\sum_{k=1}^{J} q_k}. \tag{5}$$

Defining new vehicle j's own-price elasticity of demand by

$$\varepsilon_j = \frac{dq_j}{dp_j} \frac{p_j}{q_j} \tag{6}$$

and substituting this definition into equation (5) yields

$$\varepsilon_{market-price} = \sum_{j=1}^{J} \delta_j \varepsilon_j \frac{q_j}{\sum_{k=1}^{J} q_k}. \tag{7}$$

Equation (7) has both statistics necessary to compute the market-price elasticity of demand for new vehicles: new vehicle own-price elasticities (ε_j) and diversion fractions (δ_j). The market-price elasticity of demand for new vehicles is a weighted average of the product of the own-price elasticity and the diversion fraction, where the weights are equal to new vehicle market sales shares.

Equation (7) has an intuitive interpretation. Increasing the price of vehicle j has two effects that contribute to the market-price elasticity of demand. The first effect is that sales of vehicle j fall according to vehicle j's own-price elasticity of demand. In response to a price increase, some households that would have bought vehicle j instead buy a different new or used vehicle. Those that buy a different used vehicle leave the new vehicle market, which is the second "diversion" effect of a vehicle j price change. Together the two effects define the magnitude of the new vehicle market-price elasticity.

3 Data and Estimation

In this section, I apply the method for estimating the market-price elasticity of demand for new vehicles in the United States.

3.1 Data

To estimate the market-price elasticity of demand for new vehicles, I use data on new vehicle sales, characteristics, and second choice data for the 2013 market year, which corresponds to sales from October 2012 to September 2013. New vehicle sales data are from IHS Automotive. These data are disaggregated counts of vehicle registrations by quarter. Each observation is defined by buyer type (household or fleet), quarter, model year, make, model, trim/series, fuel type, drive type, body style, and engine size (e.g., four cylinder vs. six cylinder). I drop observations for fleet vehicles since the microdata are only for household buyers.[1] I aggregate the sales data to the market year level, combining observations that share the same variable names but have different quarters or model years.[2] Therefore, each observation represents sales of a vehicle by make, model, trim/series, fuel type, drive type, body style, and engine size during the 2013 market year.

I merge with the sales data vehicle characteristics data from Wards Automotive. These data include information on horsepower, weight, and vehicle dimensions. Based on the vehicle dimensions information, I calculate each vehicle's footprint as the product of the vehicle's wheelbase and its track width. These data are merged based on all of the unique vehicle identifiers listed above. I merge fuel economy information from the Environmental Protection Agency's fuel economy database, and I merge annual average gasoline, diesel, and electricity prices from the Energy Information Administration, which are all denominated in 2013$.

I merge transaction prices from household survey data obtained from MaritzCX. This survey includes about 176,000 raw survey responses for the 2013 market year. These data are self-reported transaction prices for vehicles purchased or leased. About one-third of the observations have missing transaction price information, leaving around 100,000 usable prices.[3] I compute average transaction prices by all the unique vehicle identifiers listed above, which are merged to the sales and characteristics data using the same identifiers.

The MaritzCX survey asks respondents about vehicles that the respondents considered but did not purchase. One of the questions is whether the respondent considered any other cars or trucks when shopping for their vehicle. Respondents answer this question either yes or no. For those that answer yes, the survey asks respondents to provide vehicle characteristics for the model most seriously considered. The survey asks respondents for discrete options for the age of the second choice vehicle: new, used, or pre-owned. The data include additional details about the second choice responses, including model year, make, model, fuel type, engine size, and body style, among other characteristics. About two-thirds of the survey observations have valid responses for these questions.[4] The 2013 survey also asks respondents "If the model you acquired did NOT exist, what vehicle would you have purchased/leased?" Respondents provide the make and model for this question. To assign a second

[1]Fleet vehicles represent about 15 percent of new vehicle sales (Leard et al. 2017).

[2]Aggregating over model years avoids issues related to sales and pricing effects due to inventory effects.

[3]These data are similar to the transaction price data used in Leard et al. (2019).

[4]The survey also includes a third and fourth choice option, with the same vehicle characteristics questions. Third and fourth choice data are less frequently provided than the second choice information, but could be used for identification of preference heterogeneity. For example, Train and Winston (2007) use up to four stated second choices by survey respondents to estimate preference heterogeneity among new vehicle buyers.

choice, I match this answer to the options provided about the vehicles considered.[5] For example, if a household considered a new Camry, a used Prius, and a new Accord, but stated that they would have purchased the Accord had their acquired vehicle not existed, I code the second choice as the new Accord. I code used and certified pre-owned responses as used vehicles.

To facilitate estimation of the own- and market-price elasticities, I aggregate the merged data to the vehicle level. Since vehicle sales and non-price characteristics are initially at the vehicle level, aggregation is only required for computing average transaction prices and the second choice diversion fractions. As described above, for each of the vehicles in the final dataset, I compute an average transaction price based on self-reported transaction prices in the survey data. To obtain the diversion fractions, for each vehicle, I compute the percentage of households purchasing the vehicle that select a used vehicle as their second choice. After aggregating, I clean the sample, leaving 748 vehicle observations for estimation.[6] Summary statistics for the data appear in Table 1. Sales-weighted average transaction prices are around $32,000. The second choice data suggest a strong within-group preference for new vehicles. About 92.6 percent of new vehicle buyers state that they would have acquired a different new vehicle had their acquired new vehicle not been available. The remaining 7.4 percent of these buyers stated they would buy a used vehicle as their second choice.

3.1.1 Second Choice Used Diversion Fractions

A key input for estimating the market-price elasticity of demand is the set of diversion fractions. Vehicle j's diversion fraction is defined as the percentage of households that would leave the new vehicle market among all households that substitute away from buying new vehicle j in response to a vehicle j price increase. Following Bordley (1993), I set the diversion fractions equal to frequencies based on the second choice data. I assume that the diversion fractions are equal to the frequency that new vehicle buyers state that they would obtain a used vehicle if their purchased vehicle were not available. This assumption implies that the estimated market-price elasticity of demand should be interpreted as a long run elasticity: In response to vehicle attribute changes, in the long run households eventually replace their current stock of vehicles with other new or used vehicles.[7]

[5] The MaritzCX survey allows second choice responses to be the same new model as the one purchased, but from the prior model year. For example, a household that bought a new 2013 Honda Accord can select for the second choice a new 2012 Honda Accord. This possibility does not affect my results even though I aggregate the data over model years within a calendar year for estimation purposes. Households that select as a second choice a one year older new version of the same model are coded as selecting a different new vehicle as their second choice. It is only households that select a used vehicle that are coded as such for their second choice.

[6] See the appendix for a detailed description of the data-cleaning steps taken.

[7] Households could also decide to change the size of their vehicle stock and use other modes of transportation, such as taking public transit. This substitution, however, is likely zero or small for many households in the US that lack access to quality alternative travel options.

I compute the diversion fractions based on second choice data which are derived from a question about the availability of the purchased vehicle. I assume that these frequencies correspond to substitution patterns implied by a price increase.[8] These substitution patterns could be different from those implied by the second choice data.[9] I address this possibility in two ways. First, in this section, I explore this assumption by looking at how diversion fractions vary across income levels and vehicles. The data show plausible patterns that support this assumption. Second, in the robustness analysis (Section 3.4), I vary the diversion fractions over a range to check the sensitivity of my main results."

From the data in Table 1, this assumption implies that among all households that substitute away from vehicle j in response to a price increase for vehicle j, 7.4 percent would leave the new vehicle market and purchase a used vehicle. This degree of substitution to used vehicles is smaller than substitution to the outside good obtained from estimates of a vehicle choice model in Berry et al. (1995), which report an average substitution to the outside good of 21.5 percent.[10] Berry et al. (1995) note, however, that the values they report for consumer substitution to the outside option are high relative to their expectations.[11] Furthermore, Berry et al. (1995) define the outside option as not buying a new vehicle and they identify this substitution from annual changes in vehicle choice sets, both of which suggest that their substitution pattern is short run in nature. Short run substitution away from purchasing a new vehicle should generally be considerably higher than long run substitution, since in the short run, households considering buying a new vehicle can temporarily delay their purchase. Another possible reason why my estimate is smaller is because of time period differences.[12] Berry et al. (1995) estimate their model with vehicle sales and characteristics data from 1971 to 1990, while my sample is from market year 2013. Mean and median US household income are higher in my sample relative to household incomes in the Berry et al. (1995) sample, likely leading to less diversion to used vehicles.[13] Together, these features suggest that the average diversion fraction that I calculate based on the MaritzCX data is plausible.

[8]To see the plausibility of this assumption, suppose a buyer is planning on purchasing a new Ford Fusion. They are also considering a used Honda Accord, which would appear in the second choice data if they were surveyed by MaritzCX. Further suppose that the new Ford Fusion's price increases by 1%. Assuming that the buyer is especially sensitive to price, they decide to not purchase the new Ford Fusion given its higher price. Which vehicle would the buyer choose instead? It seems plausible that they would buy the used Honda Accord, given that they were considering it along with the new Ford Fusion in their purchase decision.

[9]The patterns refer to choices made by households that substitute away from their originally chosen vehicle to a different vehicle.

[10]This value is computed as an unweighted average of all percentages listed in Table VII of Berry et al. (1995).

[11]On the bottom of p. 881, the authors state that "...the numbers still seem a bit large to us, which may point to the need for improvements in our treatment of the outside good..."

[12]I thank a referee of this paper for suggesting this possibility.

[13]According to the US Census, in 1980, mean and median US household income were \$62,394 and \$52,461, respectively. In 2013, mean and median US household income were \$82,660 and \$58,904, respectively. See Table A-2 in Semega et al. (2020) for more details.

I plot the diversion fraction data in various ways to assess its quality. One method for verifying quality is to measure how willing different types of new vehicle buyers are to leave the new vehicle market. Prior studies have found that low-income households are more sensitive to changes in new vehicle prices (Train and Winston 2007). Moreover, low-income households tend to own fewer new vehicles than high-income households. These facts suggest that low-income households are more likely to substitute between new and used vehicles. I use a subsample of the MaritzCX data which has household self-reported income to test for this pattern. Figure 1 plots average diversion fractions by household income quintile, where quintiles are defined based on the distribution of new vehicle buyer household income. Panel (a) shows average diversion fractions across the income distribution for car buyers, and Panel (b) shows the density for light truck buyers. For both car and light truck buyers, lower income households are about twice as likely to leave the new vehicle market. This pattern in the data is consistent with the hypothesis that low-income households are more willing to substitute between new and used vehicles.

A related feature to be expected from the data is that low-priced new vehicles should be better substitutes for used vehicles. Used vehicles are generally much cheaper than new vehicles, and household sorting by vehicle price sensitivity would imply that buyers of entry-level, affordable new vehicles should be more willing to leave the new vehicle market to purchase a used vehicle. Figure 2 confirms this feature by showing the frequency of new vehicle buyers leaving the market for four groups of vehicles, where groups are based on vehicle price. The lowest-price vehicles tend to have the highest average diversion fraction.

A selected sample of model-level diversion fractions appear in Table 2. In general, diversion fractions are quite small for luxury brands such as BMW, Lexus, and Mercedes-Benz. They are much higher for entry-level models, such as the Chevrolet Cruze LS and the Honda Civic LX. This pattern at the model level is consistent with the broad pattern in Figure 2, showing that buyers of expensive luxury vehicles are less likely to leave the new vehicle market in response to an increase in new vehicle prices. This pattern is also consistent with substitution to the outside option reported in Berry et al. (1995), which find that households considering purchasing cheaper vehicles are more likely to leave the new vehicle market when the price of their preferred model increases.

Another quality check for the second choice data is the pattern of substitution between new and used vehicles. Used vehicles come in various shapes, sizes, and ages and certain used vehicles are expected to be closer substitutes to new vehicles. In particular, used vehicles that are only a few years old are expected to be closer substitutes to new vehicles. For example, when comparing a 1 year old and a 15-year-old Toyota Prius, the 1 year old is likely to be a closer substitute to a new Prius. One of the questions for the second choice vehicle in the MaritzCX survey is the vehicle's model year. Based on this information, I plot the distribution of vehicle age for second choice used vehicles in Figure 3.

The distribution is heavily skewed toward relatively young vehicles. About 80 percent of second choice used vehicles are 1, 2, or 3 years old, and 90 percent of second choice used vehicles are 5 years old or younger. This evidence is consistent with the expectation that among all used vehicles, the youngest vehicles are the closest substitutes for new vehicles.

3.2 Own-Price Elasticity of Demand Estimation

I estimate the own-price elasticity of new vehicle sales using a log-log specification. I assume that the natural log of vehicle j sales, denoted by q_j, is a linear function of the natural log of transaction price. I control for a series of other vehicle attributes, including cost per mile (measured as the gasoline price divided by miles per gallon), performance measured as the ratio of horsepower to weight, and size measured by footprint. I include a control variable for the average model year of each vehicle, and I include fixed effects for body style (e.g., pickup truck), drive type (e.g., all-wheel drive), engine size as measured by the number of cylinders, and fuel type (e.g., hybrid). The estimation equation is

$$\ln(q_j) = \beta \ln(p_j) + \theta X_j + \varepsilon_j. \tag{8}$$

The coefficient of interest is β, which represents the average own-price elasticity of demand for new vehicles. To address concerns about price endogeneity, I instrument for the log of transaction price following Berry et al. (1995) and Train and Winston (2007), using the sums of cost per mile, horsepower divided by weight, and footprint of other vehicles sold by the same manufacturer and the sum of the continuous characteristics of other vehicles sold by other manufacturers in the same body style category.

3.3 Estimation Results

Estimation results for the own-price elasticity of demand appear in Table 3. Columns (1) and (2) include ordinary least squares (OLS) estimates of the log of sales regressed on the log of purchase price and a set of non-price characteristics, including cost per mile measured as the gasoline price divided by miles per gallon, performance measured as the ratio of horsepower to weight, size measured by footprint and the average model year of each vehicle. Column (2) includes fixed effects for body style (e.g., pickup truck), engine size as measured by the number of cylinders, fuel type (e.g., hybrid), and drive type (e.g., all-wheel drive). The estimated coefficients for the continuous vehicle attributes have expected signs. The estimates are statistically significant except for horsepower divided by weight. The coefficient for the log of purchase price is interpreted as the average own-price elasticity of demand for new vehicles. This coefficient is negative and highly statistically significant for models in columns (1) and (2). The estimates range between -1.24 and -1.46. The magnitude of the elasticity is small relative to estimates typically found in the new vehicle demand literature. This is likely due to omitted variables bias.

To account for unobserved attributes in the estimation, I instrument for the log of purchase price. I construct price instruments following Berry et al. (1995), using the sums of cost per mile, horsepower divided by weight, and footprint of other vehicles sold by the same manufacturer and the sum of the continuous characteristics of other vehicles sold by other manufacturers in the same body style category. Results for instrumental variables specifications appear in columns (3) and (4). Specifications in columns (3) and (4) both include controls for the same continuous vehicle attributes, including cost per mile, performance measured as the ratio of horsepower to weight, size measured by footprint and the average model year of each vehicle. The specification in column (4) includes fixed effects for body style (e.g., pickup truck), drive type (e.g., all-wheel drive), engine size as measured by the number of cylinders, and fuel type (e.g., hybrid).[14] In the instrumental variables (IV) specifications, the own-price elasticity of demand becomes much more elastic, which is consistent with results from prior literature showing that not controlling for unobserved vehicle characteristics tend to bias the price coefficient toward zero. For the model with the full set of controls in column (4), the average new vehicle own-price elasticity of demand is estimated to be -4.59. This estimate is within the range of price elasticity estimates from prior literature (Berry et al. 1995). It is also similar to a recent estimate from Leard et al. (2019) that uses a similar level of vehicle aggregation. I use this specification as the benchmark given that it contains the most rigorous set of vehicle attribute controls.

At the bottom of Table 3, I report the market-price elasticity of demand for new vehicles. This elasticity is interpreted as the percentage change in aggregate new vehicle sales due to a one percent increase in all new vehicle prices. I compute this elasticity by plugging in the estimated own-price elasticity of demand along with vehicle sales and diversion fractions into equation (7). For the benchmark IV specification in column (4), this elasticity is equal to -0.34, suggesting an inelastic response. This response is smaller in magnitude relative to the total new vehicle price elasticity of demand assumed in the FRIA of the SAFE vehicles rule (EPA 2020).[15] Note that this is interpreted as a long run elasticity given the definition of the diversion fractions. A benefit of estimating a long run elasticity is that it is more applicable to evaluating changes to fuel economy and greenhouse gas

[14] I exclude manufacturer fixed effects from the specifications because a significant amount of variation in transaction prices appears across manufacturers. For example, the mean transaction price for a Ford vehicle is \$35,749 (representing 12% of the vehicle sample), while the mean transaction price for a BMW vehicle is \$54,650 (representing 8% of the vehicle sample). Including manufacturer fixed effects would wipe out this useful variation for identifying the log transaction price coefficient. Instead, I include a rich set of vehicle characteristics fixed effects, including body style, drive type, engine size, and fuel type, and I adopt an instrumental variables approach.

[15] In this analysis, the new vehicle market-price elasticity of demand is assumed to be -1. The assumption appears on page 868 of EPA (2020): "The price elasticity is also specified as an input, but this analysis assumes a unit elastic response of -1.0—meaning that a one percent increase in the average price of a new vehicle produces a one percent decrease in total sales."

standards because the standards have effects that persist for decades, due to the delay in passenger fleet turnover. The federal agencies then perform cost-benefit analysis of changes to the standards, NHTSA and EPA, model effects for 30 years into the future after the model year regulation. For example, effects of the 2021-2026 SAFE Vehicles Rule are modeled through the 2050 calendar year.

The market-price elasticity that I estimate is smaller than values from Berry et al. (2004) that model substitution between new vehicles and the outside option of not purchasing a new vehicle. Berry et al. (2004) set the market-price elasticity of demand for new vehicles equal to -1 based on private information from General Motors. However, this elasticity implies a large (in absolute value) own-price semi-elasticity of demand equal to -10.56. Berry et al. (2004) also calibrate their model with a market-price elasticity of -0.4, which yields an own-price semi-elasticity equal to -3.94. This implied own-price elasticity is in line with prior estimates and the estimate from this paper.

My estimate is also similar to recent estimates reported in the preliminary regulatory impact analysis (PRIA) of the SAFE vehicles rule and in a comment on the PRIA, Stock et al. (2018). The PRIA included its own time series estimation of the market-price elasticity of demand for new vehicles, with an estimate ranging between -0.2 and -0.3 (EPA 2018). Stock et al. (2018) also specify a time series model to estimate the elasticity, finding an elasticity of -0.27.

3.4 Robustness of Elasticity Estimate to Alternative Assumptions

In this section, I evaluate the robustness of the market-price elasticity assumptions. As shown by equation (7), the market-price elasticity of demand is a function of the own-price elasticity of demand, ε_j, and the diversion factor, δ_j. I vary these parameters around the central estimates to obtain a plausible range for the market-price elasticity.

Prior vehicle demand literature has estimated own-price elasticity of demand for new vehicles to range from -3 to -6 (Berry et al. 1995). Recent literature has estimated the average own-price elasticity of demand for new vehicles to range between -1.7 to -3.4, with some lower income groups having an own-price elasticity of -5 (Train and Winston 2007; Bento et al. 2009; Whitefoot et al. 2017; Leard et al. 2019). I adjust the own-price elasticity to -3 and -6 to see how the market-price elasticity varies with alternative assumptions for the own-price elasticity of demand for new vehicles. I find that a more sensitive (larger in magnitude) own-price elasticity of demand implies a larger market-price elasticity of demand. This is intuitive: as consumers become more sensitive to purchase price, a market-wide price increase will cause more consumers to leave the new vehicle market.

Prior literature has little information on plausible diversion fractions between buying new and buying used. Plausible values for diversion fractions could be higher or lower than the value reported in my sample. Diversion fractions could be higher because of the nature of the MaritzCX survey data. In particular, the MaritzCX survey does not have an option of "I would not have bought any vehicle" if a respondent's purchased vehicle had not existed. Some households may opt to have a smaller vehicle portfolio as a long run response to increases in new vehicle prices. This behavior would increase diversion fractions. To account for this possibility, for each new vehicle in the sample, I double the diversion fractions relative to benchmark values. This larger average diversion fraction is consistent with Berry et al. (1995), which finds that an average of 21.5 percent of households would leave the new car market when the price of a new vehicle increases by one percent. Berry et al. (1995) mentions, however, that its reported values are high relative to the author's expectations, suggesting further improvement in their model to accurately estimate this substitution. Moreover, as I argue in Section 3.1, the substitution reported in Berry et al. (1995) likely overstates the degree of long run substitution because their definition of the outside option and their identification strategy suggest that they are estimating short run substitution.

On the other hand, diversion fractions could be lower than the value reported in my sample because of general equilibrium effects. A price increase of all new vehicles increases the demand for used vehicles. This used vehicle demand shift increases the price of used vehicles, which reduces the quantity demanded of used vehicles, and increases the demand for new vehicles. This multi-market interaction effect dampens the equilibrium effect of a new vehicle price increase, which would result in fewer households diverting away from the new vehicle market. To account for this possibility, I reduce the diversion fraction for each vehicle by 50% relative to the benchmark.

Another potential reason that the diversion fractions could be higher or lower than those reported in the MaritzCX data is the degree to which households that do not respond to the second choice questions would select a used vehicle as their second choice.[16] It is difficult to identify, however, whether the non-responses would be more or less likely to select a used vehicle as a second choice relative to the observed frequencies. Considering a range of alternative diversion fractions – both above and below the average frequencies reported in the data – is therefore a useful exercise.

The implied sales elasticity estimates for the range of alternative assumptions appear in Table 4. The implied new vehicle market-price elasticity of demand varies between -0.11 and -0.89 depending on assumed values for the own-price elasticity of demand and the average diversion fraction. As expected, a smaller in magnitude own-price elasticity results in a smaller market-price elasticity. Assuming an own-price elasticity of demand equal to -3 implies a range of the market-price elasticity of -0.11 to -0.45. A larger average diversion fraction, on the other hand, implies a larger in magnitude market-price elasticity. With an own-price elasticity of -4.59, the market-price elasticity ranges from

[16] A lower average diversion fraction would be consistent with non-responses being less likely to select a used vehicle as their second choice than a typical household that responded to the second choice questions.

−0.17 to −0.68. Note, however, that the market-price elasticity is inelastic for the broad range of assumed values for the own-price elasticity and the average diversion fraction.

In the appendix, I show the robustness of the estimates to alternative methods for constructing the estimation sample, including aggregating the sample to the make-model level. Estimation results using the alternative sample designs imply a market-price elasticity of demand ranging between −0.26 and −0.31.

4 Simulation of the SAFE Vehicles Rule

I evaluate how the estimated long run market-price elasticity of demand in this paper affects the relationships between the stringency of fuel economy and greenhouse gas standards for passenger vehicles and relevant policy outcomes, including new vehicle sales, accident costs, and net benefits. Fuel economy and greenhouse standards in the United States currently require vehicle manufacturers to achieve a sales-weighted average fuel economy and an equivalent level of GHG emissions among vehicles sold. In 2008, the Obama administration passed legislation to double the average fuel economy requirement by 2025 relative to 2010 levels, which would have required 5 percent year-over-year increases in fuel economy between 2021 and 2025. In March 2020, the Trump administration finalized rolling back these standards beginning with the 2021 model year with the SAFE Vehicles Rule for model year 2021–2026 passenger cars and light trucks. The rollback requires only an annual 1.5 percent year-over-year increase in fuel economy, which is considerably less stringent than the Obama standards.

The federal agencies regulating fuel economy and GHG emissions for light-duty vehicles, the EPA and NHTSA, have since released a preliminary and final regulatory impact analysis, denoted respectively as PRIA and FRIA, for the rollback (EPA 2018; 2020). The analyses calculate costs and benefits of the rollback. To compute costs and benefits of the rollback, the agencies use a detailed simulation model of the passenger vehicles sector called the CAFE Compliance and Effects model, also known as the VOLPE model.[17] The VOLPE model simulates future compliance paths for every automobile manufacturer, where manufacturers are assumed to make decisions that minimize program compliance costs. To comply with the standards, manufacturers choose to adopt fuel-saving technologies, such as variable valve timing, to their existing vehicles. Each fuel-saving technology has an associated engineering cost. The engineering costs are passed through to consumers in the form of higher new vehicle prices.[18]

[17]More information on the VOLPE model can be found here: https://www.nhtsa.gov/corporate-average-fuel-economy/compliance-and-effects-modeling-system

[18]More information on how vehicle prices adjust in response to added fuel-saving technologies can be found here: https://www.nhtsa.gov/filebrowser/download/178071 (Shaulov et al. 2020).

The VOLPE model has many inputs; one recent addition to the model is an assumed market-price elasticity of demand.[19] The assumed value for the FRIA is -1.[20] With this elasticity, the rollback, by making new vehicles less expensive, causes an increase in the number of new vehicles sold and a reduction in the amount of vehicle miles traveled (VMT) by used vehicles. Since new vehicles are assumed to be safer than used vehicles, this shift in VMT reduces accident costs due to rollback.[21]

I run the VOLPE model to assess how the estimated market-price elasticity of demand in this paper alters the effect that the rollback has on new vehicle sales, traffic accident costs, and net benefits. I report outputs for the CAFE and EPA GHG programs, using 3 and 7 percent discount rates to calculate the present value of accident costs and net benefits. I compare the simulations with the estimated elasticity of -0.34 to the simulations with the FRIA assumed elasticity of -1. The sales, accident costs, and net benefits appear in Table 5. Changes in sales, accident costs, and net benefits are summed over all compliance years of the standards (2021-2026) and through calendar year 2050. Following the FRIA, I report the sum of accident costs and net benefits for model years 1978-2029, and all outputs are relative to the Obama CAFE and EPA GHG standards.

Panel (a) reports changes in new vehicle sales in response to the rollback. For the CAFE program and with an assumed elasticity of -1, new vehicle sales increase by 6.2 million. Between 2021 and 2050, this equates to an increase of about 200,000 new vehicles per year, which is about 1.25 percent of annual sales. With an assumed elasticity of -0.34, new vehicle sales increase by much less, or 2.4 million units. This represents an increase of 0.4 percent of new vehicle sales. The smaller in magnitude elasticity implies that the new vehicle sales response to lower new vehicle prices is considerably less. The sales effects of the EPA program show a similar pattern.

Panel (b) reports changes in vehicle accident costs as a result of the rollback. For the CAFE program with an assumed elasticity of -1, vehicle accident costs fall by $40.4 billion with an assumed discount rate of 7 percent. Between 2021 and 2050, this is equivalent to about $10 per US household per year.[22] Assuming a new vehicle market-price elasticity of -0.34 reduces the magnitude of the reduction in crash costs to $35 billion, which is equivalent to about $9 per US household per year.

[19] This is referred to as a price elasticity multiplier in the model.

[20] This elasticity is net of 2.5 years of fuel cost savings. For example, if a fuel-saving technology has a technology cost of $1,000 and 2.5 years of fuel cost savings of $400, then the elasticity is applied to the difference of $600.

[21] Bento et al. (2018) identify modeling flaws with the addition of this sales response. In particular, the version of VOLPE used for the PRIA showed that the effect of the rollback on new and used vehicle fleet size conflicted with basic economic theory. This could be due to the fact that VOLPE is an engineering-based model without clear underlying assumptions for consumer behavior, such as those assumed in an economic equilibrium model (see, for example, the model in Bento et al. (2009)). Another limitation of the VOLPE model is that it does not incorporate the possibility for manufacturers to directly adjust vehicle prices or non-fuel efficiency attributes (such as horsepower) or introduce brand new models as strategy for complying with the standards. Alleviating these limitations could significantly alter the implied net benefits of the standards.

[22] $40.4 billion over 30 years is $1.34 billion per year. Given that there are 128.45 million households in the US, this translates to $10.48 per US household per year.

As the rollback causes a smaller increase in new vehicle sales, less VMT is diverted to new vehicles, implying that the rollback has a smaller effect on accident costs.

Panel (c) shows changes in net benefits due to the rollback. With a 3 percent discount rate, net benefits are negative for each program, regardless of the assumed market-price elasticity. Using the -0.34 elasticity further reduces net benefits of the programs by about \$8 billion. Both programs see positive net benefits due to the rollback with a 7 percent discount rate. However, the assumed market-price elasticity drastically alters the magnitudes. For the CAFE program, using an elasticity of -0.34 reduces the net benefits from \$16.1 billion to \$9.6 billion, which is a 43 percent reduction. Using the -0.34 reduces net benefits under the EPA GHG program from \$6.4 billion to nearly zero. These drastic changes highlight the importance of adopting an accurate measure of the new vehicle market-price elasticity of demand.

5 Conclusion

In this paper, I apply a simple approach for the identification and estimation of cross-attribute demand elasticities to estimate the market-price elasticity of demand for new vehicles. My approach uses unique second survey choice data, which provides information on the propensity of new vehicle buyers leaving the new vehicle market in response to a vehicle attribute change. My central estimate for the market-price elasticity of demand is -0.34, with a plausible range that represents an inelastic demand response. This estimate has direct application to the evaluation of changes to federal fuel economy and greenhouse gas standards for passenger vehicles, which remain at the forefront of the discussion on how to address climate change.

I apply the estimate to evaluate the effects of the SAFE Vehicles Rule, which rolled back the 2021-2025 Obama fuel economy and greenhouse gas standards. By applying the same modeling framework that the federal agencies used to perform a cost-benefit analysis of the standards, I find that adopting the new vehicle market-price elasticity estimate from the current paper drastically reduces changes in new vehicle sales, accident costs, and net benefits attributable to the rollback. In particular, I find that applying a new vehicle market-price elasticity of demand is equal to -0.34 nearly eliminates net benefits of the EPA program rollback, even with a 7 percent discount rate.

The methodology that I use to estimate the market-price elasticity of demand for new vehicles can be applied to estimate a broader set of sales elasticity parameters than just the aggregate new vehicle market-price elasticity. The current approach of the agencies performing cost-benefit analysis of changes to the standards applies a single, aggregate new vehicle market-price elasticity, even though changes to the standards are likely to cause differential changes to prices of different vehicle models. For example, certain automakers may require applying more fuel-saving technology to their vehicles to comply with the standards, which would cause prices of their vehicles to increase more than other vehicles. This could cause shifts in sales across manufacturers or vehicle segments (e.g., cars vs. light trucks), which could create large and economically significant sales and welfare changes. The method that I adopt – combining estimates of own-attribute elasticities with data on diversion fractions – can be extended to estimate cross-attribute elasticities for vehicle models or segments, which can provide a more detailed assessment of the sales and welfare effects of changes to the standards.

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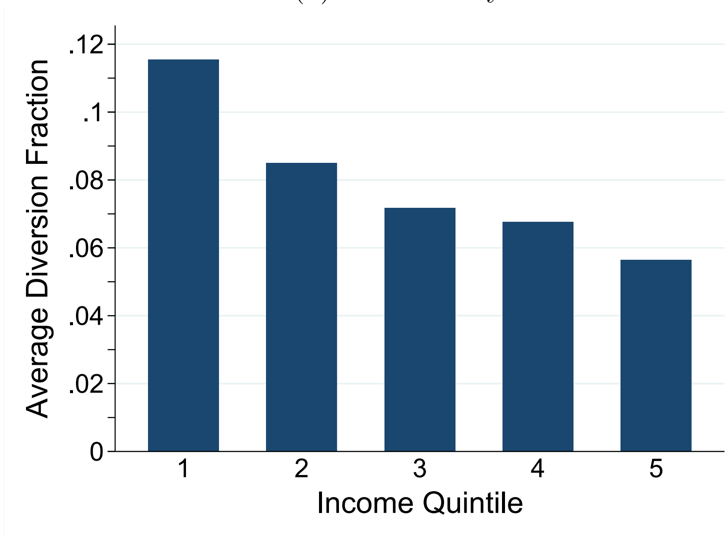
Figures

Figure 1: Average Second Choice Used Diversion Fractions by Income Quintile

Panel (a): Urban Buyers



Panel (b): Rural Buyers

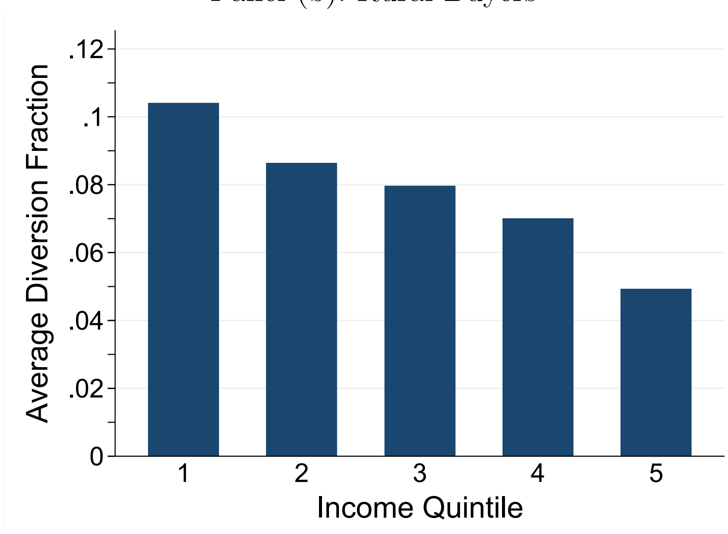
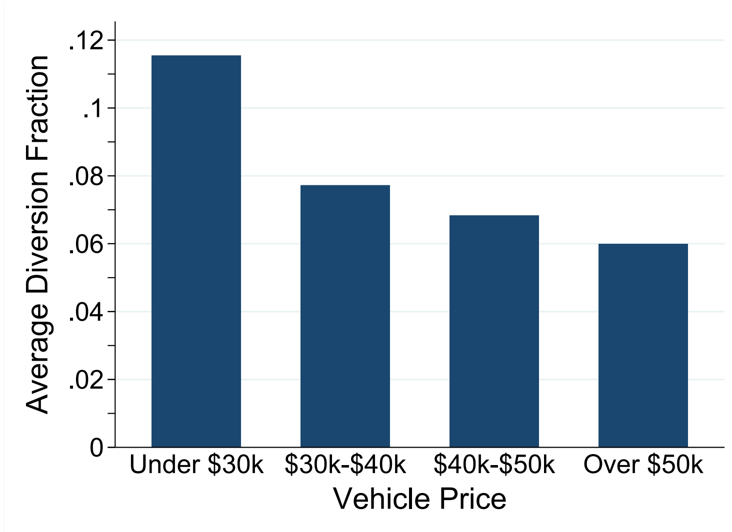


Figure 2: Average Second Choice Used Diversion Fractions by Vehicle Price

Panel (a): Car Buyers



Panel (b): Light Truck Buyers

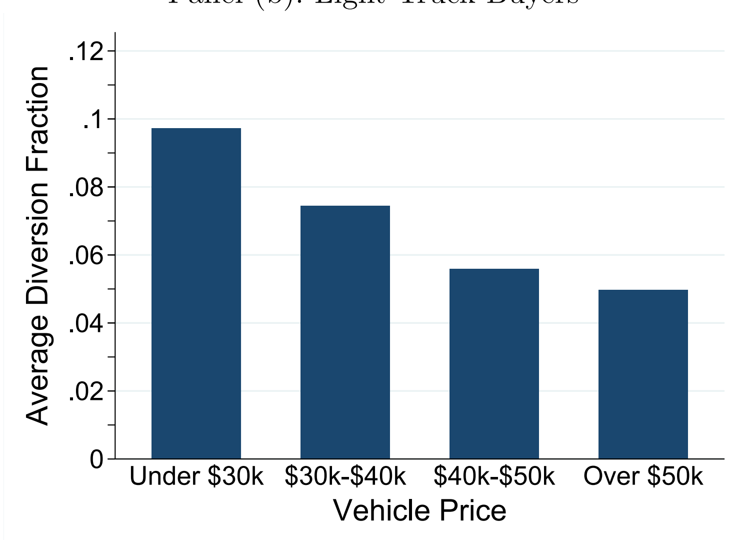
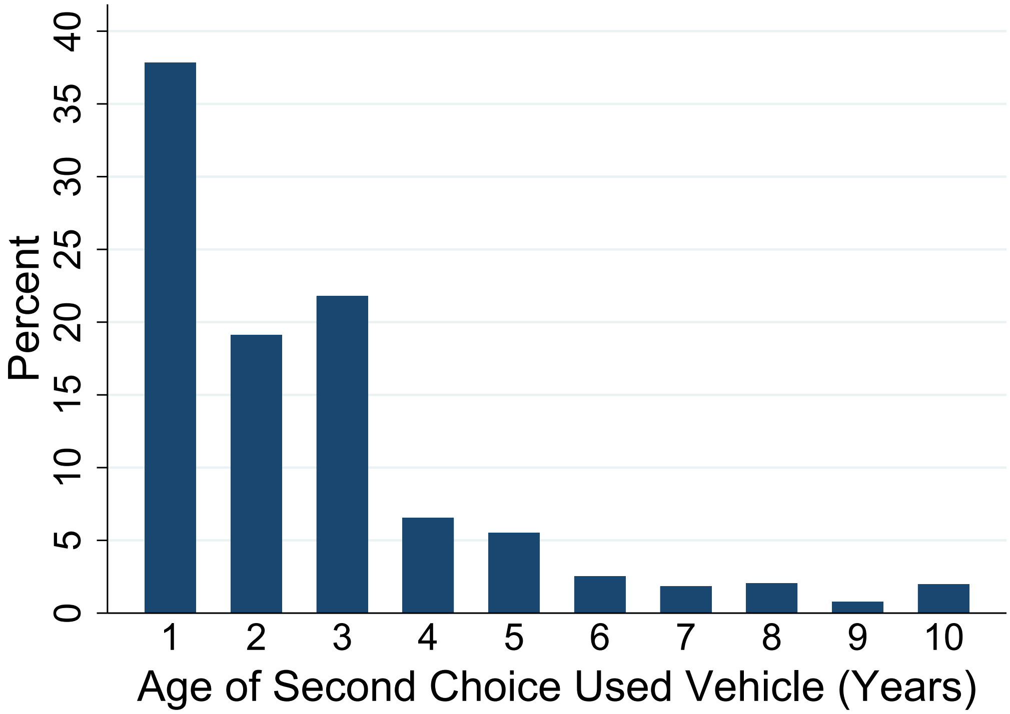


Figure 3: Frequency of Second Choice Used Vehicle Ages



Tables

Table 1: Summary Statistics for the 2013 Vehicle Sample

Variable	Mean	Std. Dev.	Min	Max
Sales	14,692	27,623	104	282,241
Transaction price	31,962	11,040	15,104	97,710
Cost per mile	0.15	0.04	0.04	0.33
Horsepower/weight	0.06	0.01	0.03	0.17
Footprint	8.21	1.17	4.51	12.58
Second choice new	0.93	0.06	0	1
Second choice used	0.07	0.06	0	1
All-wheel drive	0.17	0.38	0	1
Sedan	0.39	0.49	0	1
SUV	0.33	0.47	0	1
Hybrid	0.04	0.20	0	1
Plug-in hybrid or electric	0.01	0.07	0	1

Notes: The table reports summary statistics of characteristics and sales for new vehicles sold during the 2013 market year. Means and standard deviations are weighted by new vehicle sales. The total number of vehicle observations is 748. Vehicle transaction prices are averages from the MaritzCX microdata and are reported in 2013$. Non-price attributes are from Wards Automotive. Cost per mile is defined as the average annual fuel price divided by fuel economy, reported in 2013$ per mile. For gasoline vehicles, this is the average annual gasoline price (from the Energy Information Administration) divided by the vehicle's fuel economy. For electric vehicles, this is the average annual electricity price (from the Energy Information Administration) divided by the vehicle's electricity use per mile. For plug-in hybrid vehicles, a weighted average approach following Leard et al. (2017) is used to construct cost per mile. Horsepower/weight is the ratio of horsepower to weight, denoted in horsepower per pound. Footprint is the area between a vehicle's wheels, which is measured by the product of wheelbase and track width and denoted in square inches divided by 1000. Second choice new and second choice used are variables constructed from MaritzCX microdata. These variables represent the frequency of second choice vehicles being either purchased new or used, respectively.

Table 2: Second Choice Used Diversion Fractions for Selected New Vehicles

New Vehicle Model	Average Transaction Price	Diversion Fraction
BMW X5	60,879	0.03
Chevrolet Cruze LS	18,460	0.15
Chevrolet Silverado 1500 LT	34,012	0.03
Ford Explorer XLT	35,735	0.06
Honda Civic LX	19,808	0.13
Hyundai Elantra	21,651	0.05
Jeep Wrangler Sport	29,076	0.07
Lexus ES300h	46,184	0.03
Mercedes-Benz GL450	75,335	0.01
Nissan Sentra	20,699	0.09
Nissan Versa	16,428	0.16
Subaru Outback	28,915	0.05
Toyota Camry	30,081	0.09
Volkswagen Jetta SE	23,711	0.15

Notes: Average transaction prices are reported in 2013$. The diversion fraction represents the percentage of new vehicle buyers that stated that they would purchase a used vehicle if their purchased vehicle was not available.

Table 3: Estimation Results

	(1)	(2)	(3)	(4)
Dependent Variable: Log New Vehicle Sales				
Variables	OLS	OLS	IV	IV
Log Price	−1.46	−1.24	−2.42	−4.59
	(0.21)	(0.23)	(0.49)	(1.31)
Cost per mile	−6.19	−22.70	−4.95	−24.67
	(2.78)	(4.23)	(2.99)	(5.76)
Horsepower/weight	−2.99	−6.08	6.93	13.41
	(3.86)	5.84	(6.04)	(9.60)
Footprint	0.35	0.29	0.43	0.75
	(0.10)	(0.11)	(0.11)	(0.24)
Constant	−2,667	−1,694	−3,230	−2,934
	(893)	(816)	(927)	(1,099)
Observations	748	748	748	748
R-squared	0.19	0.28	0.15	0.02
Body style, cylinders, drive type, and fuel type f.e.	N	Y	N	Y
Market-Price Elasticity				−0.34
				(0.13)

Notes: Standard errors for the coefficients are reported in parentheses and are clustered by vehicle model, e.g., Toyota Prius. Vehicle prices and cost per mile are denominated in 2013$. The instruments used for specifications in columns (3) and (4) include the sales-weighted sum of cost per mile, horsepower divided by weight, and footprint for all other vehicles sold by the same firm and for all other vehicles sold by other firms sharing the same vehicle body style (e.g., SUV), as well as the squares of these sums. The market-price elasticity is estimated with equation (7) based on the estimated own-price elasticity of demand and diversion fractions. The standard error for the implied market-price elasticity is computed assuming that the own-price elasticity of demand is independent of the diversion fractions.

Table 4: Robustness of Market-Price Elasticity Estimates to Alternative Assumptions

Own-Price Elasticity		Diversion Fractions		
Level	Assumed Value	Level	Assumed Average	Market-Price Elasticity
Small	-3	Low	0.04	-0.11
Small	-3	Benchmark	0.07	-0.22
Small	-3	High	0.15	-0.45
Benchmark	-4.59	Low	0.04	-0.17
Benchmark	-4.59	Benchmark	0.07	-0.34
Benchmark	-4.59	High	0.15	-0.68
Large	-6	Low	0.04	-0.22
Large	-6	Benchmark	0.07	-0.45
Large	-6	High	0.15	-0.89

Notes: The own-price elasticity is defined as the percentage change in a new vehicle's annual sales in response to a one percent increase in the vehicle's own price. The market-price elasticity is defined as the percentage change in aggregate new vehicle sales due to a one percent increase in all new vehicle prices. The average diversion fraction represents the sales-weighted average percentage of new vehicle buyers that would leave the new vehicle market to purchase a used vehicle if their purchased vehicle was not available. The elasticities are computed as a sales-weighted averages across all vehicle models.

Table 5: VOLPE Model Simulation Results: Changes in Sales, Fatality Costs, and Net Benefits

Panel (a): Sales

Market-Price Elasticity	CAFE Million units	CAFE % of sales	EPA GHG Million units	EPA GHG % of sales
−1	6.9	1.25%	6.0	1.08%
−0.34	2.4	0.43%	2.0	0.37%

Panel (b): Accident Costs (billion $)

Market-Price	3% Discount Rate		7% Discount Rate	
Elasticity	CAFE	EPA GHG	CAFE	EPA GHG
−1	−62.9	−60.4	−40.4	−38.2
−0.34	−55.5	−53.7	−34.7	−33.2

Panel (c): Net Benefits (billion $)

Market-Price	3% Discount Rate		7% Discount Rate	
Elasticity	CAFE	EPA GHG	CAFE	EPA GHG
−1	−13.1	−22.0	16.1	6.4
−0.34	−21.5	−30.8	9.6	0.3

Notes: All values are reported from simulation outputs of the Compliance and Effects Modeling System, also known as the VOLPE model, for the 2020 Final Rule for Model Years 2021-2026 Passenger Cars and Light Trucks. Outputs are based on the author's runs of the VOLPE model using the same inputs as used in the FRIA for the final rule, with the exception of the runs with the market-price elasticity equal to −0.34. Changes are computed as the difference in outcomes between the Augural CAFE/EPA standards and Scenario 4 in the VOLPE model, as defined as 1.50% per year increases in fuel economy for cars and passenger trucks during 2021-2026. Accident costs include fatality and nonfatal crash costs. Sales, fatality and nonfatal crash costs, and net benefits are summed over 2017 – 2050 compliance years. Sales changes are reported in millions of vehicles. Fatality and nonfatal crash costs and net benefits are reported in billions of dollars. Accident costs and net benefits are computed with 3 and 7 percent discount rates. The market-price elasticity is the percentage change in new vehicle sales due to a one percent increase in all new vehicle prices.