Environmental Impacts of Banning Vehicle Advertising*

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Abstract

We develop a structural model of demand and pricing of vehicles which incorporates the heterogeneous effects of advertising. We estimate the model using rich data on sales and advertising at the age-group and product level from 2012-2021 in France. We disentangle the positive spillover effects of advertising from its business-stealing effects and find that advertising has a positive effect on vehicle sales and reduces consumers' price sensitivity. Our counterfactual simulations show that an outright ban on advertising does not lead to positive environmental effects. Instead, targeted advertising bans on high-emission and high-weight vehicles are more effective at reducing emissions.

Keywords: Advertising, Vehicles, Environmental Effects, Structural Model, Policy Evaluation
JEL Codes: L13, L51, Q51, M37

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1 Introduction

The transportation sector is one of the largest sources of CO_2 emissions and a major contributor to air pollution. Every second, two new vehicles are added to the roads – a number projected by the International Energy Agency (IEA) to rise to more than four by 2030. The environmental impact of cars will largely depend on how effectively we transition to more fuel-efficient vehicles. However, troubling trends suggest that consumer demand is moving in the opposite direction. The sales of Sport Utility Vehicles (SUVs) have been increasing steadily each year. On average, an SUV consumes about 20 percent more fuel than a medium-sized car to travel the same distance. Since fuel use translates directly into CO_2 emissions, SUVs also release approximately 20 percent more carbon per mile driven. A 2022 report by the IEA notes that the world's fleet of SUVs collectively emitted almost one billion metric tons of CO_2 – an amount equivalent to the combined national emissions of the United Kingdom and Germany in the same year. This trend has now extended to electric vehicles (EVs): in 2022, sales of electric SUVs surpassed those of other types of electric cars. Heavier vehicles, whether conventional or electric, require more energy to move, meaning that until global electricity generation becomes carbon-free, heavier EVs will produce more emissions. Moreover, manufacturing heavier vehicles demands more raw materials, leading to greater energy consumption and emissions during production.[1] In France, the share of SUVs among the total sales of new vehicles has doubled from 2012 to 2021, as well as the share of SUVs among the total sales of electric and hybrid vehicles.[2]

The automotive industry is among the top spenders on advertising worldwide, and represents the second-biggest sector in the French advertising market until 2019. Automotive brands are particularly dependent on television advertising. In France, the share of automotive advertising spending on TV has been growing continuously since 2012.[3] Evolving consumer needs and technological changes over the past few years have been accompanied by a shift in the industry's marketing focus. Brands have increasingly directed their advertising budgets toward their SUV ranges and their "green" (i.e., electric or hybrid) models.[4]

To date, policymakers have primarily focused on promoting technological solutions to tackle climate change, such as green innovation and emissions performance standards. However, effectively reaching the net-zero emissions target also requires shifts in consumer behavior. Governments may need to go further than issuing vehicle taxes or subsidizing electric and hybrid car purchases. Today, automotive manufacturers continue to heavily promote their most polluting products, despite the enormous amounts of CO_2 they release into the atmosphere, putting the planet at risk. The European Citizens' Initiative to ban fossil fuel advertising and sponsorships, launched by Greenpeace

[1] Sources: `https://www.iea.org`

[2] We show these trends in Figures A1 and A2 in the Online Appendix.

[3] See Figure A3 in the Online Appendix.

[4] Figures A4 and A5 in the Online Appendix respectively show the growth in shares of SUV and electric/hybrid vehicles advertising expenditure on French TV. Figure A6 shows the significant increase in advertising spending for electric and hybrid SUVs since 2019.

in 2021, collected 353,103 signatures across Europe in just one year. Following this campaign, a national ban on fossil fuel advertising has been proposed in countries such as Spain, the Netherlands, and Sweden, while France has already incorporated such a ban into its climate law. France will ban advertising for the most polluting vehicles, including many SUVs, starting in 2028.

In this paper, we evaluate the potential impacts of such an advertising ban. We use a structural model to simulate the market equilibrium outcome if firms were not allowed to advertise any (or their most polluting) vehicles. Our model finds the equilibrium market prices and age-group-specific demand for different vehicles depending on individuals' advertising exposure states. Under partial advertising bans, our model also finds the equilibrium allocation of advertising by brands.

Our demand model builds on Grigolon and Verboven (2014), who consider heterogeneity in preferences for car attributes and price sensitivities, while accounting for the discrete source of market segmentation. We enrich their model by incorporating advertising exposure and advertising spillover effects within and across brands. Accounting for the spillover effects of advertising is essential for conducting counterfactual analyses of partial advertising bans, as ignoring these effects could lead to overly optimistic estimates of the bans' positive environmental impacts. We combine longitudinal data on vehicle sales, advertising, and TV viewership during the period 2012-2021 to estimate our demand model. We observe quarterly sales of different car models at the age-group level. Our sales data include vehicle characteristics (such as horsepower, weight, body style and CO_2 emission levels), as well as vehicle retail prices. We couple this with data on product-level television advertising and detailed TV viewership measurements. Our advertising data is recorded at the occurrence level, where an occurrence is the placement of an ad for a specific product (a brand and vehicle-model pair) on a given channel on a given day and time. The viewership measurement includes daily estimates of the number of viewers of each channel by age group and time block (e.g. 06:00-08:59, 09:00-11:59, etc.). These data enable us to construct age-group-specific exposures to each advertisement. To identify the impact of product-level advertising exposure on consumers' vehicle choices, we employ an instrumental variables (IV) strategy. The advertising spillover (or business-stealing) effects within and across brands are identified through rich variation in advertising for different car models over time: most brands only advertise one specific car model at a time, while the set of advertised vehicles changes every year.

The timing of advertising decisions unfolds as follows. First, car manufacturers (firms) set the advertising budgets for each brand. Next, brands contract agencies to pre-book advertising slots from TV channels on their behalf. Finally, brands allocate their advertising slots across different vehicles by deciding which vehicle(s) to advertise. The advertising exposure states in the demand function are the discounted sums of past advertising exposures. Conditional on these exposure states, firms then determine the vehicle prices that maximize their flow variable profits across the multiple brands they own. Our model formalizes the pricing decisions of car manufacturers, taking into account the "feebate" program on French vehicle market. The feebate is a financial rebate to consumers who buy less-polluting vehicles, and an extra fee to consumers who buy more-polluting vehicles. The fee (or rebate) directly affects the net price of vehicles for consumers under this system.

To assess the impact of an outright ban on vehicle advertising, we only need to solve the first-order conditions for prices, as in Dubois et al. (2018). However, to assess the environmental impacts of targeted advertising bans on polluting vehicles, we additionally need to solve for the new advertising equilibria where brands choose which non-banned vehicles to advertise. We consider five different targeted advertising bans, each targeting different sets of polluting vehicles. Given the large number of brands and vehicle-models in this market, there is the possibility of multiple equilibria in the brands' advertising game.[5] To address this, we propose a simple and efficient method to form bounds on the environmental impacts of the various partial advertising bans, enabling us to identify the advertising ban that yields the most favorable environmental and welfare outcomes.

Findings: Our demand estimates suggest a significant positive effect of advertising on vehicle sales. The sales-weighted average own-advertising elasticities range from 1.4 to 3.3, depending on the consumer age group. Within a market segment, the positive spillover effect of advertising outweighs the business-stealing effect within the same brand, whereas across brands, the business-stealing effect dominates. The impact of advertising is heterogeneous across consumers of different age groups. In general, consumer responsiveness to advertising decreases with age. Advertising reduces the own-price elasticity for consumers across all age groups. Without advertising, consumers substitute more between products of the same brand and less between products of different brands.

An outright ban on vehicle advertising reduces the total demand for new vehicles but has little effect on the average CO_2 emissions and weight of vehicles sold. In contrast, well-targeted bans on advertising for polluting vehicles yield more positive environmental effects. Specifically, the environmental impact of banning advertising for non-electric and non-hybrid vehicles over 1,800 kilograms is comparable to that of banning advertising for all SUVs and high-CO_2 vehicles, with both policies producing more favorable outcomes than the other advertising bans we consider. Additionally, banning advertising for polluting vehicles improves welfare under the persuasive view of advertising (where advertising impacts consumers' choice probabilities, but not their realized utility). We estimate that targeted advertising bans lead to an increase of approximately €6bn in total welfare, which involves approximately €3,000 in surplus per consumer.

Related Literature and Contributions: Our paper contributes to the literature on environmental policies in the automobile market. Previous work has primarily focused on fuel economy standards (Goldberg, 1998; Jacobsen, 2013; Grigolon et al., 2018; Davis and Knittel, 2019; Levinson, 2019; Reynaert, 2020), feebate policies (Adamou et al., 2014; D'Haultfœuille et al., 2016; Durrmeyer and Samano, 2018; Durrmeyer, 2022) and electric vehicle subsidies (Remmy, 2025; Fournel, 2024;

[5] In all counterfactuals we consider, there are more than 40 billion possible advertising allocations per time period.

Barwick et al., 2024). To the best of our knowledge, this is the first academic paper that considers advertising bans on polluting vehicles as an environmental policy tool.

Accordingly, our paper contributes to the empirical literature examining the effects of TV advertising bans. Dubois et al. (2018) consider the effect of banning advertising in the junk food market. Tuchman (2019) investigates the likely consequences of banning advertising for e-cigarettes. Sinkinson and Starc (2019) measure the potential effects of banning direct-to-consumer advertising by drug manufacturers. We are the first to extend this literature to the automotive market.[6]

Our work also contributes to the literature measuring cross-advertising elasticities. Rojas and Peterson (2008) find that advertising increases the aggregate demand for beer. Liu et al. (2015) find that TV advertising induces market expansion in the yogurt market but not in the statin market. Lewis and Rao (2015) and Sahni (2016) find positive spillover effects of online display advertising. Shapiro (2018) and Sinkinson and Starc (2019) show that the positive spillover and business-stealing effects of advertising coexist in the pharmaceutical market. Abi-Rafeh et al. (2025) find a positive spillover effect of advertising within and across firms in the UK cola market. Shapiro et al. (2021) estimate the distribution of television advertising elasticities using data across 288 consumer package goods in different categories and conclude that the cross-advertising effect is likely case dependent. We find that within the same brand and car segment, advertising's positive spillover effect outweighs its business-stealing effect, whereas between brands, the business-stealing effect dominates. Overall, advertising contributes to the expansion of the new vehicle market.

From a methodological perspective, we contribute to a large literature that studies the equilibrium demand and pricing of vehicles (e.g., Berry et al., 1995, henceforth BLP, and Grigolon and Verboven, 2014). We extend previous work by incorporating the impact of advertising exposure on consumers' vehicle choices. Identifying the causal impact of advertising on demand is challenging (see, for instance, the discussion in Lewis and Rao, 2015), particularly because we rely on observational data. Previous work using observational data include Shapiro (2018) and Tuchman (2019), who exploit the discontinuity in local advertising markets (i.e., the so-called "border strategy"), and Sinkinson and Starc (2019) who exploit political advertising shocks. These two identification strategies, although being widely applied, are not suitable in our setting. The "border strategy" requires observing differentiated advertising across local markets, which is not applicable to national-level advertising campaigns, as is the case in our setting. Political advertising shocks, which affect all products in a category, cannot be used to identify the impact of product-level advertising, which is our focus. Our identification strategy is to combine variation in individuals' exposure to product-level advertising on TV using an IV strategy. We match information on the precise broadcasting time and channel of different vehicles with information on the viewing behavior of consumers in different age groups, for whom we also observe quarterly purchases of vehicles. We show that BLP-style IVs, which build on observable product attributes, can be used to instrument product-level

[6]Related, Murry (2017) focuses on how advertising decisions can impact the contracting between car manufacturers and their dealers and Barroso and Llobet (2012) focus on the informative role of vehicle advertising, building on the framework of Goeree (2008).

advertising. BLP-style instruments have the advantage of not requiring any specific market setting and can be easily constructed from observable product attributes. Finally, we propose a relatively simple approach to evaluate the potential outcomes of partial advertising bans in market equilibrium. Our approach acknowledges the possibility of multiple equilibria in the brands' advertising game and is particularly well-suited to markets with a large number of brands and products.

2 Data

2.1 New-Vehicles Sales and Characteristics

The first dataset we use is obtained from AAA Data and contains information on sales, prices, and product characteristics for all new passenger cars sold in France between 2012Q1-2021Q4. Our sales data are at the vehicle-model and age-group level at a quarterly frequency. A vehicle-model j is defined as a brand and model-name pair (e.g., Volkswagen Golf). We observe sales by four age groups: 0-24, 25-34, 35-49 and 50 and above. We directly observe the main characteristics of each vehicle such as horsepower, weight, body style (enclosed, convertible, or station wagon), engine type (including gasoline, diesel, LPG/gasoline, superethanol, electric, and six variants of hybrid engines), average fuel cost, as well as the vehicle's CO_2 emission level. The CO_2 emission level is the number of grams of CO_2 emitted per kilometer measured based on standard driving cycle tests.

Sales are defined as new vehicle registrations. Prices are suggested retail prices including VAT. We obtain net vehicle prices after adjusting these suggested retail prices to the French feebate system. The feebate is a financial rebate to consumers who buy less-polluting vehicles, and an extra fee to consumers who buy more-polluting vehicles. The exact amount of rebate or fee depends on the vehicle's CO_2 emission level. There have also been several changes to the feebate program during our sample period, which contribute to variation in net vehicle prices over time. The vehicle's fuel cost is obtained by multiplying their average fuel consumption (in liters per 100km) by the fuel price, following D'Haultfœuille et al. (2016) and Grigolon et al. (2018). Finally, monetary variables (net vehicle prices and fuel cost) are deflated to be expressed in constant 2018 euros.

We obtain data on the total French population over 2021-2021 split by the same four age groups from the French National Survey Institute (INSEE). These data are used to compute the consumers' advertising exposure states and vehicle market shares, which we detail below.

2.2 Advertising Volume and Expenditure

The second dataset we use includes product-level television advertising data over 2012-2021, obtained from Kantar Media. The advertising information is recorded at the occurrence level, where an occurrence is the placement of an ad for a specific product (a vehicle-model) on a given channel, date and time. We observe the length of each ad, together with the cost of placing it. All advertising aired on national broadcast and cable TV channels are contained in the data. We observe rich variation in the ad placements – in terms of channels and airtime – which results in differentiated exposure for consumers for different vehicle-models.

2.3 TV Viewership

The third dataset, obtained from Médiamétrie, contains daily measurements of the number of viewers of each channel by 5 age groups (0-14, 15-24, 25-34, 35-49, 50+) and different time blocks (e.g. 06:00-08:59, 09:00-11:59, etc.) for each day over 2012-2021. As documented in Zhang (2024), these age groups and time blocks capture the relevant variation in TV viewership during our sample period. We match the TV viewership data with the ad occurrences data to obtain an estimate of the number of impressions for each ad for each age group (0-14, 15-24, 25-34, 35-49, 50+).

2.4 Merging the Ad Impression and Vehicle Sales Data

Merging the advertising and sales datasets is relatively straightforward as we directly observe the precise brand and model name of each vehicle in both. The main challenge that we have to overcome is that the two datasets have a different coding standard for the same vehicle-model. We first perform approximate matching of vehicle-model names, then inspect and manually fill in the unmatched vehicle-models to build the final combined dataset. Many vehicle-models that register positive sales are not advertised in the same year. On the other hand, brands often start to advertise a new vehicle-model one year before we observe any positive sales for the model. In our modeling, we consider a vehicle-model j to be available for purchase if we observe positive sales for it during the year. We do, however, take into account the advertisements placed for a vehicle-model before it enters the market in our measurement of the consumers' advertising exposure states, which we detail in Section 3.3.

3 Descriptive Analysis

3.1 The New-Vehicles Market in France

There are between 19-22 firms active in the French new-vehicle market in each year of our data.[7] Some firms (e.g., Honda, Tesla) own only one brand, but many others (e.g., Volkswagen, Renault) own multiple brands. In total, we observe between 37-41 brands in the market each year. The majority of these offer various vehicle-models for sale. At most, we observe a brand selling 34 different vehicle-models in a year.

We use the standard international car classification system (ISO 3833-1977) to group vehicle-models into six segments. These are super-mini vehicles (segment A/B); small family vehicles

[7] In total, we observe 27 unique firms in our data but there have been two mergers and acquisitions and several entries and exits of smaller firms during the sample period. Out of these 27 firms, 16 are multinational giants (e.g., Volkswagen, PSA, Toyota) that are always active on the market.

(segment C); large family vehicles (segment D); executive-, luxury- and super-cars, also called upper class (segment E/F/S); minivans, also called multi-purpose vehicles (segment M); and SUVs (segment J). Most brands sell vehicle-models in more than three segments, but there are also eight brands that are specialized in one specific segment. For instance, the brand Jeep specializes in SUVs, while the brand Alpine specializes in the upper class segment.

After excluding vehicle-models with extremely low sales (where the combined share of vehicles we exclude is below 0.05 percent of total sales), our sample includes between 238-266 vehicles per quarter. Model-level entry and exit is very common in the new-vehicles market. A notable trend in our sample is the increase in demand for SUVs at the expense of demand for vehicles in other market segments.[8] Furthermore, electric and hybrid vehicles have seen a surge in popularity since 2020.[9]

3.2 Advertising Budgeting and Sales

In our setting, automotive advertising is mainly at the vehicle-model level, as opposed to the brand level. Brands also never advertise all their models at the same time. Instead, brands typically promote at most one specific model in a segment at a time. This is true for 94 percent of observations at the brand-segment-quarter level. Of the remaining 6 percent, 5.5 percent involve promoting two models, and the rest only 3-4 models. The most advertised (and also the most sold) vehicle-models are in the mini, small family and SUV segments, and the share of SUVs in both the advertising budget and sales is growing every year. Only a limited number of brands advertise their models in the upper class segments. The most-promoted model does not necessarily register the highest sales within a brand-segment. In practice, brands often (although not exclusively) promote their new models, but their existing models may sell better even without any advertising during the year.

At the brand level, there is no clear leader which dominates in advertising spending in all segments, even though the three oldest domestic brands (Citroën, Peugeot and Renault) tend to spend more on advertising than the other brands. Figure A8 in the Online Appendix plots the brand-level quarterly advertising expenditures of the 15 brands that spent the most on advertising in the mini, small family and SUV segments. Each color represents a brand. We observe many brands simultaneously advertise within the same segment and quarter, suggesting heavy competition between brands to promote their own models in all three segments.[10] In contrast with the correlation between advertising and sales at the vehicle-model-year-quarter level (with coefficient 0.36), advertising expenditure and sales at the aggregated segment-brand-year-quarter level is highly correlated (with coefficient 0.68); the brands which do not advertise any model in a segment also typically sell

[8] We plot this trend in Figure A1 in the Online Appendix.

[9] We plot this trend in Figure A7 in the Online Appendix.

[10] In practice, more brands than we could include in the figure with differentiated colors are advertising at the same time in the same segment.

very little in that segment.

As noted above in Section 3.1, a vehicle manufacturer (e.g., Volkswagen) may own multiple brands with various vehicle-models for sale. A firm's advertising budget is not equally divided across brands, however. Many firms own high-end brands that rarely advertise any specific model. A firm's most popular brand (in terms of sales) is generally the one that has the highest share in the advertising budget.

Overall, both advertising and sales in the automobile industry move in line with the business cycle of the overall economy. The market grew steadily over 2015-2019, after the market recovered from the crisis of 2008. It fell sharply again in 2020 due to the COVID-19 pandemic and the subsequent energy crisis.[11]

3.3 Individual Advertising Exposure

Denote the set of age groups by $\mathcal{D} = \{0\text{-}24,\ 25\text{-}34,\ 35\text{-}49,\ 50+\}$. We define the total exposure to advertising for an individual in age group $d \in \mathcal{D}$ for vehicle j in year-quarter t as:

$$a^d_{jt} = \sum_{s \in \mathcal{S}_t} w^d_{st} T_{jst} \tag{1}$$

Here, s indexes advertising slots across channels and $\mathcal{S}_t$ is the set of slots in quarter t. The variable T_{jst} is the duration in minutes vehicle-model j was advertised in slot s in quarter t. The variable w^d_{st} is the probability that someone from age group d viewed the advert in slot s. We measure this probability using $w^d_{st} = \frac{v^d_{st}}{pop^d_t}$, where v^d_{st} is the number of viewers from age group d viewing the channel during the time block containing slot s, and pop^d_t is the total number of individuals in age group d in the French population in quarter t. Together, $w^d_{st} T_{jst}$ is the expected exposure to a single ad. We sum over slots to obtain the total expected exposure a^d_{jt} over the whole quarter t.

We assume a dynamic effect of advertising on demand such that the advertising exposure state for an individual is equal to the discounted sum of current (up until the quarter before we observe the purchase being registered) and past advertising exposure, as in Erdem et al. (2008) and Dubois et al. (2018):

$$A^d_{jt} = \sum_{n=\underline{t}}^{\bar{t}} \delta^{n-1} a^d_{j,t-n} \tag{2}$$

In estimation, we use $\underline{t} = 1$, $\bar{t} = 4$, and $\delta = 0.5$.[12] Figures A11 and A12 in the Online Appendix plot the advertising exposure by age group for some popular models in different segments. Figures A13

[11] We plot the total advertising expenditure and total sales over time in Figures A9 and A10 in the Online Appendix.

[12] We use four lags and a decay parameter of 0.5 following Dubois and Majewska (2022) who also use quarterly data. We stop at four lags to avoid losing more time periods in estimation and because beyond four lags advertising exposure has negligible effects. Using $\delta = 0.5$ is also consistent with Dubois et al. (2018) who use a decay parameter of 0.9 with biweekly data: based on an average of 6.52 fortnights per quarter, $0.9^{6.52} \approx 0.503$.

and A14 in the Online Appendix compare, respectively, the flows and stocks of exposure for one brand's (Peugeot) most advertised models in each segment. Exposure to advertising for various vehicles is differentiated across age groups. Overall, individuals aged 35 and above are more exposed to car advertising than those of younger ages. Exposure to advertising for a specific vehicle over time generally follows the same pattern of variation across different age groups, but there are also exceptions. We note, for instance, the advertising exposure stock for Dacia's "Duster" model has increased between 2018 and 2020 for those aged 50 and above, but has decreased for individuals aged 34 and under (see Figure A11). Similarly, the advertising exposure stock for Renault's "Captur" model has increased between 2018 and 2021 for individuals aged 50 and above, but has decreased for those of younger ages (see Figure A12). We also note that advertising intensity varies substantially over time across vehicles and segments. This rich variation is valuable for the identification of own- and cross-advertising effects.

3.4 Identification of Advertising Exposure Effects

The main challenge when estimating the effects of advertising using observational data is that advertising is not randomly assigned. We observe rich variation in exposure to advertising at the vehicle-model level across consumer age groups and over time. Some of this variation likely reflects brands' targeting to specific age groups and/or time periods where demand is particularly susceptible to advertising. The variation in our advertising exposure measure defined in equation (1) is driven by the age-specific estimates of the viewing probability w_{sct}^d, coupled with vehicle-models assigned to each of the advertising slots T_{jst}. A threat to the identification of the effect of advertising from using this form of variation is that brands may target individuals in a particular age group based on certain characteristics of a vehicle. In our regressions, we include interactions between age and the main vehicle characteristics (body style, horsepower, fuel cost and weight), age-vehicle fixed effects, and age-quarter-year fixed effects to control for such targeting. We thus exploit the residual variation, which is age-vehicle-quarter-year specific, to estimate the causal impact of advertising on vehicle sales.[13]

Endogeneity of the advertising variable may arise if brands are able to perform sophisticated high-frequency targeting according to transient demand shocks that are unobservable (to econometricians) and specific to each age-vehicle-quarter-year. The institution of the ad-buying process in the French TV market makes such precise targeting unlikely. First, all TV advertising slots are sold in an upfront market well in advance of the ads being aired. There is not even a scatter market, like in the US, where last-minute purchases of individual advertising slots are possible. Second, car manufacturers mainly purchase advertising slots through agencies. Both advertising agencies

[13] A linear regression of the advertising exposure stock A_{jt}^d on the interactions between age and the vehicle characteristics, age-vehicle fixed effects and age-quarter-year fixed effects has an R^2 of 0.486. This indicates that, conditional on our controls for targeting, there is still substantial residual variation in the advertising exposure stock A_{jt}^d.

and TV channels could face demand from different advertisers for the same audience reach. It is unclear how they allocate advertising slots in such circumstances, but in any case, timely targeting according to viewer demographics is difficult for any advertiser.

Brands can, however, rely on their experience and professionalism to predict the market demand for a specific vehicle and advertise more in time periods where the market demand for it is particularly low. To address this potential source of endogeneity that is vehicle-quarter-year specific, we employ a set of instruments in the spirit of Berry et al. (1995). To instrument for advertising, we use the observed vehicle characteristics of product j, the sum of characteristics of other vehicle-models of the same brand and segment, and the sum of characteristics of vehicle-models from all rival brands' vehicle-models within the same market segment. Exogeneity of these instruments relies on a standard timing assumption in the demand estimation literature: the characteristics of a vehicle are chosen well before the realization of any vehicle-quarter-year-specific demand shock. Furthermore, a brand's advertising intensity for a particular vehicle is likely to depend on its own characteristics and market competition (i.e., how substitutable the different vehicles in the market are). Although some characteristics of a vehicle-model do not vary over time, the sum of the characteristics of the competing vehicles do because of the frequent model-level entry and exit in this market. We thus expect a strong relationship between our instrumental variables and the stock of advertising exposure A^d_{jt}. In addition, we also instrument for the price variable, using both the standard BLP instrument — the sum of the characteristics of all rival brands' vehicle models — together with the aforementioned instruments.

Table 1 presents reduced-form evidence of the demand response to advertising. Both the OLS and IV estimates suggest a positive and significant effect of advertising exposure on sales, but the magnitude of the effect is larger with instruments than without. Consistent with the intuition that brands advertise less during periods of high demand, estimates of the own-advertising demand elasticity would be biased downward without instruments, assuming car manufacturers can predict market demand and adjust their advertising accordingly. Our BLP IVs are helpful in controlling for such vehicle-quarter-year specific endogeneity bias. The first-stage estimates, presented in columns (2) and (5), show the significance of our BLP-instruments in explaining the variation in advertising exposure. The Cragg-Donald F-statistics indicate that our instruments are strong. In column (6), we show that a positive effect of advertising exposure on sales is also obtained when using sales and advertising exposures in levels rather than logs, indicating that the results are robust to the concerns raised by Chen and Roth (2023) regarding log-like transformations.

4 Equilibrium Model

The descriptive analysis suggests that advertising has a positive and significant impact on vehicle sales, indicating that consumers' vehicle choices can be influenced by policy interventions targeting advertising. We now specify an equilibrium model of vehicle demand and pricing, which we use to

Table 1: Causal Impact of Vehicle Advertising

Dependent variable:	Log(1 + Sales)	Log(1 + Ad Exposure)	Log(1 + Sales)	Sales	Ad Exposure	Sales
	(1)	(2)	(3)	(4)	(5)	(6)
Log(1 + Ad Exposure)	0.408		1.162			
	(0.009)		(0.063)			
Ad Exposure				1.616		1.670
				(0.196)		(0.814)
Log(Price)	0.046		−1.908			
	(0.088)		(0.422)			
Price				−6.596		−304.142
				(3.312)		(27.633)
Weight × Age group: 0-24	−1.280	0.077	−0.603	−107.376	0.672	191.614
	(0.191)	(0.147)	(0.274)	(35.685)	(1.344)	(48.555)
Weight × Age group: 25-34	−1.221	0.099	−0.561	−130.740	0.932	168.311
	(0.199)	(0.165)	(0.289)	(32.515)	(1.923)	(45.271)
Weight × Age group: 35-49	−1.318	0.144	−0.691	−245.681	2.227	53.300
	(0.210)	(0.186)	(0.307)	(61.145)	(3.078)	(64.375)
Weight × Age group: 50+	−1.415	0.183	−0.818	−185.532	4.863	113.307
	(0.199)	(0.206)	(0.309)	(63.201)	(4.901)	(67.274)
Horsepower × Age group: 0-24	0.173	0.070	0.699	27.271	0.619	432.497
	(0.084)	(0.058)	(0.151)	(10.011)	(0.413)	(41.739)
Horsepower × Age group: 25-34	0.244	0.074	0.768	34.345	0.822	439.705
	(0.087)	(0.066)	(0.155)	(9.495)	(0.585)	(41.669)
Horsepower × Age group: 35-49	0.344	0.071	0.871	63.350	0.975	468.701
	(0.092)	(0.075)	(0.160)	(16.350)	(0.929)	(45.474)
Horsepower × Age group: 50+	0.360	0.064	0.892	33.064	1.429	438.386
	(0.086)	(0.083)	(0.160)	(15.361)	(1.453)	(44.416)
Fuel Cost × Age group: 0-24	−0.063	−0.019	−0.067	−4.070	−0.010	−10.399
	(0.010)	(0.007)	(0.012)	(1.328)	(0.058)	(1.768)
Fuel Cost × Age group: 25-34	−0.068	−0.022	−0.070	−6.189	−0.087	−12.551
	(0.010)	(0.007)	(0.013)	(1.309)	(0.082)	(1.769)
Fuel Cost × Age group: 35-49	−0.069	−0.026	−0.068	−10.853	−0.229	−17.208
	(0.011)	(0.008)	(0.014)	(2.680)	(0.134)	(3.001)
Fuel Cost × Age group: 50+	−0.053	−0.029	−0.050	0.982	−0.476	−5.360
	(0.011)	(0.009)	(0.014)	(2.625)	(0.216)	(2.938)
BLP IV1: Constant		0.178			1.880	
		(0.015)			(0.264)	
BLP IV1: Weight		−0.087			−0.769	
		(0.008)			(0.129)	
BLP IV1: Horsepower		0.019			0.169	
		(0.004)			(0.063)	
BLP IV1: Fuel Cost		−0.002			−0.023	
		(0.001)			(0.009)	
BLP IV2: Constant		−0.092			−1.522	
		(0.005)			(0.087)	
BLP IV2: Weight		0.040			0.731	
		(0.002)			(0.031)	
BLP IV2: Horsepower		0.002			−0.095	
		(0.002)			(0.034)	
BLP IV2: Fuel Cost		0.002			0.024	
		(0.000)			(0.003)	
BLP IV3: Constant		0.215			−0.337	
		(0.032)			(0.613)	
BLP IV3: Weight		−0.135			−0.099	
		(0.014)			(0.237)	
BLP IV3: Horsepower		0.075			0.474	
		(0.008)			(0.132)	
BLP IV3: Fuel Cost		−0.009			−0.062	
		(0.001)			(0.022)	
Estimation	OLS	1st Stage IV	IV	OLS	1st Stage IV	IV
Age-body type fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Age-product fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Age-quarter-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Instrumenting Price	No	No	Yes	No	No	Yes
Cragg-Donald F-Statistic		50.369			42.373	
Observations	36832	36832	36832	36832	36832	36832

Note: Standard errors clustered by age-quarter-year are in parentheses. Columns (1) and (4) present the OLS estimates. Columns (3) and (6) present the IV estimates. Columns (2) and (5) present the first-stage estimates. "BLP IV1" refers to the sum of characteristics of vehicle-models from rival brands. "BLP IV2" refers to the sum of characteristics of rival brands' vehicle-models from the same market segment. "BLP IV3" refers to the sum of characteristics of other vehicles of the same brand and within the same market segment as the instrumented vehicle. In columns (3) and (6), both ad exposure and price are instrumented.

simulate the counterfactual effects of various advertising bans in Section 7.

We model the demand for vehicles using a random coefficients nested logit model, incorporating heterogeneity in advertising exposure and advertising spillover effects within and across brands. Since consumers' vehicle choices are discrete, product-level advertising inevitably leads to business-stealing effects on other products. However, advertising within a segment can attract more consumers to that segment, generating positive spillovers. Our demand model disentangles these two effects. Vehicle brands rely on agencies to purchase advertising slots from various TV channels. The agencies aim to maximize the total advertising exposure of the brands they represent, staying within their budget constraints. The timing of advertising decisions unfolds as follows. First, car manufacturers (firms) simultaneously set the advertising budgets for each brand. Next, brands contract agencies to pre-book advertising slots from TV channels on their behalf. Finally, brands simultaneously choose which vehicle-models to advertise in their booked slots. Brands take into account how their advertising choices today affect the next period's pricing equilibrium, and therefore profits. Given the advertising exposure states, firms determine the vehicle prices that maximize their variable flow profits, while accounting for the impact of the feebate program.

4.1 Demand

Our demand model builds on Grigolon and Verboven (2014) which allows for rich substitution patterns through both discrete sources of market segmentation and continuous product characteristics. An additional key feature of our model is that it incorporates the impact of advertising exposure on consumers' vehicle choices.

Specifically, time periods (quarter-years) are indexed by t and the set of time periods is $\mathcal{T}$. In each period t, there are M_t^d potential consumers in age group d. Each consumer i may either choose to purchase a vehicle j from the set of differentiated vehicles on offer $\mathcal{J}_t$ or the outside good $j = 0$. As detailed in Section 3.1, the vehicle market is segmented, and each vehicle is assigned to a segment $g \in \mathcal{G} = \{1, \dots, G\}$, where the set of segments is collectively exhaustive and mutually exclusive. We use $g = 0$ to denote the segment of the outside good.[14] Vehicle j is produced by brand b owned by firm f. The set $\mathcal{J}_{gt}$ includes all vehicles belonging to market segment g in period t, whereas $\mathcal{J}_{bt}$ includes all vehicles of brand b in period t, and $\mathcal{J}_{bgt}$ refers to the set of vehicles belonging to brand b in segment g in period t. Finally, $\mathcal{J} = \bigcup_{t \in \mathcal{T}} \mathcal{J}_t$ is the full set of products over our sample period.

We allow the indirect utility for a consumer from purchasing a vehicle j to depend on a number of variables. We include the vehicle's price p_{jt}, the vehicle's observed characteristics (horsepower, weight, body style, fuel consumption) $\boldsymbol{x}_{jt}$, and individuals' advertising exposure stock for that vehicle, A_{jt}^d. While it is reasonable to impose vehicles are substitutes (i.e., raising the price of one vehicle increase the demand for another) in this differentiated product market, there is no reason

[14]The outside good includes both second-hand vehicles and alternative means of transportation (i.e. public transportation, cycling, etc.).

to impose cross-advertising effect to have a certain sign. Advertising can be either predatory or cooperative, and may lead to either market expansion or contraction.[15] A distinctive characteristic of car advertising is that it is primarily at the product (i.e., vehicle) level rather than at the brand level. Descriptive evidence in Section 3.2 indicates that the most promoted vehicle does not always achieve the highest sales within a brand-segment, while the brands which do not advertise any vehicle in a segment also sell very little in that segment. Positive spillovers of vehicle advertising within a car segment are likely stronger within brands than across them in this market. Accordingly, we also include two further advertising exposure stocks in addition to the own-vehicle advertising stock: the sum of advertising stocks of the brand's other vehicles in the segment, $\sum_{j' \in \mathcal{J}_{bgt} \setminus \{j\}} A^d_{j't}$ and the sum of rival brands' advertising stocks in the segment, $\sum_{j' \in \mathcal{J}_{gt} \setminus \mathcal{J}_{bgt}} A^d_{j't}$.

Given this, we model consumer i from age group d's conditional indirect utility from purchasing vehicle-model j from brand b in segment g in quarter t as:

$$u^d_{ijbgt} = \alpha^d_i p_{jt} + \beta^d_o A^d_{jt} + \beta^d_w \sum_{j' \in \mathcal{J}_{bgt} \setminus \{j\}} A^d_{j't} + \beta^d_c \sum_{j' \in \mathcal{J}_{gt} \setminus \mathcal{J}_{bgt}} A^d_{j't} + \boldsymbol{x}'_{jt} \boldsymbol{\gamma}^d + \vartheta_j + \varsigma^d_t + \nu^d_g + \xi^d_{jt} + \bar{\varepsilon}^d_{ijbgt} \quad (3)$$

Here, α^d_i is the consumer's sensitivity to price p_{jt}, which is allowed to be heterogeneous across consumers and is modeled as $\alpha^d_i = \alpha^d + \sigma v_i$, where $v_i \sim \mathcal{N}(0,1)$. The parameter σ is the standard deviation of price sensitivities and the parameters α^d are the mean price sensitivities that are allowed to vary by age group. The three distinct effects of advertising in u^d_{ijbgt} are the own-vehicle advertising effect β^d_o, the within-brand spillover effect β^d_w, and the cross-brand spillover effect β^d_c. We allow these advertising effects to differ across age groups.[16] Through $\boldsymbol{\gamma}^d$ we allow for age-group-specific preferences for observable vehicle characteristics $\boldsymbol{x}_{jt}$. We also include a number of fixed effects to control for unobserved demand factors. We include vehicle-model fixed effects ϑ_j to control for time invariant vehicle attributes; age-group-specific year-quarter fixed effects ς^d_t to control for nationwide changes in overall vehicle demand, which can differ across age groups; and age-group-specific vehicle segment effects ν^d_g to control for persistent differences in preferences for vehicle segments across age groups that are not captured by our product characteristics. The term ξ^d_{jt} captures the demand shocks from age group d in year-quarter t for product j that is observable to consumers and firms, but not observable by the econometrician. Finally, $\bar{\varepsilon}^d_{ijbgt}$ is consumer i's individual-specific valuation for vehicle j. As in Grigolon and Verboven (2014), we model this as $\bar{\varepsilon}^d_{ijbgt} = \zeta^d_{igt} + (1-\rho)\,\varepsilon^d_{ijbgt}$, where ζ^d_{igt} is consumer i's idiosynratic valuation for all products in a segment, which allows for individual-specific valuations to be correlated across vehicles within the

[15] Previous literature has found both business stealing and positive spillovers effects from advertising. This includes studies in the pharmaceutical (Shapiro, 2018; Sinkinson and Starc, 2019), retail (Dubois et al., 2018; Shapiro et al., 2021), and tobacco (Tuchman, 2019) markets. To the best of our knowledge, no previous research has ever explored the possible spillover effects of advertising in the automotive industry. Murry (2017) distinguishes between manufacturer and dealer advertising but does not account for potential spillover effects of product-level advertising.

[16] In our modeling, we explored a specification where the parameters of the advertising effects were also random, but estimated the standard deviations of the advertising effects to be close to 0.

same segment. We assume that $\bar{\varepsilon}^d_{ijbgt}$ follows the distributional assumptions of the nested logit model: ε^d_{ijbgt} is Type I extreme value and ζ^d_{igt} has the unique distribution such that $\bar{\varepsilon}^d_{ijbgt}$ is extreme value. The nesting parameter ρ, proxies for the degree of preference correlation between vehicles of the same segment.

If a consumer instead chooses the outside option, they obtain the indirect utility:

$$u^d_{i0t} = \bar{\varepsilon}^d_{i0t} = \zeta^d_{i0t} + (1-\rho)\,\varepsilon^d_{i0t} \tag{4}$$

Each consumer i in period t chooses the vehicle j or outside option that maximizes her decision utility specified in equations (3) and (4). With our distribution assumption on $\bar{\varepsilon}^d_{ijgbt}$, the conditional probability that consumer i from age group d chooses vehicle j in period t takes the nested logit form:

$$\begin{aligned}\widetilde{\mathfrak{s}}^d_{ijt}\left(\boldsymbol{\delta}^d_t, v_i, \sigma, \rho\right) = & \frac{\exp\left(\left(\delta^d_{jt} + \sigma v_i p_{jt}\right)/(1-\rho)\right)}{\sum_{j\in\mathcal{J}_{gt}} \exp\left(\left(\delta^d_{jt} + \sigma v_i p_{jt}\right)/(1-\rho)\right)} \times \\ & \frac{\exp\left[(1-\rho)\log\left(\sum_{j\in\mathcal{J}_{gt}} \exp\left(\left(\delta^d_{jt} + \sigma v_i p_{jt}\right)/(1-\rho)\right)\right)\right]}{1+\sum_{g=1}^{G} \exp\left[(1-\rho)\log\left(\sum_{j\in\mathcal{J}_{gt}} \exp\left(\left(\delta^d_{jt} + \sigma v_i p_{jt}\right)/(1-\rho)\right)\right)\right]}\end{aligned} \tag{5}$$

where

$$\delta^d_{jt} = \alpha^d p_{jt} + \beta^d_o A^d_{jt} + \beta^d_w \sum_{j'\in\mathcal{J}_{bgt}\setminus\{j\}} A^d_{j't} + \beta^d_c \sum_{j'\in\mathcal{J}_{gt}\setminus\mathcal{J}_{bgt}} A^d_{j't} + \boldsymbol{x}'_{jt}\boldsymbol{\gamma}^d + \vartheta_j + \varsigma^d_t + \nu^d_g + \xi^d_{jt} \tag{6}$$

is the mean utility for product j for individuals in age group d in period t and $\boldsymbol{\delta}^d_t = \left\{\delta^d_{jt}\right\}_{j\in\mathcal{J}_t}$ is the vector of all vehicles' mean utilities for age group d in period t. Integrating out the idiosyncratic deviations from the mean utility gives the unconditional choice probability for vehicle j in period t from age group d, which is equivalent to its aggregate market share:

$$\mathfrak{s}^d_{jt}\left(\boldsymbol{\delta}^d_t, \sigma, \rho\right) = \int \widetilde{\mathfrak{s}}^d_{ijt}\left(\boldsymbol{\delta}^d_t, v_i, \sigma, \rho\right)\phi\left(v_i\right) dv_i \tag{7}$$

where $\phi(\cdot)$ is the pdf of the standard normal distribution. Our demand model is flexible enough to capture the impact of pricing and advertising on demand, regardless of which view one takes on advertising. The nested-logit specification allows advertising to shape consumers' choice sets (market segment), aligning with the informative view. Additionally, it accounts for advertising's direct influence on consumers' decision utility, consistent with the characteristic view. Moreover, the model estimates can be used to evaluate consumers' experience utility under the persuasive view (see Section 7.2 for details).

4.2 Supply

4.2.1 Advertising Decision

Advertising decisions are made at the brand level. As is common practice, a vehicle brand contracts an agency to purchase advertising slots from different TV channels on its behalf. The intermediary role of an advertising agency is to simplify the game played by the brand that it represents, reducing its action space from being highly multidimensional (entailing choices over TV channels and individual advertising slots for each vehicle) to a more straightforward decision about how to allocate its advertising slots across vehicles.[17] An agency aims to maximize the total advertising exposure of the brand under its budget constraint e_{bt}. Formally, let $\widetilde{T}_{bst}$ be the duration in minutes of slot s that the agency buys for brand b in quarter t. The agency's problem is to choose the slots to buy for the brand to maximize the brand's total advertising exposure subject to the budget constraint:

$$\begin{aligned} &\max_{\widetilde{T}_{bst} \geq 0,\, \forall s \in \mathcal{S}_t} \sum_{d \in \mathcal{D}} \widetilde{a}^d_{bt} M^d_t = \sum_{d \in \mathcal{D}} \sum_{s \in \mathcal{S}_t} w^d_{st} \widetilde{T}_{bst} M^d_t \\ &\text{subject to} \sum_{c \in \mathcal{C}_t} \sum_{s \in \mathcal{S}_t} \kappa_{st} \widetilde{T}_{bst} \leq e_{bt} \end{aligned} \tag{8}$$

where κ_{st} denotes the advertising slot price.[18] The term $\widetilde{a}^d_{bt}$ is the total expected advertising exposure of an individual in age group d in quarter t to brand b, and M^d_t is the number of potential consumers in group d. The brand then allocates each purchased slot $\widetilde{T}_{bst} > 0$ to a vehicle $j \in \mathcal{J}_{bt}$. In doing so, they are effectively choosing a total advertising exposure a^d_{jt} for each product taking the total exposure across products for their brand $\sum_{j \in \mathcal{J}_{bt}} a^d_{jt} = \widetilde{a}^d_{bt}$ as given. The brand aims to maximize its profit in the next period while considering how today's advertising choices influence the pricing equilibrium in the following period. Different brands determine their allocations of advertising slots simultaneously.

4.2.2 Pricing Decision

As detailed in Section 3.3, individuals' advertising exposure states for vehicle j depend on past advertising exposure flows, approximately according to $A^d_{jt} \approx \delta A^d_{j,t-1} + a^d_{j,t-1}$.[19] Because individuals' advertising stocks depend only on past advertising exposure, we assume firms take the exposure states as given when making pricing decisions, as in Dubois et al. (2018). Conditional on the vector of individuals' advertising exposure states $\boldsymbol{A}^d_t = \left\{A^d_{jt}\right\}_{j \in \mathcal{J}_t}$, firm f determines the retail prices of

[17] Abi-Rafeh et al. (2025) explore a similar institutional feature.

[18] Note that the advertising agency's audience-maximization program aligns with the advertiser's cost-minimization objectives (see Zhang, 2024).

[19] See equation (2).

its vehicles that maximize its flow variable profit:

$$\Pi_{ft} = \sum_{j \in \mathcal{J}_{ft}} (\tilde{p}_{jt} - c_{jt}) \left(\sum_{d \in \mathcal{D}} \mathfrak{s}_{jt}^{d}(\boldsymbol{p}_t, \boldsymbol{A}_t^d) M_t^d \right), \tag{9}$$

where $\mathcal{J}_{ft}$ denotes the set of vehicles offered by firm f and M_t^d denotes the market size (i.e., number of potential consumers of age group d).[20] Variables $\tilde{p}_{jt}$ and c_{jt} denote respectively the retail price and marginal cost of producing vehicle j. The market share of vehicle j among individuals in age group d is $\mathfrak{s}_{jt}^d$ when the vehicle retail prices – net of the environmental subsidies (or penalties) – are given by $\boldsymbol{p}_t$ and the individuals' advertising exposure states are given by $\boldsymbol{A}_t^d$. According to the French feebate system, there is a financial rebate to consumers who buy less polluting vehicles, and an extra fee to consumers who buy more polluting vehicles. The exact amount of rebate or fee varies by vehicles and over time. We denote by τ_{jt} the rebate (or fee) applied to vehicle j. The net price of vehicle j for consumers p_{jt} is equal to the sum of the vehicle's retail price set by the car manufacturer $\tilde{p}_{jt}$ and the feebate τ_{jt}: $p_{jt} = \tilde{p}_{jt} + \tau_{jt}$. The value of τ_{jt} is positive in case of a penalty (fee) and is negative in case of a subsidy (rebate).[21]

Car manufacturers have market power in this market and set their prices taking into account the demand and prices of rival manufacturers.[22] The set of price first-order conditions for firm f are:

$$\sum_{d \in D} \left(\mathfrak{s}_{jt}^d \left(\boldsymbol{p}_t, \boldsymbol{A}_t^d \right) + \sum_{j' \in \mathcal{J}_f} \left(p_{j't} - \tau_{j't} - c_{j't} \right) \frac{\partial \mathfrak{s}_{j't}^d \left(\boldsymbol{p}_t, \boldsymbol{A}_t^d \right)}{\partial p_{jt}} \right) M_t^d = 0 \quad \forall j \in \mathcal{J}_{ft}. \tag{10}$$

5 Estimation and Identification

The vector of demand parameters to be estimated is given by:

$$\boldsymbol{\theta} = \left(\left\{ \alpha^d, \beta_o^d, \beta_w^d, \beta_c^d, \boldsymbol{\gamma}^d, \{\varsigma_t^d\}_{t \in \mathcal{T}}, \left\{ \nu_g^d \right\}_{g \in \mathcal{G}} \right\}_{d \in \mathcal{D}}, \{\vartheta_j\}_{j \in \mathcal{J}}, \sigma, \rho \right). \tag{11}$$

To estimate $\boldsymbol{\theta}$, we follow the approaches detailed in Grigolon and Verboven (2014) and Conlon and Gortmaker (2020). Vehicle brands likely form accurate predictions of the vehicle-quarter-specific demand shocks ξ_{jt}^d before allocating their advertising slots $\widetilde{T}_{bst-1}$, which then determine the advertising exposure states A_{jt}^d according to equations (1) and (2). Similarly, car manufacturers likely observe the vehicle-quarter-specific demand shocks ξ_{jt}^d prior to setting their prices p_{jt}. Besides, as in

[20]Following D'Haultfœuille et al. (2019), we set the market size M_t^d based on the observation that households (which on average have two adults) on average purchase a vehicle every four years. Because we have quarterly sales data, this involves dividing the total population of an age group pop_t^d by $2 \times 4 \times 4 = 32$.

[21]Depending on the vehicle j and period t, the value of τ_{jt} can be strictly positive, or strictly negative, or zero.

[22]Note that individuals' advertising exposure states at period t does not depend on the future advertising exposure flows $t' > t$. When choosing vehicle prices for period t, firms observe all the past advertising exposure flows $t'' < t$.

the standard nested logit model, the nesting parameter interacts with the within-nest share, which is correlated with the unobserved component of demand ξ^d_{jt} by construction. We rely on different sets of instruments, that we detail below, to identify the price and the advertising coefficients, $\alpha^d, \beta^d_o, \beta^d_w, \beta^d_c$, as well as the nesting parameter ρ.

The characteristics of a vehicle $\boldsymbol{x}_{jt}$ and sum of characteristics of vehicles from rival brands $\sum_{j' \notin \mathcal{J}_{bt}} \boldsymbol{x}_{j't}$ can be used to instrument the price variable p_{jt}. The validity of these sets of instruments rely on a standard timing assumption: the characteristics of a vehicle are chosen well before the realization of vehicle-quarter specific demand shock ξ^d_{jt}. On the other hand, characteristics of vehicles are observed before (and likely to influence) their pricing and advertising decisions.

The sum of characteristics of other vehicles from the same brand in the same market segment $\sum_{j' \in \mathcal{J}_{bgt} \setminus \{j\}} \boldsymbol{x}_{j't}$ and the sum of characteristics of vehicles from rival brands in the same market segment $\sum_{j' \in \mathcal{J}_{gt} \setminus \mathcal{J}_{bgt}} \boldsymbol{x}_{j't}$ can be used to instrument the vehicle's market share within a segment, following Grigolon and Verboven (2014). As discussed in Section 3.4, these sets of instruments, together with the vehicle's own characteristics $\boldsymbol{x}_{jt}$, are also valid instruments for the own-vehicle advertising exposure stock A^d_{jt}. Under the same timing assumption, we can instrument the advertising exposure stock for the brand's other vehicles within a market segment $\sum_{j' \in \mathcal{J}_{bgt} \setminus \{j\}} A^d_{j't}$, and the rival brands' vehicles within a market segment $\sum_{j' \in \mathcal{J}_{gt} \setminus \mathcal{J}_{bgt}} A^d_{j't}$, with the same sets of variables $\boldsymbol{x}_{jt}$, $\sum_{j' \in \mathcal{J}_{bgt} \setminus \{j\}} \boldsymbol{x}_{j't}$, $\sum_{j' \in \mathcal{J}_{gt} \setminus \mathcal{J}_{bgt}} \boldsymbol{x}_{j't}$. Tables A1 to A4 in the Online Appendix show regressions that correspond to the first stage of our instrumental variables approach. The estimates indicate that our different sets of BLP-IVs explain the variation in the above endogenous variables well.

To estimate the parameter vector $\boldsymbol{\theta}$, we use a two-step GMM procedure to obtain an efficient weighting matrix. To reduce the dimensionality of the nonlinear search over parameters, we first use the within transformation according to Conlon and Gortmaker (2020) to avoid directly estimating the 349 vehicle fixed-effects ϑ_j. We then concentrate out the remaining linear parameters to only have to search over the heterogeneity in price sensitivity σ and the nesting parameter ρ.[23] We compute robust standard errors using the standard asymptotic formula. We use the Gauss-Hermite Quadrature (GHQ) method to numerically approximate the integral in equation (7). Conlon and Gortmaker (2020) find that the GHQ method is more accurate and faster compared to pseudo Monte Carlo methods when the number of random coefficients is small.

We estimate the marginal cost parameters c_{jt} by inverting the system of price first-order conditions given by equation (10). While we explore quarterly vehicle sales data by age group, we assume that the marginal cost of a vehicle remains constant within a year as our price data vary only at the annual level. We obtain an estimate of the marginal cost parameter per vehicle per year by finding the value of c_{jt} that equates the yearly average of equation (10) to zero.

[23] The linear parameters we concentrate out are the price coefficients α^d, advertising coefficients, β^d_o, β^d_w, β^d_c, effects of product characteristics $\boldsymbol{\gamma}^d$, age-year-quarter fixed effects ς^d_t, and age-segment fixed effects ν^d_g.

6 Model Estimates

6.1 Demand Estimates and Elasticities

We present the estimated coefficients of the model in equation (3) in Table 2, along with the average product-level price and advertising elasticities of demand by age group in Table A5 in the Online Appendix.[24] All the parameter estimates are statistically significant. The estimated price and advertising parameters suggest that consumers become less price-sensitive and less advertising-responsive with age.[25] The average elasticities are weighted by market shares. The average own-price elasticities range from -5 to -8, while the average own-advertising elasticities range from 1.4 to 3.3, depending on the consumer age group. Our estimates of own-price elastisities are slightly larger, in absolute terms, compared to what has been found in the literature (about -5 or -6 averaged across all age groups) when the effect of advertising on demand was ignored. This result is intuitive: Advertising makes consumers less price sensitive. The price elasticities measure the percentage change in demand following a one percent price increase while holding advertising at its observed level. Ignoring the positive advertising level (and its positive effect on demand) biases the estimated price sensitivity towards zero. The cross-price elasticities between vehicles are all positive. The degree of substitution is the strongest between vehicles within the same segment but across brands. The degree of substitution between vehicles across segments is weak.

Table A5 presents the weighted average elasticities for over 200 vehicles, with weights determined by their respective market shares. The unweighted average own-advertising elasticities range from 0.4 to 0.9, slightly higher than the figures reported in the empirical advertising literature (e.g., Honka et al., 2017; Shapiro, 2018; Shapiro et al., 2021; Abi-Rafeh et al., 2025). However, it is important to note that these prior studies estimate the effects of brand-level advertising in markets such as pharmaceuticals, cigarettes, and grocery items, which differ significantly from our estimation of product-level advertising effects in a durable goods market (vehicles). To confirm that the effects of advertising on demand are in the correct range, we first compute the marginal benefit of an additional minute of advertising a product on a brand's flow variable profit as predicted by our model (see Online Appendix C for details). We then subtract from this the observed cost of an additional minute of advertising to obtain the net return to advertising. Figure A22 in the Online Appendix reports the distribution of estimated net returns on advertising. Consistent with brands' optimal advertising strategies, the distribution is centered around zero for advertised vehicle-quarters and is predominantly negative for non-advertised ones. Cross-advertising elasticities across segments are weak but negative. Cross-advertising elasticities are positive among consumers aged above 25, ranging from 0.06 to 0.13 between vehicles within the same segment and brand. The cross-advertising

[24]The analytical formulas for the price and advertising elasticities of demand are shown in Online Appendix B.

[25]Although we find that consumers aged below 25 are less price-sensitive than those aged 25 to 50, this result should be interpreted with caution, as parents or grandparents may purchase vehicles on behalf of their children or grandchildren aged under 25.

Table 2: Demand Estimates

	All ages (1)	Ages 0-24 (2)	Ages 25-34 (3)	Ages 35-49 (4)	Ages 50+ (5)
Price: Mean		−0.685	−0.898	−0.829	−0.590
		(0.072)	(0.072)	(0.072)	(0.072)
Price: Std. Dev.	0.140				
	(0.038)				
Advertising exposure		0.042	0.020	0.021	0.020
		(0.006)	(0.004)	(0.003)	(0.002)
Exposure to other models of same brand within segment		0.002	0.004	0.004	0.002
		(0.002)	(0.001)	(0.001)	(0.001)
Exposure to rival brands' models within segment		0.001	0.001	0.001	0.001
		(0.000)	(0.000)	(0.000)	(0.000)
Weight		0.294	0.842	0.641	0.109
		(0.090)	(0.090)	(0.090)	(0.090)
Horsepower		0.764	1.172	1.021	0.539
		(0.106)	(0.107)	(0.107)	(0.107)
Fuel cost		−0.026	−0.031	−0.024	−0.020
		(0.004)	(0.004)	(0.004)	(0.004)
Nesting parameter, ρ	0.783				
	(0.024)				
Vehicle fixed effects	Yes				
Age-year-quarter fixed effects	Yes				
Age-segment fixed effects	Yes				
Age-body type fixed effects	Yes				

Note: Robust standard errors in parentheses. Price is in €10,000, weight is in 1,000 kilograms, Fuel costs are computed per 100 kilometers. Advertising exposure is estimated according to equation (2), where T_{js} is measured in minutes.

elasticities are negative between vehicles of different brands even within the same segment. In other words, within a market segment, vehicle-level advertising has a positive spillover effect on the demand for other vehicles of the same brand but has a net business-stealing effect on the other brands.

In Tables A6 to A8 in the Online Appendix, we show the price and advertising cross-elasticities of demand split by vehicle segment, CO_2 emissions and weight. The tables show the change in average demand for a vehicle in the category shown in the row with respect to a change in the average price (or advertising) of a vehicle in the category shown in the column. These tables are indicative of to what extent consumers value each of the three vehicle attributes: segment, CO_2 emission level, and weight. A low degree of substitution between vehicles of different CO_2 emission levels, for instance, would suggest that the average consumer significantly weighs this attribute in their vehicle choice. Accordingly, policies that target this particular vehicle attribute are more likely to be effective. Note that the three vehicle attributes are complementary indicators of the environmental friendliness of a vehicle. One cannot solely consider a vehicle as non-polluting based on one of the three indicators. For example, the CO_2 emission level of an electric SUV that weighs above 3,000 kilograms is 0g/km, although such a vehicle consumes significantly more energy compared to a lighter vehicle. On the other hand, EVs are generally heavier than their comparable vehicles powered by internal combustion engines.

Table A6 presents the average cross-elasticities by vehicle segment. Both price and advertising cross-elasticities across vehicle segments are close to zero. Cross-price elasticities are highest (above 1) within the upper-class segments (executive, luxury, and super cars) and the large family vehicle segment, while they are lowest within the mini vehicle segment. In the SUV segment, cross-price elasticities are approximately 0.4, ranking just above those in the mini vehicle segment. Cross-price elasticities in the small family and minivan segments fall in the middle range, at approximately 0.6. Cross-advertising elasticities are largest in absolute terms (above 0.3) within the upper-class vehicle segment, but smallest in absolute terms (less than 0.03) within the large family and minivan segments. In the mini vehicle, small family car, and SUV segments, cross-advertising elasticities remain small in absolute terms (less than 0.2).

Table A7 presents the average cross-elasticities by CO_2 emission levels. We split vehicles into three categories based on their emission level: low (less than 123g/km), medium (between 123g/km and 160g/km), and high (more than 160g/km). The estimates suggest that low-emission vehicles are close substitutes, eventually because consumers who purchase low-emission vehicles are particularly sensitive to this vehicle attribute. The business-stealing effect of advertising is also the strongest between the low-emission vehicles.

Table A8 presents the average cross-elasticities by vehicle weight. We split vehicles into three weight categories: less than 1,800 kilograms, 1,800-2,200 kilograms, and more than 2,200 kilograms. The estimates indicate that individuals who prefer light vehicles primarily substitute between light cars, while those who prefer heavier vehicles tend to substitute within the heavier vehicles. The business-stealing effect of advertising is more pronounced among light vehicles compared to heavier ones.

6.2 The Effects of Advertising on Price Elasticities

Table 3 shows the effect of advertising on the price elasticities of demand. We estimate the own- and cross-price elasticities of demand at the simulated market equilibrium with a zero advertising exposure stock for all vehicles. The results are compared to the price elasticities of demand at the baseline equilibrium with observed advertising. Overall, advertising makes consumers less price sensitive. The own-price elasticities are higher across all age groups in the absence of advertising exposure. Within a market segment, cross-price elasticities of demand for vehicles are stronger within the same brand and weaker across brands without advertising. This is because advertising's positive spillover effect outweighs its business-stealing effect within the same brand-segment, while its business-stealing effect dominates the positive spillover effect between brands. Without advertising, consumers substitute more between products of the same brand and less between products of different brands. Advertising marginally increases substitution between vehicles across segments; however, the cross-price elasticities of demand across segments remain minimal in any case.

Table 3: Average Price Elasticities of Demand

Age group:	0-24	25-34	35-49	50+
Own price elasticity	−6.157	−8.808	−7.955	−5.173
Own price elasticity (zero ad stock)	−6.315	−9.050	−8.143	−5.306
Cross price elasticity within segment, within brand	0.149	0.248	0.245	0.203
Cross price elasticity within segment, within brand (zero ad stock)	0.158	0.247	0.244	0.196
Cross price elasticity within segment, across brand	0.329	0.446	0.432	0.360
Cross price elasticity within segment, across brand (zero ad stock)	0.278	0.404	0.391	0.299
Cross price elasticity across segment	0.002	0.006	0.006	0.003
Cross price elasticity across segment (zero ad stock)	0.001	0.005	0.006	0.002

Note: Elements in the table are calculated by taking the weighted average own- and cross-elasticities of vehicles within or across segments and brands, where each pair of vehicles is weighted by the product of their market shares. The term "zero ad-stock" refers to the situation where individuals' advertising exposure states are zero for all vehicles.

6.3 Markups and Margins of Car Manufacturers

Using the estimated marginal cost c_{jt}, we compute the product-level Lerner Index which measures the markup of price above marginal cost: $L_{jt} = (\tilde{p}_{jt} - c_{jt}) / \tilde{p}_{jt}$. Table 4 presents the average levels of this markup by firm during 2012-2021. The values range from 0.08 to 0.24. On average, Renault enjoys the highest markup, followed by Suzuki. The average markup of Tata and Geely Group are the lowest.

The firm Renault-Nissan-Mitsubishi was created in 2017 following the merger of Renault-Nissan and Mitsubishi. Therefore, in our sample, the firms Renault-Nissan and Mitsubishi exist until 2017, and are then replaced by Renault-Nissan-Mitsubishi. Similarly, in 2017, PSA acquired the brand Opel from GM. This acquisition does not result in a new firm, but rather caused a significant change in markup estimates of firms PSA and GM in 2017.

Comparing the profit margin of different vehicles, measured by $\tilde{p}_{jt} - c_{jt}$, we note that mini-vehicles are the least profitable, while the profitability of other vehicle segments depends on the feebate program and advertising, which change over time. The French feebate system functions like a Pigouvian tax/subsidy that applies to consumers but is indirectly passed through to firms' vehicle prices. Upper-class vehicles were highly profitable until 2016. Under the revised feebate policy, which heavily taxes powerful, high-polluting vehicles, firms have had to reduce the retail prices of vehicles in this segment to compensate consumers for the environmental tax. However, starting in 2020, firms began advertising electric and/or hybrid upper-class vehicles, allowing them to once again realize high margins in this market segment. The profitability of SUVs has been increasing over time, boosted by advertising, irrespective of the feebate program.

7 Counterfactual Analysis

We now explore several counterfactual scenarios involving vehicle advertising bans. Using our model and parameter estimates, we simulate vehicle pricing and demand under different advertising

Table 4: Average Markup of Car Manufacturers

Firm	Avg. Margin	Firm	Avg. Margin
AIWAYS	0.091	PSA	0.172
BMW	0.095	RENAULT	0.239
DAIMLER	0.100	RENAULT-NISSAN	0.158
FCA	0.130	RENAULT-NISSAN-MITSUBISHI	0.143
FORD	0.133	SAIC	0.098
GEELY GROUP	0.075	STELLANTIS	0.129
GM	0.139	SUBARU	0.094
HONDA	0.116	SUZUKI	0.188
HYUNDAI	0.133	TATA	0.075
MAHINDRA AND MAHINDRA	0.115	TESLA	0.093
MAZDA	0.110	TOYOTA	0.111
MITSUBISHI	0.144	VOLKSWAGEN	0.118

Note: The product-level markup is measured by the Lerner Index $L_{jt} = (\tilde{p}_{jt} - c_{jt})/\tilde{p}_{jt}$. The table presents the average product-level markup by firm.

restrictions. We begin with an outright advertising ban, as advocated by some environmental activists.[26] In this scenario, individuals' exposure to vehicle advertising is entirely eliminated.

Next, we examine five partial advertising bans, each targeting a specific set of polluting vehicles. The first prohibits advertising for all SUVs. The second restricts advertising for vehicles emitting more than 123 grams of CO_2 per kilometer, aligning with the proposed regulations for 2028. The third extends this ban to include both high-emission vehicles (above 123 grams of CO_2 per kilometer) and all SUVs. In 2022, the government introduced an environmental tax on vehicles weighing over 1,800 kilograms. In light of this, the fourth partial ban prohibits advertising for all vehicles exceeding this weight threshold. Finally, we consider a fifth scenario that specifically targets non-electric and non-hybrid vehicles weighing more than 1,800 kilograms. In each of these five partial ban scenarios, brands are permitted to reallocate their advertising slots to vehicles that are not subject to restrictions.

Our analysis focuses on the short-term (one-year) effects of these advertising bans, assuming they were implemented at the start of 2018.[27] Our aim is to identify the environmental and welfare impacts of each of these possible bans.

7.1 The Environmental Impacts of Banning Vehicle Advertising

The outright advertising ban effectively sets individuals' advertising exposure flows to zero from the start of the ban (i.e., $a^d_{jt} = 0, \forall d, j$). In this counterfactual scenario, there is no need to solve for a new advertising equilibrium. Instead, we directly update the advertising exposure stocks under the ban using the ad stock formula in equation (2) with $a^d_{jt} = 0$. We then find

[26]Source: `https://www.whichcar.com.au/news/environmentalists-push-to-ban-all-car-advertising`.

[27]Assessing the long-term impacts of advertising bans is beyond the scope of this study, as it would require accounting for changes in the supply of available vehicle models and their characteristics.

Table 5: Environmental Effects of Banning Vehicle Advertising

Effect on:	*Average vehicle CO_2*		*Average vehicle weight*	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Outright ban	0.14%	0.14%	−0.40%	−0.40%
SUV ad ban	−4.34%	−2.71%	−4.09%	−3.04%
High CO_2 ad ban	−6.88%	−4.06%	−3.35%	−2.82%
Combined SUV and high CO_2 ad ban	−6.95%	−5.23%	−4.28%	−2.73%
High weight ad ban	−2.00%	−1.62%	−7.23%	−6.76%
Non-electric/hybrid high weight ad ban	−4.48%	−3.81%	−5.76%	−5.54%

Note: All results [lower bound, upper bound] are percentage changes relative to the baseline equilibrium with no advertising ban.

the market equilibrium vehicle prices and sales using the demand and pricing model specified in Section 4, taking the updated advertising exposure stocks as given. The resulting average CO_2 emissions and vehicle weight levels are reported in the first row of Table 5 and are shown graphically in Figure A17 in the Online Appendix. The percentage changes are calculated according to the formula (counterfactual average − baseline average)/(baseline average), with the averages weighted by sales. The counterfactual average is based on the model-simulated pricing equilibrium with zero advertising flows for all individuals from the beginning of the ban, while the baseline average is derived from our model-simulated advertising and pricing equilibrium in the absence of an advertising ban.[28] Advertising contributes to market expansion, shaping demand for both high- and low-emission (or high- and low-weight) vehicles. An outright ban on vehicle advertising could have reduced the total demand for new vehicles by as much as 40 percent in 2018.[29] Advertising also influences consumer preferences – some buyers may opt for more polluting cars without advertising, while others may choose cleaner alternatives. Overall, the impact of an outright ban on vehicle advertising on the average CO_2 emissions and vehicle weight of cars sold is minimal. In fact, such a ban may not lead to any significant environmental benefits.

We next consider five partial advertising bans, each targeting a specific set of polluting vehicles. The short-run decision for each vehicle brand involves allocating its advertising slots across vehicles based on the decision process described in Section 4.2.1. The allocation of advertising slots must take into account the regulation. We assume that, under the partial advertising bans, brands do not

[28] The observed stocks of advertising serve as the initial guess for determining the baseline advertising equilibrium using the algorithm described below. Figures A15 and A16 compare the model predicted baseline sales to the observed sales in data. Our model fit is very good.

[29] It is more likely that consumers substitute toward (more polluting) second-hand vehicles rather than shift to alternative modes of transportation under the outright advertising ban, although the available data do not allow us to confirm this within our model. That said, we do observe all second-hand vehicle models sold on the market. More than half of these models are highly polluting – that is, they emit more than 123 grams of CO_2 per kilometer and/or weigh over 1,800 kilograms. This suggests that outright advertising bans may lead to greater adoption of polluting vehicles.

advertise less but reallocate their current advertising slots across vehicles that are not affected by the advertising ban.[30] In 2018, 28 of the 35 brands advertised at least one product, with half of these brands selling more than 8 products. Our counterfactual scenarios have at least 40 billion possible advertising allocations per time period, each being a potential market equilibrium. Recognizing the possibility of multiple equilibria, we form bounds on the environmental outcomes across different counterfactual scenarios.[31] To begin the search for equilibrium allocations of advertising slots, we consider two extreme allocations: (i) all brands allocate slots to their least-polluting vehicles, and (ii) all brands allocate slots to their most-polluting-but-not-banned vehicles. Because our aim is to evaluate the effects of various advertising bans on the average CO_2 emission and weight levels of vehicles sold, we define the least- and most-polluting vehicles based on their respective CO_2 emission and weight levels.

For each of the two initial allocations and under all counterfactual scenarios, we first solve for the new price equilibrium and market shares. We then proceed to search for the equilibrium advertising allocations where no brand has an incentive to deviate from its choice, using an algorithm proposed by Lee and Pakes (2009) and Wollmann (2018). In short, the program assumes an ordering of decisions based on brands' market shares. The first brand chooses the allocation of its advertising slots that best responds to the allocations of all other brands.[32] The second brand similarly chooses its best response, taking as given the first brand's best response. The third brand also responds in this manner, taking the first and second brands' allocations as given. This cycle continues across all brands, with the program updating each brand's advertising allocations across vehicles until a full cycle is complete and no brand wishes to deviate further. The result is a simultaneous-move Nash equilibrium. Starting from the two extreme advertising allocations – either from the least-polluting vehicles or from the most-polluting-but-not-banned vehicles – we find the market equilibrium allocations of advertising slots that yield the highest and lowest average vehicle CO_2 emission and weight levels through this program.[33] Figure A17 in the Online Appendix presents bounds of the environmental outcomes from the five partial advertising bans. The whiskers show the range of potential environmental outcomes for each advertising ban, representing the average CO_2 emission and weight levels of vehicles sold under the two extreme advertising allocations described

[30] The demand estimates indicate that advertising increases the demand for all vehicles of the brand itself, to the detriment of demand for rival brands' vehicles (see Table A5). It is therefore optimal for brands to advertise more, rather than less, as long as their budgets allow. We also verified that, under the partial advertising bans, no brand has a monetary incentive to unilaterally reduce its advertising spending. That is, any reduction in a brand's advertising lowers its equilibrium variable profit in this regulatory setting.

[31] Note that even when brands reallocate their advertising slots from more polluting vehicles to less polluting ones, consumers still experience the positive spillover effects of advertising for the more polluting vehicles. At the aggregate level, brands with the largest advertising budgets gain greater exposure among consumers and, consequently, sell more.

[32] Because we observe brands advertise only a small number of vehicles per period, we further assume that brands continue to advertise the same total number of models in each counterfactual. This reduces the number of possible alternatives we need to consider when finding a brand's best response.

[33] We confirm that the equilibrium outcomes are not sensitive to the search order (based on brands' market share) or to the criteria used for ranking vehicle pollution levels (whether by CO_2 emissions or weight).

above.[34] The dots indicate the smallest and largest environmental effects of each advertising ban in market equilibrium. The numerical results corresponding to these equilibrium outcomes (i.e., the dots in Figure A17) are shown in Table 5.

It is important to note that we propose a fast and relatively simple method for establishing bounds on the environmental effects of vehicle advertising bans. Our algorithm simulates the equilibrium upper and lower bounds on the average CO_2 emission and weight levels of vehicles sold under these bans. Each of the upper and lower bounds represents a market equilibrium, although other equilibria where the average emission and weight levels of vehicles sold fall within these bounds may exist. Nevertheless, as shown in Table 5, most equilibrium bounds are quite narrow, enabling clear policy conclusions. The partial advertising bans have modest impacts on the total demand for new vehicles, with each ban considered reducing total new vehicle sales by approximately 10 percent in 2018. However, the environmental impacts of the partial advertising bans are more significant than those of the complete advertising ban.

Banning advertising for SUVs could lead to a wide range of potential environmental outcomes. Brands currently promoting electric SUVs might redirect their advertising efforts to other vehicles – electric or otherwise – in non-SUV segments. We estimate that, in market equilibrium, both the average CO_2 emissions and the average weight of vehicles sold could decrease by 2 to 4 percent. Banning advertising for high-emission vehicles (i.e., those emitting more than 123 grams of CO_2 per kilometer) results in a greater reduction in the average CO_2 emissions of vehicles sold (by 4 to 7 percent) but a smaller decrease in average vehicle weight (by 3 percent). Combining a ban on advertising for high-emission vehicles with a ban on all SUVs would yield a more favorable outcome: Average vehicle CO_2 emissions could decrease by 5 to 7 percent, while average vehicle weight could decline by 2 to 4 percent.

Banning advertising for high-weight vehicles (i.e., those weighing over 1,800 kilograms) results in the largest decrease in average vehicle weight (7 percent) but the smallest reduction in average CO_2 emissions (2 percent). A more-targeted ban on advertising for non-electric and non-hybrid vehicles over 1,800 kilograms could result in a similar reduction of approximately 5 to 6 percent in average vehicle weight, along with a greater decrease in average CO_2 emissions (4 percent).

The environmental effects of banning advertising for non-electric and non-hybrid vehicles over 1,800 kilograms are comparable to those of banning advertising for all SUVs and high-CO_2 vehicles. Both bans yield more favorable outcomes than other advertising restrictions.

7.2 The Welfare Effects of Banning Vehicle Advertising

In Table 6, we compare the welfare consequences of the six advertising bans. We report their resulting changes in consumer surplus, firms' profits, feebate revenues, and total welfare in billion of euros. Following Dixit and Norman (1978) and Dubois et al. (2018), we assess the welfare implica-

[34] We note that these whiskers do not represent market equilibria. Instead, they represent the environmental effects of a possible advertising reallocation from the ban.

Table 6: The Welfare Effects of Banning Vehicle Advertising

	Change in consumer welfare (persuasive view)	Change in consumer welfare (characteristic view)	Change in total firm profits	Change in total feebate revenue	Change in total welfare (persuasive view)	Change in total welfare (characteristic view)
Outright ban	[12.88, 12.88]	[-6.25, -6.25]	[-2.86, -2.86]	[-0.04, -0.04]	[9.98, 9.98]	[-9.15, -9.15]
SUV ad ban	[7.01, 8.21]	[-2.01, -1.15]	[-0.61, -0.79]	[-0.10, -0.19]	[6.01, 7.46]	[-2.76, -1.96]
High CO_2 ad ban	[6.77, 7.82]	[-1.97, -1.43]	[-0.79, -0.86]	[-0.25, -0.27]	[5.63, 6.97]	[-2.81, -2.29]
Combined SUV and high CO_2 ad ban	[6.73, 7.73]	[-1.76, -1.33]	[-0.76, -0.85]	[-0.24, -0.28]	[5.35, 6.69]	[-2.80, -2.32]
High weight ad ban	[6.50, 7.22]	[-1.85, -1.67]	[-0.88, -0.93]	[-0.05, -0.07]	[4.84, 6.22]	[-2.85, -2.50]
Non-electric/hybrid high weight ad ban	[6.97, 7.49]	[-1.69, -1.45]	[-0.80, -0.91]	[-0.25, -0.25]	[4.96, 6.27]	[-2.91, -2.29]

Note: Let $\boldsymbol{A}_t^c$ and $\boldsymbol{p}_t^c$ denote the equilibrium advertising exposure state and price vectors under the advertising bans. Denote by $\boldsymbol{A}_t^0$ and $\boldsymbol{p}_t^0$ the same under the baseline equilibrium without a ban. Following Dubois et al. (2018), the consumer's expected experience utility at $(\boldsymbol{A}_t^c, \boldsymbol{p}_t^c)$ is given by $\widehat{V}_{it}^d(\boldsymbol{A}_t^c, \boldsymbol{p}_t^c) = \mathbb{E}_\varepsilon\left[\max_{j\in\mathcal{J}_t\cup\{0\}} u_{ijbgt}^d\right] - \sum_{j\in\mathcal{J}_t}\mathfrak{s}_{jt}^d\left(u_{ijbgt}^d - \widehat{u}_{ijbgt}^d\right)$ under the persuasive view, and $V_{it}^d(\boldsymbol{A}_t^c, \boldsymbol{p}_t^c) = \mathbb{E}_\varepsilon\left[\max_{j\in\mathcal{J}_t\cup\{0\}} u_{ijbgt}^d\right]$ under the characteristic view. Accordingly, the change in consumer surplus is measured as $\int \frac{1}{\alpha_i^d}\left[\widehat{V}_{it}^d(\boldsymbol{A}_t^0, \boldsymbol{p}_t^0) - \widehat{V}_{it}^d(\boldsymbol{A}_t^c, \boldsymbol{p}_t^c)\right]\phi(v_i)\,dv_i$ under the persuasive view, and $\int \frac{1}{\alpha_i^d}\left[V_{it}^d(\boldsymbol{A}_t^0, \boldsymbol{p}_t^0) - V_{it}^d(\boldsymbol{A}_t^c, \boldsymbol{p}_t^c)\right]\phi(v_i)\,dv_i$ under the characteristic view. All results [lower bound, upper bound] are in billions of euros.

tions of the advertising bans based on both the persuasive and characteristic views of advertising. Under the persuasive view, advertising affects consumer choices but not their experience utility. Consumers choose the product with the highest value of u_{ijbgt}^d according to equation (3) (which includes advertising), but their experience utility is based on their valuation of the product in the absence of advertising:

$$\widehat{u}_{ijbgt}^d = \alpha_i^d p_{jt} + \boldsymbol{x}_{jt}'\boldsymbol{\gamma}^d + \vartheta_j + \varsigma_t^d + \nu_g^d + \xi_{jt}^d + \bar{\varepsilon}_{ijbgt}^d \tag{12}$$

Under the characteristic view, advertising affects both consumer choices and experience utility. Accordingly, consumers choose the product with the highest value of u_{ijbgt}^d, which is equal to their experience utility.

Because of multiple equilibria, we provide bounds on the welfare effects of advertising bans following a similar approach to that used for deriving their environmental effects. We begin the search for an equilibrium with two extreme allocations of advertising slots, where we allocate the advertising slots to the products that give the highest and lowest mean utility in the absence of advertising. Specifically, we define the mean utility for an individual in age group d of a product without advertising as:

$$\widehat{\delta}_{jt}^d = \alpha^d p_{jt} + \boldsymbol{x}_{jt}'\boldsymbol{\gamma} + \vartheta_j + \varsigma_t^d + \nu_g^d + \xi_{jt}^d \tag{13}$$

We set the initial guesses for a brand's advertising slots to the vehicle(s) with the highest and lowest values of $\sum_{d\in\mathcal{D}}\widehat{\delta}_{jt}^d M_t^d / \sum_{d\in\mathcal{D}} M_t^d$.[35] Then, we determine the equilibrium upper and lower bounds for changes in consumer surplus under different advertising bans, using the same search algorithm detailed in Section 7.1. The results are presented in the first two columns of Table 6.

[35]These extreme allocations for consumer surplus apply under both the persuasive and characteristic views of advertising. Because advertising positively affects the demand for the advertised vehicle, and the spillover effect is small compared to the direct effect (see Table 2), the overall impact of advertising is primarily on the promoted product.

To find the bounds on the firms' profits, we set the initial guesses for the product(s) a brand advertises to be the product(s) with the highest and the lowest margins.[36] Then, we determine the equilibrium upper and lower bounds for the change in total profits of the firms, using the same search algorithm mentioned above. Results are presented in the third column of Table 6.

Finally, to find the bounds on the change in feebate revenue, we set the initial guesses for the product(s) a brand advertises to be the product(s) with the highest and the lowest CO_2 emission levels.[37] Then, we determine the equilibrium upper and lower bounds for the change in feebate revenues, using the same search algorithm mentioned above. Results are presented in the fourth column of Table 6.

Upper and lower bounds of the changes in consumer surplus, firms' profits, and feebate revenues correspond to six different market equilibria. We calculate the changes in total welfare in each of the six market equilibria and report the minimum and maximum changes in total welfare in the last two columns of Table 6.[38]

Under the persuasive view of advertising, the bans increase consumer surplus. By banning advertising for certain vehicles, the firms' abilities to distort consumers' choices are more limited, and thus they are closer to their optimal choices without advertising. Under the characteristic view of advertising, the bans reduce consumer surplus as a non-negligible number of advertising slots are allocated to low-selling vehicles, while many consumers lose advertising exposure for the vehicles they ultimately choose. The bans also lead to a decline in total new vehicle sales, as some consumers opt for the outside option; impacts of the bans on vehicle prices are small, and as a result, total profits for firms decrease. Banning advertising for polluting vehicles increases the demand for the subsidized "green" vehicles, which results in a reduction in total feebate revenue. In absolute terms, the impact of the bans on consumer welfare is more substantial than their effects on firms' profits and feebate revenues. The bans thus enhance total welfare under the persuasive view of advertising but diminish it under the characteristic view of advertising.

The total welfare change under an outright advertising ban is significantly larger than under any partial advertising ban. However, the welfare impacts of the five partial advertising bans are broadly similar. Estimates suggest that banning advertising for polluting vehicles increases total consumer surplus by approximately €6bn (under the persuasive view of advertising), equating to a welfare gain of about €3,000 per consumer. Table A9 in the Online Appendix provides a breakdown of the changes in consumer welfare by age group. The impacts of the bans are more significant for older consumers than for younger ones.

[36] These extreme allocations for firms' profits hold because advertising primarily affects market shares rather than vehicle pricing.

[37] The feebate revenue increases with a vehicle's CO_2 emission level: it is positive for vehicles emitting more than 130g of CO_2 per kilometer but negative for those emitting less than 60g per kilometer.

[38] As a robustness check, we tested 100 random allocations of advertising slots as starting points in the equilibrium search, compared to the extreme allocations. The resulting equilibrium outcomes from these 100 random starting allocations, as reported in Figures A18 and A21 in the Online Appendix, closely align with the equilibrium bounds derived from the extreme starting allocations.

8 Conclusion

In this paper, we develop a structural model of demand and pricing of vehicles which incorporates the effect of advertising. Our model accounts for heterogeneity in advertising exposure across age groups and disentangles the spillover and business-stealing effects of advertising within and across brands. We estimate the model using rich data on sales and advertising at the age-group and product level from 2012-2021 in France. We find that advertising has a significant effect on consumers' vehicle choices and reduces their price sensitivity. Within a market segment, vehicle-level advertising has a strong positive spillover effect on the demand for other vehicles of the same brand, but "steals" business from rival brands. Overall, environmental friendly (i.e., low-emission and/or light) vehicles are close substitutes, and the business-stealing effect of advertising is strongest between them.

We use our estimated model to evaluate the potential consequences of different vehicle advertising bans. Our results suggest that vehicle advertising leads to market expansion while also driving demand substitution between more-polluting and less-polluting vehicles. An outright advertising ban would reduce the overall demand for new cars but has little effect on the average CO_2 emissions and weight of vehicles sold.

We then simulate the potential consequences of five alternative partial advertising bans, each targeting a specific set of polluting vehicles and motivated by policy interests. In these counterfactual scenarios, brands are allowed to reallocate their advertising slots to vehicles not subject to the bans. To assess the potential environmental outcomes of these partial advertising bans, we develop a simple and efficient method to form bounds on their effects in market equilibrium. Our results indicate that targeted bans on advertising for polluting vehicles can lead to positive environmental outcomes. The two most effective bans we consider are a ban on advertising for SUVs and other high-CO_2 vehicles, and a ban on advertising for non-electric/hybrid high-weight vehicles.

While our quantitative results are based on observed market conditions in the sample, this research highlights the potential for policy interventions to drive positive environmental impacts.

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Online Appendix to:

Environmental Impacts of Banning Vehicle Advertising

by Christoph Walsh and Jiekai Zhang

A Additional Figures and Tables

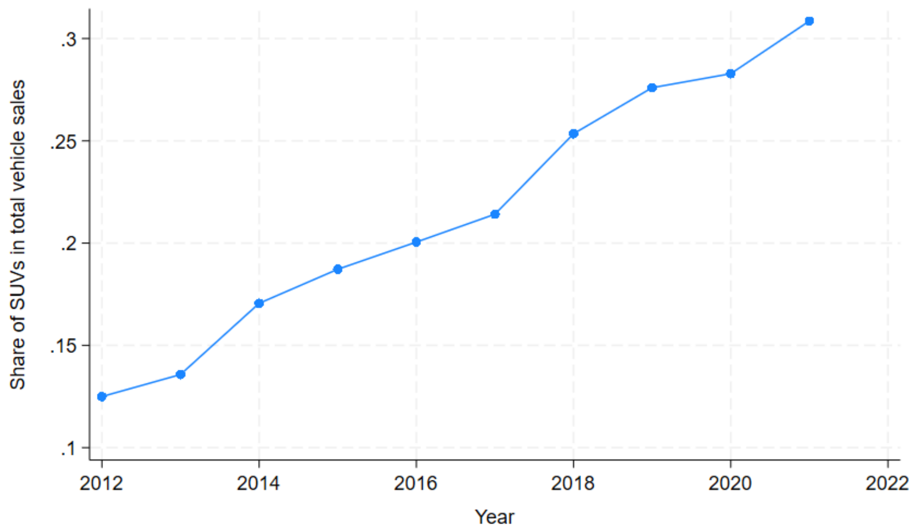


Figure A1: Share of SUVs in Total Vehicle Sales

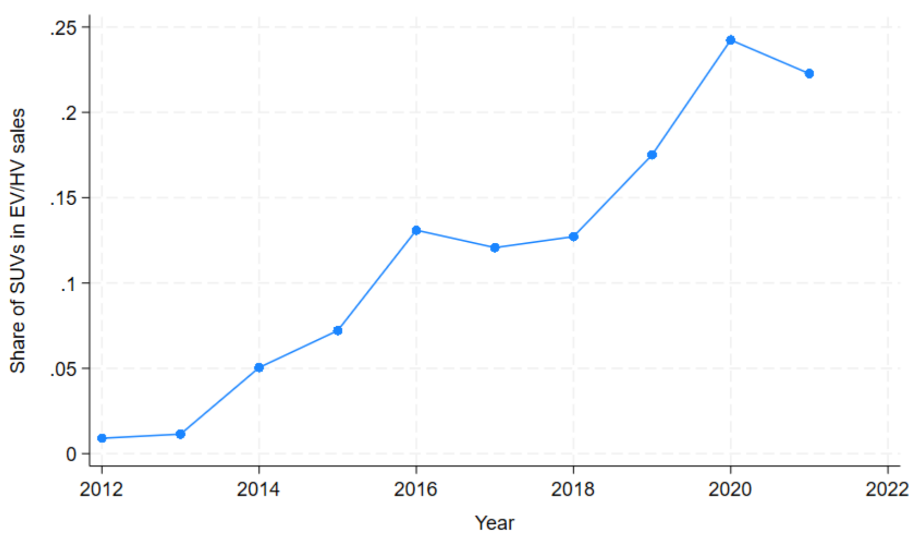


Figure A2: Share of SUVs in Electric and Hybrid Vehicle Sales

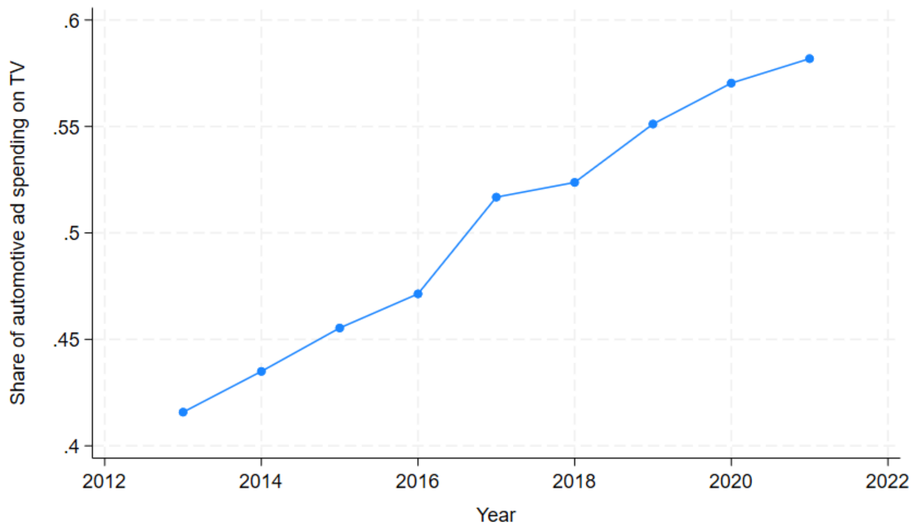


Figure A3: Share of Automotive Adverting Expenditure on TV
(Total Spending on TV/Total Spending on All Media)

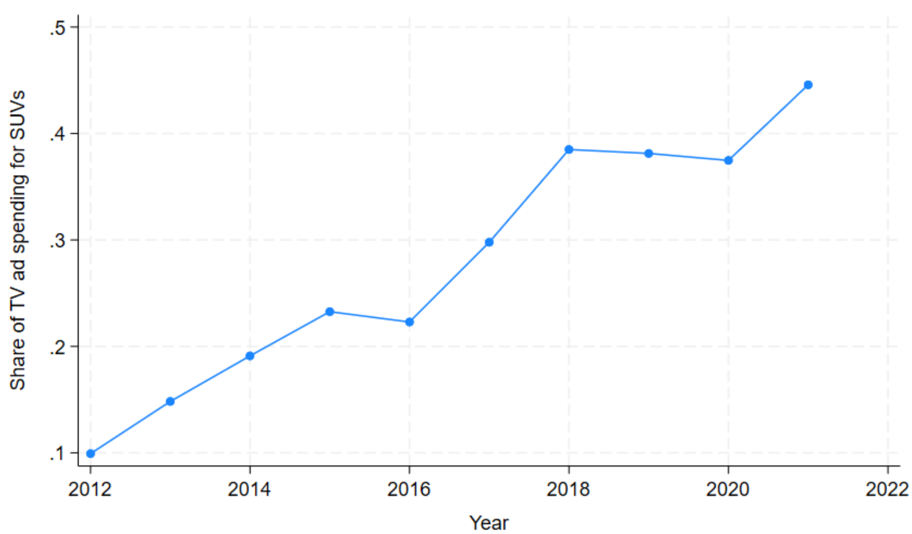


Figure A4: Expenditure Share of SUVs in TV Advertising

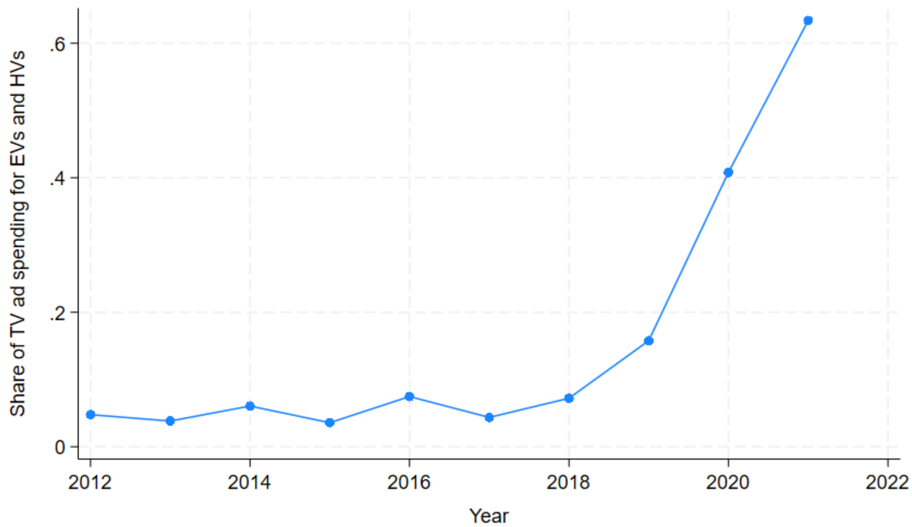


Figure A5: Expenditure Share of Electric and Hybrid Vehicles in TV Advertising

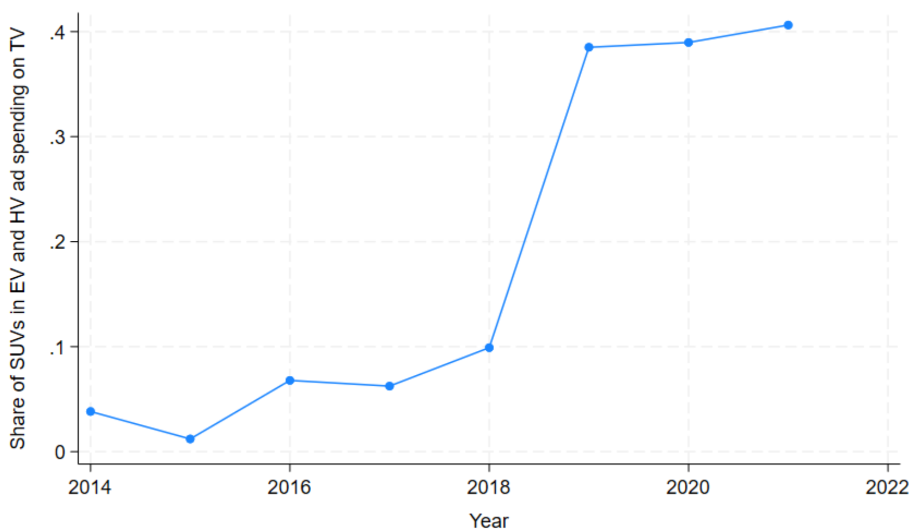


Figure A6: Expenditure Share of Electric and Hybrid SUVs in TV Advertising

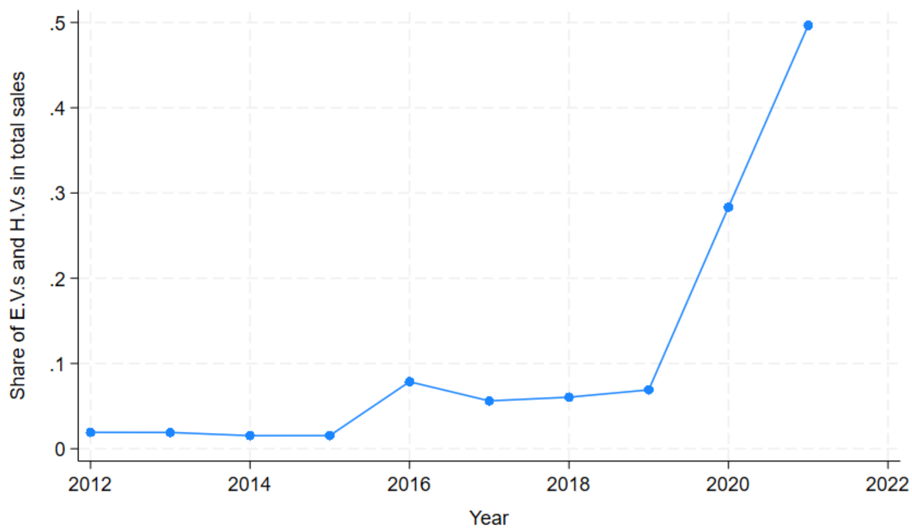


Figure A7: Share of Electric and Hybrid Vehicles in Total Sales

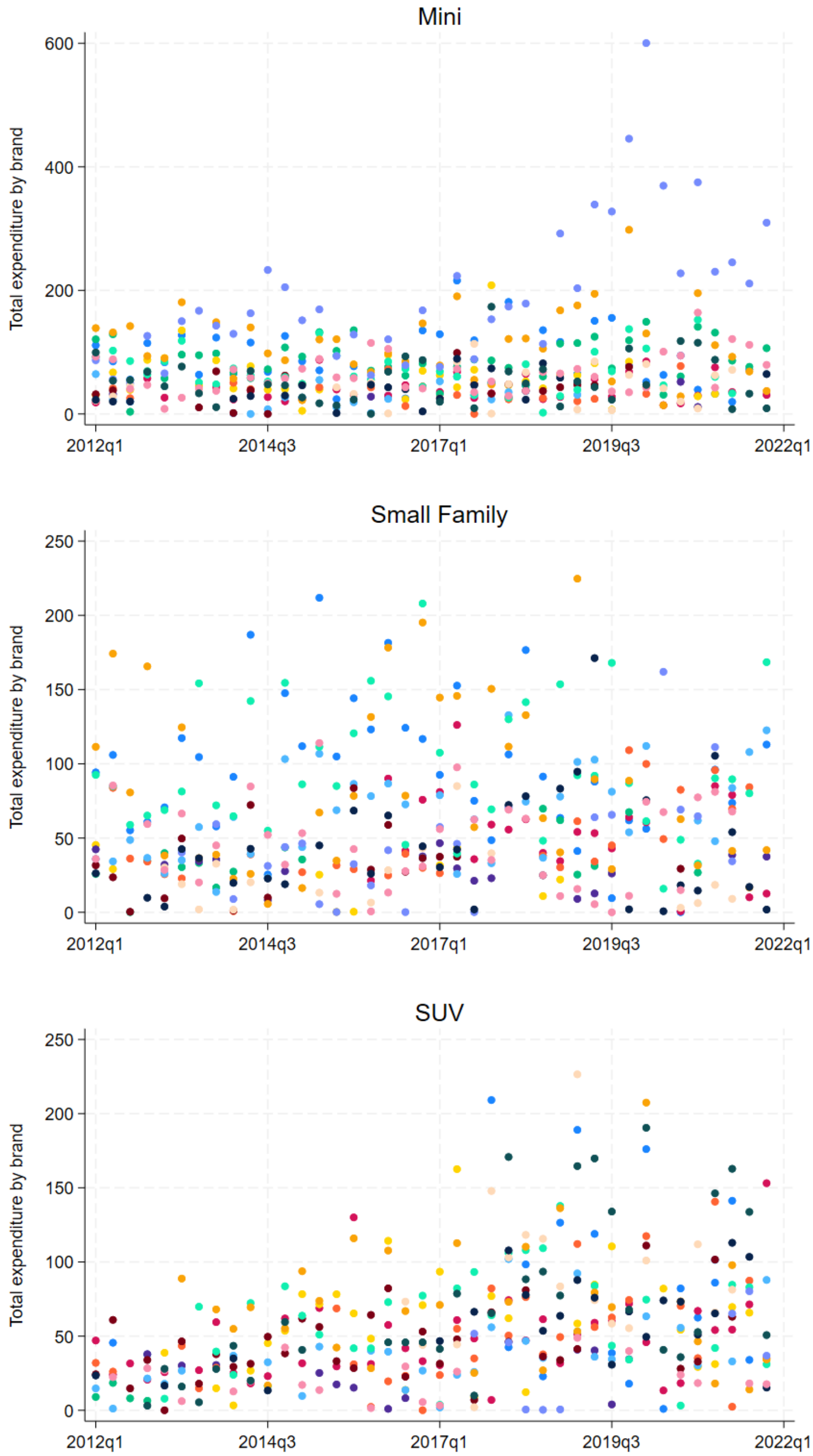


Figure A8: Total Advertising Expenditure by Brand and Segment

Note: Each dot represents a brand. Units of expenditures are not reported for confidentiality reason.

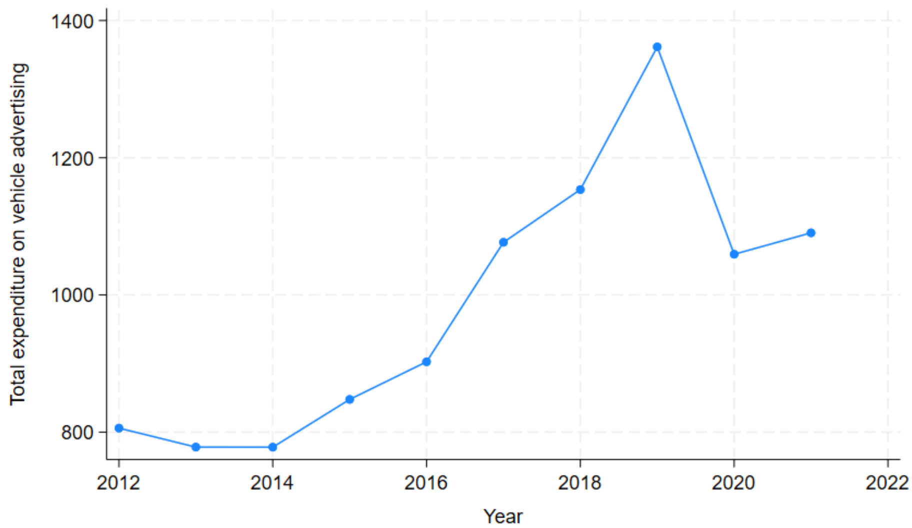


Figure A9: Total Expenditure on Vehicle Advertising

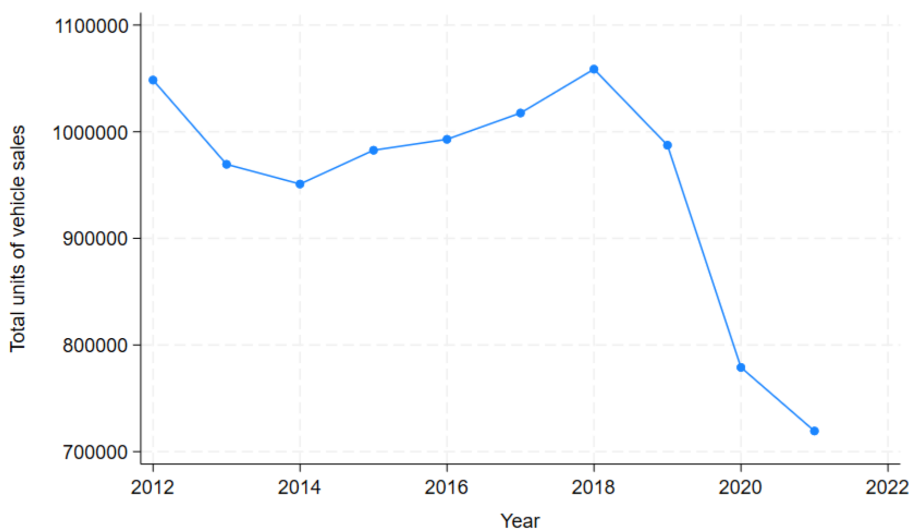


Figure A10: Total Units of Vehicle Sales

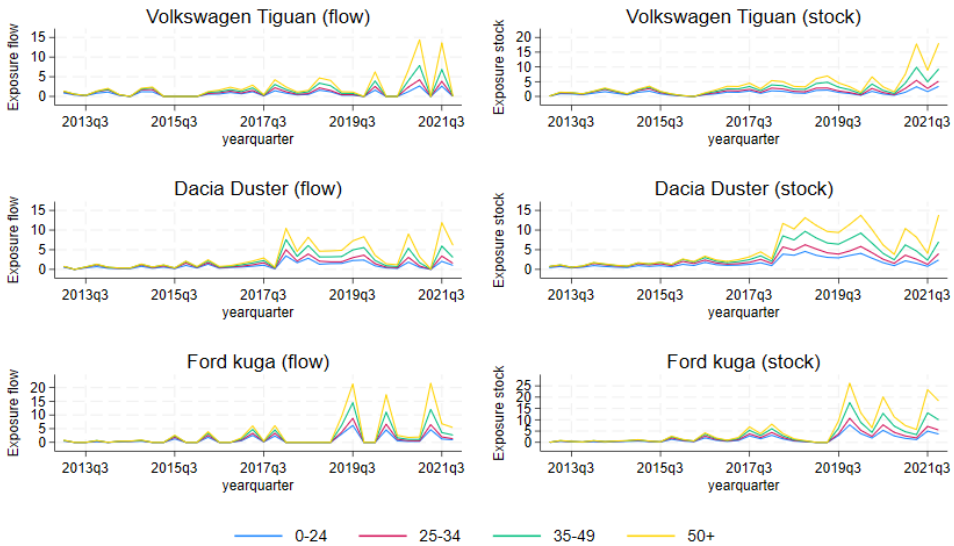


Figure A11: Flow and Stock of Advert Exposure to Three SUV Models

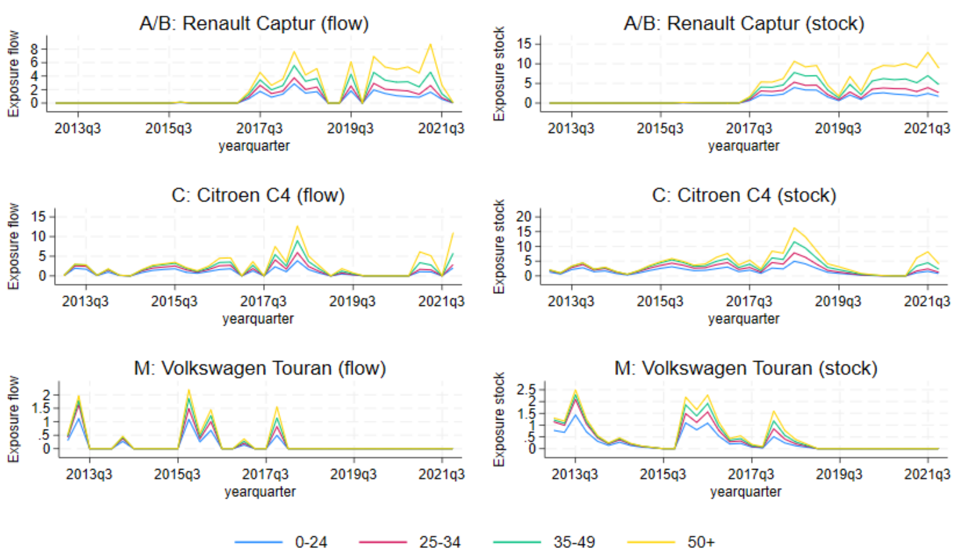


Figure A12: Flow and Stock of Advert Exposure to Three Popular Models in Segments Mini (A/B), Small Family (C), and Minivan (M)

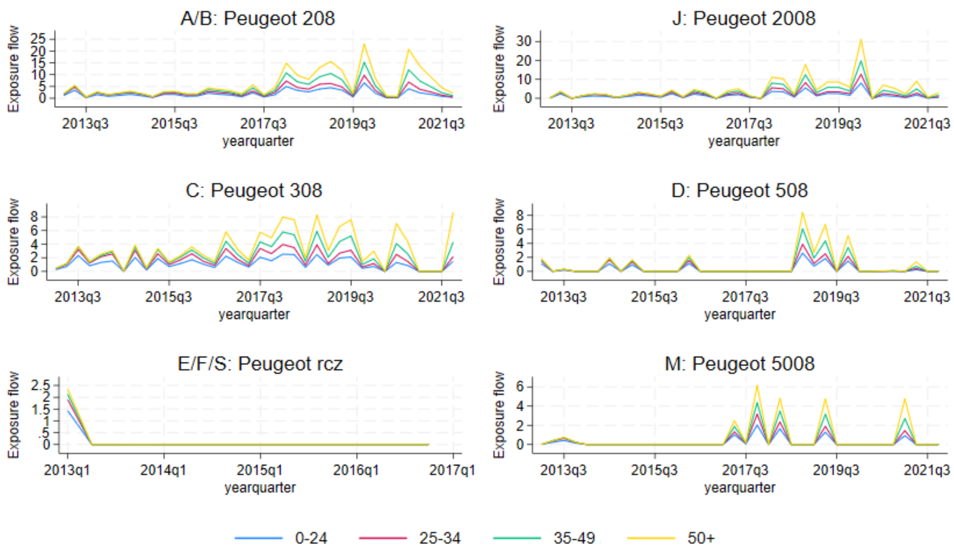


Figure A13: Flow of Advertising Exposure to Peugeot's Most Advertised Vehicles

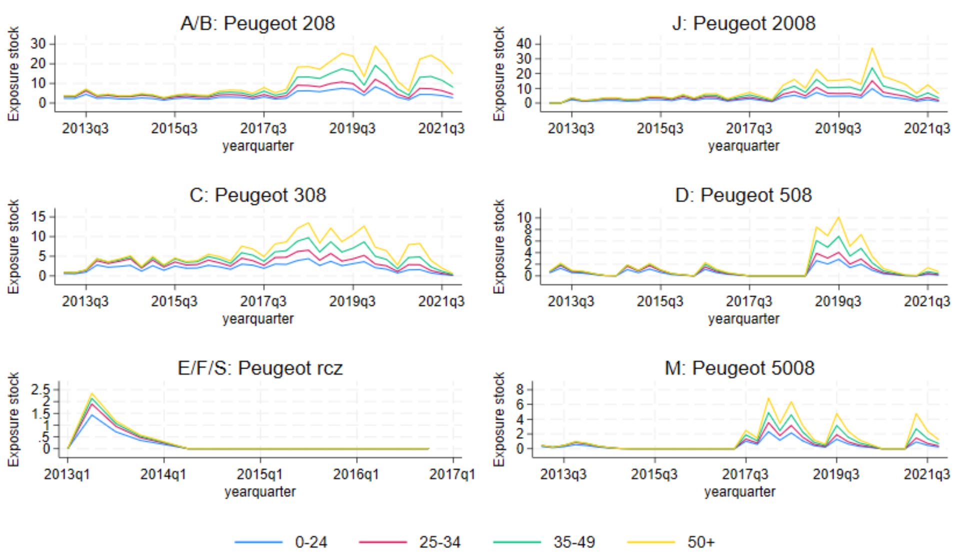


Figure A14: Stock of Advertising Exposure to Peugeot's Most Advertised Vehicles

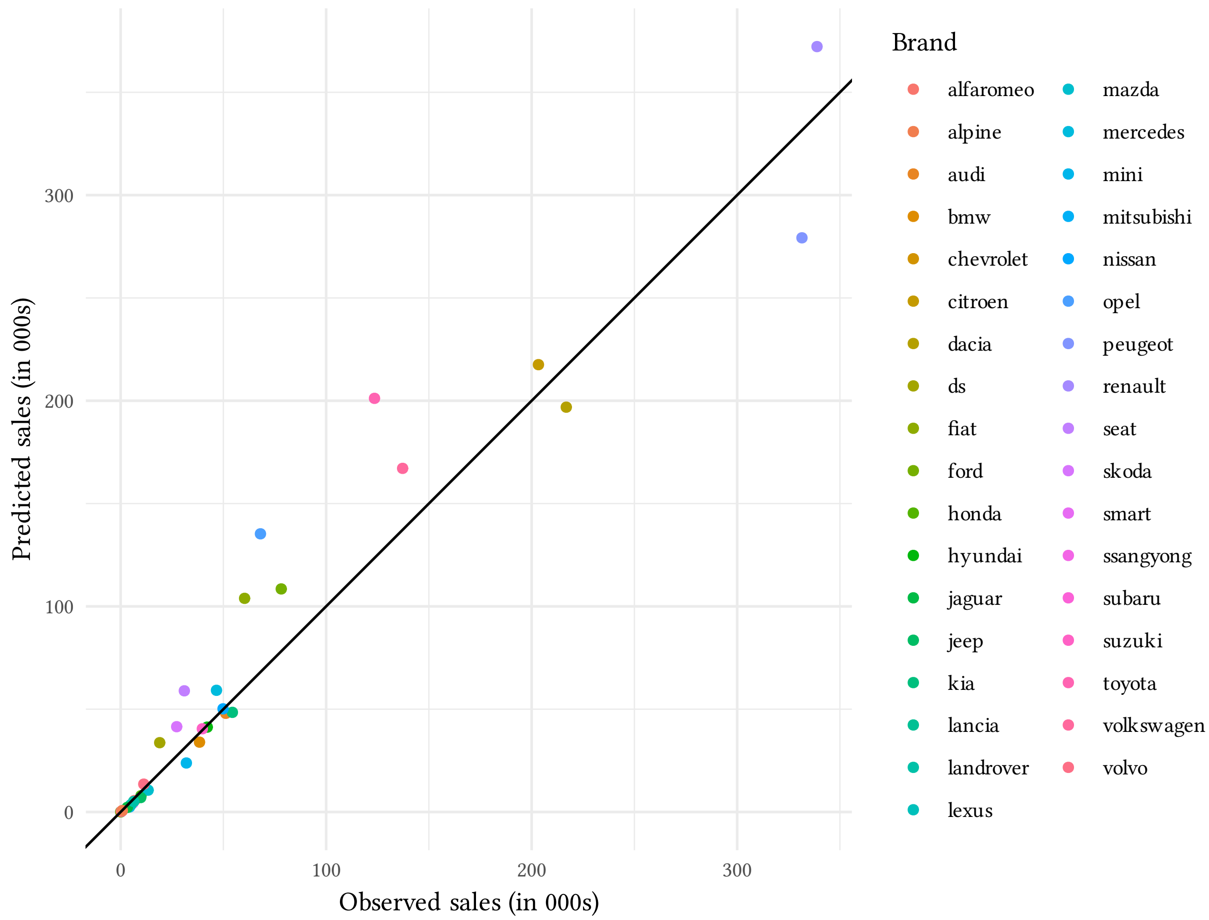


Figure A15: Model Fit: Predicted Sales versus Observed Sales, by Brand

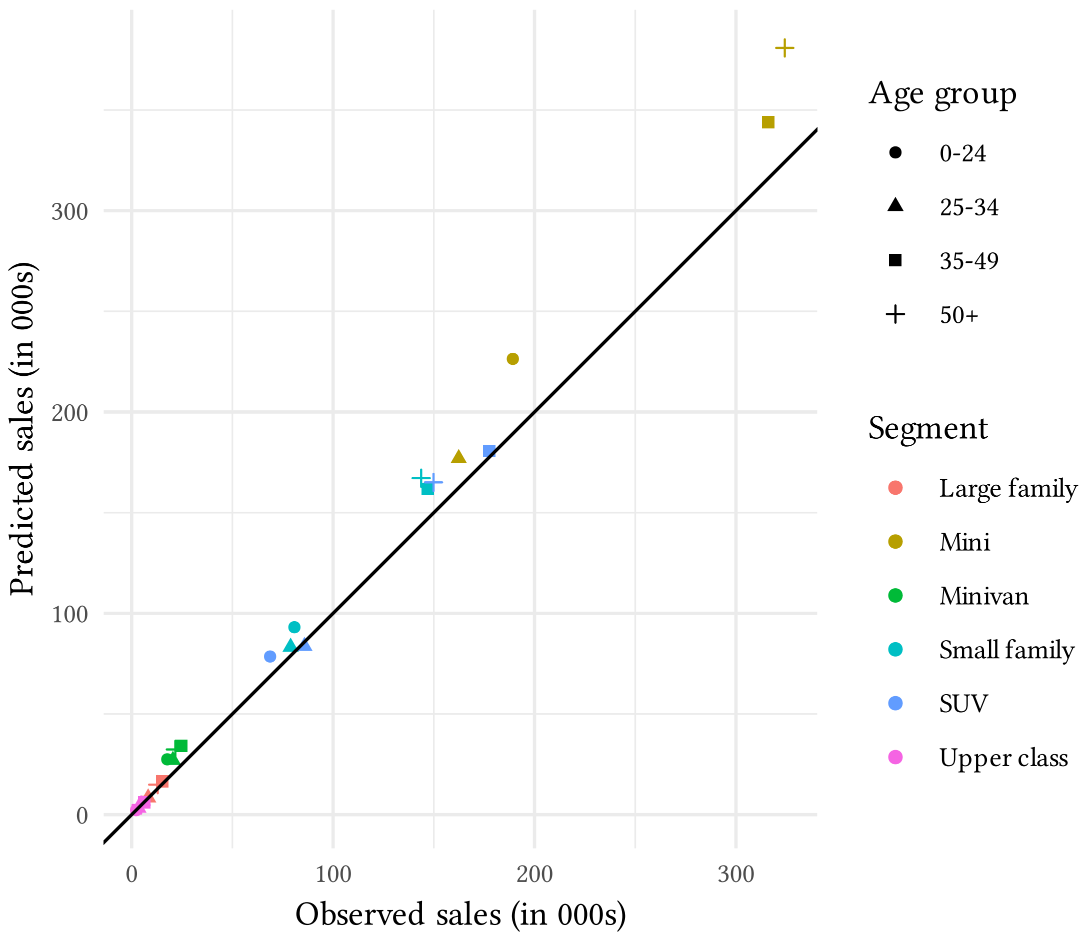


Figure A16: Model Fit: Predicted Sales versus Observed Sales, by Age-Segment

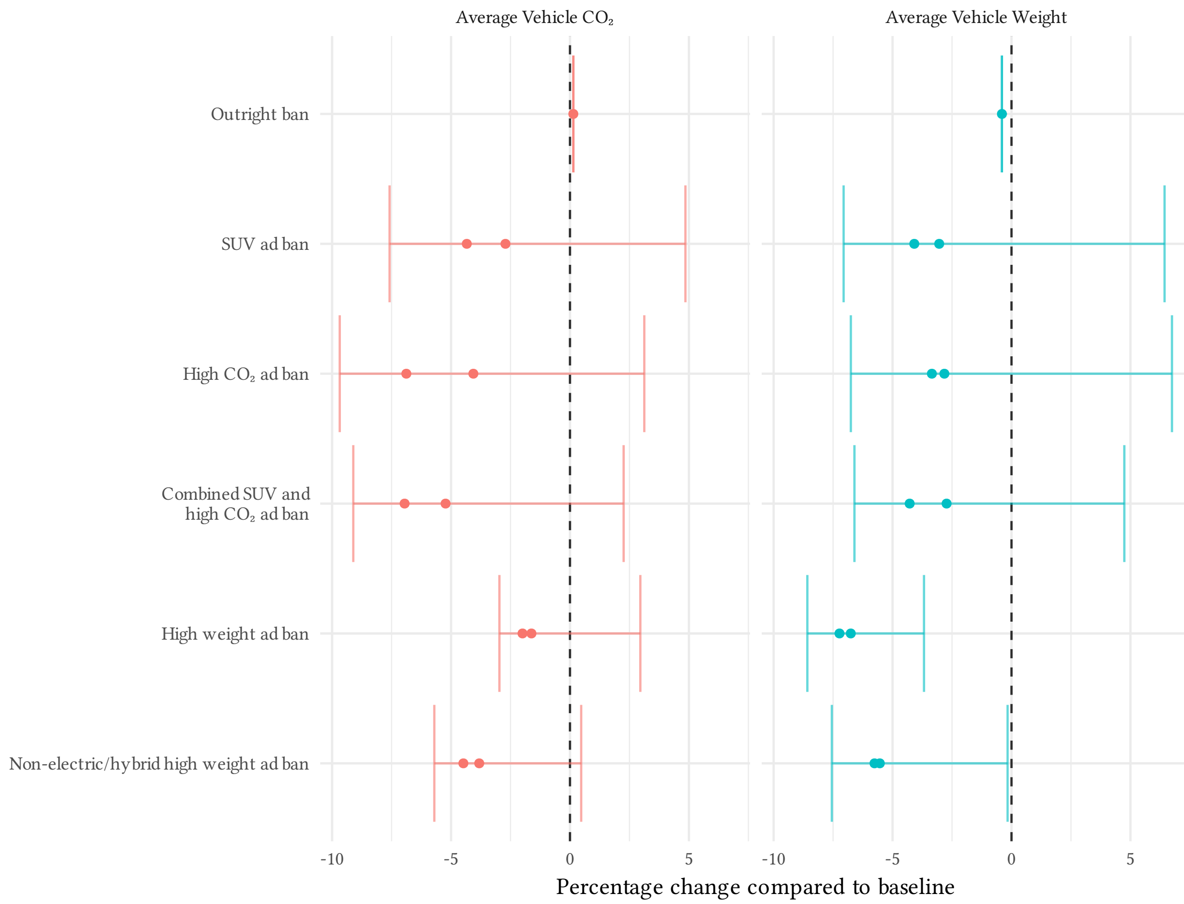


Figure A17: Environmental Effects of Advertising Bans Targeting Polluting Vehicles
Note: The whiskers show the range of potential environmental outcomes under extreme advertising allocations. The dots indicate the smallest and the largest environmental effects in our simulated equilibria.

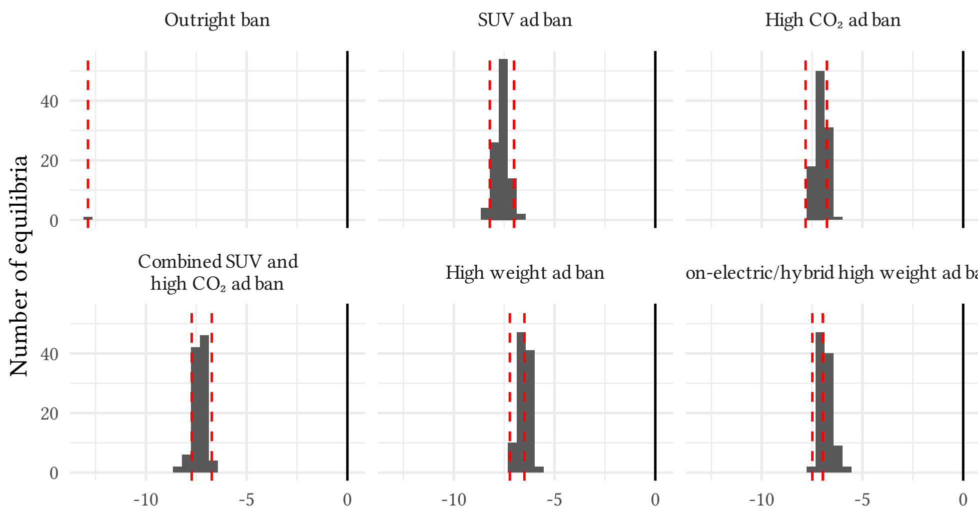


Figure A18: Equilibrium Changes in Consumer Surplus Under the Persuasive View of Advertising: Results from 100 Random Starting Allocations of Advertising Slots
Note: Dashed Lines Indicate the Equilibrium Bounds derived from the Extreme Starting Allocations

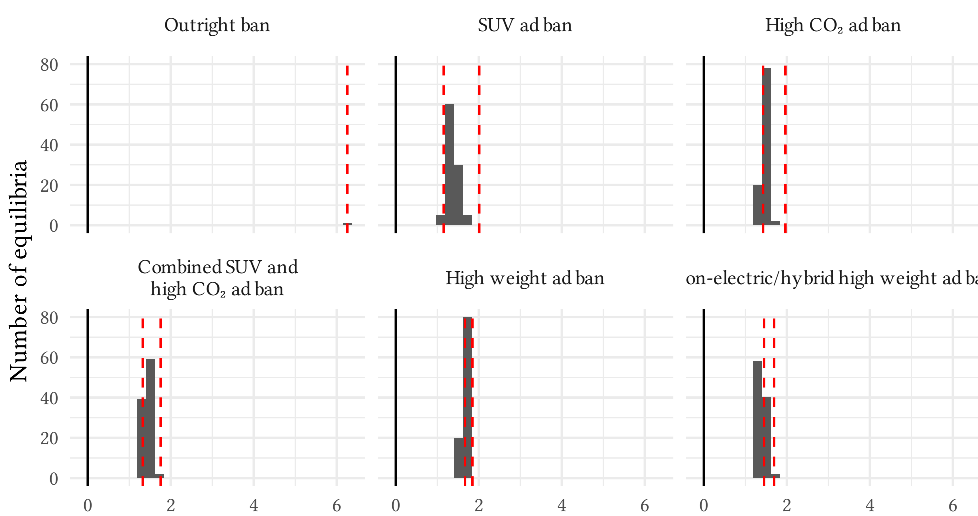


Figure A19: Equilibrium Changes in Consumer Surplus Under the Characteristic View of Advertising: Results from 100 Random Starting Allocations of Advertising Slots
Note: Dashed Lines Indicate the Equilibrium Bounds derived from the Extreme Starting Allocations

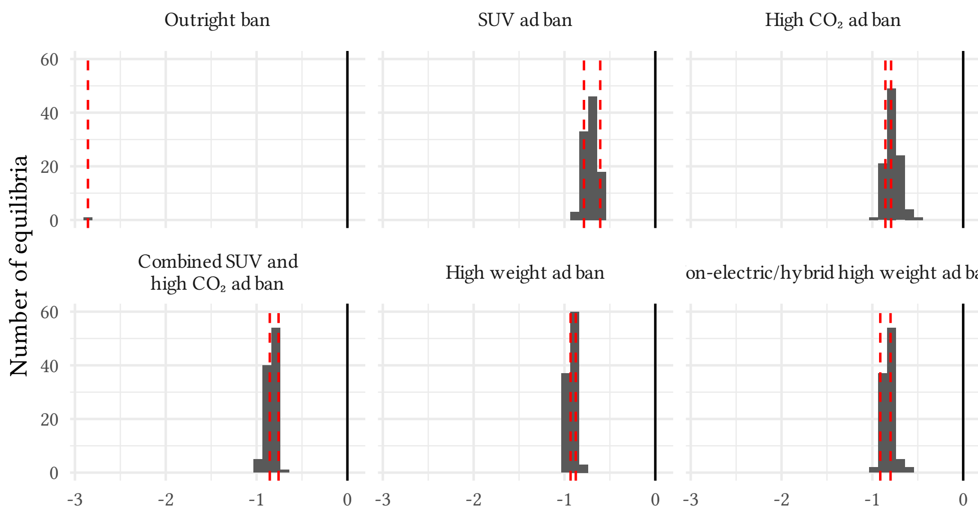


Figure A20: Equilibrium Changes in Total Profit of Firms: Results from 100 Random Starting Allocations of Advertising Slots
Note: Dashed Lines Indicate the Equilibrium Bounds derived from the Extreme Starting Allocations

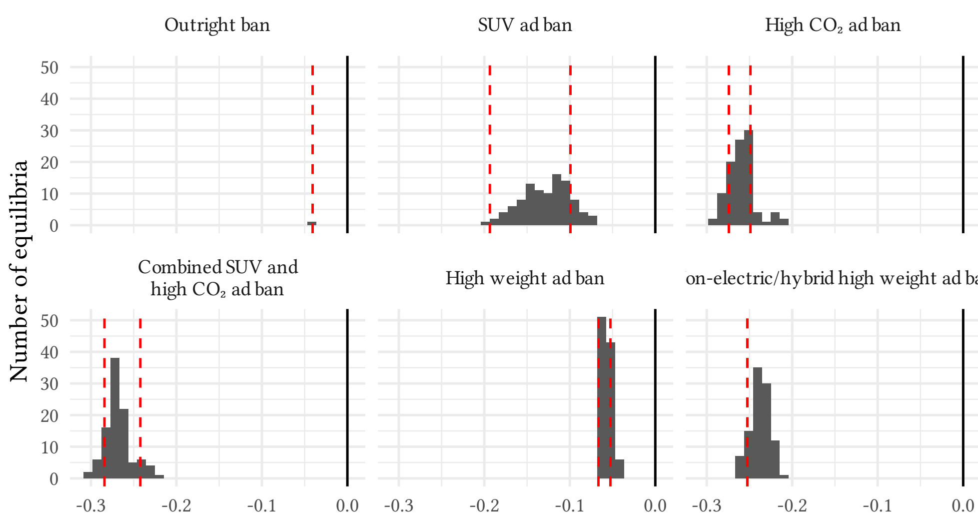


Figure A21: Equilibrium Changes in Total Feebate Revenue: Results from 100 Random Starting Allocations of Advertising Slots
Note: Dashed Lines Indicate the Equilibrium Bounds derived from the Extreme Starting Allocations

Table A1: First-Stage Regression of Structural Demand Model (I)

Dependent variable:	Price	Within-nest market share			
		Ages 0-24	Ages 25-34	Ages 35-49	Ages 50+
	(1)	(2)	(3)	(4)	(5)
Weight	1.653	−1.251	−0.905	−1.382	−1.684
	(0.039)	(0.126)	(0.125)	(0.127)	(0.127)
Horsepower	1.711	0.361	0.450	0.430	0.357
	(0.033)	(0.066)	(0.066)	(0.067)	(0.066)
Fuel cost	−0.028	−0.063	−0.081	−0.085	−0.082
	(0.003)	(0.009)	(0.008)	(0.009)	(0.009)
BLP IV Set: Sum over rival vehicles' characteristics					
Constant	0.034	0.018	−0.019	0.016	0.045
	(0.008)	(0.026)	(0.026)	(0.027)	(0.027)
Weight	−0.007	−0.005	0.010	−0.010	−0.039
	(0.003)	(0.012)	(0.012)	(0.012)	(0.012)
Horsepower	−0.017	−0.001	−0.012	−0.001	0.006
	(0.002)	(0.007)	(0.006)	(0.007)	(0.006)
Fuel cost	0.001	−0.004	−0.001	−0.002	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
BLP IV Set: Sum over rival vehicles' characteristics within market segment					
Constant	0.001	−0.021	−0.035	−0.034	−0.031
	(0.004)	(0.012)	(0.012)	(0.012)	(0.013)
Weight	0.006	0.004	0.008	0.003	0.004
	(0.002)	(0.006)	(0.006)	(0.006)	(0.006)
Horsepower	−0.011	0.010	0.010	0.015	0.007
	(0.002)	(0.006)	(0.006)	(0.006)	(0.006)
Fuel cost	0.000	−0.001	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BLP IV Set: Sum over brand's other vehicles' characteristics within market segment					
Constant	−0.074	0.041	0.044	0.010	0.090
	(0.017)	(0.061)	(0.060)	(0.062)	(0.062)
Weight	0.068	−0.146	−0.144	−0.122	−0.137
	(0.008)	(0.026)	(0.026)	(0.027)	(0.027)
Horsepower	−0.063	0.129	0.114	0.109	0.087
	(0.006)	(0.016)	(0.016)	(0.016)	(0.016)
Fuel cost	0.006	−0.012	−0.007	−0.006	−0.004
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Age-body type fixed effects	Yes	Yes	Yes	Yes	Yes
Age-segment fixed effects	Yes	Yes	Yes	Yes	Yes
Product fixed effects	Yes	Yes	Yes	Yes	Yes
Age-quarter-year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	36832	36832	36832	36832	36832

Note: Standard errors in parentheses.

Table A2: First-Stage Regression of Structural Demand Model (II)

Dependent variable: Ad exposure	Ages 0-24	Ages 25-34	Ages 35-49	Ages 50+
	(1)	(2)	(3)	(4)
Weight	−1.601	−2.240	−2.712	−2.913
	(0.460)	(0.679)	(1.091)	(1.714)
Horsepower	−0.202	−0.275	−0.511	−0.628
	(0.253)	(0.377)	(0.605)	(0.952)
Fuel cost	−0.048	−0.068	−0.113	−0.200
	(0.041)	(0.061)	(0.099)	(0.158)
BLP IV Set: Sum over rival models' characteristics				
Constant	−0.117	−0.260	−0.356	−0.532
	(0.101)	(0.148)	(0.232)	(0.355)
Weight	−0.211	−0.282	−0.380	−0.473
	(0.048)	(0.069)	(0.108)	(0.164)
Horsepower	0.190	0.268	0.376	0.512
	(0.027)	(0.038)	(0.059)	(0.090)
Fuel cost	0.013	0.024	0.033	0.045
	(0.007)	(0.010)	(0.017)	(0.026)
BLP IV Set: Sum over rival models' characteristics within big segment				
Constant	−0.728	−1.115	−1.879	−2.990
	(0.076)	(0.116)	(0.189)	(0.305)
Weight	0.314	0.490	0.878	1.471
	(0.027)	(0.041)	(0.066)	(0.106)
Horsepower	−0.002	−0.011	−0.094	−0.242
	(0.035)	(0.052)	(0.082)	(0.130)
Fuel cost	0.014	0.020	0.032	0.046
	(0.003)	(0.004)	(0.007)	(0.010)
BLP IV Set: Sum over brand's other models' characteristics within big segment				
Constant	0.219	0.190	−0.143	−0.885
	(0.281)	(0.419)	(0.663)	(1.045)
Weight	−0.357	−0.490	−0.490	−0.359
	(0.103)	(0.152)	(0.240)	(0.375)
Horsepower	0.422	0.595	0.718	0.779
	(0.079)	(0.118)	(0.183)	(0.277)
Fuel cost	−0.031	−0.035	−0.032	−0.007
	(0.018)	(0.027)	(0.043)	(0.068)
Age-body type fixed effects	Yes	Yes	Yes	Yes
Age-segment fixed effects	Yes	Yes	Yes	Yes
Product fixed effects	Yes	Yes	Yes	Yes
Age-quarter-year fixed effects	Yes	Yes	Yes	Yes
Observations	36832	36832	36832	36832

Note: Standard errors in parentheses.

Table A3: First-Stage Regression of Structural Demand Model (III)

Dependent variable: Ad exposure for brand's other models within segment	Ages 0-24	Ages 25-34	Ages 35-49	Ages 50+
	(1)	(2)	(3)	(4)
Weight	−1.826	−2.941	−4.191	−6.457
	(0.657)	(0.963)	(1.577)	(2.511)
Horsepower	3.219	4.880	7.163	10.425
	(0.544)	(0.813)	(1.327)	(2.164)
Fuel cost	−0.184	−0.270	−0.398	−0.582
	(0.075)	(0.111)	(0.182)	(0.294)
BLP IV Set: Sum over rival models' characteristics				
Constant	−0.009	−0.110	−0.107	−0.074
	(0.151)	(0.220)	(0.347)	(0.526)
Weight	−0.172	−0.216	−0.205	−0.135
	(0.072)	(0.104)	(0.167)	(0.256)
Horsepower	0.198	0.269	0.312	0.303
	(0.038)	(0.056)	(0.091)	(0.144)
Fuel cost	−0.009	−0.010	−0.025	−0.050
	(0.009)	(0.013)	(0.021)	(0.033)
BLP IV Set: Sum over rival models' characteristics within big segment				
Constant	−1.481	−2.227	−3.692	−5.698
	(0.110)	(0.165)	(0.271)	(0.433)
Weight	0.531	0.808	1.421	2.319
	(0.043)	(0.064)	(0.104)	(0.162)
Horsepower	0.217	0.330	0.455	0.621
	(0.045)	(0.066)	(0.104)	(0.158)
Fuel cost	0.017	0.022	0.028	0.022
	(0.004)	(0.006)	(0.009)	(0.014)
BLP IV Set: Sum over brand's other models' characteristics within big segment				
Constant	6.797	9.882	14.028	19.355
	(0.417)	(0.613)	(0.983)	(1.546)
Weight	−1.511	−2.160	−2.644	−2.991
	(0.159)	(0.236)	(0.378)	(0.599)
Horsepower	0.922	1.436	2.139	3.252
	(0.137)	(0.209)	(0.327)	(0.512)
Fuel cost	−0.361	−0.547	−0.864	−1.364
	(0.031)	(0.047)	(0.077)	(0.123)
Age-body type fixed effects	Yes	Yes	Yes	Yes
Age-segment fixed effects	Yes	Yes	Yes	Yes
Product fixed effects	Yes	Yes	Yes	Yes
Age-quarter-year fixed effects	Yes	Yes	Yes	Yes
Observations	36832	36832	36832	36832

Note: Standard errors in parentheses.

Table A4: First-Stage Regression of Structural Demand Model (IV)

Dependent variable: Ad exposure for rival brands within segment	Ages 0-24	Ages 25-34	Ages 35-49	Ages 50+
	(1)	(2)	(3)	(4)
Weight	9.812	14.927	28.532	48.085
	(5.083)	(7.135)	(11.402)	(17.091)
Horsepower	−13.786	−19.699	−34.422	−53.630
	(3.654)	(5.155)	(8.392)	(12.791)
Fuel cost	1.875	2.683	3.780	4.498
	(0.446)	(0.638)	(1.029)	(1.581)
BLP IV Set: Sum over rival models' characteristics				
Constant	0.966	1.239	0.964	−0.715
	(1.071)	(1.506)	(2.406)	(3.581)
Weight	−0.209	−0.121	0.555	2.417
	(0.516)	(0.724)	(1.168)	(1.752)
Horsepower	0.534	0.866	2.050	3.916
	(0.305)	(0.432)	(0.699)	(1.070)
Fuel cost	−0.045	−0.103	−0.368	−0.868
	(0.083)	(0.117)	(0.185)	(0.276)
BLP IV Set: Sum over rival models' characteristics within big segment				
Constant	−31.870	−47.407	−80.605	−124.510
	(0.774)	(1.088)	(1.701)	(2.503)
Weight	11.530	17.701	32.864	55.353
	(0.401)	(0.560)	(0.864)	(1.232)
Horsepower	5.479	7.998	10.306	12.670
	(0.346)	(0.479)	(0.745)	(1.101)
Fuel cost	0.935	1.233	1.798	2.021
	(0.030)	(0.042)	(0.067)	(0.101)
BLP IV Set: Sum over brand's other models' characteristics within big segment				
Constant	−35.375	−53.170	−87.908	−135.403
	(2.674)	(3.751)	(5.908)	(8.650)
Weight	10.941	17.276	32.241	55.682
	(1.234)	(1.721)	(2.762)	(4.119)
Horsepower	9.629	13.582	19.092	24.651
	(0.820)	(1.146)	(1.869)	(2.867)
Fuel cost	0.474	0.627	0.668	0.271
	(0.184)	(0.261)	(0.413)	(0.632)
Age-body type fixed effects	Yes	Yes	Yes	Yes
Age-segment fixed effects	Yes	Yes	Yes	Yes
Product fixed effects	Yes	Yes	Yes	Yes
Age-quarter-year fixed effects	Yes	Yes	Yes	Yes
Observations	36832	36832	36832	36832

Note: Standard errors in parentheses.

Table A5: Average Product-Level Demand Elasticities

Age group:	0-24	25-34	35-49	50+
Average own price elasticity	−6.157	−8.808	−7.955	−5.173
Average cross price elasticity within segment, within brand	0.149	0.248	0.245	0.203
Average cross price elasticity within segment, across brand	0.329	0.446	0.432	0.360
Average cross price elasticity across segment	0.002	0.006	0.006	0.003
Average own advertising elasticity	2.120	1.363	2.187	3.260
Average cross advertising elasticity within segment, within brand	−0.013	0.113	0.129	0.059
Average cross advertising elasticity within segment, across brand	−0.123	−0.080	−0.143	−0.278
Average cross advertising elasticity across segment	−0.001	−0.002	−0.004	−0.004

Note: Elements in the table are calculated by taking the weighted average own- and cross-elasticities of vehicles within or across segments and brands, where each pair of vehicles is weighted by the product of their market shares.

Table A6: Average Cross-Elasticities by Segment

Segment	Mini	Small family	Large family	Upper class	Minivan	SUV
Cross price elasticity						
Mini	0.277	0.006	0.003	0.001	0.002	0.005
Small family	0.006	0.561	0.003	0.001	0.002	0.005
Large family	0.007	0.007	1.216	0.001	0.002	0.005
Upper class	0.007	0.007	0.004	1.447	0.002	0.005
Minivan	0.006	0.007	0.003	0.001	0.587	0.005
SUV	0.006	0.007	0.004	0.002	0.002	0.427
Cross advertising elasticity						
Mini	−0.115	−0.002	0.000	−0.001	0.000	−0.003
Small family	−0.004	−0.119	0.000	0.000	0.000	−0.003
Large family	−0.004	−0.002	−0.024	0.000	0.000	−0.003
Upper class	−0.005	−0.002	0.000	−0.373	0.000	−0.003
Minivan	−0.004	−0.002	0.000	0.000	−0.025	−0.003
SUV	−0.005	−0.003	0.000	−0.001	0.000	−0.165

Note: Upper class refers to vehicles in segment E/F/S (i.e. Executive/Luxury/Super vehicles). Elements in the table are calculated by taking the weighted average cross-elasticities of vehicles within or across segments, where each pair of vehicles is weighted by the product of their market shares. The table is to be read as the change in average demand for a vehicle of the segment in a row with respect to a change in the average price (or advertising) of a vehicle of the segment in column.

Table A7: Average Cross-Elasticities by CO_2 Level

	CO_2 (g/km)	0-123	123-161	161+
Cross price elasticity				
	0-123	0.128	0.081	0.008
	123-161	0.102	0.096	0.027
	161+	0.044	0.108	0.095
Cross advertising elasticity				
	0-123	-0.052	-0.016	-0.002
	123-161	-0.039	-0.009	-0.005
	161+	-0.016	-0.009	-0.002

Note: Elements in the table are calculated by taking the weighted average cross-elasticities of vehicles within or across CO_2 levels, where each pair of vehicles is weighted by the product of their market shares. The table is to be read as the change in average demand for a vehicle of the emission level in a row with respect to a change in the average price (or advertising) of a vehicle of the emission level in a column.

Table A8: Average Cross-Elasticities by Weight Level

	Weight (1,000kg)	0-1.8	1.8-2.2	2.2+
Cross price elasticity				
	0-1.8	0.167	0.069	0.016
	1.8-2.2	0.074	0.156	0.062
	2.2+	0.046	0.094	0.133
Cross advertising elasticity				
	0-1.8	-0.067	-0.023	-0.001
	1.8-2.2	-0.031	-0.040	-0.005
	2.2+	-0.022	-0.022	-0.007

Note: Elements in the table are calculated by taking the weighted average cross-elasticities of vehicles within or across weight levels, where each pair of vehicles is weighted by the product of their market shares. The table is to be read as the change in average demand for a vehicle of the weight level in a row with respect to the a change in the average price (or advertising) of a vehicle of the weight level in a column.

Table A9: Change in Consumer Welfare by Age Group

Age group	0-24	25-34	35-49	50+
Average change in consumer welfare under persuasive view (in euro):				
Complete ad ban	[3721, 3721]	[3125, 3125]	[7150, 7150]	[8597, 8597]
SUV ad ban	[1998, 2203]	[1899, 2407]	[4200, 4994]	[4475, 5252]
High CO_2 ad ban	[2066, 2225]	[2052, 2496]	[3887, 4628]	[4221, 4901]
Combined SUV and high CO_2 ad ban	[1866, 2159]	[1978, 2453]	[4127, 4601]	[4234, 4863]
High weight ad ban	[1877, 2136]	[1700, 2181]	[3783, 4294]	[4201, 4486]
Non-electric/hybrid high weight ad ban	[2037, 2167]	[1802, 2148]	[3983, 4347]	[4534, 4784]
Average change in consumer welfare under characteristic view (in euro):				
Complete ad ban	[-2197, -2197]	[-2347, -2347]	[-3387, -3387]	[-3634, -3634]
SUV ad ban	[-679, -448]	[-907, -427]	[-1205, -616]	[-1077, -643]
High CO_2 ad ban	[-781, -566]	[-1004, -580]	[-1111, -847]	[-955, -723]
Combined SUV and high CO_2 ad ban	[-679, -483]	[-819, -527]	[-949, -758]	[-919, -724]
High weight ad ban	[-684, -568]	[-751, -567]	[-1069, -966]	[-987, -969]
Non-electric/hybrid high weight ad ban	[-610, -547]	[-666, -496]	[-991, -879]	[-920, -777]

Note: All results [lower bound, upper bound] are in euros.

B Price and Advertising Elasticities

B.1 Within-Nest and Nest Choice Probabilities

We first decompose the choice probability of consumer i in age group d in period t choosing product j in segment (nest) g into two components:

$$\widetilde{\mathfrak{s}}_{ijt}\left(\boldsymbol{\delta}_t^d, v_i, \sigma, \rho\right) = \widetilde{\mathfrak{s}}_{ij|gt}\left(\boldsymbol{\delta}_t^d, v_i, \sigma, \rho\right)\widetilde{\mathfrak{s}}_{igt}\left(\boldsymbol{\delta}_t^d, v_i, \sigma, \rho\right) \tag{14}$$

The first of these is the within-nest choice probability (the probability of choosing product j conditional on choosing a product in segment g):

$$\widetilde{\mathfrak{s}}_{ij|g,t}^d\left(\boldsymbol{\delta}_t^d, v_i, \sigma, \rho\right) = \frac{\exp\left(\left(\delta_{jt}^d + \sigma v_i p_{jt}\right)/\left(1-\rho\right)\right)}{\sum_{j\in\mathcal{J}_{gt}}\exp\left(\left(\delta_{jt}^d + \sigma v_i p_{jt}\right)/\left(1-\rho\right)\right)} \tag{15}$$

The second of these is the nest probability (the probability of choosing any product in segment g):

$$\widetilde{\mathfrak{s}}_{igt}^d\left(\boldsymbol{\delta}_t^d, v_i, \sigma, \rho\right) = \frac{\exp\left[(1-\rho)\log\left(\sum_{j\in\mathcal{J}_{gt}}\exp\left((\delta_{jt}^d + \sigma v_i p_{jt})/(1-\rho)\right)\right)\right]}{1+\sum_{g=1}^{G}\exp\left[(1-\rho)\log\left(\sum_{j\in\mathcal{J}_{gt}}\exp\left((\delta_{jt}^d + \sigma v_i p_{jt})/(1-\rho)\right)\right)\right]} \tag{16}$$

We will use these terms in our expressions for the price and advertising elasticities.

B.2 Price Elasticities

The own-price elasticity is given by $\frac{\partial \mathfrak{s}_{jt}^d\left(\boldsymbol{\delta}_t^d,\sigma,\rho\right)}{\partial p_{jt}}\frac{p_{jt}}{\mathfrak{s}_{jt}^d}$, where:

$$\frac{\partial \mathfrak{s}_{jt}^d\left(\boldsymbol{\delta}_t^d, \sigma, \rho\right)}{\partial p_{jt}} = \int \alpha_i \widetilde{\mathfrak{s}}_{ijt}^d\left(\frac{1}{1-\rho} - \frac{\rho}{1-\rho}\widetilde{\mathfrak{s}}_{ij|g,t}^d - \widetilde{\mathfrak{s}}_{ijt}^d\right)\phi\left(v_i\right)dv_i \tag{17}$$

where we have suppressed the arguments $\boldsymbol{\delta}_t^d, v_i, \sigma$ and ρ in $\widetilde{\mathfrak{s}}_{ijt}^d$ and $\widetilde{\mathfrak{s}}_{ij|g,t}^d$ to simplify notation.

The cross-price elasticity between products j and j' is given by $\frac{\partial \mathfrak{s}_{jt}^d\left(\boldsymbol{\delta}_t^d,\sigma,\rho\right)}{\partial p_{j't}}\frac{p_{j't}}{\mathfrak{s}_{jt}^d}$. The term $\frac{\partial \mathfrak{s}_{jt}^d\left(\boldsymbol{\delta}_t^d,\sigma,\rho\right)}{\partial p_{j't}}$ depends on if products j and j' are in the same segment or not. For products in the same segment:

$$\left.\frac{\partial \mathfrak{s}_{jt}^d\left(\boldsymbol{\delta}_t, \sigma, \rho\right)}{\partial p_{j't}}\right|_{j,j'\in\mathcal{J}_{gt}} = -\int \alpha_i \widetilde{\mathfrak{s}}_{ijt}^d\left(\frac{\rho}{1-\rho}\widetilde{\mathfrak{s}}_{ij'|g,t}^d + \widetilde{\mathfrak{s}}_{ij't}^d\right)\phi\left(v_i\right)dv_i \tag{18}$$

For products in different segments:

$$\left.\frac{\partial \mathfrak{s}_{jt}^{d}\left(\boldsymbol{\delta}_{t},\sigma,\rho\right)}{\partial p_{j't}}\right|_{j\in\mathcal{J}_{gt},j'\in\mathcal{J}_{g't},g\neq g'}=-\int \alpha_{i}\widetilde{\mathfrak{s}}_{ijt}^{d}\widetilde{\mathfrak{s}}_{ij't}^{d}\phi\left(v_{i}\right)dv_{i} \tag{19}$$

Each case can be written in a single equation as follows:

$$\frac{\partial \mathfrak{s}_{jt}^{d}\left(\boldsymbol{\delta}_{t},\sigma,\rho\right)}{\partial p_{j't}}=\int \alpha_{i}\left[-\widetilde{\mathfrak{s}}_{ijt}^{d}\widetilde{\mathfrak{s}}_{ij't}^{d}-\mathbb{1}\left\{j,j'\in\mathcal{J}_{gt}\right\}\frac{\rho}{1-\rho}\widetilde{\mathfrak{s}}_{ijt}^{d}\widetilde{\mathfrak{s}}_{ij'|g,t}^{d}+\mathbb{1}\left\{j=j'\right\}\frac{1}{1-\rho}\widetilde{\mathfrak{s}}_{ijt}^{d}\right]\phi\left(v_{i}\right)dv_{i} \tag{20}$$

where $\mathbb{1}\left\{\cdot\right\}$ is the indicator function.

B.3 Advertising Elasticities

The own-advertising elasticity is given by $\frac{\partial \mathfrak{s}_{jt}^{d}\left(\boldsymbol{\delta}_{t}^{d},\sigma,\rho\right)}{\partial A_{jt}^{d}}\frac{A_{jt}^{d}}{\mathfrak{s}_{jt}^{d}}$, where:

$$\begin{aligned}\frac{\partial \mathfrak{s}_{jt}^{d}\left(\boldsymbol{\delta}_{t},\sigma,\rho\right)}{\partial A_{jt}^{d}}=\int\Bigg\{&\beta_{o}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\left[\frac{1}{1-\rho}-\left(\frac{\rho}{1-\rho}+\widetilde{\mathfrak{s}}_{igt}^{d}\right)\widetilde{\mathfrak{s}}_{ij|g,t}^{d}\right]\\&-\beta_{w}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\left(\frac{\rho}{1-\rho}+\widetilde{\mathfrak{s}}_{igt}^{d}\right)\sum_{j'\in\mathcal{J}_{bgt}\setminus\{j\}}\widetilde{\mathfrak{s}}_{ij'|g,t}^{d}+\\&-\beta_{c}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\left(\frac{\rho}{1-\rho}+\widetilde{\mathfrak{s}}_{igt}^{d}\right)\sum_{j'\in\mathcal{J}_{gt}\setminus\mathcal{J}_{bgt}}\widetilde{\mathfrak{s}}_{ij'|g,t}^{d}\Bigg\}\phi\left(v_{i}\right)dv_{i}\end{aligned} \tag{21}$$

The cross-advertising elasticity is given by $\frac{\partial \mathfrak{s}_{jt}^{d}\left(\boldsymbol{\delta}_{t}^{d},\sigma,\rho\right)}{\partial A_{j't}^{d}}\frac{A_{j't}^{d}}{\mathfrak{s}_{jt}^{d}}$. The cross-advertising elasticity depends on if products are owned by the same brand, and if they are in the same segment or not. There are therefore four possibilities. For a pair of products j, j' owned by the same brand b in the same segment g:

$$\begin{aligned}\left.\frac{\partial \mathfrak{s}_{jt}^{d}\left(\boldsymbol{\delta}_{t},\sigma,\rho\right)}{\partial A_{j't}^{d}}\right|_{j,j'\in\mathcal{J}_{bgt}}=\int\Bigg\{&-\beta_{o}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\left(\frac{\rho}{1-\rho}+\widetilde{\mathfrak{s}}_{igt}^{d}\right)\widetilde{\mathfrak{s}}_{ij'|g,t}^{d}+\\&\beta_{w}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\left[\frac{1}{1-\rho}-\left(\frac{\rho}{1-\rho}+\widetilde{\mathfrak{s}}_{igt}^{d}\right)\sum_{j''\in\mathcal{J}_{bgt}\setminus\{j'\}}\widetilde{\mathfrak{s}}_{ij''|g,t}^{d}\right]-\\&\beta_{c}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\left(\frac{\rho}{1-\rho}+\widetilde{\mathfrak{s}}_{igt}^{d}\right)\sum_{j''\in\mathcal{J}_{gt}\setminus\mathcal{J}_{bgt}}\widetilde{\mathfrak{s}}_{ij''|g,t}^{d}\Bigg\}\phi\left(v_{i}\right)dv_{i}\end{aligned} \tag{22}$$

For a pair of products j, j' in the same segment g but product j is owned by brand b and product j' is owned by brand $b' \neq b$:

$$\left.\frac{\partial \mathfrak{s}_{jt}^{d}\left(\boldsymbol{\delta}_{t},\sigma,\rho\right)}{\partial A_{j't}^{d}}\right|_{j\in\mathcal{J}_{bgt},j'\in\mathcal{J}_{b'gt},b\neq b'} = \int\Bigg\{-\beta_{o}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\left(\frac{\rho}{1-\rho}+\widetilde{\mathfrak{s}}_{igt}^{d}\right)\widetilde{\mathfrak{s}}_{ij'|g,t}^{d} - \beta_{w}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\left(\frac{\rho}{1-\rho}+\widetilde{\mathfrak{s}}_{igt}^{d}\right)\sum_{j''\in\mathcal{J}_{b'gt}\setminus\{j'\}}\widetilde{\mathfrak{s}}_{ij''t|g}^{d} + \beta_{c}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\left[\frac{1}{1-\rho}-\left(\frac{\rho}{1-\rho}+\widetilde{\mathfrak{s}}_{igt}^{d}\right)\sum_{j''\in\mathcal{J}_{gt}\setminus\mathcal{J}_{b'gt}}\widetilde{\mathfrak{s}}_{ij''|g,t}^{d}\right]\Bigg\}\phi\left(v_{i}\right)dv_{i} \tag{23}$$

For a pair of products j, j' owned by the same brand b but product j is in segment g and product j' is in segment $g' \neq g$:

$$\left.\frac{\partial \mathfrak{s}_{jt}^{d}\left(\boldsymbol{\delta}_{t},\sigma,\varepsilon\right)}{\partial A_{j't}^{d}}\right|_{j\in\mathcal{J}_{bgt},j'\in\mathcal{J}_{bg't},g\neq g'} = \int\Bigg\{-\beta_{o}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\widetilde{\mathfrak{s}}_{ij't}^{d} - \beta_{w}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\sum_{j''\in\mathcal{J}_{bg't}\setminus\{j'\}}\widetilde{\mathfrak{s}}_{ij''t}^{d} - \beta_{c}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\sum_{j''\in\mathcal{J}_{g't}\setminus\mathcal{J}_{bg't}}\widetilde{\mathfrak{s}}_{ij''t}^{d}\Bigg\}\phi\left(v_{i}\right)dv_{i} \tag{24}$$

Finally, for a pair of products j, j' where product j is owned by brand b in segment g and product j' is owned by brand $b' \neq b$ in segment $g' \neq g$:

$$\left.\frac{\partial \mathfrak{s}_{jt}^{d}\left(\boldsymbol{\delta}_{t},\sigma,\rho\right)}{\partial A_{j't}^{d}}\right|_{j\in\mathcal{J}_{bgt},j'\in\mathcal{J}_{b'g't},b\neq b',g\neq g'} = \int\Bigg\{-\beta_{o}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\widetilde{\mathfrak{s}}_{ij't}^{d} - \beta_{w}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\sum_{j''\in\mathcal{J}_{b'g't}\setminus\{j'\}}\widetilde{\mathfrak{s}}_{ij''t}^{d} - \beta_{c}^{d}\widetilde{\mathfrak{s}}_{ijt}^{d}\sum_{j''\in\mathcal{J}_{g't}\setminus\mathcal{J}_{b'g't}}\widetilde{\mathfrak{s}}_{ij''t}^{d}\Bigg\}\phi\left(v_{i}\right)dv_{i} \tag{25}$$

Each case can be written in a single equation as follows:

$$\begin{aligned}\frac{\partial \mathfrak{s}_{jt}^{d}\left(\boldsymbol{\delta}_{t},\sigma,\rho\right)}{\partial A_{j't}^{d}} =& \mathbb{1}\{j'\in\mathcal{J}_{gt}\}\frac{\widetilde{\mathfrak{s}}_{ijt}^{d}}{1-\rho}\left(\beta_{o}^{d}+\beta_{w}^{d}+\beta_{c}^{d}\right)- \\ & \mathbb{1}\{j'\in\mathcal{J}_{gt}\}\widetilde{\mathfrak{s}}_{ijt}^{d}\left(\frac{\rho}{1-\rho}+\widetilde{\mathfrak{s}}_{igt}^{d}\right)\left(\beta_{o}^{d}\widetilde{\mathfrak{s}}_{ij'|g,t}^{d}+\beta_{w}^{d}\sum_{j''\in\mathcal{J}_{gt}\setminus\{j'\}}\widetilde{\mathfrak{s}}_{ij''|g,t}^{d}+\beta_{c}^{d}\sum_{j''\in\mathcal{J}_{gt}\setminus\mathcal{J}_{b'gt}}\widetilde{\mathfrak{s}}_{ij''|g,t}^{d}\right) \\ & -\mathbb{1}\{j'\notin\mathcal{J}_{gt}\}\widetilde{\mathfrak{s}}_{ijt}^{d}\left(\beta_{o}^{d}\widetilde{\mathfrak{s}}_{ij't}^{d}+\beta_{w}^{d}\sum_{j''\in\mathcal{J}_{g't}\setminus\{j'\}}\widetilde{\mathfrak{s}}_{ij''t}^{d}+\beta_{c}^{d}\sum_{j''\in\mathcal{J}_{g't}\setminus\mathcal{J}_{b'g't}}\widetilde{\mathfrak{s}}_{ij''t}^{d}\right)\end{aligned} \tag{26}$$

C The Net Return to Advertising

We find strong positive own-advertising demand elasticities and assume that brands make advertising decisions to maximize their next period's variable profits. The equilibrium outcomes in our counterfactual analysis depend on the accuracy of our demand estimates and the validity of our assumption regarding vehicle brands' advertising objectives.

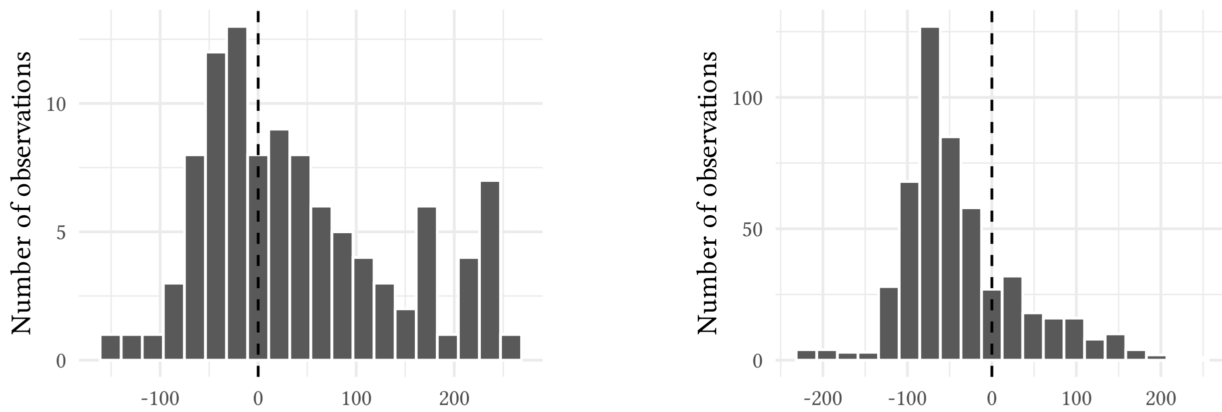
To check whether the return to advertising from our demand estimates is consistent with the observed costs of advertising, we estimate the marginal returns of advertising at the observed advertising levels using our model estimates and compare them to our data on the marginal costs of advertising. Intuitively, while advertising boosts sales, its returns diminish as spending increases. Brands should continue advertising a product until its marginal return approaches its marginal cost and cease advertising once the marginal return falls below the marginal cost. For products where the marginal return of the first minute of advertising is below the marginal cost, brands will choose the corner solution of not advertising.

Formally, let $\widehat{T}_{jt}=\sum_{s\in\mathcal{S}_t}T_{jst}$ denote the total number of minutes of advertising across slots for product j in quarter t. The brand's marginal return in the following period to advertising today is given by:

$$\begin{aligned}\frac{\partial\Pi_{bt+1}}{\partial\widehat{T}_{jt}}=\sum_{j'\in\mathcal{J}_{bt}}\Bigg[&\left(\widetilde{p}_{j',t+1}\left(\boldsymbol{A}_{t+1}\right)-c_{j',t+1}\right)\left(\sum_{d\in D}\frac{\partial\mathfrak{s}_{j',t+1}^{d}}{\partial A_{j,t+1}^{d}}\frac{\partial A_{j,t+1}^{d}}{\partial a_{jt}^{d}}\frac{\partial a_{jt}^{d}}{\partial\widehat{T}_{jt}}M_{t+1}^{d}\right)\\ &+\frac{\partial\widetilde{p}_{j',t+1}\left(\boldsymbol{A}_{t+1}\right)}{\partial\widehat{T}_{jt}}\left(\sum_{d\in D}\mathfrak{s}_{j',t+1}^{d}M_{t+1}^{d}\right)\Bigg]\end{aligned}$$

where $\widetilde{p}_{j',t+1}\left(\boldsymbol{A}_{t+1}\right)$ denotes the equilibrium retail price of product j' in period $t+1$ given the vector of advertising stocks $\boldsymbol{A}_{t+1}=\left\{\boldsymbol{A}_{t+1}^{d}\right\}_{d\in\mathcal{D}}$. The term $\frac{\partial\widetilde{p}_{j',t+1}(\boldsymbol{A}_{t+1})}{\partial\widehat{T}_{jt}}$ is the marginal change in the equilibrium price from a marginal increase in advertising.[39] Furthermore, we denote by c_{jt}^{A} the

[39]Because the equilibrium price vector in period $t+1$ is an implicit function of the advertising minutes $\widehat{T}_{jt}$, in practice we compute the derivative $\frac{\partial\Pi_{bt+1}}{\partial\widehat{T}_{jt}}$ numerically. We first calculate brand profits Π_{bt+1} under



Advertised vehicle-quarters ($\widehat{T}_{jt} > 0$) Non-advertised vehicle-quarters ($\widehat{T}_{jt} = 0$)

Figure A22: Net Returns on Advertising (in thousands of euros)

marginal cost of advertising. For this we use the observed costs of the advertisements placed.

In equilibrium, we expect that for advertised vehicle-models the marginal benefit should approximately equal marginal cost:

$$\frac{\partial \Pi_{bt+1}}{\partial \widehat{T}_{jt}} - c^A_{jt} \simeq 0 \quad \forall j \in \mathcal{J}_t \text{ where } \widehat{T}_{jt} > 0$$

For models not advertised in equilibrium, we expect the marginal cost to exceed the marginal benefit for the first minute of advertising:

$$\frac{\partial \Pi_{bt+1}}{\partial \widehat{T}_{jt}} - c^A_{jt} < 0 \quad \forall j \in \mathcal{J}_t \text{ where } \widehat{T}_{jt} = 0$$

Figure A22 plots the distributions of the model-predicted net returns on advertising, defined as $\frac{\partial \Pi_{bt+1}}{\partial \widehat{T}_{jt}} - c^A_{jt}$, across our full estimation sample, split by observations with and without advertising. Consistent with brands' optimal advertising behavior, the estimated net returns are centered around zero for advertised vehicle-quarters ($\widehat{T}_{jt} > 0$), while they are predominantly negative for non-advertised ones ($\widehat{T}_{jt} = 0$).

the observed advertising levels. We then increase the observed number of advertising minutes for product j by a small number ϵ, solve for the equilibrium price vector in period $t+1$, and recompute brand profits. The numerical derivative is the change in brand profits divided by ϵ. In practice we use $\epsilon = 1 \times 10^{-9}$.