Chair Energy & Prosperity

Working Paper

Greening the car fleet: demand characteristics, policy impacts & new product introduction

Ariane Bousquet[1]

Octobre 2025

[1] CESAER (INRAE - Dijon), Chaire Energie et Prospérité

La Chaire Energie et Prospérité

La chaire Energie et Prospérité a été créée en 2015 pour éclairer les décisions des acteurs publics et privés dans le pilotage de la transition énergétique. Les travaux de recherche conduits s'attachent aux impacts de la transition énergétique sur les économies (croissance, emploi, dette), sur les secteurs d'activité (transport, construction, production d'énergie, finance), aux modes de financement associés ainsi qu'aux problématiques d'accès à l'énergie. Hébergée par la Fondation du Risque, la chaire bénéficie du soutien de l'ADEME, de la Caisse des Dépôts, d'Engie et du groupe Renault.

Les opinions exprimées dans ce papier sont celles de son (ses) auteur(s) et ne reflètent pas nécessairement celles de la Chaire Energie et Prospérité. Ce document est publié sous l'entière responsabilité de son (ses) auteur(s).

Les Working paper de la Chaire Energie et Prospérité sont téléchargeables ici :
http://www.chair-energy-prosperity.org/category/publications/

Chair Energy and Prosperity

The Energy and Prosperity Chair was created in 2015 to inform decisions of public and private actors in managing the energy transition. The Chair research deals with the impacts of energy transition on national economies (growth, employment, debt...), on specific sectors (transportation, construction, energy , finance), on acces to energy and with the associated financing issues. Hosted by the Fondation du Risque, the chair has the support of ADEME, the Caisse des Dépôts, Engie and the Groupe Renault.

The opinions expressed in this paper are those of the author(s) and do not necessarily reflect the position of Chair Energy and Prosperity. It is therefore published under the sole responsibility of its author(s).

Chair energy and Prosperity working paper can be downloaded here:
http://www.chair-energy-prosperity.org/en/category/publications-2/

Greening the car fleet: demand characteristics, policy impacts & new product introduction

October 3, 2025

Abstract

Globally, the transport sector is the second-largest source of CO_2 emissions, with private road transportation accounting for the majority of these emissions. In this study, we use a structural model and a novel dataset of the French new and used car markets to estimate the determinants of private car demand and price sensitivity. Based on these estimates, we assess the fleet-greening potential of public policies - various feebate designs - and private-sector initiatives - such as introducing a low-end electric vehicle - aimed at making electric vehicles accessible to low- and middle-income households. Our findings demonstrate that targeting low-income households is effective from both distributive and environmental perspectives.

JEL Classification:
Keywords: used-car market, car demand, feebate, emissions, policy, France, BLP.

1 Introduction

Transportation represents one-fourth of global CO_2 emissions, out of which 18% is due to road transportation with cars representing most of it (10%). In France, where transportation is the largest source of emissions (31%), private vehicles are also responsible for the most part (17% of the country's emissions). Recognizing the urgent need for decarbonization, electrifying the automotive fleet has emerged as a key strategy. Economists advocate for carbon pricing as the optimal solution to discourage the purchase and use of internal combustion engine (ICE) vehicles. However, acceptability of carbon taxes is not easy, and in France, it has led to years of *Yellow Vest* protests.[1]

[1] Part of the literature, notably Douenne and Fabre, 2022 and Bureau et al., 2019, has delved into the various reasons behind this failure, including deficiencies in the redistribution mechanism.

Given the important acceptability problems related to carbon pricing, several countries, and in particular France, have favored subsidies for the purchase of new low-carbon vehicles. Similar policies have been adopted in several EU countries and worldwide.[2] More precisely, the main instrument in France since 2008 is the feebate policy, with a tax on high-emission vehicles in addition to subsidies for new low-carbon vehicles. The CO_2 scale for the feebate thresholds, as well as the feebate ceilings, have evolved over time. The instrument, which target the purchase of new vehicles only, has had a substantial impact on vehicles targeted by the policy but a modest overall impact on greening the fleet. Despite significant progress in the sales of electric vehicles (EVs) with 16.8% of new car sales in France, in 2023 and one out of five worldwide according to the International Energy Agency, they still represent only 2% of the French automotive fleet. This may be the case because new car sales only account for 25% of car transactions in France, out of which, more than half are made by firms, whose car demand is determined by specific considerations[3]. The other 75% of car transactions in France take place in the used-car market. Yet, this part of the market is often overlooked by both academia and public policies due to the lack of complete data and the estimation challenges that it presents. A small breakthrough of low-carbon vehicles in the new car market alone will not significantly impact emissions, at least before mid-century where we have set the carbon neutrality objective. Achieving a substantial CO_2 reduction requires a reduction of internal combustion engine (ICE) vehicle travel demand, widespread adoption of low-carbon vehicles, and an accelerated phase-out of high-emission vehicles. However, low-carbon vehicles are still significantly more expensive than ICE vehicles which makes them unaffordable for middle- and low-income households.

Given these challenges, studying the determinants of demand in the used car market becomes crucial for formulating more effective policies and accelerating the energy transition. Analyzing the used car market as we do in this paper, allows for a deeper understanding of consumer heterogeneity compared to a sole focus on the new car market, which is dominated by firms and high-income households. Our main findings regarding the determinants of car demand are as follows. In line with previous literature (Durrmeyer, 2021; D'Haultfoeille et al., 2014; Givord et al., 2018a), there is substantial heterogeneity among consumers depending on their area of residence and income. Differently from previous literature focusing solely on the French new car market, but in line with economic intuition, we find that low-income consumers are more sensitive to car and fuel prices, which suggests that implementing policies targeted to this population would prove more efficient than a generalized policy. This is

[2] These measures have been followed by a large and growing literature studying their effectiveness and efficiency, out of which : (Muehlegger & Rapson, 2022; Xing et al., 2021; Sheldon & Dua, 2019; Durrmeyer, 2021; Durrmeyer & Samano, 2017).

[3] Including specific fleet greening quotas in France.

already partly done by the French Government which has implemented a higher subsidy for low-income households on the new car market in 2023 and a small subsidy on the used-car market between January 2021 and February 2024. Our structural model allows us to evaluate ex-ante the welfare and distributive impacts of both policies. Our findings suggest that subsidies targeting the used-car market for low-carbon vehicles are progressive and could significantly accelerate the greening of the car fleet. The households that derive the greatest benefits are poor rural households, which aligns with our estimates, while the 2023 income-based subsidy fails to target low-income households and hurts middle-income households as they are excluded from the high subsidy.

Additionally, we compare these public interventions with a private-sector alternative: the introduction of a small, affordable electric vehicle. This has become a central point of public debate, as NGOs, labor unions, and mobility research institutes advocate for setting standards on the size of electric vehicles.[4] Our findings show that - as for the 2021 used-EV subsidy- rural, low-income households are also the primary beneficiaries of this intervention. However, the overall welfare gains are higher under this approach because these households gain access to new - and not used - electric cars, for which they have a clear preference. This result raises important policy considerations, particularly around the potential establishment of standards for the types of electric vehicles to be promoted. These findings are especially timely as climate justice has become an increasingly prominent issue in public debate. They also highlight the challenges of implementing a diverse range of uncoordinated policies without proper assessment of their relative efficiency.

The remainder of this paper is organized as follows. Section 2 presents our contributions to the related literature. Section 3 describes the dataset-building process and presents facts about the EV market and the French feebate policy. Section 4 develops the demand model and describes the estimation strategy. Section 5 presents the estimation results and counterfactual analyses. We conclude in Section 6.

2 Related Literature

Herein, we use a structural model to estimate household demand in both the new and used car market in France, using product and local-level data. We contribute to different strands of literature. First, since the seminal work of (Berry et al., 1995), there is a large empirical literature that models supply and demand in the new car market using structural models and product-level data. This literature focuses on improving estimation techniques, incorporating micro-data (Berry et al., 2004; Petrin, 2002; Nurski & Verboven, 2016), investigating optimal

[4]The justification is that a small electric vehicles brings lower product costs and externalities.

instruments (Reynaert & Verboven, 2014; Gandhi & Houde, 2019; Duch-Brown et al., 2023), and solving issues related to the definition of the outside option in a market (Huang & Rojas, 2014; Conlon & Mortimer, 2023). We contribute to this methodological literature by applying the most recent methods in terms of the choice of instruments, micro-data usage, and the use of random coefficients on key variables.

Concretely on France, recent papers have used structural models to perform ex-ante evaluations of French policies but only on new car transactions. Most of these papers use a common dataset from *AAA-data*[5] containing new car registrations at the municipality level for the period 2003-2008 (Durrmeyer, 2021; Durrmeyer & Samano, 2017; D'Haultfoeille et al., 2014; D'Haultfœuille et al., 2016; Givord et al., 2018b). D'Haultfoeille et al., 2014 estimate the impact of the French feebate introduced in 2008 on CO_2 emissions, using a discrete-continuous choice model of car purchase and usage. They find that the feebate could be an efficient tool but would need to be adequately designed, as it led to negative environmental impacts in 2008. Similarly, D'Haultfœuille et al., 2016 investigate the effect of two policies: an energy label implemented in 2005 and a CO_2-based feebate that started in 2008. They use a nested logit model estimated on separated demographic groups to capture consumer heterogeneity. Demographic groups correspond to three age classes, two geographical areas, and three income classes, and they assume that consumers are homogeneous within these groups. Since individual data is not observed, they use median income per age at the town level. Their study emphasizes the role of shifting preferences in the decrease in CO_2 emissions. More recently, Givord et al., 2018b investigates the impact of fuel prices on new car purchases. They evaluate ex-ante the impact of equalizing gasoline and diesel taxes as well as the impact of a carbon tax. Like D'Haultfœuille et al., 2016, they capture consumer heterogeneity by dividing the national sample into demographic groups based on income, degree of urbanization, employment status, and age. They find that a carbon tax would have only small effects on the average CO_2 intensity of new cars. Durrmeyer and Samano, 2017 uses a nested logit model on French and US data to simulate the welfare effects of two environmental policies: the fuel economy standards that where applied in the US and the feebate policies applied in France. They find that feebate policies welfare-dominates standard-type policies. Kessler et al., 2023 uses a similar approach with a more recent dataset (2014-2019) provided by the French Energy Transition Agency (ADEME) to evaluate ex-ante the impact of the projected feebate. As D'Haultfoeille et al., 2014, they find that the current feebate is not well calibrated to meet the French targets by 2050. Finally, this paper is close to Durrmeyer, 2021 that uses a random coefficient model à la Berry et al., 1995 complemented with micro-moments similar to Nurski and Verboven, 2016 to evaluate the

[5] In their case, the data were supplied directly by the French auto-makers comity (CCFA), of which AAA-data is a 100% subsidiary.

distributive effects of the French feebate. Our work builds on this rich literature by studying how alternative feebate designs affect the used-car (and new-car) market with a novel and recent database. The incorporation of the used-car market allows us to better account for consumer heterogeneity, since lower income households do not enter the new-car section of the market. In particular, the elasticities estimated in this study are designed to evaluate environmental policies and private-sector interventions for the entire French population, in contrast to the estimates from previous literature, which had a more limited scope.

Using the estimates, the structural model allows to perform several counterfactual analyses. The first set of counterfactual analyses aim to study various feebate designs that were actually implemented in France from 2021 to 2024, with the goal of targeting low-income households by making electric vehicles affordable. We first evaluate ex-ante the overall and distributive impact of the 2019 feebate, similarly to previous literature (Durrmeyer, 2021; D'Haultfœuille et al., 2016). We then study variations of this feebate, including an additional 1000€ subsidy for second-hand electric vehicles, and an income-based subsidy on the new-car market. We are the first to evaluate ex-ante these policies, as they both imply substitution patterns between new and used vehicles. Then, in the spirit of Berry et al., 2004, Petrin, 2002, Langford and Gillingham, 2023 and Xing et al., 2021, we investigate the economic effects of introducing a low-end electric vehicle in the choice set. Berry et al., 2004 and Petrin, 2002 study the economic effects of introducing respectively SUVs and minivans in the US new car market. Xing et al., 2021 investigates substitution patterns between electric vehicles and other vehicles by simulating the removal of every electric vehicle in their sample. Langford and Gillingham, 2023 studies the economic effects of introducing hybrid vehicles in the US new car market with a similar methodology.

It is worth noting that structural models close to Berry et al., 1995 ignore the existence of a used-car market and aggregate it in the *outside option*. Another strand of literature focuses specifically on modeling equilibrium in the car fleet, starting with the seminal paper of Rust, 1987 that introduces dynamic considerations while studying the optimal timing for replacing bus engines that depreciate over time. A few papers have focused on the stock of cars (Barahona et al., 2020; Gavazza et al., 2014) while others have modeled consumers' inter-temporal decision to change cars (Stolyarov, 2002; Esteban & Shum, 2007; Adda & Cooper, 2000). However, these studies often simplify their analysis by narrowing the focus solely to car vintages which does not allow an explicit estimation of demand for used-cars and consumers preferences in this market. Only (Schiraldi, 2011) and (Gillingham et al., 2022) incorporate dynamic considerations and, at the same time the whole characteristics of the choice set for consumers à la Berry et al., 1995. Their analysis is made possible by the use of individual data, which herein we do not have. The former has trading data for the small province of Isernia (Italy) and the second has trading decisions of all Danish citizens. Instead, herein we abstract from equilibrium constraints and dynamic aspects but still explicitly model the preference for car vintages. We contribute to this literature by elucidating the determinants of purchase on the used-car market.

3 Database

Herein we describe the data we have obtained as well as the matching techniques used to construct a dataset of the French new and used-car market.

3.1 Building a novel dataset of the French car market

We build a novel dataset of the French household car market, combining registration and online sales data. We use car registration data from private firm *AAA data*. The registration dataset contains every car bought by a consumer on the new and used-car markets from 2016 to 2019 at the IRIS level. IRIS comes from *"Ilots Regroupés pour l'Information Statistique"* which means "Grouped Units for Statistical Information" and refers to a geographic division used by the French National Institute of Statistics and Economic Studies (INSEE) for the purposes of gathering and analyzing statistical data. IRIS units are subdivisions of French municipalities (in French *communes*) used to provide a finer granularity for statistical analysis. Most municipalities with more than 5000 inhabitants are divided into IRIS with a population of around 2,000 inhabitants. Concretely, for each year between 2016 and 2019, we have the number of cars registered in each IRIS in mainland France.[6]. For each car, we observe its brand, model, year of first registration (hence its age), segment (or body type), fuel type, power (in kW), weight (in kg), CO_2 emissions (in g/km) under New European Driving Cycle (NEDC) standard, and unit consumption (in l/100km). For new vehicles, we also observe list prices (in €) and the amount of the purchase subsidy or tax paid by the consumer at the time of first registration.

To get used-car prices, we match the previously described car registration dataset with car price data from the popular French online sales website *Leboncoin.fr* covering the same period.[7] The used-car dataset contains car ads over the period 2016-2019. For each ad, we observe the product brand, model, fuel type, first registration date, and its price and mileage.

Before matching the two datasets, we remove rental vehicles from the registration dataset

[6]Excluding the two departments of Corsica for which we do not have the car data

[7]We thank Quentin Hoarau for his continuous and valuable help and for providing the dataset

because we cannot rationalize their prices.[8] The remaining dataset contains 93.4% of cars bought by households over the 2016-2019 period. To reduce the number of products, we keep a sample of 20 brands that represent 95% of household purchases. We complement the database by filling in the missing data on electric vehicle power with technical data from *Argus.fr*. We compute CO_2 emission values and emission factors of each fuel type by using data from the New European Driving Cycle (NEDC) testing procedure.The remaining dataset contains 89% of total private cars purchased over the period 2016-2019.

For matching purposes, we define five vintage classes (new vehicles, 1-5-year-old vehicles, 6-10, 11-15, 16-20, and vehicles above 20), and five energy groups (gasoline, diesel, gas, hybrid, and electric) in both datasets. The matching works as follows: for each brand-model-energy-vintage combination, we assign the average prices and mileages from *Leboncoin.fr* (the donor database) to car transactions (the recipient database). Since *Leboncoin.fr* does not cover all the car models present in the car dataset, about 7% of car transactions are dropped in the matching process. Then, we define eight segment categories (mini, small, medium, large, light duty, SUV, luxury, and sport) and we remove sport, luxury, and vehicles older than 20 years old[9]. Therefore, the final sample contains 74% of cars purchased by households in mainland France between 2016 and 2019. Finally, we define a product by a combination of brand-model-vintage-segment-energy and assign them sales-weighted average characteristics.

For the estimation, we aggregate transactions at the department (French *départements*) as well as at national levels to reduce computational time. For the 94 departments of mainland France, we observe median equivalized income[10] (in €), and urbanization rates (in %), by matching the car dataset with different databases from INSEE. By doing this, we consider each department as a single consumer, and we weight these consumers by the department size. The final dataset has 1,770 products in 2016, 1,894 products in 2017, 1,993 in 2018, and 2,071 in 2019. We observe these sales in the 94 departments, resulting in 726,432 observations.

For each department and each year, we compute local market shares as $s_{jtm}^{obs} = q_{jtm}/PM_{mt}$ with q_{jtm} the quantity of product j in department m at year t. PM_{mt} is the potential market, containing all households that may purchase a car in departments m on year t. As in most of the empirical literature, we define PM_{mt} as 1/4 of the number of households in the department[11]. We sum quantities and potential market size over departments to get

[8] In a recent work, Allcott et al. (WP 2024), use a nested logit model to account for leased and purchased vehicles in the same discrete choice model but they only focus on the new car market.

[9] This represents less than 5% of the remaining transactions

[10] Equivalized income is a measure of income accounting for the household size and composition. Household income is divided by the number of consumption units. Household head counts as one unit, then the second adult and children over 14 count as half unit, while children below 14 count as 1/3. OECD, 2024

[11] We also test 1/2 of the number of households and all households, and the results do not change significantly. In future work, we will estimate the size of the potential market, in the vein of (Huang & Rojas,

national market shares. The latter is used to estimate the mean valuations of consumers for car characteristics, while market shares at the department level help identify heterogeneity parameters.

For the simulations, we use the dataset at the district level to capture richer income heterogeneity. We restrict this dataset to the year 2019 and keep districts for which we have demographic data, hence 41,301 districts. We keep products that are present in both the estimation dataset and the remaining simulation dataset. In the end, the simulation dataset contains 1,787 products observed in 41,301 districts. We match each district with the corresponding median equalized income for 2019, and we assume that within a common department, districts share the same urbanization rate.

3.2 Descriptive statistics

Herein, we present descriptive statistics on product and consumer characteristics for the main dataset of the French car market, that we use for the estimations. Additional statistics can be found in the Appendix.

3.2.1 Product statistics

Table 1 presents the vintage, energy, segment categories and their relative importance within the sample for the year 2019, hence 2,071 products in 94 departments. Note that there are very few electric vehicles in the final sample since we removed all leased vehicles. For e.g., the large majority of Renault ZOE, the car that dominated the French electric vehicle market in 2019, was leased.

Class	Volumes	Frequencies (%)
new	576,204	12
1-5	1,723,657	35
6-10	1,055,806	21
11-15	1,030,550	21
16-20	527,753	12
gas	12,425	0.25
diesel	2,861,420	58
electric	17,803	0.36
gasoline	1,940,867	39
hybrid	81,455	1.7
total	4,913,970	

Table 1: Market description in 2019

2014)

	prices	power	CO_2	fuel cost	weight
mean	14544	90	144	8	1328
std	14133	37	46	2	276
min	300	29	0	0	695
25%	3958	66	115	6	1120
50%	9893	84	137	8	1305
75%	20807	105	167	10	1495
max	117358	338	428	26	2490

Table 2: Descriptive statistics of the car dataset

3.2.2 Consumer statistics

The distribution of income and urbanization rates for the year 2019 is given in Figure 1. Our approach is in line with Durrmeyer, 2021; D'Haultfœuille et al., 2016; Givord et al., 2018b. In the sample, we do not observe individual decision data. Instead, we observe product volumes per department and year, and we use median demographic data at this level. This implies that all consumers within a department, or in a demographic group as in (Givord et al., 2018b) and (D'Haultfœuille et al., 2016), are homogeneous. This poses a challenge, especially for studies exclusively centered on new vehicles, as a relatively small subset of consumers chooses new cars. There is a potential concern that, within each department, only those with higher incomes may be acquiring vehicles, possibly resulting in a misinterpretation of income attribution. The risk is somewhat mitigated in the used car market, as nearly everyone participates in purchasing used vehicles, except for very disadvantaged households unable to afford a car.

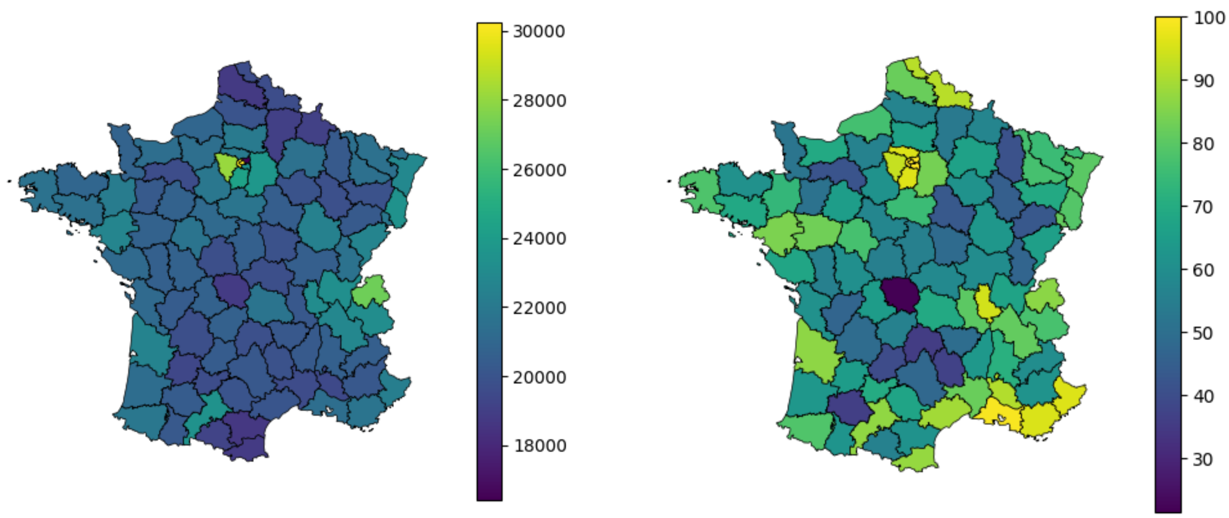

Figure 1: Median income in euros per consumption unit (left) and urbanization rate in percentage (right) for the 94 departments in continental France in 2019

As shown in Figure 1, there is substantial heterogeneity between departments in terms of urbanization rates but the heterogeneity in income is limited. In the descriptive statistics and the simulations hereafter, we use the dataset at the district level to study distributive effects of different interventions.

3.2.3 Descriptive evidence of purchase heterogeneity

To investigate consumer purchase heterogeneity, we match car characteristics, such as product price and age with local median income at the district level. We then aggregate districts in 10 income groups. Figure 2 shows the distribution of car ages at purchase within each income group.

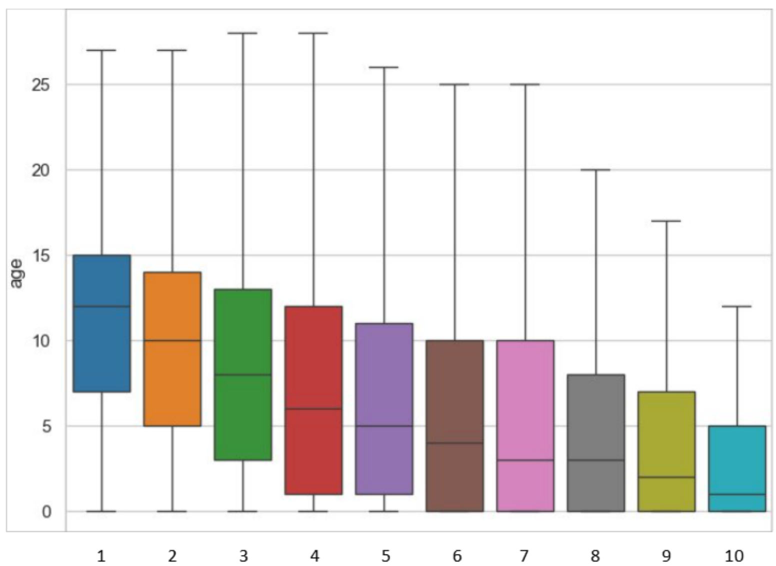

Figure 2: Distribution of car ages at purchase in each income decile, own calculation, sources: AAA-Data, Leboncoin, INSEE. The sample contains the 20 most popular brands, and sport, luxury, and cars with more than 20 years of age have been removed from the sample

We see that below median income, 75% of cars purchased are above two years old. In average, richer households tend to buy younger vehicles. 75% of cars purchased by the poorest 10% are above 7 years old, while 75% of cars purchased by the richest are less than 5 years old. This descriptive evidence underscores the importance of considering the used-car market when estimating car demand. It also emphasizes the need for a random coefficient demand model to capture heterogeneity in consumer purchasing behavior. Additional descriptive statistics are available in Appendix 7.

3.3 The French feebate policy

The French feebate was first introduced in January 2008. The objective was to align France with EU objectives of having a fleet of 130 g/km of CO_2 in 2015 and 95 g/km in 2020. The feebate consists of a tax (malus) for CO_2-emitting vehicles above a certain threshold and a subsidy (bonus) for low to zero-emitting vehicles. For eligible cars, the subsidy amount is based on 27% of the car price with different ceilings depending on the year. Since 2008 the feebate thresholds and ceilings have evolved (Figure 3). During the period 2008-2018, the subsidy CO_2 threshold has decreased and the amounts have increased. In parallel, the tax thresholds have decreased and the fees have increased in absolute value. The Yellow Vest crisis resulted in lower taxes in 2019, moving the curve to the right compared to 2018.

Several changes - not documented in our data - have occurred after 2019. There have been unusual changes in 2020 due to the change in CO_2 measurements from the New European Driving Cycle (NEDC) to the Worldwide Harmonized Light vehicles Test Procedures (WLTP) and the global Covid crisis. In this paper, we are particularly interested in two feebate changes implemented to target low-income households. First, in 2021, the French government introduced an additional subsidy of 1000€ for vehicles meeting three criteria: an emission level below the 20 g/km threshold, French registration dates back to at least 2 years, and the consumer must keep the used car for at least 2 years. The measure was removed in early 2024. The second measure is the 2023 income-based feebate on new cars, with a 7000€ subsidy for household below median income and 5000€ for households above median income. The number of subsidies attributed during this period has recently been released by France Stratégie and shows that the 2023 income-based subsidy failed to target the poorest, as only 15% of households that received a subsidy in 2023 on the new car market were below median income (see Figure 6.

Following Kessler et al., 2023, we look at the proportion of new cars affected by the policy in the working sample. Results are presented in Figure 4. Values differ slightly from Kessler et al., 2023 since we have excluded irrelevant data for our study in the dataset-building process. Figure 4 shows that, in each market, less than 2% of new car buyers benefit from a subsidy. The large majority of new car buyers in 2016 and 2017 and the majority in 2018 and 2019 is not affected by the policy. Over the period 2016-2018, the proportion of cars taxed has increased from 21% to 47%, but it has slightly decreased in 2019 while the proportion of subsidized cars has slightly increased, following the yellow vest crisis.

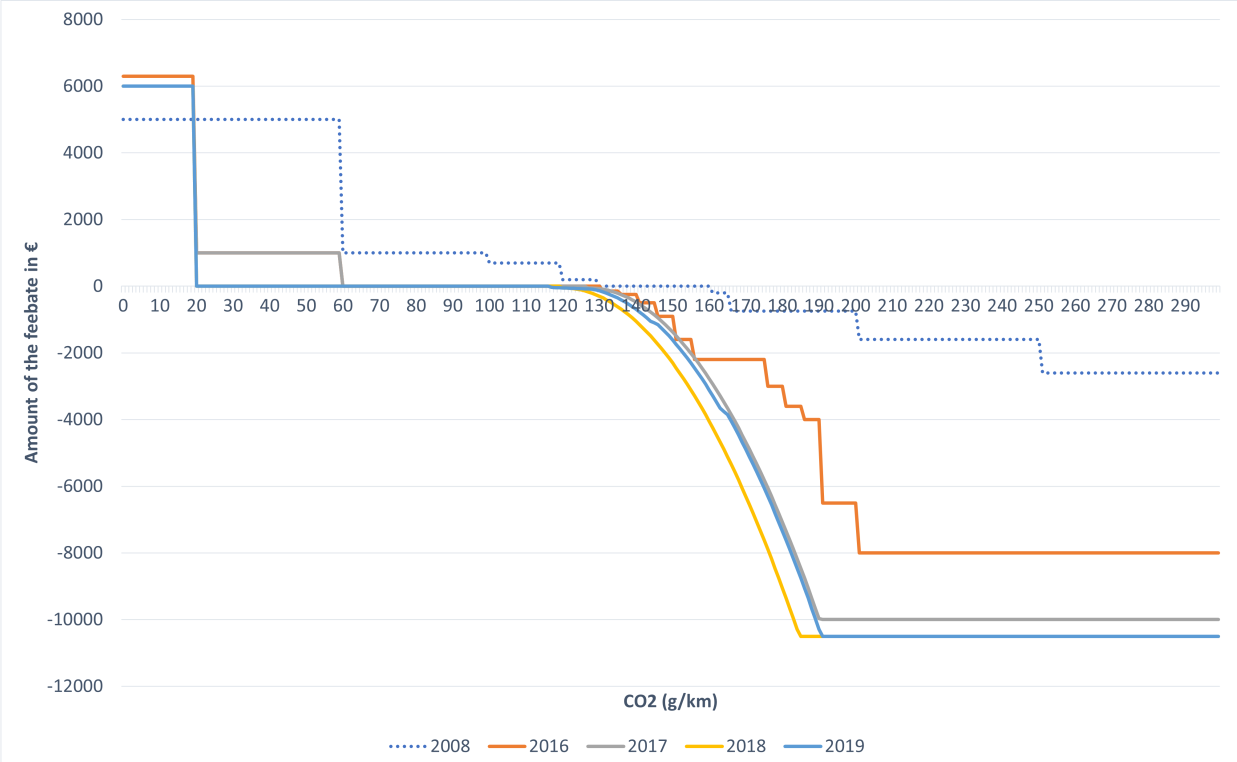

Figure 3: Feebate scale and amounts 2016-2019.

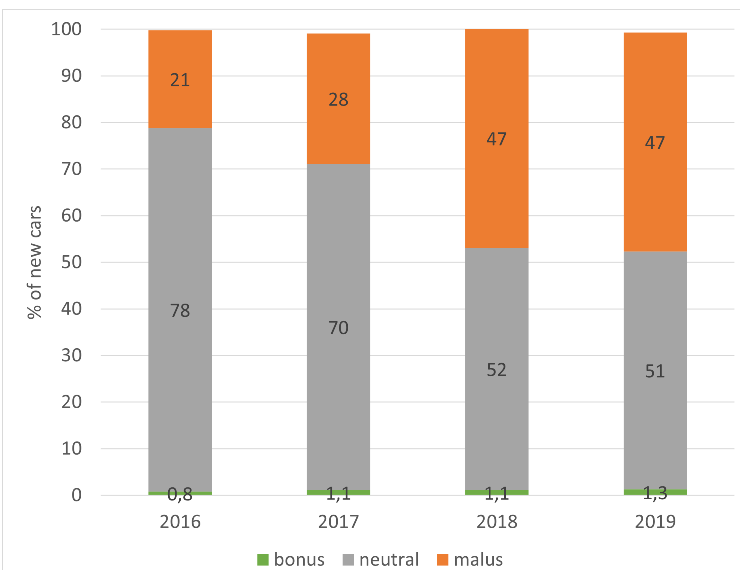

Figure 4: Percentage of new cars affected by the subsidy (bonus), the tax (malus) or not affected by the policy during the period 2016-2019

3.4 The French EV market

In France, new electric vehicles sales have increased over the period of interest (2016-2019) from 1.1% of sales in 2016 to 1.9% in 2019. Yet, the drastic increase happened after this

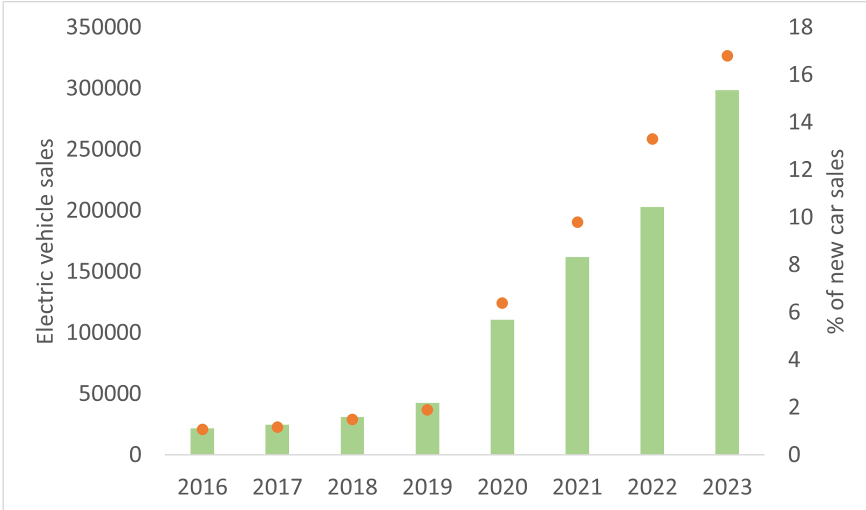

Figure 5: New electric vehicles sales and percentage of total car sales in France 2016-2023

period, from 6.4% in 2020 to 16.8% in 2023. Best-selling models in 2019 were the Renault Zoe (44% of EV sold), the Tesla Model 3 (15%), the Nissan Leaf (8.7%), and the BMW i3 (6.5%)[12].

Hereafter we simulate the economic impact of introducing a new low-end electric vehicle in the market. Instead of creating a synthetic vehicle for such simulation, we base product characteristics on an existing low-end EV: the electric Dacia Spring, which was first commercialized in 2021 and has met a great success. In 2021, it was the fourth most-sold electric vehicle, following the Tesla Model 3, Renault Zoe, and Peugeot 208. In 2022, It took second place in the ranking following the Peugeot 208 II and it kept the second place in 2023 with the Tesla Model Y as best selling electric car. Dacia Spring's price without subsidy was 18,400€ in 2021. As a comparison, Renault Zoe, one of the more popular electric vehicles at the time was 23,900€ (with leased battery) and 32,000€ (full sale) in the same period. Further details can be found in Figure 7 of the Appendix.

4 Methodology

Herein we first present our structural demand model and estimation strategy. Then, we explain how we use the estimates to compare the welfare and distributional impacts of alternative public and private-sector interventions on both the new and used-car market.

[12]As reported by the French Auto-makers committee, CCFA

4.1 Structural demand estimation

Similarly to previous literature on the estimation of household demand in the new car market (e.g. Durrmeyer, 2021), we use a random coefficient logit model of demand *à la* Berry et al., 1995 with both product and consumer heterogeneity. There are T markets, N_t consumers per market and J_t products in each market. Each product j of market t is defined as a bundle of characteristics. Consumer i finds utility in product observable and non-observable characteristics such that:

$$u_{ijt} = \beta_i x_{jt} + \alpha_i p_{jt} + \xi_{jt} + \epsilon_{ijt} \tag{1}$$

where x_{jt} is a vector of observed characteristics (other than the price), p_{jt} is the price of product j in market t, ξ_{jt} captures unobserved quality (e.g. advertising) and ϵ_{ijt} is the error term. It follows a type I extreme value distribution and can be seen as the individual specific taste for product j of market t. The coefficients β_i and α_i are consumer-specific preferences for each characteristic. Following Nevo (2001), we assume that these parameters can be written as follows:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma \nu_i$$

with $\begin{pmatrix} \alpha \\ \beta \end{pmatrix}$ mean preferences common to all consumers and D_i is a vector of d consumer characteristics. In this paper, it comes from an empirical distribution. More specifically, this paper uses median income and urbanization rates at the department level as demogr. Assuming that we observe K car characteristics, Π is a (K+1) x d matrix that measures how the taste for car characteristics varies with demographics. ν_i follows a N(0,I_{K+1}) distribution. D_i are demographics that are observed (here income and urbanization rate) while ν_i are unobserved individual characteristics, Σ is a scaling matrix. We can re-write the utility function considering a mean term $\delta_{jt} = x_{jt}\beta + \alpha p_{jt} + \xi_{jt}$ common to all consumers, and a deviation from this mean $\mu_{ijt} = [-p_{jt}, x_{jt}](\Pi D_i, \Sigma \nu_i)$.

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + \epsilon_{ijt} \tag{2}$$

We also introduce an outside good, which includes means of transport other than the car.[13] As in Durrmeyer, 2021 and Nurski and Verboven, 2016 the mean utility of the outside good is set at 0, and we specify $u_{i0t} = \epsilon_{i0t}$

[13] Some car-owners might choose to keep their car for another year and some non-motorized households might decide not to enter the market.

Since ϵ_{ijt} is extreme value distributed, the probability that consumer i chooses product j in market t has the logit form:

$$s_{ijt} = \frac{\exp(\delta_{jt} + \mu_{ijt})}{\sum_k \exp(\delta_{kt} + \mu_{ikt})} \tag{3}$$

We get market shares of product j by summing over all consumer types as follows:

$$s_{jt} = \int_i s_{ijt} dF(\nu, D) \tag{4}$$

As in previous literature, we approximate this integral by considering m Monte Carlo draws of ν from a standard normal distribution:

$$s_{jt}(\delta_t, \sigma) \approx \frac{1}{m} \sum_{i=1}^{m} \frac{\exp\left(\delta_{jt} + \mu_{ijt}\right)}{\sum_k \exp(\delta_{kt} + \mu_{ikt})} \tag{5}$$

Our estimation method is close to the estimation in Nurski and Verboven, 2016 and Durrmeyer, 2021, and conceptually close to Petrin, 2002 and Berry et al., 2004. We use the Generalized Method of Moments (GMM), with aggregate moments and micro-moments to identify mean and individual-specific utility parameters.[14] To apply GMM, we recover the unobserved quality term ξ_{jt} which enters market shares non-linearly. Following Berry et al., 1995, we invert equation (5) numerically to get δ_t. Once recovered δ_t, we compute the error term $\xi_{jt} = \delta_{jt} - x_{jt}\beta + \alpha p_{jt}$.

Aggregate moments

Following Berry et al., 1995 we use a set of instrumental variables z_{jt} to deal with price endogeneity, and we compute the aggregate moments $\mathbf{E}(\xi_{jt}|z_{jt}) = 0$. With this purpose, we assume that non-price characteristics x_{jt} are exogenous and include them in z_{jt}. We also include a vector $f(x_{jt})$ with f a function of some of these exogenous characteristics.

Given the recent methodological considerations in Gandhi and Houde, 2019, instead of using the traditional instruments for the BLP methodology (the sum of characteristics of products within the same firm and of rival firms) we follow Duch-Brown et al., 2023 and partition the dataset into groups with similar products to then sum over the characteristics of products located in the same group, distinguishing between products of the same firm and of rival firms.[15] To define the groups we use a two-step clustering process combining

[14] Nurski and Verboven, 2016 states that aggregate moments allow the identification of mean utility parameters, while micro-moments identify individual-specific utility parameters. On the other hand, Reynaert and Verboven, 2014 argues that it is unclear which instrument variable helps identify which utility parameter.

[15] Relevant instruments in these type of models should describe how distinct a product is compared to

principal component analysis (PCA) and hierarchical clustering (HC). PCA identifies the main dimensions that best summarize the data and allows a more stable clustering process (Husson et al., 2010). We use three exogenous variables to define the dimensions: power, weight, and fuel costs. HC looks for the existence of natural groups within products. 6 clusters results from this process. The process and the resulting clusters are described in detail in Appendix 7.3. Additional instruments are then the sum of power, weight, and fuel cost in each market and each cluster, for products of the same and of rival brands. The first set of moments is then:

$$g_1(\theta, \beta, \alpha) \equiv \frac{1}{T * J} \sum_t \sum_j \xi_{jt} z_{jt} = 0 \tag{6}$$

with T the number of markets and J the number of products.

Micro-moments

To identify the individual-specific terms of utility parameters we take advantage of local market data at the departement level to compute additional moments. Hence, we allow the intercept, price, and fuel costs to vary with the median income of the departement and urbanization rate, and weight to vary with the urbanization rate.[16] D_m^h is the hth consumer demographic of district m. μ_{D^h} is the mean of the hth consumer demographic. As in (Nurski & Verboven, 2016), we match observed and predicted means (i.e. for h=$\{\text{income}, \text{urbanization}\}$: $\mu_{D^h}^{obs} = \mu_{D^h}^{pred}$) which gives:

$$g_2(\theta, \beta, \alpha) \equiv \sum_t \sum_m \sum_j PM_{mt}(s_{jmt}^{obs} - s_{jmt}(\theta, \beta, \alpha))D_m^h = 0. \tag{7}$$

Following both (Durrmeyer, 2021; Nurski & Verboven, 2016), we also match theoretical and empirical covariance between product and demographic characteristics at the district level. We denote $\rho_{D^h x^k}$ the covariance between the h^{th} demographic variable D^h and the k^{th} product characteristic x^k. As with the means, matching predicted and observed covariance gives: $\rho_{D^h x^k}^{obs} = \rho_{D^h x^k}^{pred}(\theta, \beta, \alpha)$, hence:

$$g_3(\theta, \beta, \alpha) \equiv \sum_t \sum_m \sum_j PM_{mt} \left[(s_{jmt}^{obs}(D_m^h - \mu_{D^h}^{obs}) - s_{jmt}(\theta, \beta, \alpha))(D_m^h - \mu_{D^h}^{pred})\right](x_{jt}^k - \mu_{x^k}) = 0 \tag{8}$$

With μ_{x^k} the mean of k^{th} car characteristic. Resulting from all the previous steps, We recover

others in the market.

[16]Recall that PM_{mt} is the potential market at the district level m on year t.

a vector of moments with both aggregate and micro-moments $g(\theta,\beta,\alpha) = [g_1, g_2, g_3]$. The two-step optimal GMM estimator is therefore:

$$(\hat{\alpha},\hat{\beta},\hat{\theta}) = \arg\min_{\alpha,\beta,\theta} g(\theta,\beta,\alpha)' W g(\theta,\beta,\alpha) \tag{9}$$

with W the optimal weighting matrix.

4.2 Consumer Surplus in alternative policy scenarios

We then use the demand estimates to study counterfactual cases as compared to the baseline case of 2019. As cases, we consider three alternative feebate designs based on French policies and the introduction of a low-end EV. We compare these cases in terms of consumer surplus variation.

Consumer surplus is the expected utility of each consumer's best car choice. As in Durrmeyer, 2021; Petrin, 2002; Langford and Gillingham, 2023, we determine gains and losses by computing aggregate and district-specific consumer surplus variation. It corresponds to the compensating variation, hence the price reduction level each representative household would need to reach its utility before the change. Given the logit structure of the model, consumer surplus variation can be written as follows (Train, 2009).

$$\Delta\mathbf{E}(CS_d)) = \frac{1}{-\alpha_d}\Big(ln\big(\sum_{k=1}^{J_1}\exp\left(\delta_k^1 + \mu_{dk}^1\right)\big) - ln\big(\sum_{k=1}^{J_0}\exp\left(\delta_k^0 + \mu_{dk}^0\right)\big)\Big)$$

With and 0 and 1 representing respectively the reference case of 2019 and a counterfactual case. In each counterfactual analyses, we derive the average district consumer surplus and sum other the districts, weighted by market size, to get national consumer surplus.

5 Results

5.1 Demand estimation results

In Table 3, we present the results for different specifications of the model estimated using the dataset at the department level. Specification (1) is a simple logit model without heterogeneity. Specification (2) is a random coefficient model with both observed and unobserved heterogeneity. We allow the preferences for price and fuel costs to vary with income, and fuel costs, and weight to vary with the urbanization rate of the department. The Hansen test validates all of the models (for details see Appendix 7.4).

Variable	**Coef.**	**t-value**	**Coef.**	**t-value**
	(1)		**(2)**	
intercept	-7.55	-13.2	-2.68	-2.43
price	-2.97	-2.83	-3.85	-3.31
power	0.452	3.68	0.450	3.77
weight	4.35	3.68	5.84	4.84
fuel cost	-0.973	-11.9	-1.46	-14.3
new	3.94	1.79	4.08	1.89
1-5	1.68	1.76	1.75	1.86
SUV	0.810	4.01	0.843	4.08
large	-0.620	-2.58	-0.604	-2.56
medium	-0.723	-3.04	-0.713	-3.11
gasoline	2.62	9.47	2.65	9.64
electric	-5.12	-12.1	-5.14	-12.0
hybrid	-1.86	-6.38	-1.84	-6.27
electric*new	1.10	1.84	1.09	1.83
hybrid*new	1.43	3.72	1.43	3.74
income.*price			0.372	5.21
income.*fc			0.174	5.49
urban.*fc			0.132	3.27
urban.*weight			-1.78	-16.0
const.*σ_1			-11.5	-5.77
price.*σ_2			0.0484	2.31
fc*σ_3			-0.008	-1.11
Hansen				
Statistics	0.39		2.9	
p-value	0.53		0.23	

Table 3: Simple Logit and Random Coefficient Model Results with brand and market (year) fixed effects. Price and income are in 10k€, weight is in 1000kg, fuel cost is in €/100km, power is in 10kW, The reference category in each group of dummies is: "small" and "mini" for segments, "older than 5 years" for vintage and "diesel" for energy.

5.1.1 Preferences for product characteristics

The superior half of table 3 shows how characteristics influence preferences and consequently demand, on average. In both specifications, we find that the constant is negative and significant. This means that when all variables are zero or taken at their reference values (small used diesel cars over 5 years old), people prefer to hold on to their current car and not enter the market. Moreover, prices and fuel costs have negative and significant effects, and power, weight, and SUV have positive and significant effects. These results are consistent with previous literature on the new car market (Durrmeyer, 2021; Nurski & Verboven, 2016). Compared to cars older than 5 years old, consumers prefer recent -and even more - new cars.

Compared to diesel[17], consumers like gasoline vehicles and dislike electric and hybrid cars but this is less the case for new cars. For hybrid vehicles, the effect is almost reversed when the car is new, but not for EVs. These results capture at least two effects. First, consumers like new low-carbon vehicles. This could be due to the large subsidies received the new car market. Second, there is an overall disutility of low-carbon technologies in the used-car market. This may be due to the lack of supply in the used-car market since the sales of electric vehicles is only significantly large after 2019 in France.

5.1.2 Importance of heterogeneity among individuals

Individual coefficients in the bottom half of table 3 show to which extent different individuals may have different preferences on the French car market. We find that most of the coefficients are significant at the 5 or 1% level and that, as expected, higher-income households are less sensitive to car and fuel prices. We also find that urban households are less sensitive to fuel costs than rural households and value heavier cars negatively.

While the results for the average parameters are consistent with previous literature on the French new car market, there are substantial differences regarding the impact of heterogeneity. Durrmeyer, 2021 finds that rich households are more sensitive to car price increases. D'Haultfœuille et al., 2016 finds that purchase heterogeneity is mostly explained by age distribution, and, to a lesser extent, by urbanization. More surprisingly, it finds that income has a rather small effect and that the more elastic group is composed of young consumers with high incomes living in urban areas. These differences may be caused by the fact that they are only studying the new car market, which means that they only study the subsample of richer households that can afford a new car[18]. Regarding the impact of fuel costs, Givord et al., 2018a finds that income has a rather low effect in urban areas and that in rural areas rich households are more responsive to fuel price increases than lower-income households. This also differs from our results that show that higher-income and urban households are less responsive than rural and lower-income households, which is also what (Durrmeyer, 2021) finds. Reasons for these differences might lie in the fact that (Givord et al., 2018a; D'Haultfœuille et al., 2016) and (Durrmeyer, 2021) use similar demographic characteristics at the local level and consider that the representative consumer at this level purchases a new car[19]. Another difference with (D'Haultfœuille et al., 2016; Givord et al., 2018b), is that they exploit heterogeneity in consumer age as a demographic, which we do not have here.

[17]The reference is diesel and gas but diesel represent a very large majority of this category

[18]Remember we showed in Figure 2 that only the richest portion of households can afford a new car, which would explain the relatively small importance of income in previous literature studying the French market

[19]Since very few consumers buy new cars, this could result in a mismatch between vehicles and consumers.

5.1.3 Price elasticities and substitution between cars

We find a mean own-price elasticity of -4.8 and a cross-price elasticity of 0.0020. This is in line with the literature. For e.g, (D'Haultfœuille et al., 2016) finds a mean own-price elasticity of -4.5, (Nurski & Verboven, 2016) finds -3.14, and (Berry et al., 1995) finds elasticities ranging between -6.5 and -3.5. Following Conlon and Mortimer, 2023, we compute the diversion ratios between each product couple (j,k), hence the proportion of consumers of product j that moves to product k in case of price increase of product j. We also look at the diversion ratio to the outside good. The maximum diversion ratio between products is 1.4% and the diversion ratio to the outside option is 5.8%, which is relatively low, compared to the literature[20]. Hereafter we will use the estimation of the price elasticity to study the impact of a feebate policy both in the new and in the used-car market in France. This is new since we are the first to study the whole relevant market. Moreover, we will use these estimates to study the impact of such feebate as well as the impact of the introduction of a new low-end electric car.

5.2 Simulations

Herein we analyze the welfare effects of various public and private policies designed to enhance the affordability of electric vehicles. Since we only study the demand side of this market, we do not consider changes in profits and consequently our measure of welfare is simply consumer surplus.

Using the estimates of specification (2) in Table 3 and the 2019 dataset at the district level, we start by assessing ex-ante the impact of the 2019 feebate by building a counterfactual situation without the 2019 feebate. Then, we compare three interventions: in case (i) hereafter we simulate the impact of installing an additional 1000€ subsidy on top of the 2019 feebate for used electric vehicles, as was done from 2021 to 2024 in France. In case (ii) we simulate the impact of implementing an income-based subsidy. This is indeed what happened in France in 2023 where the feebate became income-based with a 7000€ subsidy for households below median income and a 5000€ subsidy for richer households. Finally, in case (iii), we simulate the introduction of an affordable low-end EV. We report the results in Table 4.

To investigate distributive effects, we further aggregate the 41,301 districts into 20 socio-demographic groups: 10 income groups (see Figure 8) separated into rural and urban house-

[20]This is because the random coefficient on the constant is large and significant. The seminal paper of Berry et al., 1995 has a diversion ratio to the outside option of 20%. Note that small parametric changes, like adding an interaction between income and the constant, bring substantial change in the diversion ratio to the outside option while keeping price elasticities relatively stable. This issue is well known and discussed in depth in Conlon and Mortimer, 2023.

holds. We compute the mean compensating variation for each group and each counterfactual and present results in Table 4. We then perform simple OLS descriptive regressions to correlate the effects of the different interventions with income and urbanization. Results can be found in Table 5.

Table 4: Consumer surplus variation for the different cases in million euros. We also report the size of the outside option, with the reference 2019 value being 0.2905. The first column gives consumer surplus variation in the presence of the feebate compared to the situation without the feebate. Cases (i) (ii) and (iii) and taken against the 2019 market conditions. Average consumer surplus variations for each socio-demographic group are in €.

	2019 feebate		**(i)**		**(ii)**		**(iii)**	
ΔCS	-1820		23.7		-12.7		31.3	
Outside good shares	0.288		0.2904		0.2904		0.2904	
Income decile	*Rural*	*Urban*	*Rural*	*Urban*	*Rural*	*Urban*	*Rural*	*Urban*
1	-12.5	-12.0	4.03	3.43	-1.82	-1.29	4.65	4.22
2	-22.4	-22.2	3.84	3.41	-1.89	-1.42	4.49	4.20
3	-28.3	-28.0	3.63	3.36	-1.89	-1.45	4.42	4.26
4	-33.6	-33.0	3.52	3.27	-1.89	-1.46	4.37	4.24
5	-38.9	-38.4	3.36	3.18	-1.90	-1.47	4.32	4.18
6	-45.2	-45.0	3.24	3.05	-1.91	-1.48	4.24	4.13
7	-54.1	-54.0	3.09	2.88	-1.92	-1.48	4.17	4.07
8	-68.5	-68.0	2.91	2.69	-1.89	-1.4	4.11	3.94
9	-102	-101	2.67	2.37	-1.90	-1.45	4.03	3.78
10	-450	-1441	2.15	1.64	-1.87	-1.44	3.84	3.17

n

Table 5: Descriptive regressions (OLS) correlating the variation of consumer surplus following the different interventions with income and urbanization rate.

Variable	**2019 feebate**	**(i)**	**(ii)**	**(iii)**
Intercept	2640^{***}	7.40^{***}	-2.64^{***}	8.63^{***}
	(0.518)	(0.00013)	(0.00012)	(0.00016)
Income	-1230^{***}	-1.06^{***}	-0.0767^{***}	-1.97^{***}
	(0.210)	(0.00005)	(0.000048)	(0.00007)
Urbanization	-105^{***}	-2.75^{***}	1.66^{***}	-0.205^{***}
	(0.507)	(0.00013)	(0.00012)	(0.00016)
R^2	0.336	0.939	0.739	0.928
Nb. Obs	73,804,887			

We also identify the products most affected by each intervention. First, we highlight the biggest losers following the implementation of the 2019 feebate compared to a scenario without it, as shown in Table 6. Next, we examine the top losers resulting from cases (i) and (iii). As vehicles replaced are the same for the two cases, we report the results together in Table 8, while results for case (ii) is reported in Table 7.

5.2.1 Impact of the 2019 feebate

We first perform an ex-ante evaluation of the 2019 feebate, comparing consumer surplus with and without the feebate for the year 2019. The overall variation in consumer surplus is large and negative (1.8 billion euros). This differs from Durrmeyer, 2021 that finds a gain of 172 million euros for the 2008 feebate policy. This is not surprising for several reasons. First, we see in Figure 3 from the descriptive statistics subsection, that cars that were given subsidies (all cars below 120g/km) or that were not taxed in 2008 (cars between 120 and 160g/km) are taxed by the 2019 feebate, with tax amounts that can reach 4,000€. Moreover, Durrmeyer, 2021 accounts for the cost of the policy, considering both uniform and proportional taxation, which we do not do herein. The positive surplus she identifies is more than offset by the policy costs, resulting in a net loss of 39 million euros. The way households are taxed to fund the policy in her framework significantly influences the distributional outcomes; therefore, we opt to set aside such considerations in our analysis.[21] In our setting, surplus losses increase with income, as described by the regression coefficients in Table 5. Indeed, an increase in 1000€ in income leads to a decrease of 123€ in surplus from the 2019 feebate. We see in Table 4 that there is little difference between urban and rural households with the exception of the richest decile where rural households loose, in average 450€ and urban households 1441€. Regression results show that a 10 percentage point increase in urbanization rate leads to a 10.5€ decrease in surplus.

In Table 6, we report the top 5 products in terms of quantity decrease following the implementation of the feebate as compared to the counterfactual no-feebate situation. Without the 2019 feebate, consumers would have purchased large quantities of new gasoline SUVs and large powerful cars, with CO_2 levels between 179 and 210 g/km.

Brand	**Model**	**Vintage**	**Energy**	**Quantity var**	**CO2**
Ford	Kuga	new	gasoline	-37,458	179
Audi	RS5	new	gasoline	-24,744	202
Mercedes	M2	new	gasoline	-21,026	210
Toyota	Land Cruiser	new	diesel	-20,477	208
Audi	RS3	new	gasoline	-18,568	191

Table 6: Top losers from the 2019 feebate in terms of cars purchase. The 2019 feebate observed situation is taken against the counterfactual no-feebate situation.

[21] If we do account for tax revenues, we find a total of 179 million euros of tax revenues from the 2019 feebate policy. This is substantial but does not compensate for the large consumer surplus losses.

5.2.2 Impact of used-EV subsidies

We analyze the impact of the used-EV subsidy based on the 2021 French additional subsidy described in Section 3.3. This subsidy consists in an additional €1,000 for used electric vehicles. The overall benefits amount to €23 million compared to the 2019 reference situation. While substantial, this amount does not offset the large and negative effects of the feebate. Nevertheless, this subsidy should be considered a relevant mechanism for targeting low-income households. The measure is indeed progressive, as it provides greater benefits to lower-income households. However, individual household benefits remain relatively low, with the difference between low and high-income households being modest—ranging from €1.64 for rich urban households to €4.03 for poor rural households. This aligns with the regression results in Table 5, which show that an increase of €1,000 in income reduces surplus by 10 cents, while a 10 percentage point increase in urbanization leads to a 27.5 cent reduction in surplus. This can be explained by the estimation results that highlight that rural households experience greater disutility from fuel costs and derive greater utility from heavier cars. Moreover, poorer households are more responsive to changes in fuel costs and prices. Therefore, it is not surprising that poor rural households would benefit from a policy that lowers the price of used electric vehicles. These second-hand vehicles are already more affordable than new vehicles, cheaper to drive than gasoline cars, and typically larger and heavier due to the need to accommodate their batteries.

5.2.3 Impact of the 2023 income-based subsidy

Herein, we simulate the overall and distributive impacts of the 2023 income-based subsidy for new electric vehicles, which offers a €7,000 subsidy for households below the median income and a €5,000 subsidy for those above it. Column (ii) of Table 4 shows that the policy results in a net loss of €12.7 million. The average loss is small, but the biggest losers are rural households in income decile 7 and, more broadly, middle-income households. This outcome is unsurprising since the subsidy amount for these households decreased by €1,000 compared to previous policies, and they tend to be more price-sensitive than high-income households. Table 5 reveals that losses decrease with urbanization, likely because urban households experience less disutility from fuel costs than rural households. While losses also decrease slightly with income, the effect is minimal. This can be attributed to the non-linear relationship between gains and income observed in Table 4. Unlike the 2021 used-car subsidy, which clearly favored the lowest income deciles, large subsidies (€7,000) on the new car market do not effectively target the poorest households. This aligns with preliminary ex-post evaluations of the policy by France Stratégie (2024) and the Institut des Politiques Publiques (2024), which found that in 2023, only 15% of new car subsidies were allocated to households below the median income. In terms of product competition, the biggest losers from the 2023 income-based subsidy are new electric vehicles, such as the Renault Zoé and the Nissan Leaf, as reported in Table 7.

Brand	Product	Vintage	Energy	case (ii)
Renault	Zoé	new	electric	-1090
Nissan	Leaf	new	electric	-475
Kia	Nero	new	electric	-394
Hyundai	Kona	new	electric	-275
BMW	I3	new	electric	-198

Table 7: Top losers in terms of quantity variation from case (ii)

As a sensitivity analysis, we isolated the effect of the additional subsidy for low-income households on the new car market by increasing the largest 2019 subsidy to €7,000 for these households while keeping other subsidies unchanged. The results show no change in consumer surplus in this scenario. Thus, in our simulations, adding a €1,000 subsidy for households below the median income, without further adjustments, is insufficient to effectively target poorer households. Ultimately, the 2023 policy's most notable impact is not in its ability to assist low-income households but rather in its reduction of subsidies for middle-income households, resulting in less new electric vehicles sold.

5.2.4 Impact of introducing a new low-end electric car

To simulate the impact of introducing a low-end electric vehicle, instead of building a synthetic electric car, we use publicly available data on the characteristics of the existing electric Dacia Spring. This car is not in the 2019 dataset as it was first commercialized in 2021. To determine the unobserved quality, our method differs from Berry et al., 2004 in that we do not use the mean of the brand unobserved quality. Instead, we look for the unobserved quality that allows us to recover the 2021 sales of the Dacia Spring[22]. The resulting unobserved quality is close to the BMW i3 model, which is unsurprising as it is one of the most popular EVs in 2019.

Household gains from introducing the Dacia Spring are relatively similar between socio-demographic groups. As case (i), the winners are poor rural households. Note that the overall gains, 31 million euros, are larger than in case (i)[23]. This is explained by the clear consumer preference for new cars. While the used-car subsidy makes used-EVs affordable

[22] Remember that Dacia's sales over the period 2021-2023 are reported in Figure 7. According to the French Auto-makers comity (OECD, 2022), 59% of new EVs are purchased and the rest is leased, leading to 6,718 cars purchased in 2021.

[23] We do not account for public spendings in the welfare calculations. This could widen the difference between the two type of measures

for low-income households, a new affordable EV is even more attractive to households since the estimation results showed that they have a clear preference for new cars.

Brand	**Product**	**Vintage**	**Energy**	**1000€ sub**	**Low-end EV**	**CO2**
Renault	Clio IV	1-5	diesel	-68	-97	88
Peugeot	208	1-5	gasoline	-66	-95	106
Peugeot	308 II	1-5	diesel	-60	-85	95
Renault	Clio IV	1-5	gasoline	-48	-68	115
Peugeot	208	1-5	diesel	-44	-62	89

Table 8: Top losers in terms of quantity variation. We compare two interventions: a used-EV subsidy of 1000€ and the introduction of a low-end EV.

Since herein we are studying the introduction of a new vehicle, it is worth exploring, aside from the variation in consumer surplus, to which extent such new vehicle substitutes polluting cars, accelerating the greening of the fleet. As reported in Table 8 Top losers from the introduction of the Dacia Spring are some of the most popular second-hand gasoline and diesel cars. This result, even if expected, is reassuring. When an affordable EV is introduced in the market, people who were buying young polluting cars buy that new low-end electric vehicle instead. Given that we have shown that there is substitution between new and old cars in this market, such substitution will most probably decrease in turn the perceived value of polluting cars making their second-hand value lower accelerating the pace at which polluting cars are retired, greening the fleet faster. The result is similar to the €1000 used-EV subsidy scenario, with a slightly larger substitution when a new vehicle is introduced. In both cases, the substituted vehicles are small used gasoline and diesel cars, which are not the highest-emission vehicles on the market. In a recent study, Xing et al., 2021 finds that electric vehicles tend to replace new, highly efficient vehicles, leading to an overestimation of CO_2 benefits. We extend this analysis by demonstrating that new electric vehicles might replace used, relatively efficient cars —not just new ones— further complicating the assessment of the CO_2 benefits of electric vehicles.

As we focus on substitutions between vehicles in a given stock rather than the evolution of the car fleet as a whole, we cannot perform direct avoided CO_2 calculations. Instead, we take a marginal approach by examining, for each intervention, which vehicles are most frequently substituted and how much they emit. In this sense, this paper sits at the intersection of studies focusing on new car sales, which estimate avoided emissions by examining the high-emitting vehicles that did not enter the fleet due to the policy, and studies focusing on the car fleet as a whole, which are better equipped to estimate the total amount of CO_2 avoided, as they also account for vehicles exiting the fleet. In this paper, we highlight a limitation of the first type of studies by showing that substitution does not always occur between new vehicles but also involves used vehicles. While our scope differs, the groundwork has been laid by (Xing et al., 2021), who emphasize the importance of accounting for substitution patterns to avoid overestimating avoided emissions.

6 Concluding remarks

Achieving carbon neutrality by 2050 requires both preventing highly-emitting cars to enter the car fleet and accelerating the widespread adoption of low-emission vehicles. This issue was a central topic in the recent legislative elections in France. Using a novel database, this paper provides the first analysis of household car demand in both the new and used car markets in France. Our estimates are used to compare the welfare, distributive effects, and competitive impacts of various public and private interventions implemented between 2019 and 2024, all aimed at making electric vehicles affordable for low- and middle-income households. We find that taxing new polluting cars effectively prevents high-emission vehicles from entering and persisting in the fleet for decades, which is a positive outcome. However, the consumer surplus loss from the feebate policy is large. Importantly, our results highlight viable pathways to make electric vehicles affordable for disadvantaged households, either by subsidizing used electric vehicles or by introducing standards on the size and affordability of new electric vehicles. In contrast, the income-based subsidy in the new car market proves disappointing, as it fails to target the poorest households and decreases overall consumer surplus, with middle-income households losing the most. This is primarily because, even with large subsidies, the price of new electric vehicles remains out of reach for many low-income households. Moreover, policy instruments and private initiatives that lower the value of polluting vehicles of the fleet could accelerate the removal of these vehicles and are therefore interesting from a fleet greening point of view. Overall, this study bridges a critical knowledge gap by shedding light on what households actually purchase, offering valuable insights for designing more effective and equitable policies.

References

Douenne, T., & Fabre, A. (2022). Yellow vests, pessimistic beliefs, and carbon tax aversion. *American Economic Journal: Economic Policy*, *14*(1), 81–110. https://doi.org/10.1257/pol.20200092

Bureau, D., Henriet, F., & Schubert, K. (2019). Pour le climat: Une taxe juste, pas juste une taxe [Place: Paris Publisher: Conseil d'analyse économique]. *Notes du conseil d'analyse économique*, *50*(2), 1–12. https://doi.org/10.3917/ncae.050.0001

Muehlegger, E., & Rapson, D. S. (2022). Subsidizing low- and middle-income adoption of electric vehicles: Quasi-experimental evidence from california. *Journal of Public Economics*, *216*, 104752. https://doi.org/https://doi.org/10.1016/j.jpubeco.2022.104752

Xing, J., Leard, B., & Li, S. (2021). What does an electric vehicle replace? *Journal of Environmental Economics and Management*, *107*, 102432. https://doi.org/https://doi.org/10.1016/j.jeem.2021.102432

Sheldon, T. L., & Dua, R. (2019). Measuring the cost-effectiveness of electric vehicle subsidies. *Energy Economics*, *84*, 104545. https://doi.org/https://doi.org/10.1016/j.eneco.2019.104545

Durrmeyer, I. (2021). Winners and losers: The distributional effects of the french feebate on the automobile market. *The Economic Journal*, *132*(644), 1414–1448. https://doi.org/10.1093/ej/ueab084

Durrmeyer, I., & Samano, M. (2017). To Rebate or Not to Rebate: Fuel Economy Standards Versus Feebates. *The Economic Journal*, *128*(616), 3076–3116. https://doi.org/10.1111/ecoj.12555

D'Haultfoeille, X., Givord, P., & Boutin, X. (2014). The environmental effect of green taxation: The case of the french bonus/malus. *The Economic Journal*, *124*(578), F444–F480. https://doi.org/https://doi.org/10.1111/ecoj.12089

Givord, P., Grislain-Letrémy, C., & Naegele, H. (2018a). How do fuel taxes impact new car purchases? An evaluation using French consumer-level data. *Energy Economics*, *74*(100), 76–96. https://doi.org/10.1016/j.eneco.2018.04.0

Berry, S., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, *63*(4), 841–890. Retrieved November 29, 2023, from http://www.jstor.org/stable/2171802

Berry, S., Levinsohn, J., & Pakes, A. (2004). Differentiated products demand systems from a combination of micro and macro data: The new car market. *Journal of political Economy*, *112*(1), 68–105.

Petrin, A. (2002). Quantifying the benefits of new products: The case of the minivan. *Journal of Political Economy*, *110*(4), 705–729. https://EconPapers.repec.org/RePEc:ucp:jpolec:v:110:y:2002:i:4:p:705-729

Nurski, L., & Verboven, F. (2016). Exclusive Dealing as a Barrier to Entry? Evidence from Automobiles. *The Review of Economic Studies*, *83*(3), 1156–1188. https://doi.org/10.1093/restud/rdw009

Reynaert, M., & Verboven, F. (2014). Improving the performance of random coefficients demand models: The role of optimal instruments. *Journal of Econometrics*, *179*(1), 83–98. https://doi.org/https://doi.org/10.1016/j.jeconom.2013.12.001

Gandhi, A., & Houde, J.-F. (2019). *Measuring substitution patterns in differentiated-products industries* (tech. rep.). National Bureau of Economic Research. https://doi.org/10.3386/w26375

Duch-Brown, N., Grzybowski, L., Romahn, A., & Verboven, F. (2023). Evaluating the impact of online market integration—evidence from the eu portable pc market. *American Economic Journal: Microeconomics*, *15*(4), 268–305. https://doi.org/10.1257/mic.20200254

Huang & Rojas. (2014). Eliminating the outside good bias in logit models of demand with aggregate data. *Review of Marketing Science*, *12*(1), 1–36. https://doi.org/10.1515/roms-2013-0016

Conlon, C., & Mortimer, J. H. (2023). Empirical properties of diversion ratios. *The RAND Journal of Economics*, *52*(4), 693–726. https://doi.org/https://doi.org/10.1111/1756-2171.12388

D'Haultfœuille, X., Durrmeyer, I., & Février, P. (2016). Disentangling sources of vehicle emissions reduction in france: 2003–2008. *International Journal of Industrial Organization*, *47*, 186–229. https://doi.org/https://doi.org/10.1016/j.ijindorg.2016.05.002

Givord, P., Grislain-Letrémy, C., & Naegele, H. (2018b). How do fuel taxes impact new car purchases? an evaluation using french consumer-level data. *Energy Economics*, *74*, 76–96. https://doi.org/https://doi.org/10.1016/j.eneco.2018.04.042

Kessler, L., Morvillier, F., Perrier, Q., & Rucheton, K. (2023). An ex-ante evaluation of the french car feebate. *Energy Policy*, *173*, 113335. https://doi.org/https://doi.org/10.1016/j.enpol.2022.113335

Langford, R. P., & Gillingham, K. (2023). Quantifying the benefits of the introduction of the hybrid electric vehicle. *International Journal of Industrial Organization*, *87*, 102904. https://doi.org/https://doi.org/10.1016/j.ijindorg.2022.102904

Rust, J. (1987). Optimal replacement of gmc bus engines: An empirical model of harold zurcher. *Econometrica*, *55*(5), 999–1033. Retrieved January 25, 2024, from http://www.jstor.org/stable/1911259

Barahona, N., Gallego, F., & Montero, J.-P. (2020). Vintage-specific driving restrictions. *Review of Economic Studies*, *87*(4), 1646–1682. https://EconPapers.repec.org/RePEc:oup:restud:v:87:y:2020:i:4:p:1646-1682.

Gavazza, A., Lizzeri, A., & Roketskiy, N. (2014). A quantitative analysis of the used-car market. *American Economic Review*, *104*(11), 3668–3700. https://doi.org/10.1257/aer.104.11.3668

Stolyarov, D. (2002). Turnover of Used Durables in a Stationary Equilibrium: Are Older Goods Traded More? *Journal of Political Economy*, *110*(6), 1390–1413. https://doi.org/10.1086/343745

Esteban, S., & Shum, M. (2007). Durable-goods oligopoly with secondary markets: The case of automobiles. *The RAND Journal of Economics*, *38*(2), 332–354. Retrieved January 25, 2024, from http://www.jstor.org/stable/25046309

Adda, J., & Cooper, R. (2000). Balladurette and juppette: A discrete analysis of scrapping subsidies. *Journal of political Economy*, *108*(4), 778–806.

Schiraldi, P. (2011). Automobile replacement: A dynamic structural approach. *The RAND Journal of Economics*, *42*(2), 266–291. https://doi.org/https://doi.org/10.1111/j.1756-2171.2011.00133.x

Gillingham, K., Iskhakov, F., Munk-Nielsen, A., Rust, J., & Schjerning, B. (2022). Equilibrium Trade in Automobiles. *Journal of Political Economy*, *130*(10), 2534–2593. https://doi.org/10.1086/720463

OECD. (2024). Glossary:equivalised income [https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Equivalised_income].

Husson, F., Josse, J., & Pages, J. (2010). Principal component methods-hierarchical clustering-partitional clustering: Why would we need to choose for visualizing data. *Applied Mathematics Department*, *17*.

Train, K. (2009). Discrete choice methods with simulation. https://eml.berkeley.edu/books/choice2.html

OECD. (2022). Ccfa report [https://ccfa.fr/wp-content/uploads/2024/02/CCFA-2022-FR-WEB.pdf].

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, *50*(4), 1029–1054. Retrieved January 29, 2024, from http://www.jstor.org/stable/1912775

7 Appendix

7.1 Additional descriptive statistics

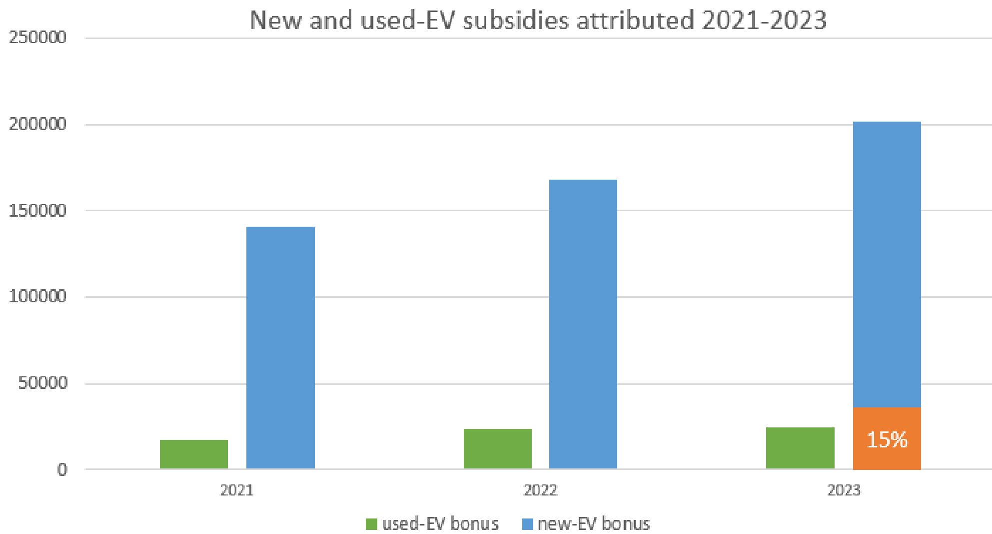

Figure 6: Number of new and used EV subsidies attributed between 2021 and 2023. 15% of 2023 new subsidies were attributed to households below median income.

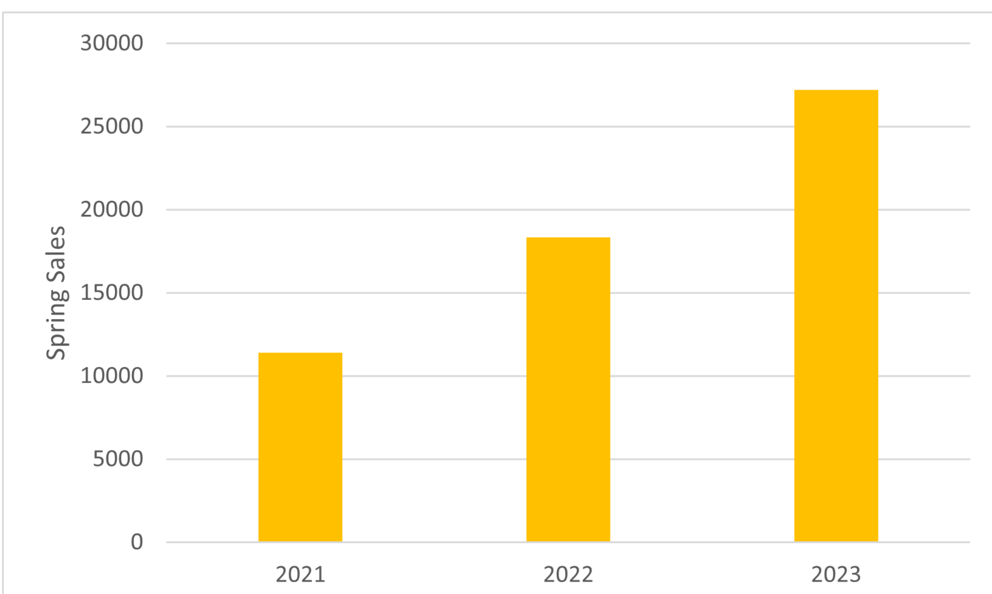

Figure 7: New Dacia Spring sales 2021-2023 in France

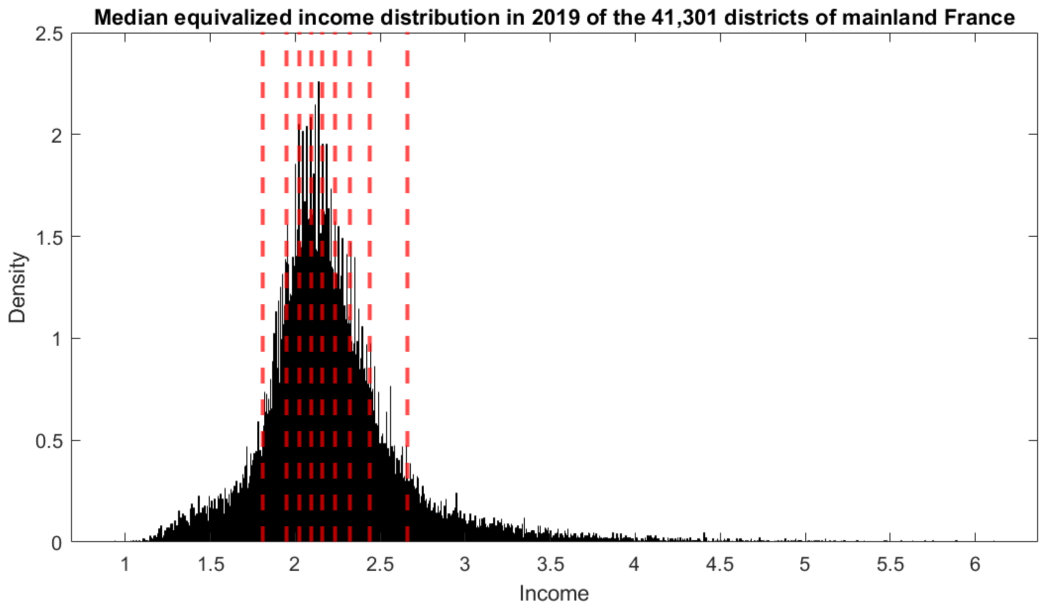

Figure 8: Distribution of median equivalised income of mainland France 94 districts, with quintile edges in red. Income is in 10k€, density corresponds to the number of districts.

7.1.1 Hybrids

The dataset aggregates plug-in and full hybrids to form a single energy type. We could have grouped plug-in hybrids with battery electric vehicles, as it is sometimes done. In this paper, we chose to separate zero-tailpipe-emission vehicles (electric, hydrogen) from the rest. Moreover, a 2024 report of the European Commission, using data from real-world fuel consumption of cars driven in 2021 showed that plug-in hybrid CO2 emissions were on average 3.5 times higher than the announced values European Commision, 2024.

7.2 Almost proportional substitution

In the logit model, the independence of irrelevant alternative (IIA) property brings proportional substitution: a change in the price of alternative j increases the probabilities for all the other alternatives by the same percentage (Train, 2009). The cross-price elasticity is

$$\eta_{jk} = -\alpha p_j s_j$$

thus it is the same for all k. This leads to unrealistic substitution patterns. The random coefficient model used in this model allows more flexible substitution patterns but Table 8 shows that substitution is almost proportional. If relative substitution is the same for all cars, the top losers in absolute value will be cars with the highest market shares. Therefore, results in Table 8 must be taken with caution.

7.2.1 Substitution to the outside good

In random coefficient models, the intercept is the utility value when all variables are zero or taken at their reference value[24]. Therefore it governs the substitution patterns between inside goods (purchasing a new or used car) and the outside option (keeping the current car for another year or never entering the car market). Herein, we are interested in the substitution from inside goods to the outside option. To some extent, introducing a new vehicle or implementing an environmental policy decreases the size of the outside option. This will have an impact on both CO2 emissions and consumer surplus. the more a product brings consumers to the market, the higher total consumer surplus will be (Conlon & Mortimer, 2023). Therefore it is key to correctly model the parameters that govern the inside good vs outside good substitution.

(Conlon & Mortimer, 2023) shows that consumer surplus is a function of own market shares, price sensitivity, and diversion to the outside good. Across model specifications, the first two parameters are stable. Hence consumer surplus is largely driven by the change in diversion ratio to the outside option. (Conlon & Mortimer, 2023) studies the effects of parametric restrictions of random coefficient models on diversion ratios. Depending on the original model[25], they find that adding or removing random coefficients on price and the constant impact substantially diversion ratios. As suggested in their paper, I run a nested logit estimation putting all inside goods in a single nest. The estimated nesting parameters ($\rho = 0.91$) can be seen as a proxy of a diversion ratio to the outside good. The extent of the diversion ratio in this model is controlled by the presence of a random coefficient on the constant. The significance of this coefficient disappears when I allow the constant to also vary with income. In this specification, the diversion ratio is around 20%, while it is 5.8% when the interaction with income is omitted. The second model better matches the nesting parameter $\rho = 0.91$ of the nested logit specification. Moreover, with its large and significant random coefficient on the constant, the second specification allows to have a total variance of utility that is not solely driven by the error term. This is also an argument in favor of this model, at least to study welfare effects (Gentzkow 2007).

[24] Small and mini cars for segment dummies, diesel for energy dummies, 'above 5 years old' for vintage dummies.

[25] They use well-known examples of BLP and Nevo

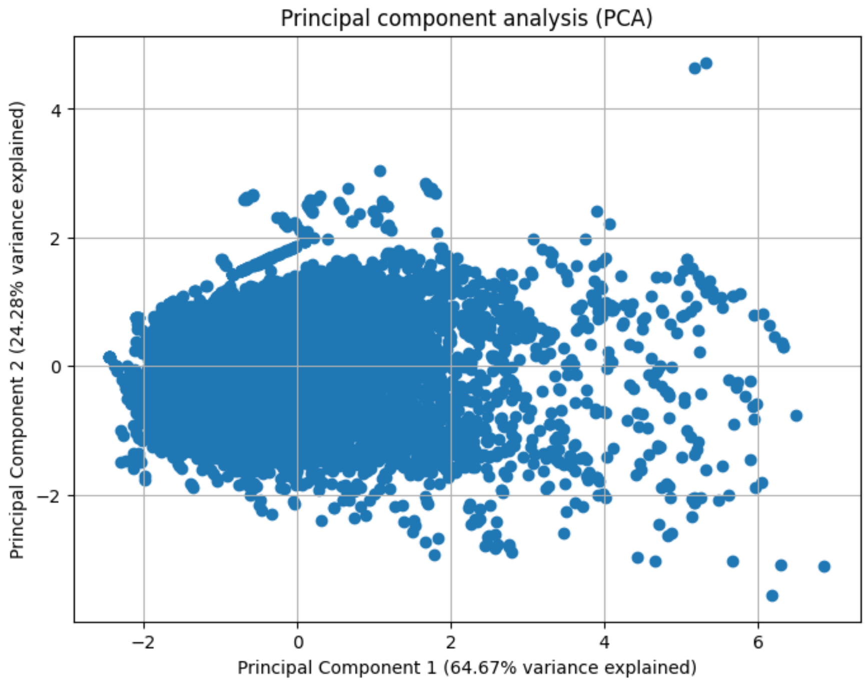

Figure 9: Principal Component Analysis on the car dataset

7.3 Building Cluster Instruments

To build clustering instruments, we need to partition products into clusters. We use hierarchical clustering to look for the existence of natural groups within the data. Following (Husson et al., 2010), we use Principal Component Analysis as a first step, to make hierarchical clustering more stable.

7.3.1 Principal component analysis

Principal Component Analysis (PCA) looks for the two-dimensional subspace that best summarizes the data. Formally, if there are K variables describing the products and J product observations, PCA considers product observations as a cloud of points in a K multidimensional space. If K≥4, direct visualization of the cloud of points is not possible. Therefore, PCA combines variables and suggests principal dimensions that capture most of the variability in the data. It can be seen as a way of separating signal and noise[26], with the first principal dimensions capturing most of the signal, and the other dimensions capturing noise. I choose to focus on three exogenous 'active' variables for the analysis: power, weight, and fuel costs.

Figure 9 presents the results of PCA for the dataset used in the estimations. The two

[26]For a more detailed explanation, see http://factominer.free.fr/more/HCPC_husson_josse.pdf

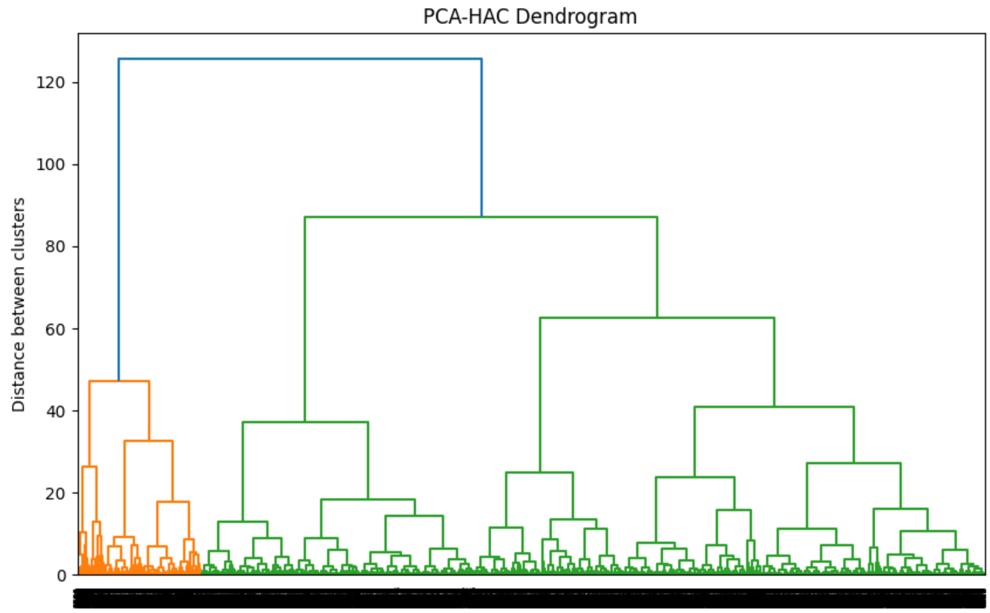

Figure 10: Result of hierarchical ascendant clustering (HAC) on the principal components

dimensions capture 89% of variability within my dataset.

7.3.2 Hierarchical clustering

We use hierarchical clustering on the principal components identified in the previous step.

Formally, considering K variables, Q clusters of products, and J_q products in each cluster, the multidimensional variance is:

$$\underbrace{\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{j=1}^{J_q}(x_{jqk}-\bar{x}_k)^2}_{\text{total variance}} = \underbrace{\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{j=1}^{J_q}(x_{jqk}-\bar{x}_{qk})^2}_{\text{within-cluster variance}} + \underbrace{\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{j=1}^{J_q}(\bar{x}_{qk}-\bar{x}_k)^2}_{\text{between-cluster variance}} \tag{10}$$

With x_{iqk} the value of variable k for observation j in cluster q, $\bar{x}_{qk}$ the mean value of k in cluster q and $\bar{x}_k$ the mean of variable k across all clusters. We use Ward's criterion to aggregate observations into clusters. The algorithm considers each product as a cluster, and at each step, aggregates the most similar clusters together, according to Ward's measure of similarity:

$$\Delta_{ward}(A,B) = \frac{I_A I_B}{I_A + I_B} d^2(\mu_A, \mu_B) \tag{11}$$

With μ_q and J_q the barycentre and size of cluster q, respectively. The algorithm iterates all observations are grouped into a single cluster.

The result of hierarchical clustering is presented in the dendrogram Figure 10. There is a trade-off when choosing the appropriate number of clusters to then compute the instruments.

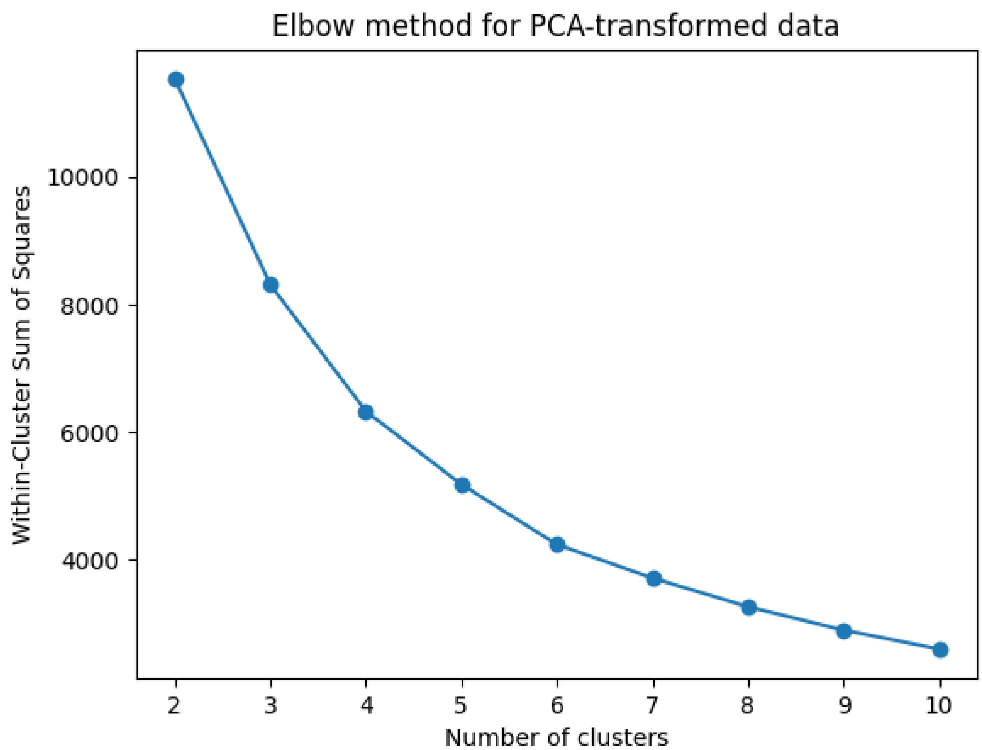

Figure 11: Elbow plot

A small number of clusters will not capture substitutability between products while a large number of clusters will lead to a very small number of observations per cluster. To compute strong instrumental variables, we need to identify the smaller group of products for which we have a high substitutability within the group, hence very similar products. We use the visualization of the dendrogram and the *elbow* method to determine an appropriate number of clusters. Setting the distance at 40 on the dendrogram leads to an optimal number of 6 clusters. Additionally, the *elbow method* calculates the Within-Cluster Sum of Squares (WCSS) and plots it as a function of the number of clusters. The result is presented in Figure 11. The elbow plot allows for the identification of the number of clusters for which the WCSS takes off, which is when we go from 6 to 5 clusters in Figure 11.

Cluster description

Table 9: This table presents the proportion of each vehicle type in the overall population (last column) and in each cluster, from 1 to 6.

Cluster	**1**	**2**	**3**	**4**	**5**	**6**	**All**
new	6	6	14	0	13	15	13

Cluster	1	2	3	4	5	6	All
1-5	31	15	32	1	44	37	33
6-10	37	36	20	48	14	19	21
11-15	1	8	14	24	4	5	10
16-20	25	36	20	28	25	24	23
mini	0	0	14	0	0	0	7
small	0	0	66	31	0	6	37
medium	6	3	6	49	18	60	27
large	18	47	0	15	46	10	10
SUV	76	35	9	2	34	22	16
K	0	15	4	2	3	2	3
gas	0	0	0	1	0	0	0
diesel	69	70	50	1	82	79	61
gasoline	30	29	49	98	14	19	37
elec	0	0	0	0	0	1	0
hybrid	0	1	1	0	3	2	1
AUDI	28	8	1	3	13	4	4
B.M.W.	12	19	0	5	14	3	3
CITROEN	0	6	13	5	11	8	11
DACIA	0	0	5	1	0	2	4
DS	0	2	1	0	2	2	1
FIAT	0	1	5	1	0	2	3
FORD	0	1	4	4	5	5	4
HYUNDAI	0	0	1	0	2	1	1
KIA	0	4	1	0	1	1	1
MERCEDES	0	8	1	2	9	3	2
MINI	0	0	0	5	0	2	1
NISSAN	0	2	1	1	3	6	3
OPEL	0	3	4	4	4	5	4
PEUGEOT	0	8	22	26	9	23	21
RENAULT	0	29	28	32	11	16	22
SEAT	0	0	2	1	1	2	2
SKODA	0	0	1	0	1	1	1
SUZUKI	0	0	1	0	1	1	1
TOYOTA	0	8	3	0	2	3	3
VOLKSWAGEN	60	1	6	10	11	11	8

7.4 Robustness of model specifications

The model is over-identified since it has K parameters to estimate and r moment conditions, with $r > K$. We perform Hansen, 1982's Overidentifying Restriction test. The objective of the test is to assess the validity of the additional restrictions imposed by the overidentified model. The null hypothesis H_0 is that the population moment conditions hold in expectation, which means that the instruments do identify model parameters, hence that $E[g(\theta, \beta, \alpha)] = 0$. The alternative hypothesis H_1 is that the additional restrictions do not hold, indicating model misspecifications. To validate the specified model, the statistic should be close to zero with a large p-value. In all specifications presented in Table 3, we fail to reject H_1, which validates the models.

7.5 Simulations: additional results

Table 10: WLS Regression Results using department level data. Standard errors are clustered at the department level.

Variable	**2019 feebate**	**(i)**	**(iii)**
Intercept	399.74***	7.93***	8.84***
	(0.642)	(0.00286)	(0.00508)
Income	-200.86***	-1.17***	-2.22***
	(0.314)	(0.00140)	(0.00249)
Urban	-9.97***	-2.84***	0.104***
	(0.542)	(0.00241)	(0.00429)
R-squared	0.737	0.962	0.842
Nb.Obs	194674		