

Givord, Pauline; Grislain-Letrémy, Céline; Naegele, Helene

Article — Accepted Manuscript (Postprint)

How do fuel taxes impact new car purchases? An evaluation using French consumer-level data

Energy Economics

Provided in Cooperation with:

German Institute for Economic Research (DIW Berlin)

Suggested Citation: Givord, Pauline; Grislain-Letrémy, Céline; Naegele, Helene (2018) : How do fuel taxes impact new car purchases? An evaluation using French consumer-level data, Energy Economics, ISSN 0140-9883, Elsevier, Amsterdam, Vol. 74, pp. 76-96, <https://doi.org/10.1016/j.eneco.2018.04.042>

This Version is available at:

<https://hdl.handle.net/10419/225346>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<http://creativecommons.org/licenses/by-nc-nd/4.0/>

How do Fuel Taxes Impact New Car Purchases? An Evaluation using French Consumer-Level Data

Pauline Givord, Céline Grislain-Letrémy, Helene Naegele

Abstract

This study evaluates the impact of fuel taxes on new car purchases, using exhaustive individual-level data of monthly new car registrations in France. We use information on the car holder to account for heterogeneous preferences across purchasers, and we identify demand parameters through the large oil price fluctuations of this period. We find that the short-term sensitivity of demand with respect to fuel prices is low, particularly for corporate purchases. Using our estimates to compute elasticities, we assess the impact of a policy equalizing diesel and gasoline taxes. Such a policy reduces the share of diesel-engines without substantially changing the average fuel consumption or CO₂ intensity of new cars. Alternatively, we find that a (revenue-equivalent) carbon tax has only small effects on average fuel consumption and CO₂ intensity of new cars.

Keywords: fuel prices, automobile demand, carbon dioxide emissions, environmental tax.
C25, D12, H23, L62, Q53.

Highlights

- The car purchase decisions is modeled as a nested logit.
- Corporate purchases react less to fuel price changes than private purchases.
- Two reforms are simulated: an alignment of diesel and gasoline tax, and a carbon tax.
- Both policies have small impact on fuel efficiency and CO₂ intensity in the short-run.
- Aligning diesel and gasoline tax shifts consumption away from diesel cars.

© <2020>. This manuscript version is made available under the CC-BY-NC-ND 4.0 license
<http://creativecommons.org/licenses/by-nc-nd/4.0/>



1. Introduction

Road transportation is one of the main contributors to climate change: in France, similarly to other industrialized countries, cars and trucks account for nearly one third of CO₂ emissions and a larger share of other greenhouse gases. On the one hand, this problem might be alleviated by a shift to diesel-fueled cars: typically, a diesel car produces less CO₂ per km than a similarly-sized gasoline-fueled car. On the other hand, diesel cars also produce medically hazardous fine particles (in particular black carbon) and nitrogen oxides (NO_x). Thus, policy makers are facing both a global climate problem as well as a local health issue; shifting toward more diesel cars might alleviate the global externality, but increases local concerns.

For decades, European policy makers have encouraged small fuel-efficient cars with high fuel taxes. Further, in many countries, they have opted to support diesel vehicles.¹ This preference for diesel is especially salient in France (Hivert, 2013), where the gap between gasoline and diesel prices is one of the highest in Europe.² In Japan and the US, diesel cars make up about 2% of all vehicles (Cames and Helmers, 2013), while they represent more than 62% in France. Incentives to reduce CO₂ emissions, as the feebate introduced in France in 2007,³ reinforce consumer preferences for diesel cars. However, as stressed by Mayeres and Proost (2001), for instance, the environmental benefits of diesel cars might have been overestimated, and new technologies decrease the spread between the CO₂ intensity of diesel and gasoline cars. The production of diesel-models is more CO₂ intensive because they are heavier. Additionally, recurrent episodes of smog have sparked a renewed debate about the French support for diesel.⁴

Faced with this conundrum of how to deal with global and local pollution, the French government announced in 2015 a progressive reduction of the relative tax advantages for diesel fuel.⁵ This

¹Partly for historical reasons and with the objective to reduce energy dependency, as European countries import virtually all of their petroleum products; see for instance https://www.transportenvironment.org/sites/te/files/publications/2015_10_Europes_tax_deals_for_diesel_FINAL.pdf. For Miravete et al. (2015), the diesel-friendly policies in Europe are essentially a non-tariff trade barrier against American manufacturers.

²In 2011, the consumption tax on energy products (French lump-sum tax on fuel consumption) reached €0.61 per liter of gasoline, while it was €0.44 per liter of diesel.

³Feebates, a system combining fees (for more polluting cars) and rebates (for less polluting cars) were implemented in several European countries in the 2010s. This mechanism is expected to shift consumer expenses toward less polluting goods, and to be self-financed as the fees should compensate the rebates. See D'Haultfoeulle et al. (2014) for an evaluation of the French experience.

⁴In December 2016, air quality in France was so poor that the government heavily restricted driving and Paris authorities banned the oldest and most polluting vehicles from the city center, pledging “an end to diesel in Paris” by 2020.

⁵The difference was reduced from 14.9 cent in 2015 to 11.7 cent in 2016, and 9.4 cent in 2017. The path to full equalization, as described in this study, is yet to be defined; see <http://www.douane.gouv.fr/articles/a12285-carburants-gazole-super-e10-taux-de-taxe-par-region> Retrieved on 05/09/2017. This reform is in line with the revision of the European Commission’s Energy Tax Directive proposed in 2011 (but voted down in 2012 by the European Parliament) that would have eliminated the tax advantage to diesel fuel by basing fuel taxes both on their energy content and on the related carbon dioxide (see Frondel and Vance, 2014).

tax alignment adds to a previously implemented “carbon tax”, first at a modest €7 per tonne of CO₂ in 2014 progressively raised to €30.5 per tonne of CO₂ in 2017. A carbon tax is proportional to the carbon content of each fuel, aiming at aligning the private cost to the consumer with the externality cost to society.

These tax reforms are expected to reduce total emissions from road traffic by two main mechanisms. First, the reforms have an impact on the usage of vehicles (intensive margin), as one might expect that motorists drive fewer miles when fuel prices increase. For example, in a recent study on German data, Frondel and Vance (2014) observe that the fuel elasticity with respect to distance driven is around -0.5, with no significant differences between diesel and gasoline fuel. Second, the reforms affect the type of vehicles in use (extensive margin), as consumers are expected to choose more fuel-efficient cars when fuel prices are high. As cars are durable goods, such a change in the composition of new vehicles has long-term effects on emissions. The magnitude of this extensive effect depends on the way car purchasers take into account the cost of driving. Despite a large literature on the impact of fuel prices on car choice (Greene, 2010, surveys as much as 28 papers on how consumers value fuel economy), the question is still controversial. Several studies emphasize an “energy paradox,” meaning that consumers systematically undervalue future economies of energy-efficiency (e.g. Allcott and Wozny, 2014); others find no evidence of such consumer myopia (e.g. Sallee et al., 2016; Busse et al., 2013). Meta-studies (Helfand et al., 2011; Greene, 2010) find that the empirical evidence about the energy paradox is inconclusive. Most papers focus on the US market, and there is little evidence about the European market. One notable exception is Klier and Linn (2013) who evaluate the effect of fuel prices on new vehicle fuel economy in the eight largest European markets, including France, and observe strong differences between the European and the US markets. Finally, two additional (indirect) effects can be anticipated: higher fuel price may reduce car lifetime, by encouraging drivers to scrap old fuel-inefficient vehicles (see for instance Li et al., 2009; Adda and Cooper, 2000). Moreover, some authors find that consumers increase their mileage when they buy a more fuel-efficient car (“rebound effect”, e.g. Small and Van Dender, 2007).

In this study, we estimate how French car purchasers react in the short term to changes in fuel prices, in order to predict whether fuel taxes change the average vehicle in use. This study thus concentrates on the car choice (extensive margin) and relies on simplifying assumptions on all other margins. More specifically, we focus on fuel efficiency and the share of diesel cars, as they have an impact on climate change and local pollution, respectively.

We use French passenger vehicle registration data from 2003 to 2007. Our dataset is exhaustive, so that we observe also purchases from companies, which represent more than one-third of new car purchases in France over our period and, as far as we know, are rarely analyzed in existing studies. Our data links detailed technical car characteristics to car holder information. We define consumer types, depending for instance on location areas, age and activity status for private consumers, which allow us to account for heterogeneity in preferences across purchasers.

As common in the related literature, we rely on a static discrete choice model, assuming that the decision to buy a specific car depends on car characteristics, including the cost per kilometer. We model substitution patterns depending on car market segments and on fuel-type versions using a nested logit specification. We identify the impact of fuel cost on car choice exploiting cross-sectional differences in fuel consumption between car models and time variation in fuel prices.⁶ We deduce the elasticity of automobile demand with respect to an increase in fuel taxes, as well as the willingness to pay for fuel efficiency.

Our results suggest that the short-term sensitivity of demand with respect to fuel prices is generally low, but presents significant heterogeneity across consumers. The difference between private and corporate purchases is particularly salient: firms are less reactive than households and have a strong preference for diesel. We use our estimates to predict the short-run impact of two hypothetical policies: the equalization of diesel and gasoline taxes and a carbon tax. Both policies increase taxes relative to the *status quo* but are calibrated to be revenue-equivalent to each other. Assuming that consumers react identically to price changes from fuel tax and from oil market fluctuations, our results suggest that equalizing diesel and gasoline taxes reduce the market share of diesel cars (from 69% to 65%) in the short-run without notably changing average fleet fuel consumption or CO₂ intensity. The carbon tax leaves the diesel share almost constant and has a small impact on the other two outcomes. Overall, our results do not suggest a strong short-term impact of fuel prices on car choices from the demand side. This does not rule out an impact in emissions *via* a reduction in the mileage driven by car holders, nor a long-term change from the supply side.

The article is organized as follows. Section 2 explains our assumptions on the decision making process. Section 3 presents the data and descriptive statistics. The model is presented in Section 4. Section 5 discusses results, and Section 6 concludes.

⁶During the estimation period the fuel prices varied considerably: prices range between €1.01 per liter and €1.38 per liter of gasoline, and between €0.75 and €1.21 per liter of diesel.

2. Choice model

2.1. Sequential automobile choice

To model market shares of new vehicles, we rely on a standard discrete choice model with differentiated products. We assume that the purchaser buys one product maximizing her utility, which is a linear function of vehicle characteristics and a vehicle-specific unobserved effect, like e.g. Allcott and Wozny (2014), tracing back to seminal work by McFadden (1978). A product corresponds to a bundle of characteristics. Following common practice, our definition includes brand, nameplate (Corolla, Kangoo, etc.), body style (city-car, sedan, etc.), CO₂ intensity class, and fuel-type (diesel or gasoline).⁷

The individual utility of choosing the product with model j , fuel-type f and segment s , for purchaser i at month t is written:

$$u_{ijft} = \alpha_i + \beta_i^* C_{ijft} + \gamma_{1i} p_{jft} + \gamma_{2i} X_{jft} + \xi_{ijft} + \epsilon_{ijft}, \quad (1)$$

where p_{jft} denotes the car price at time t with the model j of fuel-type f , C_{ijft} is consumer i 's discounted expected operating cost from fuel along the car's lifetime and X_{jft} represents other observable characteristics of the car, for instance the horsepower category and the number of doors. ξ_{ijft} measures the unobserved preference for product jf .

We assume that the consumer decision can be modeled as a hierarchical choice (see Figure A.2 in the Appendix for a graphical illustration), choosing first a car segment (i.e. SUV, compact, etc.; see list in Table 1) or not buying any new vehicle (the outside option), then a model within this segment, and finally one of the two fuel-type versions of this model. Fuel-type versions differ not only by the type of engine, but are usually bundled with a set of other attributes (e.g., acceleration performance, size, luxury features, etc.). Formally, such a decision sequence is modeled using a nested logit assumption on the error term of the model:

$$\epsilon_{ijft} = \nu_{ist} + (1 - \sigma_{2i})(\nu_{ijt} + (1 - \sigma_{1i})e_{ijft}), \quad (2)$$

where ν_{ist} is the consumer's overall preference for segment s , for example status symbol value of SUVs, and ν_{ijt} measures the individual preference for unobserved characteristics of model j

⁷In practice the definition of products should be detailed enough to avoid the aggregation of heterogeneous products but not too narrow, as we have to exclude all market shares equal to zero. We exclude electric and hybrid vehicles in the estimations as they constitute a tiny share of the French market over the examined period and have zero sales in many months.

common to both fuel versions, for example design. The remaining error e_{ijft} is assumed to be independent and identically distributed according to an extreme value distribution. There is a unique distribution for ν_{ist} and ν_{ijt} such that ϵ_{ijft} follows an extreme value distribution (Cardell, 1997); this specification is standard in the literature (see in particular Berry, 1994). The nested logit specification allows for heterogeneous substitution patterns between products that are more or less similar; for instance, a sporty BMW Z3 is more substitutable to a BMW Z4 than to a bulky Renault Kangoo.

The parameters σ_{1i} and σ_{2i} capture the correlation between individual preferences for cars within a nest, as defined above. As shown by McFadden (1978), the nested logit model is consistent with random utility maximization for values of σ_{1i} and σ_{2i} between 0 and 1. $\sigma_{1i} = 0$ means that substitution effects are identical across and within models,⁸ while a high σ_{1i} implies a high correlation between preferences for both fuel-type versions of the same model. $\sigma_{2i} = 0$ implies that the purchaser is *a priori* indifferent to substitute between models within and across segments (see Verboven, 1996, for a more complete discussion of these terms).

A drawback of the nested logit specification is that it relies on a rigid and *ad hoc* substitution pattern between products. While the market segments we rely on are widely used in the related literature, our choice of using an additional level corresponding to the two fuel versions of the same model is more original and may be questioned. Unfortunately, there is no direct way of testing these assumptions. Nevertheless, we find that an unconstrained estimation of the model leads to parameter values that are compatible with the random utility model in McFadden (1978), as σ_{2i} and σ_{1i} both range between 0 and 1 for all estimations.⁹

2.2. Vehicle choice and fuel prices

Fuel prices affect the car choice *via* the consumer's expectations of the future operating costs of each vehicle. As a car is a durable good, the decision to buy a given product jf at time t depends on the consumer's discounted expected value of the future fuel costs associated with this vehicle. Formally, the expected discounted operating cost C_{ijft} is composed of several elements

⁸“Within-model” substitution refers to the substitution between the gasoline-powered and the diesel-powered versions of the same model.

⁹Moreover, we estimate two alternative specifications that relax this assumption. In the first alternative, we drop the last nest level. In the second, we rely on a simple logit model, but allows for model specific effects (as in Klier and Linn, 2013). Both these alternative specifications leave our main conclusions unchanged (see Section G in the Appendix).

(like e.g. Allcott and Wozny, 2014):

$$C_{ijft} = E_t \left[\sum_{a=1}^{L_{max}} \delta_i^a m_{ijfa} \phi_{jff} p_s^f \nu_{jfa} \right] \quad (3)$$

where δ_i is the discount factor of consumer i , m_{ijfa} is her mileage using the vehicle jf of age a , ϕ_{jff} is the fuel consumption per km of the vehicle j with fuel type f .¹⁰ p_s^f is the future fuel price of fuel f at date $s = t + a$. Finally, ν_{jfa} is the probability that the vehicle jf survives to age a and L_{max} is the maximum age of a vehicle.

We assume that the changes in fuel price are independent of the other variables. We also take the most simple assumption on how purchasers forecast future gasoline prices: according to Anderson et al. (2013), consumer beliefs regarding future fuel prices are indistinguishable from a no change forecast or a random walk, such that expected future price is equal to the contemporaneous price.¹¹ This approach is in line with the literature: the meta-study by Greene (2010) identifies 28 studies on this subject, of which 27 use an assumption equivalent to ours.¹² Moreover, we assume that consumers are equally sensitive to fluctuations in the oil price as they are to changes in fuel taxes. We discuss this assumption more in detail in the conclusion.

As we focus on car choice and do not know the elasticity of mileage, both to fuel prices and vehicle efficiency, we take the simple assumption that individual mileage is constant and perfectly inelastic.¹³ We then rewrite the equation (1) as:

$$u_{ijft} = \alpha_i + \beta_i p_{jft}^{km} + \gamma_{1i} p_{jft} + \gamma_{2i} X_{jft} + \xi_{ijft} + \epsilon_{ijft}, \quad (4)$$

where p_{jft}^{km} corresponds to the expected future operating cost of driving one kilometer with vehicle j with engine f at date t , and the parameter β_i encompasses the model demand parameter β_i^* , as well as the previously discussed unobserved consumer expectations on discount factor, expected

¹⁰Fuel consumption is usually expressed in L/100km, as commonly used in Europe, and is the inverse of fuel efficiency in miles per gallon (MPG), as typically used in the US. We abstract here from the problem that realized fuel consumption might not equal the announced fuel consumption, measured under standardized technical conditions, and that it might evolve over the car's lifetime.

¹¹Formally,

$$\forall s > t : E_t(p_{jfs}^{km}) = p_{jft}^{km} = 1/100 \times \phi_{jff} \left[\mathbb{1}_{f=diesel} p_t^D + \mathbb{1}_{f=gas} p_t^G \right],$$

where p_t^D and p_t^G denote the fuel prices including tax for one liter of diesel and gasoline, respectively, ϕ_{jff} the fuel consumption of new vehicle j with engine f (in L/100 km).

¹²Alternative approaches in the literature include using moving averages, which are, for example, consistent with a purchaser belief in mean-reversion of fuel prices. In a model similar to ours, Klier and Linn (2013) use both contemporaneous fuel prices and moving averages, finding that this assumption has no significant impact on parameter estimates, but standard errors are larger with moving averages.

¹³Alternatively, one could take an elasticity estimate from the literature, but estimates differ widely and no estimates are available for firms.

mileage, and vehicle lifetime probability.

A frequently discussed issue is how to model the heterogeneity in preferences among consumers, as not accounting for heterogeneity may result in biased estimates. Pakes et al. (1993) propose an ingenious way of taking into account such heterogeneity in preferences when only aggregate data on car sales are available. Such random-coefficient models allow preferences to be shaped by the aggregate distributions of household demographics. However, this comes at the cost of high computational complexity, which is shown to lead to numerical instability in some cases: Knittel and Metaxoglou (2014) find that results often depend on starting values and optimization algorithms (see also Grigolon and Verboven, 2014). Another strand of the literature relies on the use of household survey data. Such data contain very detailed information on consumer characteristics, including those who buy a used and those who do not buy any car (thus opting for the outside option). For example, Goldberg (1995, 1998) estimates nested logit models of choice using the US Consumer Expenditure Survey and makes the parameters a linear function of household characteristics; this approach is similar to ours consisting in estimating parameters separately for groups determined by the intersection of observed consumer characteristics, albeit Goldberg’s method is more constrained (and also adapted to the use of survey data with limited sample size).

3. Data and descriptive evidence

3.1. Characteristics of new vehicles and their purchasers

We use an exhaustive dataset of all new car registrations in France from January 2003 to November 2007, provided by the Association of French Automobile Manufacturers (CCFA, *Comité des Constructeurs Français d’Automobiles*).¹⁴ This transaction-level dataset includes all information necessary for the registration of a new car, i.e. both technical specifications of the car (including horsepower, weight, number of doors, etc.) and demographic information on its owner.

The CCFA links these data to list prices of new cars as provided by the car manufacturers. List prices may differ from the actual unobserved selling prices. This measurement error, as well as the endogeneity of prices can induce biased estimates – in the following, we use instrumental variables to deal with this estimation issue.

¹⁴Data is also available for 2008. As a feebate scheme was introduced in January 2008, which dramatically changed the demand for fuel economy, we only use data up to the date of its announcement in November 2007. See D’Haultfoeille et al. (2014) for an analysis of this policy and a description of this dataset.

Our main dataset contains over 7 million observed registrations of more than 2,000 different products,¹⁵ as defined by the attributes in Table 1. More descriptive statistics are available in the Table B.6 in the Appendix.

Figure 1 provides the evolution of aggregate sales. The overall number of new registrations is strongly seasonal, but is virtually constant over the years. Since 2010, the number of diesel cars sold has consistently been higher than the number of gasoline cars in France, and this difference was increasing over the period under study here.

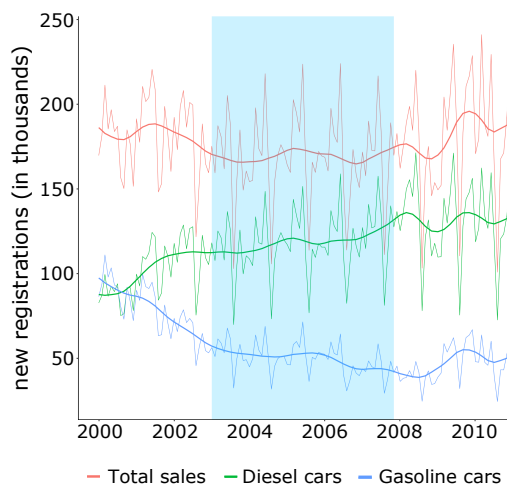


Figure 1: Monthly new registrations by fuel-type (in thousands, raw and smoothed series, studied period shaded in blue)
Source: CCFA, authors' calculations.

We further use monthly fuel prices from the French Ministry of Environment.¹⁶ The final fuel tax rates result from the combination of a fuel-type specific lump-sum tax (*Taxe intérieure de consommation sur les produits énergétiques*, named "consumption tax on energy products" hereafter) and the proportional VAT.¹⁷ From January 2003 through November 2007, both gasoline

¹⁵Given the outlined structure of the decision process, we exclude models available with only one fuel-type; this is only the case for exceptional cars, which represent about 7% of total sales. We verify that excluding these models is not crucial for the results, see Section G in the Appendix.

¹⁶We use sales-weighted national average prices available at <http://www.developpement-durable.gouv.fr/Prix-de-vente-moyens-des,10724.html>. For diesel prices, we use the price of car diesel oil ("gazole"), while for gasoline price, we use premium unleaded gasoline ("super sans plomb 95"). All price indications in this study are deflated by the French National Statistical Institute (INSEE) consumer price index, taking January 2008 as reference. Local fuel prices are available only since 2007 and cannot be used here. However, the spatial variation is much lower than the temporal variability: the relative standard deviation is below 2 % for monthly fuel prices measured at the local (French "département") level in 2007, while it is above 10% for national monthly prices over the 2003 to 2007 period. Pre-tax prices for gasoline and diesel are highly correlated (correlation over 0.95) and their difference is small (between -3 and 9 cents), so we assume price variations of both depend equally on oil prices.

¹⁷The fuel price can be decomposed as:

$$p_t^f = (1 + t^{VAT}) [p_t^e + \mathbb{1}_{f=diesel}(t_D) + \mathbb{1}_{f=gas}(t_G)], \quad (5)$$

where p_t^e is the pre-tax fuel price, t_D and t_G are the consumption lump-sum taxes for one liter of diesel and gasoline, respectively, and t^{VAT} the VAT rate.

Table 1: Descriptive statistics: main characteristics of new car registrations 2003-2007

	Products	Sales-weighted		Products	Sales-weighted
<i>By type of car-body</i>			<i>By class of CO₂ (g/km)</i>		
City-car	3%	7%	≤100	0%	0%
Compact	14%	34%	101 to 120	4%	18%
Sedan	33%	24%	121 to 140	9%	27%
Minivan	13%	24%	141 to 160	14%	33%
Utilitarian	6%	4%	161 to 200	29%	21%
Sport	20%	3%	201 to 250	26%	6%
All-road/SUV	10%	5%	>250	18%	2%
<i>By horsepower</i>			<i>By type of fuel</i>		
≤60	14%	34%	Gasoline	57%	32%
61 to 100	35%	60%	Diesel	42%	74%
101 to 140	27%	10%			
141 to 180	13%	2%			
>180	10%	1%			
Number of products and observations			2,148	7,828,903	

Source: CCFA, authors' calculations.

and diesel prices increased by almost 30% and 40%, respectively (see Figure C.4 in the Appendix). The fuel cost per km for diesel cars is lower than for gasoline cars by about 20%, because of the lower taxes on diesel and the lower fuel consumption of diesel cars. The changes in aggregate registrations can be linked to fuel price fluctuations, as higher fuel prices incite purchasers to buy more fuel-efficient cars. For instance, Busse et al. (2013) observe that higher fuel prices increase the sales of the most efficient quartiles of car models in the US. We observe a similar pattern in our data when we aggregate the sales according to their quartile of fuel consumption (see Section C in the Appendix).

Our dataset also includes individual characteristics of the purchaser. Importantly, we distinguish between private buyers and firms. Private purchases represent 62% of the sample, for which we observe the consumer's age and activity status (whether she is employed or not); for corporate purchases, we observe the business sector of the firm. In both cases, we additionally observe the residence/registration location postal code (the French *commune*¹⁸). We merge this postal code with supplementary information. First, we use detailed information on tax income available at the postal code level from official statistics collected by French National Statistical Institute (INSEE). For each private car purchaser, we proxy her income with the median earnings of her age group in her postal code. Second, we use an INSEE classification of the type of areas (urban, suburban, rural).¹⁹

¹⁸The 36,600 French communes are rather small in comparison to the European standard, with a median area is 10.73 square kilometers and a median population of 380 inhabitants.

¹⁹As defined in <https://www.insee.fr/fr/information/2115011> (in French).

3.2. Consumer types

In order to account for heterogeneous preferences, we split our sample into consumer types based on demographic characteristics. In practice, we conduct separate analyses for each of these consumer types. We first separate private households and firms into different consumer types, as we believe their preferences are fundamentally different. We further classify consumer types according to the features that may impact annual mileage. The definition of these types should be fine enough to guarantee that they correspond to homogeneous preference groups, but should ensure that we observe sufficient group-level sales for all products. This trade-off results in the definition of 30 distinct consumer types.

For private consumers, we consider three occupational states (young employed under the age of 30, employed over 30, and not employed, with the latter including retirees and unemployed). We sort areas of residence between urban Paris, suburban Paris (larger metropolitan region),²⁰ other urban areas, and suburban/rural zones. Finally, we define two income groups (income proxy above or below the national median income). As group sizes are smaller in urban Paris, we do not distinguish along the income dimension for this area.

We relate this typology of purchasers to the available information on mileage. According to the French National Transport and Travel Survey Survey, we observe large variation in mileage depending on consumer type (Table 2, private households only).²¹ Activity status is an important factor for private owners, as employed consumers have larger mileage across all geographic areas. As shown in Clerc and Marcus (2009), the elasticity to fuel prices of French private consumers largely depends on whether the consumer uses her car to go to work, as commuting represents the majority of kilometers driven in France. Compared to the rest of the country, the average yearly mileage is consistently smaller in urban Paris with its dense public transportation network.²²

The factors influencing fuel-price sensitivity and mileage of firms are *a priori* not clear, because firms are not included in typical transportation surveys and this is the first study, to our knowledge, that explicitly accounts for company car purchases. Additionally, firms do not always pay the operating cost of the vehicles they purchase. This is obviously the case for the car rental sector.

²⁰In the following, we use the term “Paris” or “urban Paris” for Paris and its close and densely populated suburbs (departments Paris (75), Hauts-de-Seine (92), Seine-Saint-Denis (93), Val-de-Marne (94) and some adjoining municipalities) while “suburban Paris” describes the rest of the Île-de-France region.

²¹Information on annual mileage is only available for households and not by age group, computed from INSEE National Transportation and Travel Survey 2007, conducted at the end of the period studied here.

²²See also Baccaini et al. (2007) (in French), who illustrate the variation in average travel times and distances depending on the type of residence areas. Urban Paris is an outlier as reflected in Figure B.3 in the Appendix, as this area has an exceptionally low share of people using their car to go to work.

In other business sectors, company cars sometimes constitute a benefit in kind for employees ("take-home vehicles" that can be used privately). In such a case, fuel expenditures are partly incurred by the employee and partly by the firm. As far as we know, there are no official statistics on the mileage of company cars, nor on the share of take-home vehicles. As mileage and preferences are likely to differ by sector, we distinguish industry/agriculture, car rental, and trade/services. We further use a similar geographic distinction as for households. Firms belonging to the car rental sector are mainly located in urban areas. While car rentals constitute a large share of corporate car purchases (see Table B.7 in the Appendix), the number of observations for these firms is small in rural and suburban areas.

French taxation on company fleets is even more in favor to diesel cars than for private owners. The VAT rates applying to diesel bought by firms is only 4%, much below the normal rate of 19.6%. Firms face also an annual tax on their company car fleet related to the horsepower (before 2004) and CO₂ class (since 2004),²³ which additionally increases the attractiveness of fuel-efficient cars, which are often diesel-fueled.

4. Empirical approach

4.1. Nested logit estimation on consumer type-level aggregate sales

We assume consumer decision making follows the model of equation (1); aggregating across consumers and integrating over the error term distribution of equation (2) allows us to recover the market share of each product jf (model j of fuel-type f) up to an identifying normalization. In order to take into account the heterogeneous preferences among different types of consumers, the data is aggregated separately for each consumer type. As usual in the literature, identification stems from the normalization of the outside good's value to zero. With this normalization, the log-ratio of the market shares (at consumer type-level) of a product jf and the outside good is a linear expression of car characteristics. Consequently, estimating this (standard) equation requires the outside good's market share.

Our dataset of newly registered cars does not provide information on potential buyers who choose the outside option. In the related literature, it is common to calculate the outside good's market share as the difference between the entire potential market size and aggregate sales. While aggregate sales are easily recovered from the data, the true potential market size is usually unknown

²³The yearly amount of the tax ranges from €750 for small cars to €4,500 for the biggest ones in 2014.

Table 2: Average mileage by purchaser type (private households only), km/year

Income	Not employed		Employed	
	Low	High	Low	High
Urban	10,850	10,950	14,950	15,600
Suburban/rural	10,750	14,300	16,250	18,850
Paris urban	9,750		14,050	
Paris suburban	11,950		18,350	

Source: INSEE National Transport and Travel Survey 2007, authors' calculations.

and, thus, approximated using most recent estimates of the population size or the number of people holding a driver's license (for instance, the seminal paper by McFadden, 1978). This number probably dramatically overstates the actual market size with durable goods like cars, because in each given month only a small fraction of consumers considers buying a car. Moreover, when a large portion of new car registrations are made by firms and not by private owners, the number of driving license holders is not necessarily relevant. Huang and Rojas (2014) show both theoretically and practically that coefficients estimated using such an incorrect approximation of market size may be biased. To avoid this potential bias, we follow a suggestion by Huang and Rojas (2014) and move the log of the outside good's quantity to the right-hand side of equation (6) and estimate it as part of the time-specific constant. Our main estimation equation is then:

$$\ln(q_{djft}) = \alpha_d + \beta_d p_{jft}^{km} + \gamma_{1d} p_{jft} + \gamma_{2d} X_{jft} + \sigma_{1d} \ln(s_{df|j}) + \sigma_{2d} \ln(s_{dj|s}) + y_d + m_d + \xi_{djft}, \quad (6)$$

where q_{djft} stands for the aggregate number of sales of product jf at time t by consumer type d , $s_{df|j} = \frac{q_{djft}}{q_{dj}}$ is the relative share of purchases of fuel-type f within purchases of model j in each month t and $s_{dj|s} = \frac{q_{djft}}{q_{dst}}$ is the relative share of model j within the sales of segment s , y_d and m_d are respectively year and month dummies that indirectly capture the outside option.^{24, 25} X_{jft} corresponds to observable vehicle characteristics other than the purchasing price p_{jft} and the cost per kilometer p_{jft}^{km} , measuring the expected fuel cost at time t needed to drive one km with the car jf . The cost per km p_{jft}^{km} depends on the car's fuel consumption ϕ_{jft} in L/100km, its fuel-type f (diesel or gasoline) and the expectations about fuel prices. Under the assumption that consumers have random walk expectations on fuel prices, they rely on the observed contemporaneous price.²⁶

²⁴The related literature typically – and equivalently – uses an equation of the log-ratio of market shares $s_{jf} = \frac{q_{jf}}{M}$ and $s_0 = \frac{q_0}{M}$, where q_0 is the number of consumers choosing the outside good and M is the overall market size. In the equation 6 the latter is simplified and the former is indirectly estimated by temporal dummies.

²⁵We also test an alternative specification with a full set of temporal dummies that leaves the main results unchanged, see Section G in the Appendix.

²⁶Given that new cars are rarely sold “off the rack,” it usually takes a few months between purchase and the actual delivery and registration, which is the point of data collection. Thus, we use a three month lag of fuel prices

Equation (6) is estimated using the generalized method of moments separately for each consumer type, assuming these types are homogeneous enough to include only buyers with the same demand parameters. Apart from the main variables of interest, the set of control variables includes horsepower class, CO₂ class,²⁷ number of doors, fuel-type, car body (sedan, sport, compact, etc.), and brand, as well as year and calendar month dummies for long-term temporal trends and yearly seasonality in aggregate new car sales.²⁸

4.2. Endogenous variables and instruments

Fuel prices can be considered as exogenous in the French case, as France represents about 2% of global oil consumption and produces less than 0.1% of the world production.²⁹ French fuel prices are defined by the international energy market, on which France has only a limited weight (which may be not the case for the US, cf. Davis and Kilian, 2011).

By contrast, the vehicle purchasing price p_{jft} is an endogenous result of demand and supply that varies with the unobserved attractiveness ξ_{dft} . Moreover, we only observe list prices, which are not necessarily the actual transaction prices. As usual in the literature, we use a set of instruments based on the characteristics of potential substitutes, in order to capture market concentration and thereby mark-ups. More specifically, in a multi-product Bertrand competition framework, one can derive a set of instruments based on the sums of each characteristics of other models produced by the *same firm* in the same segment and those of *competing firms* (Berry et al., 1995, henceforth “BLP”). This measure is computed twice; once over all products within the same nest and another time over all products in all other nests. Using yearly list prices, we assume that purchase prices do not vary with fuel prices. In the short term, this is likely to be true, as list prices are fixed on a longer horizon than fuel prices; in the medium-run, list prices can obviously adapt to fuel price variation.

Armstrong (2016) argues that in markets with a large number of heterogeneous goods, BLP instruments are no longer sufficiently strong. To address this problem, we add cost-shifters, such as the prices of raw materials, that provide exogenous variations in market prices as they are related to supply but not to demand. Thus, we use the price indices of iron (contemporaneous

rather the contemporaneous fuel price. Empirically, we see a slightly stronger correlation between sales and lagged fuel price, but our results are not fundamentally different when compared to using the contemporaneous fuel price.

²⁷Dummies for CO₂ classes account for marketing-based preferences for CO₂ classes (Koo et al., 2012) beyond direct valuation of fuel cost savings and corporate car registration taxes.

²⁸We have to exclude observations with zero market shares. We test for robustness by excluding not only months with market share equal to zero, but all “rare” models with sales of 0-2 units per month. This leaves results unchanged, see Section G in the Appendix.

²⁹In 2009, see <http://www.eia.gov/countries/country-data.cfm>. Retrieved on 14/03/2015.

and lagged value) and indices of export prices of tires as instruments, both multiplied by the car's weight. In our data, these cost shifters are strongly correlated with vehicle prices.

The within-segment market share $s_{dj|s}$ is endogenous by definition. As for the price, we use BLP-style instruments for this variable and further add the number J_s of offered goods per segment s .

Finally, we instrument the within-model market share $s_{df|j}$ by the difference in characteristics of gasoline and diesel versions (fuel consumption, proportion of 3- or 5-door versions, weight, horsepower etc.), capturing the relative attractiveness of each version, as well as the difference in costs shifters for these two versions.

As pointed out by Bound et al. (1995), using many over-identifying restrictions can lead to misleading results if the instruments are weak. In case of only one endogenous variable, it is now common to test the strength of the instruments by using the first-stage F-values, as proposed by Stock and Yogo (2005). Sanderson and Windmeijer (2016) extend this method to regressions with multiple endogenous variables: for each endogenous variable, the relevant test statistic is then the first-stage F-value *conditional* on the other two endogenous regressors, which can be compared to the values tabulated by Stock and Yogo (2005). We compute these test statistics for each of our three endogenous variables and for each consumer type. At a 5% significance level, for most regressions we reject a bias of the 2SLS regression relative to an OLS of more than 5%; in two cases (out of eighty) we can only reject biases superior to 20% (cf. Section F in the Appendix). One case is problematic, as we cannot reject that our instruments are too weak to identify the within-model parameter σ_{1d} for the purchases by car rental companies in suburban Paris. This result can be explained by the very small sample size. This type represents less than 0.1% of the entire sample, and aggregate results are virtually identical when we drop this group.

5. Empirical results

5.1. Main parameter estimates

Generally speaking, the estimates are in line with theoretical expectations.³⁰ We find substantial heterogeneity across consumer types in the magnitude of coefficient β_d corresponding to the fuel cost per km (Table E.9 in the Appendix). For instance, we observe that the estimated coefficients are lower for not employed private consumers compared to employed consumers. Working

³⁰The estimated parameters are not directly economically interpretable. This is why we refer the interested reader to our detailed result tables in Section E of the Appendix

people have to drive more and are thus expected to be the more responsive to fuel price changes. In urban Paris, more public transport alternatives are available and for all types of consumers the estimates are small or non significant.

The estimated coefficients for firms are lower than for private consumers. In some cases estimates obtained for firms are not significant, which may be due to small sample sizes for these types.³¹ For the rental sector in urban Paris, we obtain a positive coefficient, implying negative preferences for fuel economy. This counterintuitive results may be explained by the fact that the fuel for rental cars is typically paid by the hirers and – given the mostly urban location – individual distances tend to be small. This coefficient may then reflect preferences for other attributes of vehicles (for instance, luxury features) that are linked with fuel efficiency (see e.g. Helfand et al., 2011, for a discussion of the choice of vehicles as a positional good).

The estimates for substitution between gasoline and diesel versions of the same model σ_{1d} , as well for as substitution within segment σ_{2d} lie within the unit interval (without being technically constrained to this range), which is a crucial condition to allow a random utility interpretation (McFadden, 1978). Within-segment correlation σ_{2d} is relatively low, on average 0.2, implying a significant but weak correlation within segments (Table E.11 in the Appendix). Within-model correlation σ_{1d} is small in magnitude for corporate purchasers, while for private consumers σ_{1d} is around 0.5, implying a high correlation between the two fuel-type versions of the same model (see Table E.10 in the Appendix). This pattern is consistent with our expectations: purchasers have a preference for a particular model and substitute easily between gas and diesel versions when fuel prices change, rather than switching to a different model. This intensity of substitution between the gasoline and diesel versions of the same model appears to be higher in urban areas (including urban and suburban Paris) than in rural areas. Indeed, while diesel cars yield savings in running costs for long journeys, this advantage is not clear-cut for city driving.

5.2. Elasticities of aggregate fleet characteristics and willingness to pay

The magnitude of the estimated parameters is not directly informative, but they allow us to recover more meaningful economic parameters, such as the elasticities of the aggregate fleet characteristics with respect to fuel prices and the willingness to pay for fuel efficiency.

We provide the elasticities of the share of diesel cars, of average fleet fuel consumption (in L/100km) and of average CO₂ intensity, as these are the outcomes of interest for a policy maker

³¹In suburban Paris, corporate sales represent less than 0.5% of the sample, see Table B.7 in the Appendix.

in this context. While the first variable is crucial for local pollution, the others are more linked to global warming issues.³²

As diesel engines are on average more efficient, an increase in fuel prices (from oil market fluctuations) raises the share of diesel cars among new purchases π^D (see elasticity η_D in Table 3).³³ Consequently, both the average fleet fuel consumption and the average CO₂ intensity decrease (see η_ϕ and η_{CO_2} in Table 3).

Additionally, we use the estimates on consumer preferences to calculate the consumer's willingness to pay for fuel efficiency in € per €/km, as it simply corresponds to the ratio between the coefficient of the price per kilometer β_d and the coefficient of the purchasing price γ_d .³⁴ A back-of-the-envelope calculation allows us to provide information on the consumer's trade-off between purchasing price and the expected discounted operating cost over the car's lifetime. In order to approximate the operating cost, we use yearly average mileage from the household Transportation Survey conditional on residence area and occupational status (see Table 2). We assume a discount rate of 11%, a fixed car lifetime of 15 years, and constant annual mileage. Under these assumptions, private consumers seem to dramatically undervalue fuel economy (see Table 4): they are only willing to pay between 1.4 and 9.6 cents in order to reduce the net present value of their operating costs by 1€.

These results can be compared to previous estimates obtained in the literature. Greene (2010) provides a detailed review of the existing literature and derives willingness to pay from the empirical evidence provided by more than 25 studies. In comparison, our estimates of the willingness to pay for fuel efficiency are relatively low, without being extreme. For instance, the results of Berry et al. (1995) suggest a smaller willingness to pay (less than 1%), similar to Feng et al. (2005). Many other studies observe higher willingness to pay. However, almost all the papers reviewed by Greene (2010) focus on the U.S. market. As far as we know, the evidence on the French market comparable to our results is scarce. As reviewed for instance in Helfand et al. (2011), the undervaluation of future fuel economy may be explained, for instance, by bounded rationality or difficulty in calculating expected fuel savings.

³²See Section D in the Appendix for details on the computation of these elasticities. For the sake of illustration, we compute different elasticities $\eta_{j\mathbf{f}}$ for some of the most popular cars in our data (see Table E.13 in the Appendix). An increase in fuel prices (both gasoline and diesel) reduces demand for all cars ($\eta_{j\mathbf{f}} < 0$), but the magnitude varies. For instance, the elasticity of the demand for the Peugeot 307 gasoline model with respect to fuel price is -0.17, while it is -0.34 for the Citroen C3 gasoline model.

³³ π^D is the market share of diesel cars *among purchased cars* whereas the market shares s_j , s_s etc. are defined on the whole market, including the outside good.

³⁴The price coefficient γ_d is multiplied by 10,000 as the vehicle price is expressed for 10,000 € (for readability).

Table 3: Elasticities with respect to fuel prices: diesel share, average fleet fuel consumption (L/km) and CO₂ intensity (g/km)

	Diesel share	Fuel cons.	CO ₂
	η_D	η_ϕ	η_{CO_2}
Households	0.026*** (0.003)	-0.013*** (0.001)	-0.015*** (0.001)
Firms	0.017*** (0.003)	-0.004*** (0.001)	-0.006*** (0.001)
Total	0.029*** (0.003)	-0.010*** (0.001)	-0.012*** (0.001)

Source: CCFA, authors calculations. Estimates rely on the parameters of Equation (6) estimated by GMM separately for each type of consumers. Standard errors are estimated by bootstrap (500 replications).

Using aggregate data on the largest European car markets, Klier and Linn (2011) estimate that a 1\$ increase in fuel prices per gallon increases the average miles-per-gallon (MPG) efficiency in France by 0.21, implying an average fuel consumption elasticity η_ϕ of -0.017.³⁵ This value is similar to our estimate and much lower than the value they find for the US: there, 1\$ decreases the average MPG by 1.03, implying an average fuel consumption elasticity of -0.042. Our estimate is smaller than the estimates of Clerides and Zachariadis (2008), who find a short-term elasticity of average fleet fuel consumption to fuel prices equal to -0.08 for the EU, using aggregate data.

5.3. Tax alignment

We moreover predict the impact of a tax change, assuming consumers react identically to fuel price changes from market fluctuations and from tax reforms. The first policy studied in this paper aligns diesel and gasoline taxes. Leaving gasoline taxes unchanged, this policy raises diesel taxes by almost one-third, from 43 cent/liter to 60 cent/liter. Furthermore, this policy abandons the VAT advantage for corporate diesel cars, raising it to the standard rate of 19.6%.

As expected, the induced variation of the diesel share is negative and strong: since taxes only increase for diesel, the reform incites many purchasers to substitute with gasoline-fueled cars. We find that such a policy reduces the aggregate share of diesel cars in overall sales by $\Delta^{tCO_2}\eta_D = 5.9\%$, that is from 69% to 65% (Table 5). This decrease in diesel sales comes mostly from households which substitute more easily away from diesel engines, rather than from firms (7.4% and 3.6% reduction, respectively).

This result can be compared to Klier and Linn (2013), who also evaluate a hypothetical policy of equalizing diesel and gasoline prices. At the European level, their estimates suggest that the

³⁵Li et al. (2009) also obtain a short-term elasticity to fuel prices of similar magnitude. Brons et al. (2008) analyze more in detail the aggregate elasticity of fuel demand, resulting of the elasticities of mileage, fuel consumption and car ownership; their meta-study also finds this elasticity to be empirically small.

Table 4: Willingness to pay for fuel economy in % of net present value of this fuel economy (back-of-the-envelope calculations)

Income	Not employed		Young employed (<30)		Employed (>30)	
	Low	High	Low	High	Low	High
Urban	1.94%	1.61%	5.68%	3.48%	5.18%	9.59%
Suburban/rural	1.48%	1.49%	2.15%	3.93%	1.90%	6.45%
Paris urban		3.46%		2.39%		4.21%
Paris suburban		1.40%		2.19%		5.04%

Source: CCFA, authors calculations. Estimates rely on the parameters of Equation (6) estimated by GMM separately for each type of consumers. The discounted expected number of kilometers over the car's lifetime are computed using type-specific annual mileage, a discount rate of 11% and an expected lifetime of 15 years. Willingness to pay (in € per €/km) is calculated by dividing β_d by $\gamma_d * 10^{-6}$; willingness to pay is then converted to willingness to pay in % of net present value by multiplying with discounted expected mileage.

impact of such a policy on the market share of diesel cars is negligible (less than 1%). Two elements explain this difference. First, our analysis is focused on France, where the gap between gasoline and diesel taxes is the highest of all countries they consider: the hypothetical policy change is strong, which is not the case for other countries.³⁶ Second, as they emphasize, Klier and Linn (2011) cannot distinguish between company cars and privately owned cars in their data. According to our estimates, firms are less sensitive to fuel prices (Table 3).

According to our estimations, the resulting substitution between gasoline and diesel cars has only a marginal impact on fuel consumption of the new vehicle fleet and CO₂ intensity. This is consistent with the fact that gasoline cars consume more liters of fuel per km but produce less CO₂ per liter of fuel.³⁷ The alignment policy *increases* fuel consumption (Table 5) and *reduces* the average CO₂ intensity of newly purchased cars. Both effects are statistically significant, but small: in spite of the large jump in diesel tax, average fleet fuel consumption increases only by 0.44% and average CO₂ intensity decreases by 0.12%. In absolute terms, fuel consumption increases by 26 mL/100km from the average of 6L/km and CO₂ intensity is reduced by 180mg/km from the average of 152g/km.

5.4. Carbon tax

We also predict the impact of a carbon tax, proportional to the carbon emissions of each fuel-type. For the sake of comparability, the amounts are calibrated such that the government revenue is equal to the previous tax alignment policy, yielding a price of €51 per tonne of CO₂ (thus more

³⁶Estimates detailed by countries are available in a previous working paper (Klier and Linn, 2011). They find that the diesel market share in France decreases by 1.4 percentage points. This reduction is higher than the effect in most other countries they examine.

³⁷One liter of gasoline is transformed to 2.33 kg of CO₂, while one liter of diesel is transformed to 2.63 kg of CO₂; see, for example, Demirel (2012). The mass of CO₂ per liter of fuel that weighs less than a kg might seem surprising; it is a result of the association of carbon elements from the fuel and ambient oxygen.

Table 5: Percentage impact of a carbon tax and a tax alignment on diesel share, average fleet fuel consumption (L/km) and CO₂ intensity (g/km)

	Tax alignment			Carbon tax		
	Diesel share $\Delta^{t_D} \eta_D$	Fuel cons. $\Delta^{t_D} \eta_\phi$	CO ₂ $\Delta^{t_D} \eta_{CO_2}$	Diesel share $\Delta^{t_{CO_2}} \eta_D$	Fuel cons. $\Delta^{t_{CO_2}} \eta_\phi$	CO ₂ $\Delta^{t_{CO_2}} \eta_{CO_2}$
Households	-7.43*** (0.36)	0.50*** (0.03)	-0.13*** (0.01)	0.15** (0.07)	-0.43*** (0.02)	-0.43*** (0.02)
Firms	-3.55*** (0.46)	0.28*** (0.09)	-0.11* (0.06)	0.65*** (0.12)	-0.21*** (0.03)	-0.15*** (0.03)
Total	-5.94*** (0.32)	0.44*** (0.04)	-0.12*** (0.02)	0.59*** (0.07)	-0.37*** (0.02)	-0.33*** (0.02)

Source: CCFA, authors calculations. Estimates rely on the parameters of Equation (6) estimated by GMM separately for each type of consumers. Instrumental variables for prices are the price indices of iron (contemporaneous and lagged value) and indices of export prices of tires, interacted with the car model's weight. Standard errors are estimated by bootstrap (500 replications).

ambitious that the current level of the carbon tax in France, which is €30.5/tCO₂ in 2017). This results in an increase of 11.9 cent/liter of gasoline and 13.4 cent/liter of diesel, representing around 9% of the average end-user price.³⁸

The impact $\Delta^{t_{CO_2}} \eta_D$ of this carbon tax policy on the share of diesel engines sold is positive, but small: it increases the diesel share by 0.6% (Table 5). The carbon tax reduces average fleet fuel consumption, as well as average CO₂ intensity (Table 5). The impacts are significant but small. The fuel consumption decreases by 0.37%, which is only around 22 mL/100km from the average of 6L/km; CO₂ emission intensity shifts by 0.33% which is down 500mg/km from the average of 152g/km.

6. Discussion and concluding remarks

All in all, according to our estimates, the willingness to pay of French consumers for fuel efficiency is low: less than 10 cents to save 1€ of discounted expected operating cost. However, these conclusions rely on several assumptions, that we will discuss here in more detail.

First, the demand model does not take into account long-run shifts on the supply side. While one can be confident that the monthly fuel price variation used for identification in this article does not impact the characteristics of available cars instantaneously, the producers probably react in the long run: if fuel efficiency becomes more valuable, the producers might, in the medium-run, adjust their list prices and, in the long-run, adjust the products developed and offered. For Klier and Linn (2013), this means that these short-run results underestimate the true impact on fuel efficiency and emissions, which would be enhanced by the producers' reactions. Verboven (2002) argues on

³⁸This scenario maintains the VAT rebate for diesel cars of corporate consumers.

the opposite that the producers' price reaction counteracts the consumers' reaction to changes in fuel taxes. In practice, one could argue, like Goldberg (1998), that a short-term consumer reaction as small as suggested by our estimates has probably little impact on the producers.

Another limitation to the extension of our results is that our effects are identified on fuel price variation. One may question whether consumers indeed react identically to fuel price changes from oil market fluctuations and to tax reforms. If consumers place more weight on certain (rather than uncertain) price changes for behavioral reasons like salience, or have a reversal to the mean expectation that is impacted more strongly by taxes than by oil price fluctuations, our methodology underestimates the impact of fuel tax reform. Similarly, if consumers are loss averse (in the sense of prospect theory, see Greene, 2011), reducing uncertainty increases the incentives to invest in fuel efficiency, so that our methodology again underestimates the effect of the reforms. However, if consumers are risk averse, fuel efficiency is more valuable the more prices are volatile (reducing final volatility of operating costs and thus serving as an insurance); in that case, our methodology overestimates the impact. Our methodology cannot account for behavioral effects, such as asymmetric responses for price increases and decreases (discussed in Greene, 2010).

Finally, we rely on strong simplifying assumptions about usage: mileage, as well as car lifetime, may also be expected to change with fuel prices. Ultimately, the aim of environmental policy is not to increase fuel efficiency, but rather to decrease total emissions, which result from the interaction of fuel consumption rates and mileage. Previous research suggests that the rebound effect might counter-balance the positive impact on fuel consumption (e.g. Austin and Dinan, 2005; Frondel et al., 2012), meaning that the (already small) estimated effects become even less economically and environmentally significant. Nevertheless, the change in the composition of the vehicle fleet impacts fuel efficiency in the long run as cars usually circulate for about 15 years. To our knowledge, there is no study that includes mileage elasticity to fuel prices and to fuel efficiency, as well as potentially elastic lifetime, so these computations usually remain back-of-the-envelope sketches (e.g. Grigolon et al., 2014; Allcott and Wozny, 2014; Busse et al., 2013).³⁹

In spite of these limitations, this study has original features that deserve to be emphasized. The transaction-level registration dataset allows to account for purchaser heterogeneity in a simple but innovative way. Indeed, consumer types react differently to fuel tax changes. A large part of the aggregate market reaction comes from households, and in particular from urban and non-working

³⁹These papers account for mileage at a detailed car- or consumer-level but assume zero elasticity; they can thus not account for the "rebound effect" (Small and Van Dender, 2007).

consumers. To our knowledge, the important distinction between household and firm purchases is not accounted for in earlier related literature, even though firm purchases constitute about a third of the market in our sample. Corporate purchases are particularly important for the diesel share, as firms buy mostly diesel-powered cars and we show that they are less likely to substitute away from them in the short term. As far as we know, this is the first study documenting this difference on the car market and we lack previous evidence to compare these results. Further research is needed to clarify whether this is due to differences in mileage or whether there are behavioral and organizational factors at play.

Acknowledgements

The authors thank Pio Baake, Xavier D'Haultfœuille, Éric Dubois, Christian von Hirschhausen, Emmanuel Massé, Giulia Pavan, Corinne Prost, and Hannes Ullrich for their insightful comments. This paper also benefited from comments by participants at the 12th Louis-André Gérard-Varet seminar, the fifth World Congress of Environmental and Resource Economists, the 41th annual conference of the European Association for Research in Industrial Economics, and the 29th annual congress of the European Economic Association. The authors also thank the CCFA (*Comité des Constructeurs Français d'Automobiles*) for providing them with the data.

- Adda J and Cooper R (2000) Balladurette and juppette: A discrete analysis of scrapping subsidies. *Journal of political Economy*, 108(4): 778–806.
- Allcott H and Wozny N (2014) Gasoline prices, fuel economy, and the energy paradox. *Review of Economics and Statistics*, 96(5): 779–795.
- Anderson S. T, Kellogg R, and Saltee J. M (2013) What do consumers believe about future gasoline prices? *Journal of Environmental Economics and Management*, 66(3): 383–403.
- Armstrong T. B (2016) Large market asymptotics for differentiated product demand estimators with economic models of supply. *Econometrica*, 84(5): 1961–1980.
- Austin D and Dinan T (2005) Clearing the air: the costs and consequences of higher CAFE standards and increased gasoline taxes. *Journal of Environmental Economics and Management*, 50(3): 562–582.
- Baccaini B, Sémécurbe F, and Thomas G (2007) Les déplacements domicile-travail amplifiés par la périurbanisation. *INSEE Première*, 1129: 1–4.
- Berry S, Levinsohn J, and Pakes A (1995) Automobile prices in market equilibrium. *Econometrica*, 63(4): 841–890.
- Berry S. T (1994) Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, 25(2): 242–262.
- Bound J, Jaeger D, and Baker R (1995) Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *Journal of the American Statistical Association*, 90(430): 443–450.
- Brons M, Nijkamp P, Pels E, and Rietveld P (2008) A meta-analysis of the price elasticity of gasoline demand. A SUR approach. *Energy Economics*, 30(5): 2105 – 2122.
- Busse M. R, Knittel C. R, and Zettelmeyer F (2013) Are consumers myopic? Evidence from new and used car purchases. *American Economic Review*, 103(1): 220–56.
- Cames M and Helmers E (2013) Critical evaluation of the European diesel car boom-global comparison, environmental effects and various national strategies. *Environmental Sciences Europe*, 25(1): 1–22.

- Cardell N. S (1997) Variance components structures for the extreme-value and logistic distributions with application to models of heterogeneity. *Econometric Theory*, 13(2): 185–213.
- Clerc M and Marcus V (2009) Élasticités-prix des consommations énergétiques des ménages. Working Papers of the DESE 8, INSEE.
- Clerides S and Zachariadis T (2008) The effect of standards and fuel prices on automobile fuel economy: an international analysis. *Energy Economics*, 30(5): 2657–2672.
- Davis L. W and Kilian L (2011) Estimating the effect of a gasoline tax on carbon emissions. *Journal of Applied Econometrics*, 26(7): 1187–1214.
- Demirel Y (2012) *Energy: Production, Conversion, Storage, Conservation, and Coupling*: Springer.
- D’Haultfœuille X, Givord P, and Boutin X (2014) The environmental effect of green taxation: the case of the French bonus/malus. *The Economic Journal*, 124(578): F444–F480.
- Feng Y, Fullerton D, and Gan L (2005) Vehicle choices, miles driven, and pollution policies. NBER Working Papers 11553, National Bureau of Economic Research, Inc.
- Fronzel M, Ritter N, and Vance C (2012) Heterogeneity in the rebound effect: further evidence for Germany. *Energy Economics*, 34(2): 461 – 467.
- Fronzel M and Vance C (2014) More pain at the diesel pump? An econometric comparison of diesel and petrol price elasticities. *Journal of Transport Economics and Policy (JTEP)*, 48(3): 449–463.
- Goldberg P. K (1995) Product differentiation and oligopoly in international markets: the case of the U.S. automobile industry. *Econometrica*, 63(4): 891–951.
- (1998) The effects of the corporate average fuel efficiency standards in the US. *The Journal of Industrial Economics*, 46(1): 1–33.
- Greene D. L (2010) How consumers value fuel economy: a literature review. Technical Report, Environmental Protection Agency.
- (2011) Uncertainty, loss aversion, and markets for energy efficiency. *Energy Economics*, 33(4): 608 – 616, Special Issue on The Economics of Technologies to Combat Global Warming.

- Grigolon L, Reynaert M, and Verboven F (2014) Consumer valuation of fuel costs and the effectiveness of tax policy: evidence from the European car market. Discussion Paper 10301, CEPR.
- Grigolon L and Verboven F (2014) Nested logit or random coefficients logit? A comparison of alternative discrete choice models of product differentiation. *Review of Economics and Statistics*, 96(5): 916–935.
- Helfand G, Wolverton A et al. (2011) Evaluating the consumer response to fuel economy: a review of the literature. *International Review of Environmental and Resource Economics*, 5(2): 103–146.
- Hivert L (2013) Short-term break in the French love for diesel? *Energy Policy*, 54: 11–22.
- Huang D and Rojas C (2014) Eliminating the outside good bias in logit models of demand with aggregate data. *Review of Marketing Science*, 12(1): 1–36.
- Klier T and Linn J (2011) Fuel prices and new vehicle fuel economy in Europe. Working Papers 1117, Massachusetts Institute of Technology, Center for Energy and Environmental Policy Research.
- (2013) Fuel prices and new vehicle fuel economy: comparing the United States and Western Europe. *Journal of Environmental Economics and Management*, 66(2): 280–300.
- Knittel C. R and Metaxoglou K (2014) Estimation of random-coefficient demand models: two empiricists’ perspective. *Review of Economics and Statistics*, 96(1): 34–59.
- Koo Y, Kim C. S, Hong J, Choi I.-J, and Lee J (2012) Consumer preferences for automobile energy-efficiency grades. *Energy Economics*, 34(2): 446 – 451.
- Li S, Timmins C, and von Haefen R. H (2009) How do gasoline prices affect fleet fuel economy? *American Economic Journal: Economic Policy*, 1(2): 113–37.
- Mayeres I and Proost S (2001) Should diesel cars in Europe be discouraged? *Regional Science and Urban Economics*, 31(4): 453 – 470, Evaluating Policies to Reduce Transportation Air Pollution.
- McFadden D (1978) Modeling the choice of residential location. *Transportation Research Record*, 673: 72–77.

- Miravete E. J, Moral M. J, and Thurk J (2015) Innovation, emissions policy, and competitive advantage in the diffusion of European diesel automobiles. Discussion Paper 10783, CEPR.
- Pakes A, Berry S, and Levinsohn J. A (1993) Applications and limitations of some recent advances in empirical industrial organization: Price indexes and the analysis of environmental change. *American Economic Review*, 83(2): 241–46.
- Sallee J. M, West S. E, and Fan W (2016) Do consumers recognize the value of fuel economy? Evidence from used car prices and gasoline price fluctuations. *Journal of Public Economics*, 135: 61–73.
- Sanderson E and Windmeijer F (2016) A weak instrument F-test in linear IV models with multiple endogenous variables. *Journal of Econometrics*, 190(2): 212–221.
- Small K. A and Van Dender K (2007) Fuel efficiency and motor vehicle travel: the declining rebound effect. *The Energy Journal*: 25–51.
- Stock J. H and Yogo M (2005) Testing for weak instruments in linear IV regression. in D. W. K. Andrews and J. H. Stock (eds.) *Identification and Inference for Econometric Models*: Cambridge University Press: 80–108, Cambridge Books Online.
- Verboven F (1996) International price discrimination in the European car market. *The RAND Journal of Economics*, 27(2): 240–268.
- (2002) Quality-based price discrimination and tax incidence: evidence from gasoline and diesel cars. *The RAND Journal of Economics*, 33(2): 275–297.

Appendices

A. Nested decision-making structure

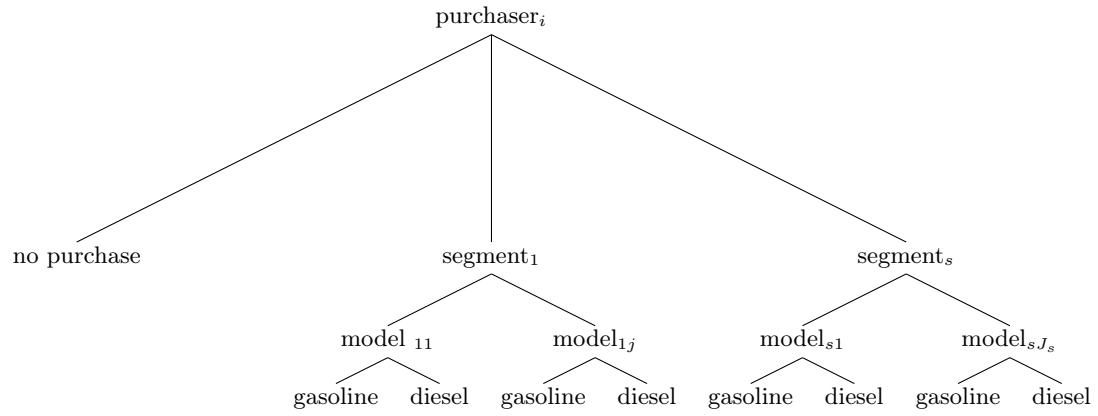


Figure A.2: Nested decision-making structure of the car purchaser

B. Descriptive statistics

Table B.6: Descriptive statistics of car characteristics

	Mean	Coefficient of variation (%)	Percentiles		
			25%	Median	75%
Gasoline (N= 2,376,527)					
Car price (€)	16,606	69.4	11,738	13,975	18,800
Cost of driving 100 km (€)	8.4	22.7	7.3	8.1	9.1
Horsepower (kW)	70	48.8	54	60	80
Fuel consumption (L/100km)	6.8	21.7	6.0	6.5	7.4
CO ₂ intensity (g/km)	159.3	21.7	139.0	152.0	172.0
Diesel (N= 5,452,376)					
Car price (€)	22,968	41.0	16,783	21,875	26,236
Cost of driving 100 km (€)	5.7	27.1	4.8	5.4	6.3
Horsepower (kW)	78	34.6	63	78	88
Fuel consumption (L/100km)	5.6	24.5	4.7	5.4	6.0
CO ₂ intensity (g/km)	147.0	24.5	124.0	141.0	157.0

Note: The coefficient of variation, or unitized risk, is the ratio of the standard error to the mean.

Source: CCFA, authors' calculations.

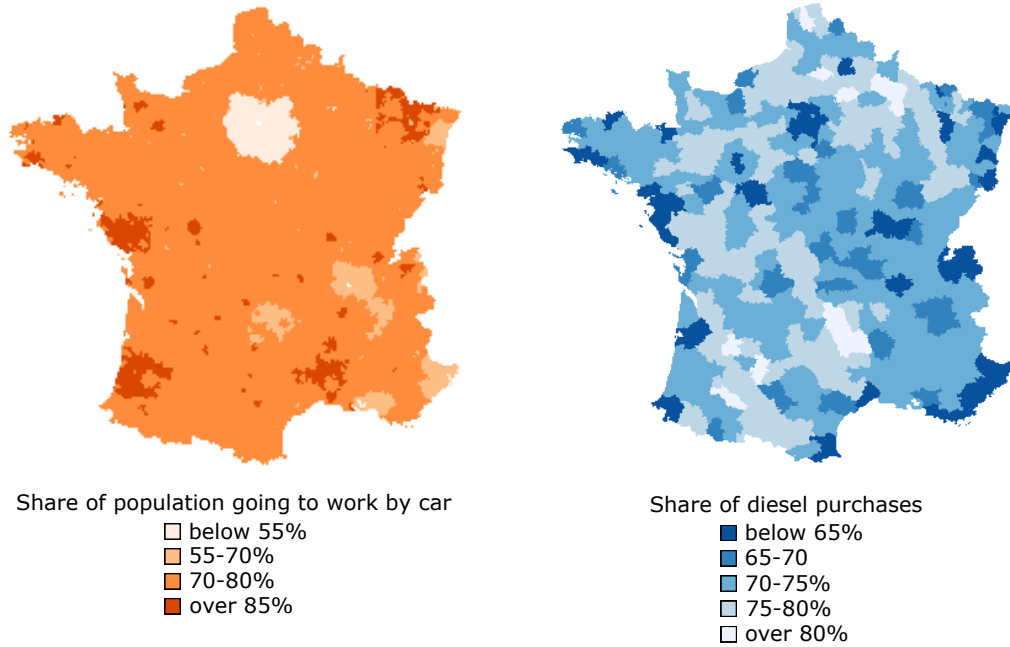


Figure B.3: Overview of spatial variation in share of diesel cars and mileage
Source: CCFA (left graphic) and INSEE National Transport and Travel Survey 2007 (right graphic), authors' calculations.

Table B.7: Distribution of consumer types in our data (%)

<i>Private consumers</i>							
Income	Not employed		Young employed (<30)		Employed (≥30)		Total
	Low	High	Low	High	Low	High	
Urban	150,214	82,692	389,903	192,957	679,981	646,949	2,142,696
	5.0%	2.5%	8.7%	8.3%	1.7%	1.5%	27.6%
Suburban/rural	136,187	116,348	246,876	331,066	450,728	564,686	1,845,891
	1.7%	1.5%	3.2%	4.2%	5.8%	7.2%	23.6%
Paris urban	40,298		186,758		486,700		713,756
	0.5%		2.4%		6.2%		9.1%
Paris suburban	11,069		45,160		81,893		138,122
	0.1%		0.6%		1.0%		1.8%
Total	536,808		1,392,720		2,910,937		4,840,465
	11.3%		27.3%		23.5%		62.1%
<i>Firm purchases</i>							
	Industry & agriculture	Car rental		Trade & services	Total		
Urban	307,871	1,261,364		374,754	1,567,383		
	3.9%	16.1%		4.8%	24.8%		
Suburban/rural	113,947	66,416		137,182	383,855		
	1.5%	0.8%		1.8%	4.1%		
Paris urban	203,606	313,880		172,532	565,762		
	2.6%	4.0%		2.2%	8.8%		
Paris suburban	7,674	4,083		25,129	47,902		
	0.1%	0.1%		0.3%	0.5%		
Total	633,098	1,645,743		709,597	2,564,902		
	8.1%	21.0%		9.1%	38.2%		

Source: CCFA, authors' calculations.

C. Fuel price variation and aggregate estimates

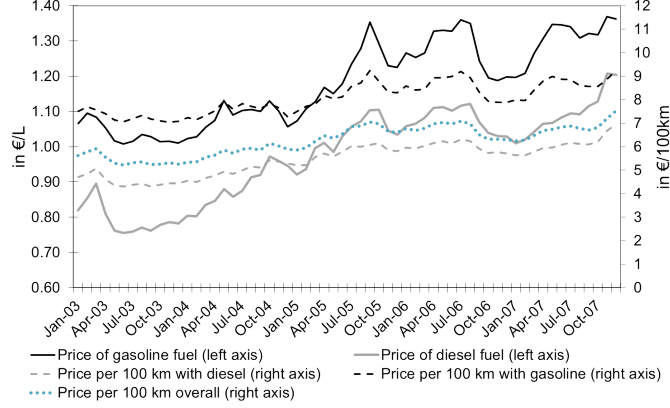


Figure C.4: Monthly consumer fuel prices (incl. taxes) and cost per km (resulting from fuel prices (€) and fuel consumption (L/km) of new car purchases)
Source: French Ministry of Ecology and CCFA, authors' calculations.

Following Busse et al. (2013), we provide a preliminary test of the impact of fuel price fluctuations on the structure of new car market. For this, we compute the quartiles of fuel consumption on products not weighted by sales and then compute sales by quartile.

We then estimate whether there is a correlation between these aggregate quartile sales and fuel prices. In practice, we estimate the following equation:

$$\log Q_{kt} = \gamma_0 + \gamma_1(p_t^f \times ConsumptionQuartile_k) + \gamma_2 ConsumptionQuartile_k + \tau_t + \mu_t + \epsilon_{kt} \quad (C.1)$$

where Q_{kt} is then the national quantity sold within a *ConsumptionQuartile* k in month t , $ConsumptionQuartile_k$ are dummies corresponding to the four quartiles and p_t^f is the fuel price at time t (lagged by three months). We include fixed effects for the quartiles $ConsumptionQuartiles_k$, for year τ_t and for month-of-year μ_t .

The results in Table C.8 show that even in this reduced-form regression with only 232 observations, we identify a differentiated significant impact of fuel prices on car purchases: when fuel prices increase, the sales of models with high fuel consumption (least efficient) decreases while those of more efficient models increases.

Table C.8: Fuel price coefficients γ_1 in the aggregate quantity regression

Fuel economy	Coefficient	Mean market share	Percent change in market share
Consumption quartile 1 (most efficient)	0.85 (0.21)	45.79%	133.96%
Consumption quartile 2	0.06 (0.21)	30.49%	6.18%
Consumption quartile 3	-0.50 (0.21)	17.34%	-39.35%
Consumption quartile 4 (least efficient)	-0.62 (0.21)	6.38%	-46.21%
N	232		

Source: CCFA, authors' calculations. Least squares regression following equation (C.1), including an intercept, time dummies and dummies for *ConsumptionQuartile_{kt}* (not listed).

D. Details on the computation of the elasticities

The demand elasticity $\eta_{\mathbf{sjf}}$ for a given product with respect to oil price p_t^e exclusive of tax at a given point in time can be computed using parameters corresponding to the demand model. The difference to the usually computed price elasticity stems from the fact that fuel prices affect *all* products, proportionally to their fuel consumption: both the nominator and the denominator of the market shares are impacted. In order to find this elasticity, let us differentiate the standard equation of market share $\log(s_{djf}/s_{d0})$ for the model j in segment s and of fuel-type f , using the definition of the cost per kilometer of equation (11). The fuel prices, including tax, for one liter of fuel is given by equation (5), where p_t^e is the pre-tax fuel price, t_D is the lump-sum taxes for diesel, t_G lump-sum taxes for gasoline fuel, and t^{VAT} the VAT rate. For the sake of readability, we omit the index for consumer types and do not state the obvious aggregation over these types for all equations in this section.

$$\frac{\partial s_{sjf}}{s_{sjf}} - \frac{\partial s_0}{s_0} = \beta \partial p_t^e (1 + t^{VAT}) \phi_{sjf} + \sigma_1 \left(\frac{\partial s_{sjf}}{s_{sjf}} - \frac{\partial s_j}{s_j} \right) + \sigma_2 \left(\frac{\partial s_j}{s_j} - \frac{\partial s_s}{s_s} \right) \quad (\text{D.1})$$

or slightly rearranged:

$$\partial s_{sjf} - \frac{\partial s_0}{s_0} s_{sjf} = \beta \partial p_t^e (1 + t^{VAT}) \phi_{sjf} s_{sjf} + \sigma_1 (\partial s_{sjf} - s_{sjf} \frac{\partial s_j}{s_j}) + \sigma_2 s_{sjf} (\frac{\partial s_j}{s_j} - \frac{\partial s_s}{s_s}) \quad (\text{D.2})$$

We then aggregate this last equation over both fuel-type versions of the same model, to obtain the change in the market share of one model j in one segment s :

$$\begin{aligned} \partial s_j - \frac{\partial s_0}{s_0} s_j &= \sum_{f \in j} (\partial s_{sjf} - \frac{\partial s_0}{s_0} s_{sjf}) \\ &= \beta \partial p_t^e (1 + t^{VAT}) \underbrace{\sum_{f \in j} \phi_{sjf} s_{sjf}}_{\bar{\phi}_j s_j} \\ &\quad + \sigma_1 \left(\underbrace{\sum_{f \in j} \partial s_{fjs}}_{\partial s_j} - \frac{\partial s_j}{s_j} \underbrace{\sum_{f \in j} s_{sjf}}_{\partial s_j} \right) \\ &\quad + \sigma_2 \left(\frac{\partial s_j}{s_j} - \frac{\partial s_s}{s_s} \right) \underbrace{\sum_{f \in j} s_{sjf}}_{s_j} \end{aligned}$$

We define $\bar{\phi}_j$ as the sales-weighted average fuel consumption of both fuel-type versions of the

same model j . Thus, we obtain that

$$(1 - \sigma_2) \frac{\partial s_j}{s_j} = \beta \partial p_t^e (1 + t^{VAT}) \bar{\phi}_j - \sigma_2 \frac{\partial s_s}{s_s} + \frac{\partial s_0}{s_0} \quad (\text{D.3})$$

Aggregating further, we recover the relative variation in the market share of segment s ($\frac{\partial s_s}{s_s}$) or of the outside good ($\frac{\partial s_0}{s_0}$) by summing on respectively all cars in the same segment and all new cars. For segment s , we obtain that:

$$\frac{\partial s_s}{s_s} = \beta \partial p_t^e (1 + t^{VAT}) \bar{\phi}_s + \frac{\partial s_0}{s_0}$$

while for the overall number of sold cars we get:

$$\frac{\partial s_0}{s_0} = -\beta \partial p_t^e (1 + t^{VAT}) \bar{\phi} (1 - s_0)$$

Combining these expressions in equation (D.1) we finally compute the elasticity η_{sjf} as:

$$\begin{aligned} \eta_{\text{sjf}} &= \frac{\partial s_{sjf} / s_{sjf}}{\partial p_t^e / p_t^e}, \\ &= \beta (1 + t^{VAT}) p_t^e (\rho_1 \phi_{sjf} + (\rho_2 - \rho_1) \bar{\phi}_j - (\rho_2 - 1) \bar{\phi}_s) - \beta (1 + t^{VAT}) p_t^e \bar{\phi} (1 - s_0), \\ &\approx \beta (1 + t^{VAT}) p_t^e (\rho_1 (\phi_{sjf} - \bar{\phi}_j) + \rho_2 (\bar{\phi}_j - \bar{\phi}_s) + \bar{\phi}_s). \end{aligned} \quad (\text{D.4})$$

where $\rho_i = \frac{1}{1 - \sigma_i} \in [1, +\infty]$. The demand elasticity depends on the parameter β measuring sensitivity to fuel prices, the VAT rate t^{VAT} ,⁴⁰ as well as on the contemporaneous price of fuel and the car's fuel consumption ϕ_{sjf} relative to the average fuel economy of its substitutes (within the same model $\bar{\phi}_j$, within its segment $\bar{\phi}_s$, and among all sales $\bar{\phi}$). The share of the outside good s_0 is close to 1, as a monthly frequency is high compared to vehicle lifetime: most people do not buy a car in any given month and monthly sales are small compared to the market size. Thus, the second term involving $\bar{\phi}(1 - s_0)$ is negligible.

The easier purchasers substitute between fuel-type versions of the same model, resp. between models within a segment, the higher is σ_1 , resp. σ_2 , and, thus, the higher is ρ_1 , resp. ρ_2 . Intuitively speaking, a higher correlation of preference for similar products (same nests) leads to a relatively

⁴⁰This is specific to the French form of petrol tax: as the fuel-type specific taxes are of a lump-sum form, they do not play a role here. The t^{VAT} is the same for both fuel-types.

higher weight put onto the comparison with these similar products.

Obviously, diesel taxes affect cars differently depending on their fuel-type. Using the main model defined in Equation (6), the elasticity $\eta_{\mathbf{s}j\mathbf{f}}^{t_D}$ of demand for a given car sjf with respect to an increase in diesel tax (holding gasoline tax constant) is computed as:

$$\begin{aligned}\eta_{\mathbf{s}j\mathbf{f}}^{t_D} &= \frac{\partial s_{sjf} / s_{sjf}}{\partial t_D / t_D}, \\ &= \beta(1 + t^{VAT})t_D \left(\rho_1(\mathbb{1}_{f=diesel}\phi_{sjf} + (\rho_2 - \rho_1)\pi_j^D \bar{\phi}_j - (\rho_2 - 1)\pi_s^D \bar{\phi}_s) \right. \\ &\quad \left. - \beta(1 + t^{VAT})t_D \bar{\phi}^D \pi^D (1 - s_0), \right. \\ &\approx \beta(1 + t^{VAT})t_D \left(\rho_1(\mathbb{1}_{f=diesel}\phi_{sjf} - \pi_j^D \bar{\phi}_j) + \rho_2(\pi_j^D \bar{\phi}_j - \pi_s^D \bar{\phi}_s) + \pi_s^D \bar{\phi}_s \right). \quad (\text{D.5})\end{aligned}$$

where the indicator $\mathbb{1}_{f=diesel}$ takes the value 1 if the vehicle sjf is running on a diesel engine, π_{sj}^D is the share of diesel in sales of model j , π_s^D is the share of diesel in sales of segment s , and π^D is the overall market share of new diesel cars (among purchases). $\bar{\phi}^D$ is the mean fuel consumption of new diesel cars (sales-weighted average). Again, $(1 - s_0)$ is close to zero and this elasticity can be closely approximated by the first part of the equation.

Intuitively, an increase in the diesel tax rate has a direct negative impact for all diesel cars. However, this effect may be reduced if its substitutes are also impacted by this increase. The effect for gasoline cars of a diesel tax is expected to be positive.

On a more aggregate level, we examine the impact of an increase in fuel prices on the composition of the automobile fleet, with a particular focus on the number of diesel cars purchased. For this, we evaluate the elasticity of the share of diesel cars among new purchases π^D . Assuming again that an international oil price shift equally affects both gasoline and diesel pre-tax prices, such a price shift changes the share of diesel cars by $\eta_{\mathbf{D}}$. In the simple logit demand, this change can be computed as:

$$\begin{aligned}\eta_{\mathbf{D}} &= \frac{\partial \pi^D / \pi^D}{\partial p_t^e / p_t^e}, \\ &= \frac{\sum_{s,j,f} \mathbb{1}_{f=diesel} s_{sjf} \eta_{\mathbf{s}j\mathbf{f}}}{\sum_{s,j,f} \mathbb{1}_{f=diesel} s_{sjf}} - \frac{\partial(1 - s_0)}{\partial p_t^e} \frac{p_t^e}{1 - s_0}, \\ &= \beta(1 + t^{VAT})p_e \left(\rho_1(\bar{\phi}^D - \bar{\phi}_j) + \rho_2(\bar{\phi}_j - \bar{\phi}_s) + \bar{\phi}_s - \bar{\phi} \right), \\ &= \frac{\beta(1 + t^{VAT})p_e}{\pi^D(1 - s_0)} \sum_{s,j} s_j \left(\underbrace{\rho_1 \pi_j^D (\phi_j^D - \bar{\phi}_j)}_{S_1} + \underbrace{\rho_2 (\pi_j^D - \pi_s^D) \bar{\phi}_j}_{S_2} + \underbrace{(\pi_s^D - \pi^D) \bar{\phi}_s}_{S_3} \right), \quad (\text{D.6})\end{aligned}$$

which involves weighted averages of fuel consumption, where the weights are given by the share of diesel sales.⁴¹ $\tilde{\bar{\phi}}_j = \sum_{s,j} \frac{\pi_j^D s_j}{\pi^D(1-s_0)} \bar{\phi}_j$ is the average fuel consumption weighted by the share of diesel per model, whereas $\tilde{\bar{\phi}}_s = \sum_s \frac{\pi_s^D s_s}{\pi^D(1-s_0)} \bar{\phi}_s$ is the average weighted by the diesel share per segment. ϕ_j^D is the fuel consumption of the diesel version of model j . π_j^D , resp. π_s^D , is the share of diesel among purchases of model j , resp. of segment s .

The interpretation of this equation is not straightforward. In the simplest logit case ($\sigma_1 = \sigma_2 = 0$), $\eta_D = \beta(1 + t^{VAT})p_e(\bar{\phi}^D - \bar{\phi})$. Naturally, η_D depends on the average fuel consumption of diesel cars relative to the overall average fuel consumption. $\bar{\phi}^D - \bar{\phi}$ is always negative because diesel cars are more fuel-efficient. β is negative as well, meaning that η_D is positive: if fuel prices increase, purchasers substitute to more fuel-efficient diesel cars and their share among purchases increases.

In a nested setup, the effect is less straightforward, but we still expect a positive sign. Indeed, the first term S_1 in Equation (D.6) involves the difference between diesel fuel consumption and average fuel consumption; again, this change is expected to be negative as diesel engines tend to be more fuel-efficient. However, we do not have such an unambiguous relation for the two other terms S_2 and S_3 .⁴² Both ρ_1 and ρ_2 are positive and larger than one. In practice ρ_2 is smaller than ρ_1 , such that η_D is most strongly impacted by the first element of the parenthesis, which is likely to be positive.

Similarly, the elasticity of the share of diesel cars π^D to a change in fuel taxes (holding gasoline taxes constant) $\eta_D^{t_D}$ is:

$$\eta_D^{t_D} = \frac{\partial \pi^D / \pi^D}{\partial t_D / t_D},$$

$$= \beta(1 + t^{VAT})p_e \left(\rho_1(\bar{\phi}^D - \widetilde{\pi_j^D \bar{\phi}_j}) + \rho_2(\widetilde{\pi_j^D \bar{\phi}_j} - \widetilde{\pi_s^D \bar{\phi}_s}) + \widetilde{\pi_s^D \bar{\phi}_s} - \bar{\phi} \right). \quad (D.7)$$

$$(D.8)$$

This elasticity $\eta_D^{t_D}$ depends only on the fuel consumption of diesel cars and on the share of diesel cars among total purchases: the lower their fuel consumption, the smaller the impact of a

⁴¹For any variable A , we denote $\tilde{A} = \sum_{s,j,f} \frac{s_{sjf}}{\pi^D(1-s_0)} A_{sjf} \mathbb{1}_{f=diesel}$ this variable A weighted by the share of the diesel version amongst all diesel cars (for example, $\tilde{\phi}_{sjf}$ corresponds to the average fuel consumption of diesel cars $\bar{\phi}^D$)

⁴²For example, the last term does not have a well defined sign. In the case of only two segments in proportion s_1 and $(1 - s_1)$, this term is proportional to $s_1(1 - s_1)(\pi_{s_1}^D - \pi_{s_2}^D)(\bar{\phi}_{s_1} - \bar{\phi}_{s_2})$. One cannot exclude that this term is positive, for example if cars have a much higher fuel consumption on average in the segment with the higher share of diesel cars.

diesel tax increase.

Finally, we compute the elasticity η_ϕ (respectively η_{CO_2}) of the average fuel consumption (respectively of average CO₂ intensity) of new cars with respect to fuel prices p_t^e and to fuel taxes.

$$\begin{aligned}\eta_\phi &= \frac{\partial \bar{\phi} / \bar{\phi}}{\partial p_t^e / p_t^e}, \\ &= \beta(1 + t^{VAT}) \frac{p_e}{(1 - s_0)\bar{\phi}} \sum_{j,s,f} (\phi_{sjf} s_{sjf} (\rho_1(\phi_{sjf} - \bar{\phi}_j) + \rho_2(\bar{\phi}_j - \bar{\phi}_s) + \bar{\phi}_s - \bar{\phi}))\end{aligned}\quad (\text{D.9})$$

For example, in the simple logit demand model, η_ϕ simplifies to:

$$\eta_\phi = \beta(1 + t^{VAT}) p_t^e \left(\frac{\overline{\phi^2} - \bar{\phi}^2}{\bar{\phi}} \right), \quad (\text{D.10})$$

where $\overline{\phi^2}$ is the mean of squared fuel consumption of new vehicles. Thus, the impact of an oil price shock on average fuel consumption depends on the ratio of the variance and the mean of fuel consumption. Both the variance and the mean of ϕ are always positive, resulting in η_ϕ always being negative in the simple logit case: when fuel prices increase, we expect to find that average fuel consumption is reduced. In the more realistic nested logit demand model, the conclusion is less straightforward. Again, we have some intuition for the first term of Equation (D.9), which is of first order in the sum: it can be simplified and rewritten as $\beta \rho_1 \sum_{s,j} \pi_j^D (1 - \pi_j^D) s_j (\phi_j^D - \phi_j^G)^2$ and is thus expected to be negative.

The elasticity of average fuel consumption $\eta_\phi^{t_D}$ (respectively $\eta_{\text{CO}_2}^{t_D}$) to a change in diesel tax (holding gasoline tax constant) can be written in case of a simple logit demand model:

$$\begin{aligned}\eta_\phi^{t_D} &= \frac{\partial \bar{\phi} / \bar{\phi}}{\partial t_D / t_D}, \\ &= \beta t_D (1 + t^{VAT}) \underbrace{\frac{\beta \pi^D}{\bar{\phi}}}_{<0} \left(\underbrace{\overline{\phi_D^2} - \bar{\phi}_D^2}_{>0} + (1 - \pi^D) \bar{\phi}_D \underbrace{(\bar{\phi}_D - \bar{\phi}_G)}_{<0} \right).\end{aligned}\quad (\text{D.11})$$

This elasticity depends on the fuel consumption of diesel cars and on their relative share among purchases compared with the average fuel consumption. The sign is not clear-cut. An increase in the diesel tax reduces the share of diesel cars, which are more fuel-efficient. The higher the gap between the average fuel consumption of gasoline and diesel cars, the higher the increase in the average fuel consumption of new cars. This effect is partially offset by the dispersion in fuel consumption of diesel cars, as we expect that an increase in diesel prices has more impact

on less fuel-efficient cars. Overall, we expect that a rise in diesel tax increases the average fuel consumption of new cars if diesel cars are more fuel-efficient than gasoline cars and the diesel share is not too high.

E. Detailed estimation results (main specification)

Table E.9: Estimates for the coefficient on cost per km β_d

<i>Private consumers</i>						
	Not employed		Young professional		Employed (>30)	
Income	Low	High	Low	High	Low	High
Urban	-0.11*** (0.02)	-0.08*** (0.02)	-0.15*** (0.02)	-0.13*** (0.02)	-0.13*** (0.02)	-0.14*** (0.01)
Suburban/rural	-0.08*** (0.02)	-0.11*** (0.02)	-0.10*** (0.02)	-0.15*** (0.02)	-0.10*** (0.02)	-0.15*** (0.01)
Paris urban	-0.10*** (0.02)		-0.09*** (0.02)		-0.10*** (0.01)	
Paris suburban	-0.03 (0.02)		-0.08*** (0.02)		-0.10*** (0.01)	
<i>Firm purchases</i>						
	Agriculture & industry		Car rental		Trade & services	
Urban	-0.09*** (0.02)		-0.16*** (0.03)		-0.10*** (0.01)	
Suburban/rural	-0.01 (0.01)		-0.03 (0.04)		-0.06*** (0.01)	
Paris urban	-0.07*** (0.02)		0.08*** (0.02)		-0.01 (0.01)	
Paris suburban	-0.01 (0.02)		0.01 (-)		-0.04 (0.02)	

Source: CCFA, authors' calculations. Equation (6) is estimated by GMM separately for each type of consumers. Other controlling variables include horsepower, brand fixed effects, segment fixed effects, class of CO₂, month-year effects, and price. Instrumental variables for prices are the price index of iron (contemporaneous and lagged value, interacted with the car's weight), index of export prices of tires (interacted with the car's weight), BLP-style instruments and differences of characteristics between gasoline and diesel versions. The estimation of car rental purchases in suburban Paris does not converge for all bootstrap draws, which could be due to the very small sample size for this group (see Table B.7).

Table E.10: Estimates for coefficient σ_{1d} (substitutability within model, between engine types)

<i>Private consumers</i>						
Income	Not employed		Young professional		Employed (>30)	
	Low	High	Low	High	Low	High
Urban	0.41 *** (0.04)	0.48 *** (0.04)	0.51 *** (0.03)	0.51 *** (0.03)	0.55 *** (0.02)	0.59 *** (0.02)
Suburban/rural	0.45 *** (0.04)	0.41 *** (0.03)	0.38 *** (0.03)	0.41 *** (0.03)	0.55 *** (0.02)	0.52 *** (0.02)
Paris urban		0.30 *** (0.04)		0.62 *** (0.03)		0.62 *** (0.02)
Paris suburban		0.10 (0.06)		0.34 *** (0.04)		0.57 *** (0.03)
<i>Firm purchases</i>						
Sector	Agriculture & industry		Car rental		Trade & services	
Urban	0.33 *** (0.03)		0.18 *** (0.04)		0.23 *** (0.03)	
Suburban/rural	0.29 *** (0.03)		0.26 *** (0.08)		0.24 *** (0.03)	
Paris urban	0.17 *** (0.04)		-0.16 *** (0.04)		0.18 *** (0.03)	
Paris suburban	0.77 *** (0.05)		0.42 (-)		0.60 *** (0.05)	

Source: CCFA, authors' calculations. Equation (6) is estimated by GMM separately for each type of consumers. Other controlling variables include horsepower, brand fixed effects, segment fixed effects, class of CO₂, month-year effects, and price. Instrumental variables for prices are the price index of iron (contemporaneous and lagged value, interacted with the car's weight), index of export prices of tires (interacted with the car's weight), BLP-style instruments and differences of characteristics between gasoline and diesel versions. The estimation of car rental purchases in suburban Paris does not converge for all bootstrap draws, which could be due to the very small sample size for this group (see Table B.7).

Table E.11: Estimates for coefficient σ_{2d} (substitutability within segment, between models)

<i>Private consumers</i>						
Income	Not employed		Young professional		Employed (>30)	
	Low	High	Low	High	Low	High
Urban	0.11 *** (0.02)	0.13 *** (0.02)	0.22 *** (0.02)	0.19 *** (0.02)	0.32 *** (0.01)	0.39 *** (0.01)
Suburban/rural	0.14 *** (0.02)	0.16 *** (0.02)	0.23 *** (0.01)	0.21 *** (0.01)	0.28 *** (0.02)	0.34 *** (0.01)
Paris urban		0.17 *** (0.02)		0.26 *** (0.02)		0.37 *** (0.02)
Paris suburban		0.21 *** (0.02)		0.20 *** (0.02)		0.30 *** (0.02)
<i>Firm purchases</i>						
Sector	Agriculture & industry		Car rental		Trade & services	
Urban	0.07 *** (0.02)		0.08 *** (0.03)		0.16 *** (0.02)	
Suburban/rural	0.08 *** (0.02)		0.16 *** (0.03)		0.01 (0.02)	
Paris urban	0.12 *** (0.03)		0.10 *** (0.02)		0.24 *** (0.02)	
Paris suburban	0.28 *** (0.03)		0.22 (-)		0.32 *** (0.03)	

Source: CCFA, authors' calculations. Equation (6) is estimated by GMM separately for each type of consumers. Other controlling variables include horsepower, brand fixed effects, segment fixed effects, class of CO₂, month-year effects, and price. Instrumental variables for prices are the price index of iron (contemporaneous and lagged value, interacted with the car's weight), index of export prices of tires (interacted with the car's weight), BLP-style instruments and differences of characteristics between gasoline and diesel versions. The estimation of car rental purchases in suburban Paris does not converge for all bootstrap draws, which could be due to the very small sample size for this group (see Table B.7).

Table E.12: Estimates for coefficient γ_{1d} of the purchasing price

<i>Private consumers</i>						
	Not employed		Young professional		Employed (>30)	
Income	Low	High	Low	High	Low	High
Urban	−0.63*** (0.05)	−0.57*** (0.05)	−0.30*** (0.04)	−0.31*** (0.04)	−0.21*** (0.03)	−0.12*** (0.03)
Suburban/rural	−0.65*** (0.05)	−0.66*** (0.05)	−0.42*** (0.04)	−0.30*** (0.04)	−0.36*** (0.03)	−0.15*** (0.03)
Paris urban	−0.36*** (0.05)		−0.32*** (0.04)		−0.21*** (0.03)	
Paris suburban	−0.20*** (0.05)		−0.25*** (0.04)		−0.14*** (0.03)	
<i>Firm purchases</i>						
Sector	Agriculture & industry		Car rental		Trade & services	
Urban	−0.01 (0.03)		0.14*** (0.05)		−0.00 (0.03)	
Suburban/rural	−0.22*** (0.03)		−0.29*** (0.08)		−0.10*** (0.03)	
Paris urban	−0.01 (0.03)		−0.03 (0.04)		−0.09*** (0.03)	
Paris suburban	−0.14*** (0.03)		−0.28 (−)		−0.27*** (0.05)	

Source: CCFA, authors' calculations. Equation (6) is estimated by GMM separately for each type of consumers. Other controlling variables include horsepower, brand fixed effects, segment fixed effects, class of CO₂, month-year effects, and price. Instrumental variables for prices are the price index of iron (contemporaneous and lagged value, interacted with the car's weight), index of export prices of tires (interacted with the car's weight), BLP-style instruments and differences of characteristics between gasoline and diesel versions. The purchasing price is divided by 10,000 for readability of the coefficients. The estimation of car rental purchases in suburban Paris does not converge for all bootstrap draws, which could be due to the very small sample size for this group (see Table B.7).

Table E.13: Demand elasticity for selected models with respect to fuel prices

model (segment)	fuel	CO ₂ (g/km)	fuel cons. (L/km)	η_{jf}	$\Delta^{tD} \eta_{jf}$ (%)	$\Delta^{tCO_2} \eta_{jf}$ (%)
Audi A6 (sedan)	gasoline	236.9	10.2	−0.22*** (0.03)	1.17*** (0.22)	−6.73*** (0.89)
Audi A6 (sedan)	diesel	200.1	7.6	−0.29*** (0.02)	−18.20*** (1.55)	−9.39*** (0.60)
Citroen C3	gasoline	147.8	6.4	−0.34*** (0.02)	2.46*** (0.23)	−10.62*** (0.51)
Citroen C3	diesel	112.8	4.3	−0.19*** (0.01)	−13.48*** (0.69)	−6.55*** (0.32)
Peugeot 307 (sport)	gasoline	192.7	8.3	−0.17*** (0.01)	1.57*** (0.08)	−4.29*** (0.21)
Peugeot 307 (sport)	diesel	159.0	6.0	−0.32*** (0.01)	−18.62*** (0.87)	−9.41*** (0.43)
Renault Twingo (compact)	gasoline	137.0	5.9	−0.32*** (0.01)	0.86*** (0.03)	−9.78*** (0.44)
Renault Twingo (compact)	diesel	113.0	4.3	−0.25*** (0.01)	−15.62*** (0.93)	−7.30*** (0.37)

Source: CCFA, authors' calculations. Equation (6) is estimated by GMM separately for each type of consumers. Standard errors are estimated by bootstrap (500 replications).

F. Testing for weak instruments

Table F.14: Conditional F-values of the weak instrument test – instruments for the *price*

	<i>Private consumers</i>					
	Not employed		Young employed (<30)		Employed (>30)	
Income	Low	High	Low	High	Low	High
Urban	35.1***	31.9***	51.8***	51.7***	47.8***	49.0***
Suburban/rural	31.7***	37.6***	64.8***	70.9***	51.3***	51.5***
Paris urban	20.4***		42.2***		44.2***	
Paris suburban	16.3**		36.6***		39.4***	
	<i>Firm purchases</i>					
	Industry & Agriculture		Car rental		Trade & services	
Urban	42.2***		11.5**		39.7***	
Suburban/rural	45.9***		34.9***		37.2***	
Paris urban	52.4***		36.3***		34.6***	
Paris suburban	14.2**		14.1**		15.4**	

Note: Stars denote conditional F-values beyond the critical value (at 5% significance level) for different levels of maximal bias of the IV estimator relative to OLS; *** stands for a maximal bias of 5%, ** for 10%, * for 20%.

Table F.15: Conditional F-values of the weak instrument test – instruments for the *market share of the model within its segment* $s_{dj|s}$

	<i>Private consumers</i>					
	Not employed		Young employed (<30)		Employed (>30)	
Income	Low	High	Low	High	Low	High
Urban	68.1***	71.3***	61.4***	62.4***	60.7***	53.6***
Suburban/rural	71.5***	73.3***	71.1***	64.0***	58.9***	55.7***
Paris urban	53.4***		58.3***		49.3***	
Paris suburban	36.5***		53.5***		54.8***	
	<i>Firm purchases</i>					
	Industry & Agriculture		Car rental		Trade & services	
Urban	45.9***		34.9***		37.2***	
Suburban/rural	42.2***		11.5**		39.7***	
Paris urban	52.4***		36.3***		34.6***	
Paris suburban	14.2**		14.1**		15.4**	

Note: Stars denote conditional F-values beyond the critical value (at 5% significance level) for different levels of maximal bias of the IV estimator relative to OLS; *** stands for a maximal bias of 5%, ** for 10%, * for 20%.

Table F.16: Conditional F-values of the weak instrument test – instruments for the *market share of a fuel-type within its model nest* $s_{df|j}$

	<i>Private consumers</i>					
	Not employed		Young employed (<30)		Employed (>30)	
Income	Low	High	Low	High	Low	High
Urban	26.5***	22.6***	32.6***	32.3***	41.9***	44.7***
Suburban/rural	23.6***	27.9***	31.7***	38.1***	43.7***	44.3***
Paris urban	15.0**		27.3***		31.7***	
Paris suburban	16.7**		22.2***		26.5***	
	<i>Firm purchases</i>					
	Industry & Agriculture		Car rental		Trade & services	
Urban	24.2***		21.6***		25.8***	
Suburban/rural	32.4***		6.3*		28.6***	
Paris urban	15.2**		21.0***		20.8***	
Paris suburban	11.7**		2.9		10.4*	

Note: Stars denote conditional F-values beyond the critical value (at 5% significance level) for different levels of maximal bias of the IV estimator relative to OLS; *** stands for a maximal bias of 5%, ** for 10%, * for 20%.

G. Robustness checks: elasticities and policy impacts

We estimate several alternative specifications not just to check that our results are not driven by specification choices, but also to emphasize the impact of the individual hypothesis underlying the main specification. Detailed estimates are available upon requests. This Appendix provides aggregate elasticities (Table G.17) and the predicted impact of our two policy scenarios (tax alignment and carbon tax, Table G.18). The first alternative specification includes “degenerate” nests, i.e. all models including those that are available only with either gasoline or diesel motor. The second alternative specification uses a more commonly used model accounting only for two levels: purchasers choose a segment and then a product within that segment. The third alternative specification estimates a simple logit (no nests), adding model fixed effects. The fourth alternative specification corresponds to the main specification with additionally the full set of time dummies (interactions of month and year dummies). The fifth alternative specification excludes models with strictly less than three unit sales over a month. Finally, the last specification estimates the model jointly for all consumer types, which means we do not account for consumer heterogeneity. On the whole, the estimated impact of our policy scenarios remains at a similar order of magnitude across specifications.

Table G.17: Robustness checks: elasticities with respect to fuel prices of diesel share, average fleet fuel consumption (L/km) and CO₂ intensity (g/km)

	Diesel share	Fuel cons.	CO ₂
	η_D	η_ϕ	η_{CO_2}
<i>Main specification + degenerate nests (gas/diesel-only models)</i>			
Households	0.044*** (0.003)	-0.015*** (0.001)	-0.018*** (0.001)
Firms	0.017*** (0.003)	-0.004*** (0.001)	-0.006*** (0.001)
Total	0.045*** (0.002)	-0.011*** (0.001)	-0.015*** (0.001)
<i>Alternative specification – only one nesting level (segment>model)</i>			
Households	0.042*** (0.003)	-0.014*** (0.001)	-0.017*** (0.001)
Firms	0.015*** (0.004)	-0.004*** (0.001)	-0.006*** (0.001)
Total	0.044*** (0.003)	-0.010*** (0.001)	-0.014*** (0.001)
<i>No nest structure + model fixed effects</i>			
Households	0.046*** (0.002)	-0.019*** (0.001)	-0.016*** (0.001)
Firms	0.008*** (0.002)	-0.005*** (0.001)	-0.004*** (0.000)
Total	0.034*** (0.001)	-0.015*** (0.001)	-0.012*** (0.001)
<i>Main specification + full set of time dummies</i>			
Households	0.046*** (0.002)	-0.019*** (0.001)	-0.016*** (0.001)
Firms	0.008*** (0.002)	-0.005*** (0.001)	-0.004*** (0.000)
Total	0.033*** (0.001)	-0.014*** (0.001)	-0.011*** (0.001)
<i>Main specification – excluding rare models</i>			
Households	0.022*** (0.003)	-0.014*** (0.001)	-0.012*** (0.001)
Firms	0.020*** (0.004)	-0.009*** (0.001)	-0.008*** (0.001)
Total	0.023*** (0.002)	-0.012*** (0.001)	-0.010*** (0.001)
<i>Main specification – without purchaser heterogeneity</i>			
Total	0.039*** (0.004)	-0.028*** (0.003)	-0.025*** (0.002)

Source: CCFA, authors calculations. Estimates rely on the parameters of Equation (6) estimated by GMM separately for each type of consumers. Standard errors are estimated by bootstrap (500 replications).

Table G.18: Robustness checks: percentage impact of carbon tax and tax alignment on diesel share, average fleet fuel consumption (L/km) and CO₂ intensity (g/km)

	Tax alignment			Carbon tax		
	Diesel share $\Delta^{t_D} \eta_D$	Fuel cons. $\Delta^{t_D} \eta_\phi$	CO ₂ $\Delta^{t_D} \eta_{CO_2}$	Diesel share $\Delta^{t_{CO_2}} \eta_D$	Fuel cons. $\Delta^{t_{CO_2}} \eta_\phi$	CO ₂ $\Delta^{t_{CO_2}} \eta_{CO_2}$
<i>Main specification + degenerate nests (gas/diesel-only models)</i>						
Households	-9.37*** (0.35)	0.80*** (0.03)	0.02*** (0.01)	0.55*** (0.08)	-0.50*** (0.02)	-0.47*** (0.02)
Firms	-3.85*** (0.41)	0.24*** (0.08)	-0.19*** (0.05)	0.70*** (0.11)	-0.23*** (0.02)	-0.17*** (0.03)
Total	-7.15*** (0.32)	0.62*** (0.04)	-0.06*** (0.02)	0.99*** (0.06)	-0.44*** (0.02)	-0.36*** (0.02)
<i>Alternative specification – only one nesting level (segment>model)</i>						
Households	-9.17*** (0.38)	0.79*** (0.03)	0.02*** (0.01)	0.49*** (0.08)	-0.48*** (0.03)	-0.45*** (0.02)
Firms	-3.51*** (0.54)	0.22*** (0.09)	-0.17*** (0.06)	0.59*** (0.14)	-0.22*** (0.03)	-0.16*** (0.03)
Total	-6.84*** (0.40)	0.59*** (0.05)	-0.05*** (0.02)	0.97*** (0.08)	-0.42*** (0.02)	-0.35*** (0.02)
<i>No nest structure + model fixed effects</i>						
Households	-7.11*** (0.42)	0.51*** (0.03)	-0.09** (0.04)	0.76*** (0.05)	-0.54*** (0.04)	-0.49*** (0.04)
Firms	-2.24*** (0.49)	0.14* (0.08)	-0.11*** (0.04)	0.20*** (0.06)	-0.18*** (0.02)	-0.16*** (0.02)
Total	-5.13*** (0.36)	0.38*** (0.04)	-0.10*** (0.03)	0.63*** (0.04)	-0.42*** (0.03)	-0.37*** (0.03)
<i>Main specification + full set of time dummies</i>						
Households	-7.11*** (0.43)	0.51*** (0.04)	-0.09** (0.05)	0.76*** (0.05)	-0.54*** (0.04)	-0.49*** (0.04)
Firms	-2.04*** (0.43)	0.13* (0.07)	-0.10*** (0.03)	0.20*** (0.06)	-0.17*** (0.02)	-0.15*** (0.02)
Total	-4.89*** (0.34)	0.37*** (0.04)	-0.10*** (0.03)	0.62*** (0.04)	-0.41*** (0.03)	-0.36*** (0.03)
<i>Main specification – excluding rare models</i>						
Households	-6.59*** (0.37)	0.41*** (0.03)	-0.15*** (0.01)	0.10 (0.08)	-0.40*** (0.03)	-0.40*** (0.02)
Firms	-5.06*** (0.62)	0.44*** (0.10)	-0.12* (0.07)	0.46*** (0.11)	-0.30*** (0.05)	-0.26*** (0.05)
Total	-6.37*** (0.45)	0.47*** (0.05)	-0.13*** (0.03)	0.25*** (0.07)	-0.36*** (0.02)	-0.35*** (0.02)
<i>Main specification – without purchaser heterogeneity</i>						
Total	-7.45*** (0.77)	0.45*** (0.07)	-0.26*** (0.02)	0.26*** (0.05)	-0.61*** (0.06)	-0.60*** (0.05)

Source: CCFA, authors calculations. Estimates rely on the parameters of Equation (6) estimated by GMM separately for each type of consumers. Instrumental variables for prices are the price indices of iron (contemporaneous and lagged value) and indices of export prices of tires, interacted with the car model's weight. Standard errors are estimated by bootstrap (500 replications).