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

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Abstract

This study evaluates the impact of fuel taxes on new car purchases, using exhaustive individual-level data of monthly registration of new cars in France. We use information on the car holder to account for heterogeneous preferences across purchasers, and 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 would reduce the share of diesel-engines in new car purchases without substantially changing the average fuel consumption or CO_2 intensity of new cars. Alternatively, we find that a (revenue-equivalent) carbon tax has only small effects on average fuel consumption or average CO_2 intensity of new cars.

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

Highlights

- A nested logit model of new car purchase decisions is estimated.
- Corporate purchases react less to fuel tax than private purchases.
- Two policies are simulated: alignment of diesel and gasoline tax and a carbon tax.
- Both policies have only small impacts on fuel efficiency and carbon emissions.
- Aligning diesel and gasoline tax shifts consumption away from diesel cars.

1. Introduction

In France, road transport produces more than a third of total CO_2 emissions and much higher shares of other greenhouse gases.[1] On the one hand, this problem might be alleviated by a shift to diesel-fueled cars, as diesel is more dense in energy and diesel-engines particularly efficient in using it: typically, a diesel car produces less CO_2 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-fueled cars might alleviate the global externality, but increase local concerns.

Facing the conundrum between global and local pollution, European policy makers have for a long time opted to support diesel vehicles, particularly in France (Hivert, 2013). Recent episodes of smog have now sparked a renewed debate about this support for diesel. In December 2016, air quality in France dropped so low that the government heavily restricted driving and Paris authorities have banned the oldest and most polluting vehicles from the city center, pledging "an end to diesel" in Paris by 2020. As stressed, for instance by Mayeres and Proost (2001), environmental benefits of diesel cars have been overestimated: the environmental costs of diesel cars are much higher than those of gasoline cars. Diesel cars emit more fine particles and NO_x that harm human health, and new technology decreases the spread between CO_2-emission-efficiency of diesel and gasoline cars.[2] The production of diesel-models is also more CO_2 intensive because they are heavier. Against this background, the French government announced in 2015 the progressive reduction of the relative tax advantages for diesel fuel.[3] This tax alignment adds to a previous "carbon tax" passed in France in 2003 at a modest €15 per tonne of CO_2. A carbon tax is proportional to the amount of CO_2 emitted, aiming at aligning the private cost to the consumer and the externality cost to society.

Emissions from road transport depend heavily on the vehicle fleet in circulation, as cars are durable goods, thus, regulation that affects the entry of new vehicles has long-time effects on emissions. While mandatory standards (command-and-control regulation) were the most prominent regulation until the 1990s, alternative regulations have been tested since, in particular economic

[1] See `http://www.citepa.org/en/air-and-climate/analysis-by-sector/transports` Retrieved on 14/03/2015.

[2] Miravete et al. (2015) go as far as to argue that diesel-friendly policy in Europe is essentially a non-tariff trade barrier against American manufacturers.

[3] The 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 such as described in this study has 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.

incentives such feebates or fuel taxes.[4,5] Fuel taxes have the advantage of affecting both the present and future emissions: car owners are immediately encouraged to drive less with their current car when fuel prices rise, while at the same time investment in fuel-efficient cars becomes more attractive: this paper focuses on the latter aspect. Some previous results on car choice, based mostly on the US market, emphasize an "energy paradox," meaning that consumers systematically undervalue future economies of energy-efficiency (e.g. Allcott and Wozny, 2014); others, like Sallee et al. (2016) or Busse et al. (2013) find no evidence of such consumer myopia. Although the literature on the subject is large,[6] meta-studies (Helfand et al., 2011; Greene, 2010) find that the empirical evidence about the energy paradox is inconclusive.

Aside the mileage, the effect of fuel taxes on carbon emissions is mediated by the extent to which car purchases react, i.e. whether such taxes change the composition of the vehicle fleet toward more fuel efficiency (greenhouse gases) and the share of diesel cars (local pollution). This study estimates the short-term sensitivity of automobile purchases to changes in fuel prices in France. We evaluate the impact of two (hypothetical) fuel tax policies on aggregate characteristics of the vehicle fleet in circulation, leaving aside the question whether consumers adjust their mileage both to changing fuel prices and to changing fuel efficiency of their car (potential rebound effect).[7] We contribute to the literature by addressing the aggregate impact on the composition of the vehicle fleet in circulation, disregarding whether a low sensitivity to fuel prices is due to elastic mileage or to consumer myopia.

We use French car registration data from 2003 to 2007, which includes exhaustive information about both household and firm automobile purchases. Our main focus lies on the aggregate impact of fuel taxes on fuel consumption, CO_2 emission intensity and the share of diesel purchases. Our dataset links technical car characteristics to information on the car holder. This enables us to define consumer types to account for heterogeneity in preferences across purchasers. In particular,

[4]Besides recent scandals show that standards seem difficult to enforce effectively.

[5]Feebates, 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. However, D'Haultfœuille et al. (2014) show that the French experience has led to unexpected results. In absence of previous empirical evidence on consumers elasticities to car prices, the feebate system has resulted in a sharp increase in car sales, but also in CO_2 intensity. This disappointing result is partly explained by a "rebound effect": with a more fuel-efficient car, the cost per kilometer is lower, which may induce more driving.

[6]Greene (2010) cite as much as 28 papers on this question.

[7]There are four components to the reaction of total emissions to fuel taxes: the direct mileage elasticity to fuel prices, the elasticity of the new car's fuel efficiency to fuel prices (analyzed here), the elasticity of mileage to this new fuel efficiency and the elasticity of car lifetime. Frondel and Vance (2014), for example, examine the first point and find that the elasticity of mileage to fuel prices is not significantly different for diesel and gasoline drivers. We examine the second point. Small and Van Dender (2007) examine the third point. Adda and Cooper (2000) work on the fourth point.

we distinguish between private consumers and firms. While the latter represent more than one-third of purchases of new cars in France (over our period), virtually no evidence exists so far on their responsiveness to changes in fuel prices.[8,9]

As it is common in this literature, we rely on a static discrete choice model assuming that the decision to buy a specific car depends on several car characteristics, including the cost per kilometer. The nested logit specification enables us to model substitution patterns depending on car market segments and on fuel-type versions. We identify the impact of fuel cost in car choice using time variation in fuel prices and cross-sectional differences in fuel efficiency. We deduce the elasticity of demand for cars with respect to an increase in fuel taxes.

Our results suggest that short-term sensitivity of demand with respect to fuel prices is generally low, but presents significant heterogeneity across purchasers. The difference between private and corporate purchases is particularly salient: firms are much less reactive than households. We use our estimates to simulate 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 they are calibrated to be revenue-equivalent to each other.[10] 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 would reduce the market share of diesel cars (from 69% to 65%) in the short-run without notably changing average fleet fuel consumption or CO_2 intensity. The carbon tax leaves the diesel share almost constant and has a similarly small impact on the other two outcomes. Overall, our results do not suggest a strong short-term impact of fuel taxes on car choices.

This study is in line with the literature on the impact of fuel prices on the automobile sector. Most papers focus on American data (Allcott and Wozny, 2014; Busse et al., 2013; Klier and Linn, 2010) and concentrate on the question of consumer rationality, as reviewed in Greene (2010) and Helfand et al. (2011), while we choose to take a policy maker's perspective and concentrate on the aggregate vehicle fleet characteristics. Klier and Linn (2013), who evaluate the effect of fuel prices on new vehicle fuel economy in the eight largest European markets (including France), observe strong differences between European and American markets. Much of this existing literature relies on data with little or no information on consumers, while we have individual data matching cars

[8]Goldberg (1995) notes that private sales underestimate total sales of new vehicles because of the "existence of fleet sales".

[9]Virtually nothing is known about the utilization behavior (mileage) of firms, which is why we refrain from attempting to calculate the overall impact of the policies on carbon emissions.

[10]As a consequence, our carbon tax scenario is more ambitious than the tax voted in France.

to consumers and can identify corporate purchases. Previous results for France suggest that the elasticity of fuel demand to fuel prices in France is heterogeneous across demographic groups (Clerc and Marcus, 2009), depending notably on working status. We only estimate short-run reactions, as we take supply as given: list prices can be adjusted in the medium-term and the set of available cars might change in the long-run.

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

2. Choice model

To model market shares of new vehicles, we rely on a standard discrete choice model with differentiated products. More specifically, we assume that the purchaser buys one product maximizing his utility that is a linear function of new vehicle characteristics and a vehicle-specific unobserved effect. The individual valuation of these vehicles may vary among individuals, like e.g. Allcott and Wozny (2014), tracing back to seminal work by McFadden (1978).

We assume that the consumer decision can be modeled as a hierarchical choice, choosing first a car segment (i.e. SUV, compact, etc; see list in Table 1), then a model (combination of nameplate and car body style) within this segment, and, finally, one of the two fuel-type versions of this model.[11] While this structure is largely ad hoc, it seems empirically validated by our parameter estimates (see Appendix D). We nevertheless perform robustness checks with less hierarchical decision trees (see Section 5.4). The nested logit model yields 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. We also consider an outside option, which is not to buy any new vehicle.[12] This substitution pattern is represented in the tree diagram of Figure 1.

The individual utility of choosing the product with model (combination of nameplate and car body style) j, fuel-type f and segment s, for purchaser i at month t is written:

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

[11] In order to clarify the vocabulary, *nameplate* refers to the brand name of the car, for instance Corolla, Prius. Within the same nameplate, there are usually several *models* that are defined in this study by the intersection of a nameplate and a body style, i.e. Corolla sedan or Corolla station wagon. Each *model* typically exists as two different *products*, i.e. in a diesel- and a gasoline-version.

[12] As we consider monthly sales, the outside option's market share is likely to be much larger than any other option's share. For the sake of comparison, over the period the number of new cars registered a month ranges from 75,000 to 160,000 vehicles, for around 37.5 millions of drivers in France.

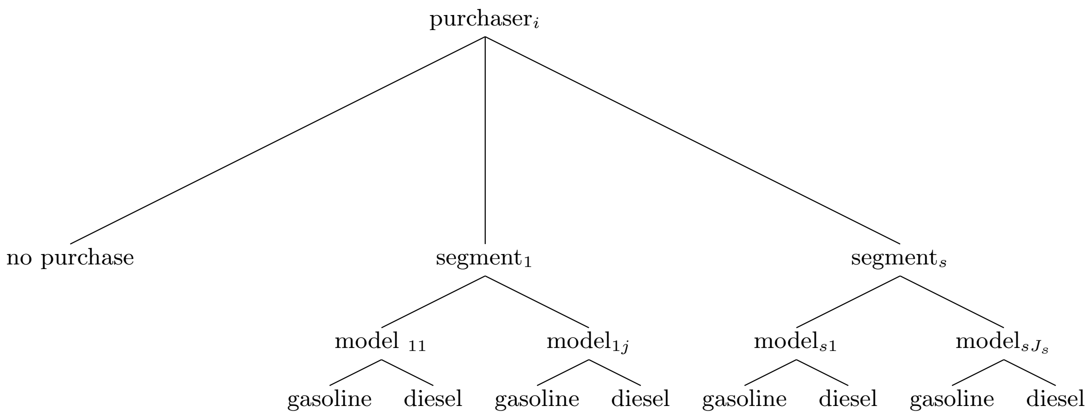

Figure 1: Nested decision-making structure of the car purchaser

where p_{jft} denotes the car price and X_{jft} represents the characteristics of new cars. p_{jft}^{km} is the cost at time t for the amount of fuel needed to drive one km with the model j of fuel-type f.[13] ξ_{ijft} measures the unobserved (to the econometrician) preference for product jf. As such, it captures attributes like perceived quality, design and reputation.

We rely on a nested logit specification with two nesting levels to reflect our decision process of Figure 1. This means we assume the error term can be decomposed as:

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

where ν_{ijt} measures the individual preference for unobserved characteristics of model j common to both fuel versions, for example design, while ν_{ist} is the consumer's overall preference for segment s, for example status symbol value of SUVs. 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 this literature (see in particular Berry, 1994).

The parameters σ_{1i} and σ_{2i} capture the correlation between individual preferences for cars within nests, 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 model,[14] while a high σ_{1i}, approaching 1, implies

[13] Another way to look at this would be to multiply the fuel consumption by the number of kilometers expected by the purchaser and using some sort of discounting; this is equivalent to our presentation if β_i is defined to include this expected number of kilometers and discount factor of purchaser i.

[14] "Within-model" substitution refers to the substitution between the gasoline-powered and the diesel-powered versions of the same model.

a high correlation between preferences for both fuel-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 for example Verboven, 1996 for a more complete discussion of these terms).

This nest structure is based on the commonly agreed structure of the automobile market, but its order with the fuel-type versions is largely ad hoc. We therefore present robustness checks with alternative nest structures at the end of the results in Section 5. This does not alter our conclusions fundamentally.

3. Data and descriptive evidence

3.1. New vehicle registrations

We use the exhaustive dataset of all new cars registered in France from January 2003 to November 2007, provided by the Association of French Automobile Manufacturers (CCFA, *Comité des Constructeurs Français d'Automobiles*), giving us over 7 million observed registrations. 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.[15]

Our data includes all information necessary for the registration of a new car, i.e. both technical specifications of the car as well as demographic information on the purchaser. The CCFA has further linked this data to list prices of new cars as provided by the car manufacturers.[16]

A product is defined by brand, nameplate (Corolla, Kangoo, etc.), fuel-type (diesel or gasoline),[17] CO_2 intensity class and body style (for instance city-car and sedan).[18] Moreover, the dataset contains other characteristics like number of doors, horsepower, weight, cylinder capacity. Given 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 overall 7% of sales.[19]

3.2. Types of consumers: demographic groups

Our administrative registration data match every sale of a new car with information on the new car owner. We can distinguish between private buyers and firms. Fuel price elasticities are likely

[15]See D'Haultfœuille et al. (2014) for an analysis of this policy and a description of this dataset.

[16]List prices may differ from the actual selling prices, which are unobserved.

[17]We exclude electric and hybrid vehicles as they constitute a tiny share of the French market over the examined period.

[18]The definition seeks to be detailed enough to avoid the aggregation of heterogeneous products. At the same time, a too narrow definition yields many zero monthly market shares, which have to be dropped by definition: the logit model does not accommodate zero market shares, conceptually, and we cannot take the log of zero, practically. The definition used here is similar to Allcott and Wozny (2014) and somewhat more detailed than those used in most of the literature (e.g. Goldberg, 1995, and Verboven, 1996).

[19]One of the robustness checks verifies that this assumption is not crucial for the results, cf. Section 5.4.

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

	Products	Sales-weighted		Products	Sales-weighted
By type of car-body			*By class of CO_2 (g/km)*		
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%
By horsepower			*By type of fuel*		
≤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.

to be related to consumer characteristics such as income, working status and area of residence. Most of the relevant literature on fuel elasticity relies on aggregate data, but as noted by Bento et al. (2012), this omission might entail erroneous findings about fuel economy valuation.

In order to account for heterogeneous preferences, we split our sample into consumer types based on demographic characteristics: we differentiate three firm sectors and three occupational types of private consumers. We further differentiate types based on geography and income, resulting in 30 distinct consumer types. These categories aim at capturing factors essential to vehicle choice and fuel-price sensitivity: mileage and preference for diesel cars, as well as a comfort-price trade-off. The location additionally captures the extent to which a buyer can substitute with other means of transports (bike, public transport, etc.). The groups are designed in a way to explain as much variation in diesel share, annual mileage[20] and car price as possible.

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

	Not employed		Employed	
Income	Low	High	Low	High
Urban	10,850	10,950	14,950	15,600
Suburb./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, author's calculations.

For both private consumers and firms, we differentiate between types of residence areas. Resi-

[20]Information on annual mileage is available for households only and not by age group, computed from INSEE National Transport and Travel Survey 2007, see Table 2.

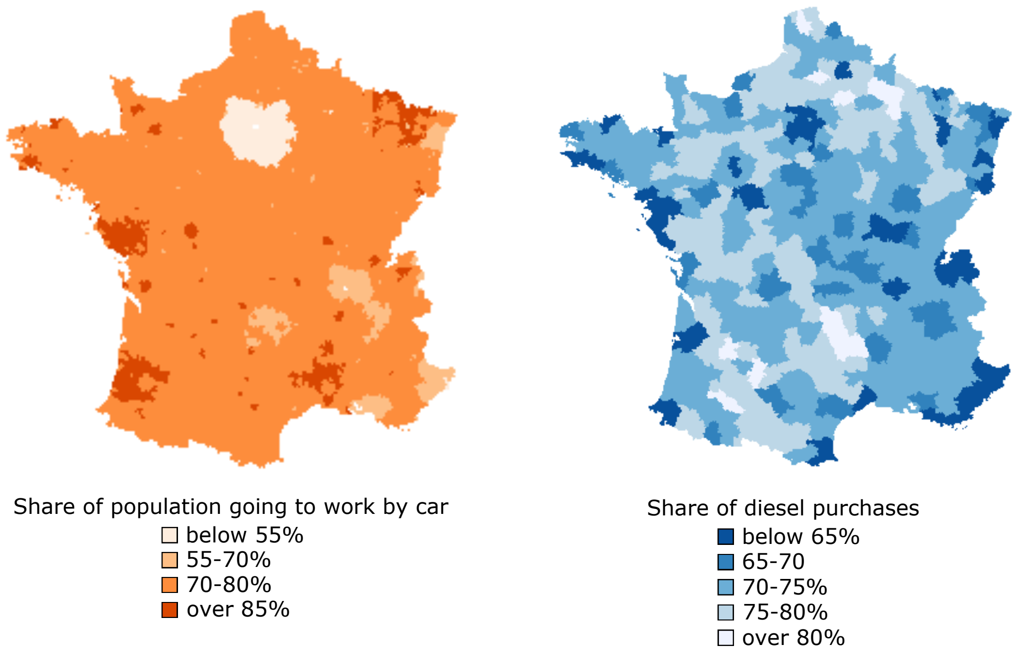

Figure 2: Overview of spatial variation in share of diesel cars and mileage
Source: CCFA (left graphic) and INSEE National Transport and Travel Survey 2007 (right graphic), authors' calculations.

dence area (rural or urban) accounts for differences in average travel distance and the availability of means of transport other than the car. Residence area is derived from the postal code: we sort areas of residence between urban Paris, the larger Paris metropolitan region,[21] other urban areas and suburban/rural zones. Different types of residence areas have considerably different average travel times and distances (Baccaini et al., 2007). The average yearly mileage is consistently smaller in the Paris region with its dense public transportation network than in other comparable areas.

Activity status is an additional important factor for private owners, as employed consumers have larger mileage across all geographic areas, shown in Table 2. Indeed, the difference between average yearly mileage ranges from around 10,000 km/year for non-active households living in urban Paris, to almost twice more for working households living in wealthy suburban areas. As shown in Clerc and Marcus (2009), French private consumer elasticity to fuel prices largely depends on whether the consumer uses their car to go to work, as commuting represents the majority of kilometers driven in France. The Paris region is again special to this extent as reflected in Figure 2, which shows that this region has an exceptionally low share of people using their car to go to work.

[21] In 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 "Paris metropolitan region" or "suburban Paris" describe the rest of the Île-de-France region.

We consider the three groups: young employed under the age of 30, employed (over 30-year-old), and not employed, with the latter including retirees and unemployed.

We moreover split households according to income. We proxy the buyer income by the median earnings of their age group at the precise municipality (*"commune"*) of each consumer and define two groups corresponding to the upper and lower half of this distribution. As group sizes are smaller in the Paris region, we do not distinguish along income dimensions for this region (see Table A.6 in the Appendix for group sizes).

Little is known about the factors of heterogeneity in mileage for firms; thus, we use the same geographic partition as for households as it is partly related to infrastructure facilities. We also differentiate with respect to the business sector that is available in the data: industry and agriculture, rental, and trade/services. To our knowledge, this is the first study to explicitly account for firm purchases, so that we do not know a priori what factors are important for their fuel-price sensitivity.

3.3. Diesel and gasoline cars

As shown by Hivert (2013), the advantage given to diesel cars in France is particularly salient in international comparison. Figure 3 illustrates this specific position of France among European countries. Outside Europe, policies are much less favorable for diesel and diesel-engines virtually do not exist: in both Japan and the US, diesel cars make up about 2% of the overall vehicle fleet in circulation (Cames and Helmers, 2013).

Fuel prices varied considerably between €1.01 per liter and €1.38 per liter of gasoline, and between €0.75 and €1.21 per liter of diesel;[22] this variation is about the same order of magnitude as the policies we consider in this study. In order to address potential concerns, Appendix B gives some more detail on the fuel price evolution and performs preliminary reduced-form regressions.

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. The final fuel tax rates result from the combination of a fuel-type specific lump-sum

[22] Monthly fuel prices are obtained from the French Ministry of Environment; we 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 prices are available only since 2007 and cannot be used here. However, the spatial variation is much lower than the temporal variation: the relative standard deviation is below 2 % for monthly fuel prices measured at the local (French "département") level in 2007, while it above 10% for national monthly prices over the period 2003-2007.

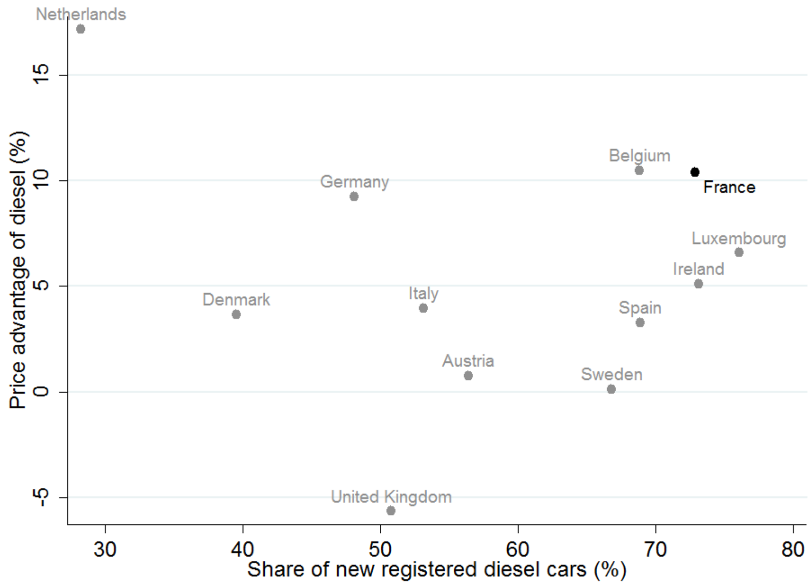

Figure 3: Diesel fuel prices and market shares in Europe in 2012
Source: European Automobile Manufacturer's Association (ACEA). Price advantage of diesel is defined as the price differential (including taxes) between diesel and super unleaded gasoline (95 RON) divided by the latter.

tax[23] and the proportional VAT of 19.6%. For firms, VAT is reduced to 4% for diesel. Over the whole examined period, diesel fuel prices are significantly lower than gasoline prices because of the lower lump-sum tax on diesel fuel: in 2011, the consumption tax on energy products reached €0.61 per liter of gasoline, while it was €0.44 per liter of diesel.

Diesel has a higher energy content so it produces more CO_2 per liter than gasoline: one liter of gasoline is transformed to 2.33 kg of CO_2 while one liter of diesel is transformed to 2.63 kg of CO_2.[24] Besides this important global greenhouse gas, diesel cars also emit local pollutants like NO_x, as well as fine particles (see e.g. Cames and Helmers, 2013). As a consequence, the French government has decided to adjust diesel taxation.

Beyond fuel taxation, firms face an annual tax related both to the CO_2 class and to the fuel-type.[25] As it may impact the preferences of firms toward one or other class, we use dummies for CO_2 classes in our estimations. This also accounts for marketing-based preferences for CO_2 classes (Koo et al., 2012) beyond direct valuation of fuel cost savings.

[23] Consumption tax on energy products, "Taxe intérieure de consommation sur les produits énergétiques" (TICPE).

[24] The differences in CO_2 intensity are due to the differences in density of the fuel-types, see for example Demirel (2012). The mass of CO_2 per liter of fuel that weighs less than a kg might seem surprising; it results of the association of carbon elements from the fuel and ambient oxygen.

[25] The yearly amount of the tax ranges from €750 for the smaller cars to €4,500 for the biggest ones in 2014.

3.4. Expected cost per kilometer

Our focus lies on the consumer sensitivity to fuel prices when buying a new vehicle, via the cost of driving. We thus focus on the impact of the expected cost $E(p^{km}_{jft})$ at time t for the amount of fuel f needed to drive one km with the car jf. By definition, it depends on the car's fuel consumption ϕ_{jf} in L/100km, its fuel-type f (diesel or gasoline) and the expectations about fuel prices.

$$E(p^{km}_{jft}) = 1/100 \times \phi_{jf} \left[\mathbb{1}_{f=diesel} E_t(p_D) + \mathbb{1}_{f=gas} E_t(p_G) \right], \tag{3}$$

where p_D and p_G denote the fuel prices including tax for one liter of diesel and gasoline, respectively. ϕ_{jf} denotes the car's fuel consumption, measured in L/100km, which is the inverse of fuel efficiency as typically used in the US, measured in miles per gallon (MPG). Note that it is not equal to the total amount of fuel consumed, which results from the product of fuel consumption and mileage.

As a car is a durable good, the decision to buy a given product jf at time t should take into account the discounted utility of the future utilization of this car net of operating cost. In line with the literature, we 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, consistent also with a random walk. However, given 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 our point of data collection. Thus, in our estimates, we do not use the contemporaneous fuel price but rather a three months lag of fuel prices. Alternative 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 current fuel prices and moving averages, and find that this assumption has no significant impact on parameter estimates, but standard errors are larger with moving averages.[26]

We thereby assume that consumers are equally sensitive to fluctuations in the oil price as to changes in fuel taxes. If consumers place more weight on certain price changes (for behavioral reasons like salience) or have a reversal to the mean expectation, our methodology underestimates

[26] In an earlier version of this study, we estimated the results using moving averages over 6 months preceding the purchase without finding significantly different results.

the true effect of a fuel tax reform. However, if consumers are loss averse, our methodology overestimates the true effect. Our methodology cannot account for behavioral effects either, such as asymmetric responses for prices increases and decreases (discussed in Greene, 2010).

Across different cars in our data, the price of driving one kilometer, i.e. the product of fuel price p_f and fuel consumption ϕ in liters per 100 km, covers a wide range from €2.60 per 100 km up to €30.9 per 100 km depending on the car. We reproduce the aggregate reduced-form estimation of Busse et al. (2013) in order to verify that the variation is large enough and significance is not only driven by the sheer size of our dataset (Appendix B).

4. Econometric approach

4.1. Nested logit estimation

We take advantage of the fact that our data matches consumers and products: we assume that systematic differences in the valuation of the different characteristics are captured by consumer types that are based on demographic characteristics. We thus use the 30 consumer types as specified in Section 3.2 and estimate our model separately for each consumer type. Our approach is an alternative to two common ways to include demographic variation: random coefficient models *à la BLP* (Berry et al., 1995) and linear specifications as in Goldberg (1998). First, random coefficient models allow preferences to be shaped by aggregate distributions of household demographics, which is useful when only aggregate data is available.[27] As relevant heterogeneity is assumed to be observed and captured by the demographic groups here, we can refrain from using such complex models (see also Grigolon and Verboven, 2014). Second, Goldberg (1995, 1998), for instance, makes certain parameters linearly dependent on household demographics by including interactions of purchaser and product characteristics. Our methodology nests such a linear specification, as we estimate parameters separately for each consumer type.

We thus aggregate individual choices within each consumer type, in order to recover the market shares of each product jf (model j of fuel-type f) up to an identifying normalization. As usual in the literature, identification stems from the normalization of the outside good's value to zero. As an intermediary step, we thus obtain a linear specification for the market share s_{djft} of the product jf at time t among consumer type d relatively to s_{d0t} the market share of the outside

[27] However, this comes at the cost of high computational complexity. This complexity is also shown to lead to numerical instability in some cases: Knittel and Metaxoglou (2014) find results often depend on starting values and optimization algorithms.

good for that same demographic group:

$$\ln(s_{djft}) - \ln(s_{d0t}) = \alpha_d + \beta_d p^{km}_{jft} + \gamma_{1d} p_{jft} + \gamma_{2d} X_{jft} + \sigma_{1d} \ln(s_{df|j}) + \sigma_{2d} \ln(s_{dj|s}) + \xi_{djft}, \quad (4)$$

where $s_{df|j} = \frac{s_{djft}}{s_{djt}}$ is the relative share of purchases of fuel-type f within purchases of model j in each month t and $s_{dj|s} = \frac{s_{djt}}{s_{dst}}$ is the relative share of model j within the sales of segment s.

However, these shares are defined over the entire potential market size, which in our case – as in virtually all cases – is unknown. Indeed, this market size should contain only those who consider buying a car in a given period (and maybe *decide* not to). As detailed information on this market size is unknown, using some approximation is a standard procedure in this literature (for instance the seminal papers by McFadden, 1978; Goldberg, 1995), using for example most recent estimates of the population size or the number of people holding a driver's license. This number dramatically overstates the actual market 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, it is not clear whether the number of driving license holders is relevant. Huang and Rojas (2014) show both theoretically and practically that coefficients estimated using such a wrong market size may be considerably biased.

To avoid this potential bias, we follow a suggestion by Huang and Rojas and reformulate Equation (4): by using quantities rather than market shares, the market size cancels out on the left-hand side. We are left with the log of the outside good's quantity, which we can move to the right-hand side and estimate it as part of the time-specific constant. Given the highly seasonal fluctuations of the number of purchases in Figure B.5, we allow this constant to vary with year and calendar month. The overall market size and the outside good quantity are not necessary to compute the relative shares $s_{dj|s}$ and $s_{df|j}$. Our main estimation equation is thus:

$$\ln(q_{djft}) = \alpha_d + \beta_d p^{km}_{jft} + \gamma_{1d} p_{jft} + \gamma_{2d} X_{jft} + \sigma_{1d} \ln(s_{df|j}) + \sigma_{2d} \ln(s_{dj|s}) + y_d + m_d + \xi_{djft}, \quad (5)$$

where q_{djft} stands for the number of sales of product jf. The characteristics of the new car, namely horsepower, CO_2 class, number of doors, fuel-type, car body (sedan, sport, compact, etc.) and brand are controlled for. Year and calendar month dummies, y_d and m_d, account for temporal trends as well as seasonality in aggregate new cars purchases.[28]

The main parameter of interest is the parameter β_d measuring sensitivity to fuel prices. We use the parameters of Equation (5) to compute the fuel price elasticity, which takes into account both direct and indirect effects of an increase in fuel prices in the market share of one specific car. This elasticity can be approximated by:[29]

$$\begin{aligned}\eta_{\mathbf{dsjf}} =& \frac{\partial s_{dsjf}/s_{dsjf}}{\partial p^e/p^e}, \\ \approx& (1+t^{VAT})p^e\left(\frac{\beta_d}{1-\sigma_{1d}}\phi_{sjfd} + \left(\frac{\beta_d}{1-\sigma_{2d}} - \frac{\beta_d}{1-\sigma_{1d}}\right)\bar{\phi}_{sjd} + \frac{\beta\sigma_{2d}}{1-\sigma_{2d}}\bar{\phi}_{sd}\right). \qquad (6)\end{aligned}$$

Equation (5) is estimated using the generalized method of moments separately for each demographic group, assuming these groups homogeneous enough to include only buyers with the same demand parameters.

4.2. Endogenous variables and instruments

Gas prices can be considered as exogenous in the French case, as France represents about 2% of world oil consumption and produces less than 0.1% of the world production.[30] French gas 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, see Davis and Kilian (2011) for a discussion).

By contrast, the vehicle price p_{jft} is endogenous, as it is the result of demand and supply which by assumption vary with the unobserved attractiveness ξ_{djft}. As it is usual in the literature, we use a set of instruments based on the characteristics of potential substitutes aiming at capturing market density, and thus beyond production cost, the variation in 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. Importantly, we use yearly list prices and thus assume that purchase prices do not to vary with fuel prices. In the short term, this is likely to be true, as list prices are set on a much longer horizon than fuel prices; in the medium-run, list prices can obviously adapt to fuel price variation.

[28] Note that we 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 0-3 units per month. This leaves results virtually unchanged; results are available upon request.

[29] Details of elasticity computation are given in Appendix C.

[30] In 2009, see `http://www.eia.gov/countries/country-data.cfm`. Retrieved on 14/03/2015.

Armstrong (2016) argues that in markets with a large number of heterogeneous goods, BLP instruments are no longer sufficiently strong. Thus, 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 demand. Thus, we use the price indices of iron (current and lagged value) and indices of export prices of tires as instruments, both weighted by the car's weight. These cost shifters appear strongly correlated to vehicle prices.

Within segment, the 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...), as well as the difference in costs shifters for these two versions, capturing the relative attractiveness of each version.

As pointed out by Bound et al. (1995), using many over-identifying restrictions as we do 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 on the first-stage F-values, as proposed by Stock and Yogo (2005). As shown by Sanderson and Windmeijer (2016), this method can be extended 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, that 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 demographic group. At a 5% significance level, we can reject for most regressions a bias of the 2SLS regression relative to an OLS of more than 5%; in only two cases (out of eighty) we can only reject biases superior to 20% (cf. Tables E.14, E.15 and E.16 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 the Paris suburban area. This group is small and aggregate results are virtually identical if we drop it. Thus, we are confident that our results are not biased by weak-instrument effects.

5. Empirical results

Our aggregate outcomes of interest are: the share of diesel cars (local pollution), average fleet fuel consumption (international fuel dependency) and average CO_2 intensity (global pollution).

The presentation of the empirical results proceeds in three steps: first, we present the aggregate elasticities of market shares, diesel share, fuel consumption, and CO_2 emission intensity.[31] Then, these elasticities are used to compute ex ante estimates of the impact of two policies, one equalizing tax on diesel and gasoline; the other taxing carbon directly. The two policy scenarios are calibrated such that they are revenue-equivalent for the implementing government in absence of consumer reaction. The raw coefficients cannot be interpreted directly, but we discuss them in the Appendix D, where we also compute the demand elasticities for some popular car models.

5.1. Aggregate elasticities to fuel price variation

We model the aggregate elasticities to a change in fuel prices (both gasoline and diesel) through an international oil price shock. As diesel engines tend to be more efficient with an average fleet fuel consumption of 5.6L/100km versus 6.8L/100km for gasoline engines (Table A.7 in the Appendix), an increase of fuel prices raises the share of diesel cars among new purchases π^D (see elasticity η_D in Table 3).[32] Consequently, the average fleet fuel consumption decreases as well as average CO_2 intensity. However, all these effects have a small magnitude.

These results can be compared to some previous estimates obtained in the literature. Using aggregated data on several European car markets, Klier and Linn (2011) estimate that a 1$ increase in fuel prices per gallon would increase the average miles-per-gallon (MPG) efficiency in France by 0.21, implying an average fuel consumption elasticity η_ϕ of -0.017.[33] 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 by 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. Klier and Linn (2011) also estimate that a hypothetical policy equalizing diesel and gasoline prices reduces the diesel market share in France by 1.4 percentage points only; much less than suggested by our estimate of around 4 percentage points.

5.2. Tax alignment

These estimates allow us to simulate the impact of a policy that aligns diesel and gasoline taxes. Leaving gasoline taxes unchanged, this policy raises diesel taxes by almost a third, from

[31] See Appendix C for details on the computation of these elasticities.

[32] 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.

[33] 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 3: Elasticities with respect to fuel prices: diesel share, average fleet fuel consumption (L/km) and CO_2 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 (5) estimated by GMM separately for each type of consumers. Standard errors are estimated by bootstrap (500 replications).

43 cent/liter to 60 cent/liter. Futhermore, this policy abandons the VAT advantage for corporate diesel cars, increasing it to the standard rate of 19.6%.

As expected, the induced variation in diesel share is negative and strong: since taxes only increase for diesel, they would push many purchasers to substitute for a gasoline-fueled car. We find that such a policy would reduce the aggregate share of diesel cars in overall sales by 5.9%, that is from 69% to 65% (Table 4). This decrease in diesel sales comes mostly from households who substitute much more easily away from diesel engines, rather than from firms (7.4% and 3.6% reduction, respectively).

This result can be compared to the one in Klier and Linn (2011) who also evaluate a hypothetical policy of equalizing diesel and gasoline prices. At the European level, their estimates suggest that the impact of such a policy on the market share of diesel cars would be 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.[34] Second, as they emphasize, Klier and Linn (2011) cannot distinguish in their data company cars from privately owned cars. According to our estimates, firms are much less sensitive to fuel prices (Table 3).

Gasoline cars consume more liters of fuel per km but produce 13% less CO_2 per liter of fuel, as gasoline is a less energy-rich combustible. The effect of a demand shift toward gasoline cars on CO_2 is thus a priori ambiguous. According to our estimations, substitutions between gasoline and diesel cars have only a marginal impact on both fuel consumption of the new vehicle fleet and CO_2 intensity. It *increases* fuel consumption (Table 4) and *reduces* the average CO_2 intensity of newly purchased cars. Both effects are significant but small: in spite of the large jump in diesel

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

tax, average fleet fuel consumption increases only by 0.44% and average CO_2 intensity decreases by 0.12%. The absolute magnitudes of these changes are small: fuel consumption increases by 26 mL/100km from the average of 6L/km and CO_2 intensity is reduced by 180mg/km from the average of 152g/km.

5.3. Carbon tax

We also predict the impact of a carbon tax, i.e. a tax increase that is proportional to the carbon emissions of each fuel-type. 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 CO_2. 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.[35] A very similar but less ambitious policy has been voted in France in 2014, leading to a progressive increase in fuel taxes up to €30.5/tCO2 in 2017.[36]

The impact $\Delta^{t_c}\eta_D$ of this carbon tax policy on the share of diesel engines sold is positive, but very small: it increases the diesel share by 0.6% (Table 4). This is the result of two contrasting effects: on the one hand, the carbon tax is higher on diesel than on gasoline, but on the other hand, diesel cars are more fuel-efficient. The incentive for purchasers to buy more fuel-efficient cars seems to dominate. The carbon tax reduces average fleet fuel consumption as well as average CO_2 intensity (Table 4). The impacts are significant but again very small. The fuel consumption decreases by 0.37%, which is however only around 22 mL/100km from the average of 6L/km; CO_2 emission intensity shift by 0.33% which is 500mg/km from the average of 152g/km.

Table 4: Percentage impact of a carbon tax and a tax alignment on diesel share, average fleet fuel consumption (L/km) and CO_2 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 $\Delta^{t_c}\eta_D$	Fuel cons. $\Delta^{t_c}\eta_\phi$	CO_2 $\Delta^{t_c}\eta_{CO_2}$
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 (5) estimated by GMM separately for each type of consumers. Instrumental variables for prices are the price indices of iron (current 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).

[35] This scenario maintains the VAT rebate for diesel cars of corporate consumers.

[36] See the website of the French ministry of environment: `https://www.ecologique-solidaire.gouv.fr/fiscalite-carbone` Retrieved on 09/09/2017.

The impact of both policies on fuel consumption and CO_2 intensity is economically small. The main difference is that leveling out the diesel tax advantage induces a noticeable shift away from diesel engines, thus reducing local pollution. Moreover, the carbon tax achieves a larger reduction in CO_2 intensity and furthermore reduces fuel consumption, thus leading – on its modest level – to a lower dependency on foreign petrol imports.

5.4. Robustness checks

We estimate several alternative specifications to check that results are not driven by our main specification choice, but also to emphasize the impact of individual hypothesis underlying this main specification. On the whole, the estimated impact of our policy scenarios remains at a similar order of magnitude across specifications.

Our first test includes all models, i.e. including those that are available only with either gasoline or diesel motor. In our main specification, we drop these models as they lead to "degenerate" nests at the end of the decision tree, where a model-branch only includes one product. While the aggregate elasticities (Table F.17 in the Appendix) appear similar to our main specification, the policy simulation shows that this model slightly over-estimates the policy impact while leading broadly to the same conclusions.

In the same spirit, our second test uses a more commonly used model accounting only for two levels: purchasers choose a segment and then a product within that segment. The two fuel-type versions of a model then count as independent products, which is the same as constraining all σ_{1d} coefficients to zero. The elasticities are similar to the previous test (Table 5) and just slightly stronger than our main specification. Although the changes are small, we still reject this more constrained model as in our main estimation σ_{1d} was significantly different from zero for almost all demographic groups (Table D.10 in the Appendix).

Our third test drops the cost-shifter instruments and includes only the BLP-style instruments. Again, the elasticities are very similar and the policy impacts give the same intuition, but overstate the impact of a carbon tax on the diesel share.

As a last test, we estimate the model jointly for all demographic groups, which means we do not account for consumer heterogeneity. Bento et al. (2012) suggest that unaccounted heterogeneity biases estimated elasticity downwards, which we do not find here (Table F.17 in the Appendix). Quite the contrary, elasticities and estimated policy impacts overstate the consumer reaction in our case (Table 5).

Table 5: Robustness checks: percentage impact of carbon tax and tax alignment on diesel share, average fleet fuel consumption (L/km) and CO_2 intensity (g/km)

	Tax alignment			Carbon tax		
	Diesel share	Fuel cons.	CO_2	Diesel share	Fuel cons.	CO_2
	$\Delta^{t_D}\eta_D$	$\Delta^{t_D}\eta_\phi$	$\Delta^{t_D}\eta_{CO_2}$	$\Delta^{t_c}\eta_D$	$\Delta^{t_c}\eta_\phi$	$\Delta^{t_c}\eta_{CO_2}$
Main specification - including degenerate nests (gas- and diesel-only models)						
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)
Alternative specification - Nests (segment>model)						
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)
Main specification - BLP-instruments only						
Households	-8.67^{***} (0.39)	0.60^{***} (0.04)	-0.13^{***} (0.01)	0.28^{***} (0.08)	-0.51^{***} (0.02)	-0.50^{***} (0.02)
Firms	-3.12^{***} (0.55)	0.29^{***} (0.10)	-0.06 (0.06)	0.65^{***} (0.15)	-0.16^{***} (0.03)	-0.10^{***} (0.03)
Total	-6.27^{***} (0.42)	0.49^{***} (0.05)	-0.10^{***} (0.02)	0.84^{***} (0.07)	-0.42^{***} (0.02)	-0.36^{***} (0.02)
Main specification - without purchaser heterogeneity						
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 (5) estimated by GMM separately for each type of consumers. Instrumental variables for prices are the price indices of iron (current 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).

Our main specification still seems most appropriate, but these alternative specifications do not dramatically change the implications of this study.

6. Conclusion

This paper estimates the short-term impact of fuel prices on new automobile purchases of both households and firms. These estimates allow us to compute elasticities which we aggregate to estimate ex ante the impact of two tax reforms. Using a nested logit specification, we control for hedonic valuation of a large range of car characteristics. We also account for taste heterogeneity between consumer groups, in particular between private and corporate purchases.

Our aggregate outcomes of interest are: the share of diesel cars (local pollution), average fleet fuel consumption (international fuel dependency), and average CO_2 intensity (global pollution). We use our estimates to examine a (hypothetical) policy equalizing tax levels on gasoline and diesel. We find that this policy decreases the share of diesel cars in sales from 69% to 65%. As purchasers would substitute to (less efficient) gasoline cars, the average fuel consumption would rise in response to this policy, while at the same time average CO_2 intensity would slightly *decrease* as gasoline cars emit less CO_2 per liter of used fuel. The examined carbon tax – which implements a much higher carbon price than the recently voted French policy – is expected to slightly increase the share of diesel cars among new purchases. It decreases both fuel consumption and CO_2 intensity significantly, but the overall amounts stay low.

All in all, the estimated effects of these two tax policies are significant but economically small in the short-run, i.e. holding supply constant. This is even more noteworthy, as one might argue that our policy scenarios are somewhat overly ambitious and might not be politically feasible. Overall, we find cannot find evidence of a strong impact of fuel prices on car choices in the short-run.

An important advantage is provided by our individual registration data, as we can account for purchaser heterogeneity and our estimates are thus less prone to omitted sorting bias. Indeed, consumer types react differently to fuel tax changes. A large part of aggregate market reaction comes from households, and particularly from urban and non working consumers. To our knowledge, this important distinction between household and firm purchases is not accounted for in earlier related literature, although firm purchases constitute about a third of the market in our sample. Corporate purchases are particular important for the diesel share, as firms buy a lot more diesel-powered cars and are less likely to substitute away from them.

A limitation of this study is that our simple 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, it is likely that producers react more to long-term shifts: if fuel efficiency becomes more valuable, they might in the medium-run adjust their list prices and in the long-run adjust the products developed and offered. For Klier and Linn (2011) this means that these short-run results underestimate the true impact on fuel efficiency and emissions, which would be enhanced by the producer's reactions. However, as shown by Verboven (2002), producer price reaction should counteract purchaser reaction to changes in differential fuel taxation. However, one could argue like Goldberg (1998) that a short-term consumer reaction as small as suggested by our estimates is unlikely to shift supply, so that the long-run effect should be small as well.

A TRAVAILLER... Moreover, consumers might react differently to fuel price changes, which might be temporary, than to fuel tax changes, which are announced to be permanent.

The aim of environmental policy is ultimately not to increase fuel efficiency, but to decrease CO_2 emissions which result from the interaction of fuel consumption and mileage. Additional research is needed to clarify the impact of fuel efficiency on car mileage. Previous research suggests that rebound effects might reduce any impact on fuel consumption (see for example Austin and Dinan, 2005; Frondel et al., 2012), so that our (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 circulate on average for 13 years in France (Bilot et al., 2013).

We do not use any data on mileage nor assume anything on car lifetime and discounting, so that we remain agnostic on the actual profit a consumer realizes with fuel efficiency. As a consequence, we cannot evaluate welfare effects of the policy such as Bento et al. (2009) or Bureau (2011) or the rationality (or myopia) of consumers such as reviewed in Greene (2010) and Helfand et al. (2011). 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 that computations usually remain back-of-the-envelope sketches (e.g. Grigolon et al., 2014; Allcott and Wozny, 2014; Busse et al., 2013[37]).

Nevertheless, our estimated consumer reactions are too small to fully account for the change in operating cost if utilization does not change. In this light, it may seem surprising that corporate

[37] These papers account for mileage at a detailed car- or consumer-level but assume zero elasticity; they can thus not account for well documented phenomena such as the "rebound effect" (Small and Dender, 2007).

purchases are even less reactive to fuel price changes than household purchases. However, similar results have been obtained on the market for airline tickets. Firms benefit from fuel tax advantages in France, so that firms in general pay less for fuel. Firms can also deduce total fuel cost from taxes and may pass costs through to consumers. These factors may explain why they react less to fuel prices than households. This is the first study documenting this difference on the car market. Further research is needed to clarify whether this is due to differences in mileage or whether there are behavioral and organizational factors at play.

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A. Descriptive statistics

Table A.6: Distribution of demographic groups among buyers (%)

	Private consumers						
	Not employed		Young employed (<30)		Employed (≥30)		
Income	Low	High	Low	High	Low	High	Total
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%
	Firm purchases						
	Industry & agriculture		Car rental & repairing		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.

Table A.7: 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
Horse power (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
Horse power (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.

B. Is there enough variation in fuel prices?

The variation identifying our main parameter of interest stems from the product of product-specific fuel-efficiency and temporal variation in fuel prices. Within the time frame of the data used in this study, from January 2003 through November 2007, gasoline and diesel prices became more variable, with a general upward trend, after some time of relative stability, as shown in Figure B.4.

In France until 2017, the number of diesel cars sold has consistently been higher than the number of gasoline cars, and this difference has been increasing over the period under study in this study (Figure B.5). The overall number of new registrations is strongly seasonal, but is virtually constant over the years. The details of the choice between diesel and gasoline cars is amply discussed by Rouwendal and de Vries (1999).

In order to verify that fuel price fluctuations present enough variation to identify their impact on the car market, we follow the procedure of equation (7) in Busse et al. (2013), estimating the following equation:

$$\log Q_{kft} = \gamma_0 + \gamma_1 (p_{ft}^{fuel} \times ConsumptionQuartile_{kf}) + \gamma_2 ConsumptionQuartile_{kf} + \tau_t + \mu_t + \epsilon_{kft} \tag{B.1}$$

where we previously attributed each product to a quartile of the fuel consumption (among available models not weighted by sales) by fuel type.[38] Q_{kft} is then the national quantity sold within a $ConsumptionQuartile$ k in month t, γ_0 is an intercept, p_{ft}^{fuel} is the fuel price of the fuel-type corresponding to the $ConsumptionQuartile_{kf}$, γ_1 and γ_2 are vectors of dimension 8×1. We include fixed effects for the quartiles $ConsumptionQuartiles_{kf}$, for year τ_t and for month-of-year μ_t.

The results in Table B.8 (following Table 5 of Busse et al., 2013) show that even in this reduced-form regression with only 384 observations, fuel prices have a significant effect on car purchases: when fuel prices increase, the relative market share of models with high fuel consumption (least efficient) decreases while the relative market share of more efficient models increases. This relationship holds significantly for both fuel types.

[38] Busse et al. (2013) do not take into account fuel types, but they work on US data, where there is virtually no diesel. We believe that fuel-types play a central role in our case and should be accounted for.

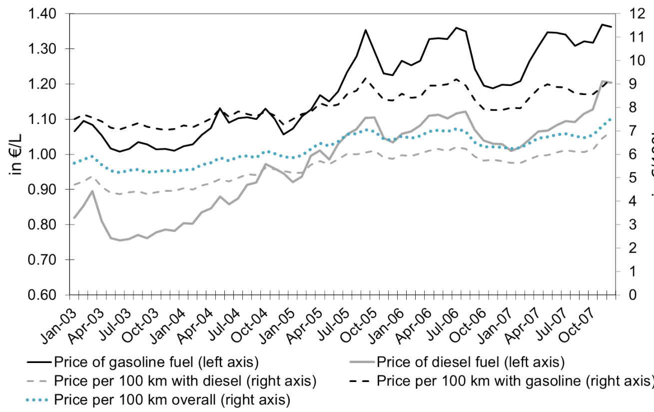

Figure B.4: Monthly consumer fuel prices (incl. taxes) and cost per km (resulting from fuel prices (€) and fuel consumption (L/km) of new car purchases)
Source: French Ministry of Ecology and CCFA, authors' calculations.

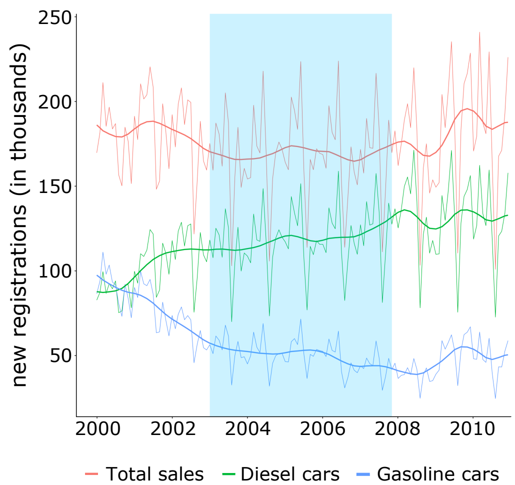

Figure B.5: Monthly new registrations by fuel-type (in thousands, raw and smoothed series, studied period shaded in blue)
Source: CCFA, authors' calculations.

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

Fuel economy	Coefficient	SE	Mean market share	Percent change in market share
Gasoline				
Consumption quartile 1 (most efficient)	0.31	0.15	12.6	36.4
Consumption quartile 2	0.26	0.15	11.1	29.7
Consumption quartile 3	-0.10	0.15	4.5	-9.1
Consumption quartile 4 (least efficient)	-0.50	0.15	1.6	-39.3
Diesel				
Consumption quartile 1 (most efficient)	0.27	0.19	29.2	30.6
Consumption quartile 2	0.23	0.19	26.6	26.2
Consumption quartile 3	-0.19	0.19	8.5	-17.2
Consumption quartile 4 (least efficient)	-0.82	0.09	5.8	-55.9
N				384

Source: CCFA, author's calculations. Least squares regression following equation (B.1), including an intercept, time dummies and dummies for $ConsumptionQuartile_{kft}$ (not listed).

C. Details on the computation of the elasticities

The demand elasticity $\eta_{\mathbf{sjf}}$ for a given product with respect to oil price p^e exclusive of tax at a given point in time can be computed using parameters corresponding to the demand model. 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 Equation (4) for the model j in segment s and of fuel-type f, using the definition of the cost per kilometer of equation (3). Note that we the fuel prices including tax for one liter of diesel and gasoline are respectively $p_D = (1+t^{VAT})(p^e + t_D)$ and $p_D = (1+t^{VAT})(p^e + t_D)$ where p^e is the pre-tax fuel price, t_D and $t-G$ lump-sum taxes for diesel and gasoline fuel respectively, and t^{VAT} the VAT rate. For the sake of readability, we omit the index for demographic groups and do not state the obvious aggregation over these groups for all equations in this Section.

$$\frac{\partial s_{sjf}}{s_{sjf}} - \frac{\partial s_0}{s_0} = \beta \partial p^e (1+t^{VAT})\phi_{sjf} + \sigma_1 (\frac{\partial s_{sjf}}{s_{sjf}} - \frac{\partial s_j}{s_j}) + \sigma_2 (\frac{\partial s_j}{s_j} - \frac{\partial s_s}{s_s}) \tag{C.1}$$

or slightly rearranged:

$$\partial s_{sjf} - \frac{\partial s_0}{s_0} s_{sjf} = \beta \partial p^e (1+t^{VAT})\phi_{sjf} s_{sjf} + \sigma_1 (\partial s_{sjf} - s_{sjf}\frac{\partial s_j}{s_j}) + \sigma_2 s_{sjf} (\frac{\partial s_j}{s_j} - \frac{\partial s_s}{s_s}) \tag{C.2}$$

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:

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

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

$$(1-\sigma_2)\frac{\partial s_j}{s_j} = \beta \partial p^e (1+t^{VAT})\bar{\phi}_j - \sigma_2 \frac{\partial s_s}{s_s} + \frac{\partial s_0}{s_0} \tag{C.3}$$

Aggregating further, we can also 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:

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

while for the overall number of sold cars we get:

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

Combining these expressions in equation (C.1) we finally can compute the elasticity $\eta_{\mathbf{sjf}}$ as:

$$\begin{aligned}
\eta_{\mathbf{sjf}} =& \frac{\partial s_{sjf}/s_{sjf}}{\partial p^e/p^e}, \\
=& \beta(1+t^{VAT})p^e \left(\rho_1 \phi_{sjf} + (\rho_2-\rho_1)\bar{\phi}_j - (\rho_2-1)\bar{\phi}_s\right) - \beta(1+t^{VAT})p^e\bar{\phi}(1-s_0), \\
\approx& \beta(1+t^{VAT})p^e \left(\rho_1(\phi_{sjf}-\bar{\phi}_j) + \rho_2(\bar{\phi}_j-\bar{\phi}_s) + \bar{\phi}_s\right).
\end{aligned} \tag{6}$$

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},[39] as well as on the current 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 very 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

[39]This 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 our main model defined in Equation (5), the elasticity $\eta^{t_D}_{\mathbf{sjf}}$ of demand for a given car sjf with respect to an increase in diesel tax (holding gasoline tax constant) can be computed as:

$$
\begin{aligned}
\eta^{t_D}_{\mathbf{sjf}} =& \frac{\partial s_{sjf}/s_{sjf}}{\partial t_D/t_D}, \\
=& \beta(1+t^{VAT})t_D \left(\rho_1(\mathbb{1}_{f=diesel}\phi_{sjf} + (\rho_2-\rho_1)\pi_j^D\bar{\phi}_j - (\rho_2-1)\pi_s^D\bar{\phi}_s\right) \\
& - \beta(1+t^{VAT})t_D\bar{\phi}^D\pi^D(1-s_0), \\
\approx& \beta(1+t^{VAT})t_D \left(\rho_1(\mathbb{1}_{f=diesel}\phi_{sjf} - \pi_j^D\bar{\phi}_j) + \rho_2(\pi_j^D\bar{\phi}_j - \pi_s^D\bar{\phi}_s) + \pi_s^D\bar{\phi}_s\right). \qquad \text{(C.4)}
\end{aligned}
$$

where the indicator $\mathbb{1}_{f=diesel}$ takes the value 1 if the vehicle sjf is running on a diesel engine, π^D_{sj} is the share of diesel in sales of model j, π^D_s 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 very 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 amount of diesel cars purchased. More specifically, 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 would change the share of diesel cars by $\eta_{\mathbf{D}}$. In the simple logit demand, this change can be computed as:

$$
\begin{aligned}
\eta_{\mathbf{D}} &= \frac{\partial \pi^D/\pi^D}{\partial p^e/p^e}, \\
&= \frac{\sum_{s,j,f}\mathbb{1}_{f=diesel}s_{sjf}\eta_{\mathbf{sjf}}}{\sum_{s,j,f}\mathbb{1}_{f=diesel}s_{sjf}} - \frac{\partial(1-s_0)}{\partial p^e}\frac{p^e}{1-s_0}, \\
&= \beta(1+t^{VAT})p_e\left(\rho_1(\bar{\phi}^D - \tilde{\bar{\phi}}_j) + \rho_2(\tilde{\bar{\phi}}_j - \tilde{\bar{\phi}}_s) + \tilde{\bar{\phi}}_s - \bar{\phi}\right), \\
&= \frac{\beta(1+t^{VAT})p_e}{\pi^D(1-s_0)}\sum_{s,j} s_j\left(\rho_1\underbrace{\pi_j^D(\phi_j^D - \bar{\phi}_j)}_{S_1} + \rho_2\underbrace{(\pi_j^D - \pi_s^D)\bar{\phi}_j}_{S_2} + \underbrace{(\pi_s^D - \pi^D)\bar{\phi}_s}_{S_3}\right), \qquad \text{(C.5)}
\end{aligned}
$$

which involves weighted averages of fuel consumption, where the weights are given by the share of diesel sales.[40] $\widetilde{\bar{\phi}}_j = \sum_{s,j} \frac{\pi_j^D s_j}{\pi^D(1-s_0)} \bar{\phi}_j$ is the average fuel consumption weighted by the share of diesel per model, whereas $\widetilde{\bar{\phi}}_s = \sum_s \frac{\pi_s^D s_s}{\pi^D(1-s_0)} \bar{\phi}_s$ 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 ($\sigma_1 = \sigma_2 = 0$), $\eta_{\mathbf{D}} = \beta(1+t^{VAT})p_e(\bar{\phi}^D - \bar{\phi})$. Naturally, $\eta_{\mathbf{D}}$ 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, so that $\eta_{\mathbf{D}}$ 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 (C.5) 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.[41] Both ρ_1 and ρ_2 are positive and larger than one. In practice ρ_2 is smaller than ρ_1, so that $\eta_{\mathbf{D}}$ 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) $\eta_{\mathbf{D}}^{t_D}$ may be written:

$$
\begin{aligned}
\eta_{\mathbf{D}}^{t_D} &= \frac{\partial \pi^D / \pi^D}{\partial t_D / t_D}, \\
&= \beta(1+t^{VAT})p_e \left(\rho_1(\bar{\phi}^D - \widetilde{\pi_j^D \bar{\phi}_j}) + \rho_2(\widetilde{\pi_j^D \bar{\phi}_j} - \widetilde{\pi_s^D \bar{\phi}_s}) + \widetilde{\pi_s^D \bar{\phi}_s} - \bar{\phi} \right). \qquad \text{(C.6)} \\
& \qquad \text{(C.7)}
\end{aligned}
$$

This elasticity $\eta_{\mathbf{D}}^{t_D}$ depends only on the fuel consumption of diesel cars and on their relative share among purchases: the lower their fuel consumption, the smaller the impact of a diesel tax increase.

[40] With 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 weighted by the share of the diesel version amongst all diesel cars (for example, $\widetilde{\phi}_{sjf}$ corresponds to the average fuel consumption of diesel cars $\bar{\phi}^D$)

[41] The last term for example does not have a well defined sign. For example 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.

Finally, we can also compute the elasticity η_ϕ (respectively $\eta_{\mathbf{CO_2}}$) of the average fuel consumption (respectively of average CO_2 intensity) of new cars with respect to fuel prices p^e and to fuel taxes.

$$\begin{aligned}
\eta_\phi &= \frac{\partial\bar{\phi}/\bar{\phi}}{\partial p^e/p^e}, \\
&= \beta(1+t^{VAT})\frac{p_e}{(1-s_0)\bar{\phi}}\sum_{j,s,f}\left(\phi_{sjf}s_{sjf}\left(\rho_1(\phi_{sjf}-\bar{\phi}_j)+\rho_2(\bar{\phi}_j-\bar{\phi}_s)+\bar{\phi}_s-\bar{\phi}\right)\right) \qquad \text{(C.8)}
\end{aligned}$$

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

$$\eta_\phi = \beta(1+t^{VAT})p^e(\frac{\overline{\phi^2}-\bar{\phi}^2}{\bar{\phi}}), \qquad \text{(C.9)}$$

with $\overline{\phi^2}$ is the mean of squared fuel consumption of new vehicles. The impact of an oil price shock on average fuel consumption depends thus on the ratio of the variance and the mean of fuel consumption. Both the variance and the mean of ϕ are always positive, so that η_ϕ is always 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 (C.8) which is of first order in the sum: it can be simplified 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 $\eta_{\mathbf{CO_2}}^{t_D}$) to a change in diesel tax (holding gasoline tax constant) can be written in case of a simple logit demand model:

$$\begin{aligned}
\eta_\phi^{t_D} &= \frac{\partial\bar{\phi}/\bar{\phi}}{\partial t_D/t_D}, \\
&= \beta t_D(1+t^{VAT})\underbrace{\frac{\beta\pi^D}{\bar{\phi}}}_{<0}\left(\underbrace{\overline{\phi_D^2}-\bar{\phi}_D^2}_{>0}+(1-\pi^D)\bar{\phi}_D\underbrace{(\bar{\phi}_D-\bar{\phi}_G)}_{<0}\right). \qquad \text{(C.10)}
\end{aligned}$$

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 can reduce 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 emissions of new cars. This effect may be partially offset by the dispersion in fuel emissions 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 emissions of new cars if diesel cars are much more fuel-efficient that gasoline cars and that the diesel share is not too high.

D. Complementary results for the main specification

D.1. Raw coefficients

Tables for estimated coefficients are not directly interpretable. This is why the body of this article concentrates on elasticities and counterfactual policy impacts. The coefficients β_d measure each demographic group's direct sensitivity to fuel prices. As expected, β_d is statistically significant for most demographic groups and is always negative when significantly different from zero: as fuel prices increase, the utility from any given car decreases (Table D.9).

We find substantial heterogeneity in the relative magnitude of β_d across consumer types. The heterogeneity in this sensitivity parameter depends on three main factors: first, the flexibility of the consumer's car usage (if he can adjust his car mileage, the fuel efficiency becomes less important for his purchasing decision); second, whether the consumer buys fuel-efficient cars no matter what (there might not be much of a margin to react on for some consumers); and finally, the consumer's income and preferences for other characteristics of the car.

Among private consumers, the effect of fuel price increases is stronger for employed consumers (Table D.9). Working people have to drive more and travel distances cannot be easily reduced; they are thus expected to be the more responsive to fuel price changes. This effect is less strong in the Paris region, where more public transport alternatives are available.

Generally, firms react less strongly to fuel prices than private consumers. Among other factors this may be due to firms' ability to pass through fuel costs to the consumer and to smaller absolute fuel price variations when VAT refund is taken into account. Within firms, we see considerable heterogeneity (Table D.9). The most responsive firms are in urban areas except Paris. In the Paris metropolitan region, sensitivity is particularly low and almost never significant.

However, because of the nested logit specification, the magnitude of the parameters is not directly informative on the actual fuel prices elasticities. One has to consider indirect effects due to the correlation (and thus higher potential substitution) between gasoline and diesel versions of the same model captured by σ_{1d}, as well as substitution within segment σ_{2d}. The estimates for these parameters are as expected all between 0 and 1. σ_{1d} is on average 0.5 implying a relatively high correlation between the two fuel-type versions of the same model (Table D.10, while σ_{2d} is

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

	Private consumers					
	Not employed		Young professional		Employed (>30)	
Income	Low	High	Low	High	Low	High
Urban	-0.11^{***}	-0.08^{***}	-0.15^{***}	-0.13^{***}	-0.13^{***}	-0.14^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Suburb./rural	-0.08^{***}	-0.11^{***}	-0.10^{***}	-0.15^{***}	-0.10^{***}	-0.15^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Paris urban	-0.10^{***}		-0.09^{***}		-0.10^{***}	
	(0.02)		(0.02)		(0.01)	
Paris suburban	-0.03		-0.08^{***}		-0.10^{***}	
	(0.02)		(0.02)		(0.01)	

	Firm purchases		
Sector	Agriculture & industry	Car rental	Trade & services
Suburban/rural	-0.01	-0.03	-0.06^{***}
	(0.01)	(0.04)	(0.01)
Urban	-0.09^{***}	-0.16^{***}	-0.10^{***}
	(0.02)	(0.03)	(0.01)
Paris urban	-0.07^{***}	0.08^{***}	-0.01
	(0.02)	(0.02)	(0.01)
Paris suburban	-0.01	0.01	-0.04
	(0.02)	(–)	(0.02)

Source: CCFA, authors' calculations. Equation (5) is estimated by GMM separately for each type of consumers. Other controlling variables include horsepower, brand fixed effects, segment fixed effects, class of CO_2, month-year effects, and price. Instrumental variables for prices are the price indices of iron (current and lagged value) and indices of export prices of tires (both 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 the Paris suburban area appears to have a problem of weak instruments (see Section 4.2) and does not converge for all bootstrap draws, so that we give no bootstrap error term for it.

relatively low, on average 0.2, implying a relatively low correlation within segments (Table D.11). If the purchaser has a preference for a particular model, he substitutes easily between gas and diesel versions when fuel prices change, rather than switching to a different model and only reluctantly switches segment. Intensity of substitution between the gasoline and diesel versions of the same model appears to be higher in urban areas (including Paris urban and metropolitan areas) 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.

The signs of other variables' coefficients are as expected; in particular, the vehicle price impacts utility negatively (Table D.12).

D.2. Demand for selected car models

For a given product, the demand elasticity to fuel prices depends on the car's fuel consumption (relative to competing products) and on the preferences of the consumer types that buy this car (Table D.13). For the sake of illustration, we compute different elasticities $\eta_{\mathbf{jf}}$ implied by the previously presented parameters for some selected cars, as well as the shifts in demand $\Delta^{t_c}\eta_{\mathbf{jf}}$ and $\Delta^{t_D}\eta_{\mathbf{jf}}$ corresponding to the equalization of diesel and gasoline taxes (t_D) and the carbon tax (t_c),

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

	Private consumers					
	Not employed		Young professional		Employed (>30)	
Income	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)
Suburb./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)	

	Firm purchases		
Sector	Agriculture & industry	Car rental	Trade & services
Suburban/rural	0.29*** (0.03)	0.26*** (0.08)	0.24*** (0.03)
Urban	0.33*** (0.03)	0.18*** (0.04)	0.23*** (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 (5) is estimated by GMM separately for each type of consumers. Other controlling variables include horsepower, brand fixed effects, segment fixed effects, class of CO_2, month-year effects, and price. Instrumental variables for prices are the price indices of iron (current and lagged value) and indices of export prices of tires (both 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 the Paris suburban area appears to have a problem of weak instruments (see Section 4.2) and does not converge for all bootstrap draws, so that we give no bootstrap error term for it.

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

	Private consumers					
	Not employed		Young professional		Employed (>30)	
Income	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)
Suburb./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)	

	Firm purchases		
Sector	Agriculture & industry	Car rental	Trade & services
Suburban/rural	0.08*** (0.02)	0.16*** (0.03)	0.01 (0.02)
Urban	0.07*** (0.02)	0.08*** (0.03)	0.16*** (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 (5) is estimated by GMM separately for each type of consumers. Other controlling variables include horsepower, brand fixed effects, segment fixed effects, class of CO_2, month-year effects, and price. Instrumental variables for prices are the price indices of iron (current and lagged value) and indices of export prices of tires (both 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 the Paris suburban area appears to have a problem of weak instruments (see Section 4.2) and does not converge for all bootstrap draws, so that we give no bootstrap error term for it.

Table D.12: Estimates for coefficient γ_d

	Private consumers					
	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)
Suburb./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)	

	Firm purchases		
Sector	Agriculture & industry	Car rental	Trade & services
Suburban/rural	-0.22^{***} (0.03)	-0.29^{***} (0.08)	-0.10^{***} (0.03)
Urban	-0.01 (0.03)	0.14^{***} (0.05)	-0.00 (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 (5) is estimated by GMM separately for each type of consumers. Other controlling variables include horsepower, brand fixed effects, segment fixed effects, class of CO_2, month-year effects, and price. Instrumental variables for prices are the price indices of iron (current and lagged value) and indices of export prices of tires (both 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 the Paris suburban area appears to have a problem of weak instruments (see Section 4.2) and does not converge for all bootstrap draws, so that we give no bootstrap error term for it.

respectively.

An increase in fuel prices (both gasoline and diesel) reduces demand for all cars ($\eta_{\mathbf{jf}} < 0$), but the magnitude varies: Table D.13 gives only a sample of the most popular cars in our data, where the Peugeot 307 gasoline model had an elasticity with respect to fuel price of -0.17, while the Citroen C3 gasoline model had an elasticity of -0.34. An increase in diesel fuel tax strongly lowers the demand for diesel cars ($\Delta^{t_D}\eta_{\mathbf{jf}} < 0$); for example the sales of the Audi A6 with diesel engine would decrease by 18.2% (Table D.13). At the same time, such a policy has a small but significantly positive effect on the demand for gasoline cars, reflecting a substitution effect.

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

model (segment)	**fuel**	**CO_2 (g/km)**	**fuel cons. (L/km)**	$\eta_{\mathbf{jf}}$	$\Delta^{t_D}\eta_{\mathbf{jf}}$ **(%)**	$\Delta^{t_c}\eta_{\mathbf{jf}}$ **(%)**
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 (5) is estimated by GMM separately for each type of consumers. Standard errors are estimated by bootstrap (500 replications).

E. Testing for weak instruments

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

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

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

	Private consumers					
	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***	

	Firm purchases		
	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%.

F. Robustness checks: elasticities

Table F.17: Robustness checks: elasticities with respect to fuel prices of diesel share, average fleet fuel consumption (L/km) and CO_2 intensity (g/km)

	Diesel share	Fuel cons.	CO_2
	η_D	η_ϕ	η_{CO_2}
Main specification - including degenerate nests (gas/diesel-only models)			
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)
Alternative specification - Nests (segment>model)			
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)
Main specification - BLP-instruments only			
Households	0.033^{***} (0.003)	-0.015^{***} (0.001)	-0.017^{***} (0.001)
Firms	0.017^{***} (0.004)	-0.003^{***} (0.001)	-0.004^{***} (0.001)
Total	0.039^{***} (0.003)	-0.011^{***} (0.001)	-0.014^{***} (0.001)
Main specification - without purchaser heterogeneity			
Total	0.039^{***} (0.004)	-0.028^{***} (0.003)	-0.025^{***} (0.002)

Source: CCFA, authors calculations. Estimates rely on the parameters of Equation (5) estimated by GMM separately for each type of consumers. Standard errors are estimated by bootstrap (500 replications).