RUHR ECONOMIC PAPERS

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Drive Less, Drive Better, or Both? Behavioral Adjustments to Fuel Price Changes in Germany

rwi #892

Imprint

Ruhr Economic Papers

Published by

RWI – Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

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Ruhr Economic Papers #892

Responsible Editor: Manuel Frondel

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ISSN 1864-4872 (online) – ISBN 978-3-96973-032-4

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Bibliografische Informationen der Deutschen Nationalbibliothek

The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available on the Internet at **http://dnb.dnb.de**

RWI is funded by the Federal Government and the federal state of North Rhine-Westphalia.

http://dx.doi.org/10.4419/96973032
ISSN 1864-4872 (online)
ISBN 978-3-96973-032-4

Anna Alberini, Marco Horvath, and Colin Vance[1]

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Abstract

The demand for motor fuel should decline when its price rises, but how exactly does that happen? Do people drive less, do they drive more carefully to conserve fuel, or do they do both? To answer these questions, we use data from the German Mobility Panel from 2004 to 2019, taking advantage of the fluctuations in motor fuel prices over time and across locales to see how they affect Vehicle Kilometers Traveled (VKT) and on-road fuel economy (expressed in kilometers per liter). Our reduced-form regressions show that while the VKTs driven by gasoline cars decrease when the price of gasoline rises, their fuel economy tends to get worse. It is unclear why this happens. Perhaps attempts to save on gasoline-cutting on solo driving, forgoing long trips on the highway, driving more in the city-end up compromising the fuel economy. By contrast, both the VKTs and the fuel economy of diesel cars appear to be insensitive to changes in the price of diesel. Latent class models confirm our main findings, including the fact that while fuel prices, car attributes, and household and location characteristics explain much of the variation in the VKTs, it remains difficult to capture the determinants of on-road fuel economy. Since the price elasticity of fuel consumption is the difference between the price elasticity of VKT and the price elasticity of the fuel economy, our results suggest that the fuel economy might be the "weakest link" of price-based policies that seek to address environmental externalities, such as a carbon tax.

JEL-Code: Q41, Q53, Q54, R41

Keywords: On-Road fuel economy; price elasticity; vehicle kilometers traveled; motor fuel prices

January 2021

1 Anna Alberini: AREC, University of Maryland, and Charles University Environment Center; Marco Horvath, RWI; Colin Vance, RWI and Jacobs University Bremen. *- Alberini gratefully acknowledges support from the Czech Science Foundation under grant no. 19-26812X. Horvath and Vance have received support by the Federal Ministry of Education and Research under grant 01LA1809C (Project DIPOL) and by the Collaborative Research Center "Statistical Modeling of Nonlinear Dynamic Processes" (SFB 823) of the German Research Foundation (DFG), within Project A3, "Dynamic Technology Modeling.* *- All correspondence to: Colin Vance, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: colin.vance@rwi-essen.de*

1. Introduction

The demand for motor fuel should decline when its price rises, but what is the mechanism for this? Do people simply drive less, or do they change their driving style so that they also improve their fuel economy while driving less? Or are they by now, at a time when fuel prices are relatively low, virtually insensitive to modest fluctuations in the price of motor fuels?

Three streams of literature are particularly relevant to these questions. Two of these estimate the percent change in either the consumption of fuel or in the distance driven given a percent change in the fuel price. The magnitude of such estimates varies widely across studies, typically ranging from below -0.1 to -0.3 in North American-based studies (Goetzke and Vance, 2020: Hughes et al., 2008; Linn, 2016; Liu, 2014) to between -0.3 and -0.6 in studies from Europe (De Borger et al., 2016; Frondel and Vance, 2018; Gillingham and Munk-Nielsen, 2019). By measuring the responsiveness to fuel price fluctuations, these estimates serve to quantify the effect of price-based instruments like fuel taxes in reducing global pollutants, such as carbon dioxide (CO_2). They also provide key inputs into benefit-cost analyses of fuel economy regulations (NHTSA, 2011, 2020) and shed light about the likely magnitude of rebound effects (Sorrell and Dimitropoulos, 2008).

The third stream of literature addresses the related question of how the fuel price influences the fuel economy, i.e., the kilometers driven per unit of fuel. Much of this literature focuses on new car purchases, recognizing that higher gasoline and diesel prices should encourage motorists to buy more fuel-efficient vehicles (Kilian, 2008). But what happens to the fuel economy of existing cars—cars that are already part of the fleet at a specified locale—when the price of fuel changes? In this instance, driving decisions—such as where, when, and how fast to drive—enter as crucial determinants of fuel economy alongside the car's technical features. Several studies have documented a growing divergence between official and real-world fuel economy values (Fontaras et al., 2017; Pavlovic et al., 2018), reaching a mean of about 36% for the German car fleet (Tietge et al., 2017). Driving style is regularly identified as a contributing factor to this divergence, though the relation between driving style, fuel costs, and fuel economy has not received much attention.

Straddling these lines of inquiry, we use data from the German Mobility Panel from 2004 to 2019 to estimate the determinants of both distance driven and on-road fuel economy. In each of three years, panel participants are asked to record the odometer reading at the beginning of the observation period in the spring—along with liters of fuel bought, price per liter, and total expenditure at each refueling during the observation period. These records are summarized into monthly distance driven (in kilometers) and an average fuel economy (kilometers per liter of fuel) for that survey wave.

We use this information to estimate the price elasticity of fuel consumption, which is then employed to assess the implications of fuel price increases planned under Germany's Climate Action Programme 2030. Since the price elasticity of fuel consumption is comprised of two parts—the fuel price elasticity of kilometers traveled (VKT), minus the fuel price elasticity of the fuel economy, we fit two reduced-form models where log VKTs and the log fuel economy are regressed on fuel prices, car attributes, controls for the stock of cars owned by the household, and household sociodemographics. We include household and county-by-year fixed effects to control for unobserved heterogeneity. Since we control for the stock of cars of the household (which changes little from one wave of the survey to the next), we interpret our results as short-run elasticities.

We find that the kilometers logged on *gasoline* cars decline with the price of gasoline. The price elasticity is around -0.25, and this finding is stable across broad income groups and rural v. urban location. By contrast, diesel cars are driven more, and have better fuel economy, but their

VKTs are insensitive to changes in diesel prices. This finding is consistent with a an extensive v. intensive margin argument: People who must drive many miles for work- or family-related reasons buy diesel vehicles as their cost per kilometer is lower than for gasoline cars, but then don't adjust their driving as the price of diesel changes.

Another key finding is that though we might expect motorists to adjust driving style to conserve fuel in the face of price shocks, our model of fuel economy indicates the opposite response: For drivers of gasoline cars, higher gas prices are associated with *worse* fuel economy. The explanation for this response, which is not observed among diesel car drivers, is not immediately clear. It may be that high gasoline prices lead households to engage in less solo driving, forgo longer highway trips, or drive more in the city, all of which could worsen fuel economy. The fuel economy would thus appear to be the "weakest link" in the relationship between price and motor fuel demand, and to have the potential to limit the effectiveness of a carbon tax in reducing emissions.

We complete the analysis by estimating latent class models to capture the influence of unobserved heterogeneity in kilometers driven or driving style and their relationship with the fuel price and other covariates. The results from these models confirm our main results. Moreover, they underscore that while we can do a reasonable job explaining the VKTs and how they change with fuel prices, the factors that affect on-road fuel economy remain elusive.

Consolidating the econometric estimates of VKT and fuel economy, our calculation of the elasticity of fuel consumption with respect to the fuel price is the net result from two opposing channels at play: Higher prices reduce fuel consumption through less driving, but this effect is partially offset by higher fuel consumption through less efficient driving. We use our derived elasticity estimate to predict the CO_2 impacts of future fuel price increases stipulated under the

Climate Action Programme 2030. We find the predicted CO_2 reductions to be small—less than 1% of the total CO_2 of passenger cars in Germany, in part because the modest carbon tax (25€/ton to 55€/ton) implies minor price hikes, on the order of about ten cents by 2025, and in part because the overall price elasticity of fuel consumption is small.

The remainder of the paper is organized as follows. Section 2 provides background information. Section 3 presents the data. Section 4 describes the model, and section 5 the results. Section 6 concludes.

2. Background

2.1. Key Concepts

The fuel efficiency or economy of a vehicle is defined as useful work (for example, driving ten kilometers) divided by the fuel input required by that useful work (for example, one liter of gasoline) (Sorrell, 2009). The reciprocal of the fuel economy is the fuel consumption rate. Better fuel economy figures imply lower fuel consumption rates.

The central aim of this paper is to estimate how the consumption of fuel (C) changes in response to changes in the fuel price (p), expressed in elasticity form as $\frac{\partial C}{\partial p} \cdot \frac{p}{C}$. Since fuel consumption is equal to vehicle kilometers traveled (VKT) divided by fuel economy (FE), $C = \frac{VKT}{FE}$, where FE equals the kilometers driven per liter of fuel, this elasticity can be decomposed as:

(1) $$\frac{\partial C}{\partial p} \cdot \frac{p}{C} = \frac{1}{FE^2}\left[\frac{\partial VKT}{\partial p} \cdot FE - \frac{\partial FE}{\partial p} \cdot VKT\right] \cdot \frac{p}{C} = \frac{\partial VKT}{\partial p} \cdot \frac{1}{FE} \cdot \frac{p}{(\frac{KVT}{FE})} - \frac{\partial FE}{\partial p} \cdot \frac{KVT}{FE} \cdot \frac{1}{FE} \cdot \frac{p}{(\frac{KVT}{FE})} =$$

$$= \frac{\partial VKT}{\partial p} \cdot \frac{p}{VKT} - \frac{\partial FE}{\partial p} \cdot \frac{p}{FE}.$$

Expression (1) shows that the elasticity of fuel consumption with respect to fuel price is the difference between the fuel price elasticity of kilometers traveled, $\frac{\partial VKT}{\partial p} \cdot \frac{p}{VKT}$, and the fuel price elasticity of the fuel economy, $\frac{\partial FE}{\partial p} \cdot \frac{p}{FE}$.

The three terms in Equation (1) each encapsulate three respective strands of literature addressing the environmental impacts of car travel. Research addressing the effects of fuel prices on fuel consumption as well as VKTs has been summarized in reviews by Graham and Glaister (2002), Goodwin et al. (2004), and Dimitropoulos et al. (2018). Aside from identifying relatively low fuel price elasticities, one of the main findings of this literature is that elasticities derived from VKT are generally lower than those derived from fuel consumption. This may follow from the fact that fuel consumption elasticities allow for additional adjustments, including in the sales of new vehicles, and within-household switching between cars of different fuel economies (Archsmith et al., 2020; De Borger et al., 2016).[1] Other work has focused on improving the quality of the price data and on distinguishing the effect of pre-tax fuel prices from that of the taxes, finding the latter to be 3-4 times larger than the former (Li et al., 2014; Rivers and Schaufele, 2015).

Studies that estimate the effects of fuel prices on fuel economy have primarily been concerned with new car sales (Kilian, 2008). The empirical evidence is ambiguous. For example, Hastings and Shapiro (2013) find that when the price of gasoline rises, people don't buy cars with

[1] De Borger et al. (2016) use information from the Danish vehicle registry from 2004 to 2010, merged with information about the owners of the cars and car characteristics. They select households who own 2 cars and do not change them during the study period (N=22,801, for a total of 45,602 cars), and fit two reduced-form equations—one for the primary car and one for the other car. The kilometers logged are calculated from the difference in subsequent odometer readings. The changes in the log kilometers driven are regressed on the changes in the prices per kilometer for the primary and the secondary car, income, and other controls. De Borger et al. show that ignoring substitution between cars would lead to a substantial overstatement of the elasticity of VKT with respect to price: The estimated elasticities, namely -0.98 and -1.41 for the primary and secondary car, respectively, become -0.32 and -0.45 when one accounts for substitution. By contrast, Archsmith et al. (2020) focus on two-car households in California that did replace one of their vehicles in 2001-2007, finding evidence of substitution between *car attributes* as well as miles driven.

better fuel economy: They simply substitute towards lower-grade gasoline. Langer and Miller (2013) find that automakers offer discounts and rebates on fuel-inefficient models when the price of gasoline rises. On examining new car sales or the registration records of the entire fleet, Li et al. (2009), Klier and Linn (2010), and Rivers and Schaufele (2017) all find fuel price elasticities of the fuel economy below 0.2.

2.2 Fuel Economy in Existing Cars

Relatively fewer studies have investigated what affects the fuel economy of an *existing* car, and of these, we are aware of only one, Rouwendal (1996), that investigates the role of fuel prices. Based on self-reported cross-sectional data from a sample of motorists in the Netherlands, he estimates that a 1% increase in the fuel price is associated with 0.15% increase in on-road fuel economy. In more recent work on the European market, Fontaras et al. (2017) find that the important factors affecting fuel economy include the mass of the vehicle, aerodynamic resistance, tires, and auxiliary systems (e.g. heating, a/c, and steering assist systems).

Studies outside of Europe include Greene et al.'s (2017) examination of over 600,000 self-reported entries by US motorists to the myMPG.gov portal. Since the same driver reported multiple measurements of the fuel economy for the same vehicle, Greene et al. effectively develop a longitudinal dataset and find evidence of considerable variation in fuel economy *within* the same vehicle as well as *across* vehicles. The explanatory variable that accounts for most of the variation in on-road miles per gallon (MPG) is the test-cycle MPG. Temperature also has some effect on the fuel economy—both direct (by affecting the efficiency of combustion) and indirect (heating and air conditioning hamper the fuel economy), as do powertrain characteristics and self-reported driving style, while geography has very little explanatory power. Regarding driving style, Barkenbus (2010) and Jeffreys et al. (2018) find that "eco-driving" in the US and Australia, respectively, can reduce fuel consumption by 5-25% depending on traffic conditions and length of the trip.

One important question is whether one should expect the on-road fuel economy performance to be consistently worse than the "official," test-cycle fuel economy measured by the automakers or by government agencies. Government assessments of proposed tightening of the Corporate Average Fuel Economy (CAFE) standards, for example, *assume* a 20% gap between test-cycle fuel economy and actual, on-road fuel economy (NHTSA, 2011, 2020).

2.3 Fuel Economy in Germany

Germany does not have specific fuel economy policies in place, and indeed has one of the least fuel-efficient, and highest-emitting, fleets in the EU, despite regular improvement over the last decade as a result of the EU CO_2 emissions regulations.[2] In internal combustion engines, the CO_2 emissions rate is inversely proportional to the fuel economy, implying that the latter should have improved over time—for new cars because it is required by the regulations, and in the fleet as a whole as older and more inefficient vehicles are retired and replaced with new ones. Figure A.1 in the Appendix shows that the fuel economy of new cars sold in Germany improved steadily from 2001 to 2016, in anticipation of, and as a result of, the CO_2 emissions regulations, but then plateaued and even worsened in 2017-18.[3]

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[2] As part of the EU, Germany is subject to EU CO_2 emissions regulations, which became effective in 2011 and have since required automakers to produce and sell vehicles with emissions rates below specified targets. The targets are tightened over time, from 130 g CO_2/km in 2012 to 95 g CO_2/km in 2020 (https://ec.europa.eu/clima/policies/transport/vehicles/cars_en).

[3] The CO2 emissions rates of new cars followed a similar pattern. Figure A.2 shows that the emissions rates of new cars sold in Germany were consistently higher (and the fuel economy lower) than those for the EU as a whole, as well as those of a neighboring country, France.

Some incentive to purchase new cars with lower emissions rates, and hence better fuel economy, has arisen since 2009 as a result of annual circulation taxes that are a linear function of the CO_2 emissions rate (for a given engine size and type of fuel). The registration taxes are, however, modest, and so are their effects on new vehicle sales (Alberini and Horvath, 2020; Klier and Linn, 2015).

Turning to *existing* cars, Tietge et al. (2017) examine on-road fuel economy figures reported by German drivers to the online portal spritmonitor.de. The dataset covers cars manufactured from 2001 to 2014, and the fuel economy observations appear to have been collected in 2014. Tietge et al. regress the on-road fuel consumption rate on test-cycle fuel consumption rate,[4] weight, engine size, and dummies for model-year, finding that the coefficients on the latter are positive and statistically significant, and increase monotonically with model-year.[5] In other words, the more recently a car was manufactured, the larger the difference between the certified and actual fuel consumption rates.

One possible explanation is that the test procedure used in the European Union (the NEDC) is based on an outdated sequence of driving modes that no longer mirrors current driving conditions. Alternatively, automakers have become increasingly sophisticated at optimizing performance during the test (by using slightly overinflated tires, no cargo, ideal test environment temperatures, etc.). In the meantime, in September 2017 the EU adopted the Worldwide

[4] In Europe, until recently passenger vehicles were subject to the New European Driving Cycle (NEDC), which simulates a sequence of driving cycles including accelerations, decelerations, periods of constant speed, and is thus supposed to mimic city and highway driving. The tailpipe gases are collected and their CO_2 content determined to arrive at the car's CO_2 emissions rate in grams per kilometer. The fuel consumption rate is calculated from the CO_2 emissions rate by multiplying the latter by a fuel-specific constant.

[5] The regression explains over 88% of the variation in on road fuel economy for gasoline cars and over 89% for diesel cars. Adding the year dummies per se however improved the R square by only 1 point compared to simpler models that include only the NEDC fuel consumption rate, weight and engine capacity.

Harmonised Light Duty Test Procedure (WLTP) which is expected to result in closer on-road and test-cycle performance.

With existing cars, one would expect fuel prices to be a determinant of kilometers driven as well as on-road fuel economy. In Germany, taxes account for a considerable portion of the price of motor fuels: Since 2002, German motorists have paid a tax of 65.45 cents per liter of gasoline and 47.04 cents per liter of Diesel, plus a VAT of 19%, which means that taxes account for about 60% of the fuel price. The excise tax amount has remained unchanged during our study period (2004-2019), while the VAT was only increased once from 16% to 19% in the beginning of 2007, implying that any changes in fuel prices during our study period were due solely to fluctuations in world oil prices and/or local demand and supply conditions.[6]

In the remainder of this paper, we estimate the fuel price elasticities of kilometers traveled and fuel economy, and thus use the decomposition in Equation (1) to assess their role in the determination of the overall fuel price elasticity of fuel consumption. Distinguishing from work to date, both estimates are based on actual, on-road micro-level data drawn from a panel of households. While earlier research investigates the "extensive margin," i.e., the decision to purchase a car, in this paper we analyze the intensive margin—the usage of cars already owned by a household.

[6] Frondel et al. (2020) and Horvath (2019) examine retail motor fuel prices in Germany, concluding that—especially after the adoption of a federal requirement that each gas station post its prices daily on an online portal accessible to regulators and members of the general public—competition became more intense, reducing profit margins and bringing quicker pass-through of world oil prices.

3. Materials: The Data

We use data from the German Mobility Panel (GMOP) from 2004 to 2019. The GMOP was started in 1994. Participating households remain in the panel for 3 years, then are rotated out and replaced by a new cohort.[7]

During a total of six weeks in the spring, participating households record the odometer reading of each of their vehicles at the beginning of the observation period, and every time they refuel their vehicle. At the pump, they also record the price per liter of gasoline or diesel, the number of liters they bought, and the total amount paid. A final odometer reading is done at the end of the observation period. The kilometers driven during the observation period are then computed as the difference between the final and initial odometer reading, and are converted to a monthly equivalent.[8] We compute the average fuel economy during the observation period as the total number of kilometers driven divided by the total number of liters of gasoline purchased.

Attention in this paper is restricted to households with at least one car.[9] Information about our sample is provided in table A.1 in the Appendix. Our sample follows a total of 5622 households. Only 34% stayed in the GMOP for three years; about 37% of the sample participated for only one year, and 29% participated for two years.

Our sample contains a total of 8358 cars. About 71% of the households own only one car, 26% own two, 3% three, and less than 1% own four or more cars. About 71% of all cars are

[7] Some participants drop out of the survey before the due completion time. See Chlond et al. (2015) for a discussion of attrition rates. Chlond et al. report that attrition is highest among young adults (persons aged 26-35) after the first year; nevertheless, of those who remain in the panel, 87% completes the third round of data collection. The attrition rate in the age groups is approximately 80% after the first year, and of the remainder about 86% complete the third year.

[8] The difference between subsequent odometer readings is the number of kilometers driven between refueling operations. The total kilometers driven can also be obtained as the sum of all kilometers driven in between gas station visits.

[9] Households with at least one car account for some 86% of the households in the Germany Mobility Panel.

gasoline cars and 26% are diesel cars. The remaining 3.56% run on alternative fuels, such as natural gas or LPG. Company cars account for only 6% of the observations.

The turnover of vehicles is similar to what can be expected in the population: Every year about 4.39% of the cars are new additions to the family's stock of cars (compared to the previous year), 2.25% exit and are not replaced, and 6.50% of the households replace one or more cars, keeping the total number of cars owned by the household unchanged.

The average car is driven about 1129 km per month, or 13,548 km on an annual basis. Figures 1 and 2 display histograms of the annual kilometers driven, comparing gasoline v. diesel, and gasoline with alternative fuel cars. The distributions of annual kilometers driven are positively skewed, and diesel and alternative fuel cars are generally driven more than gasoline cars. That's unsurprising: People who must—for whatever reason—drive a lot often buy diesel or natural gas cars because they are more fuel-efficient and, taking fuel prices into account, the cost of driving them is lower than the cost of driving gasoline cars.

Figure 3 shows that the actual, on-road fuel economy of the cars in our sample—namely the actual kilometers driven on a liter of motor fuel—displays considerable variation, and is generally more favorable among diesel cars. The fuel economy is on average 13 km/liter among gasoline cars and 15 km/liters among diesel cars.

Figure 4 compares the average, on-road fuel economy in the GMOP with that of new cars sold in Germany between 2011 and 2019. The on-road fuel economy has grown slowly but steadily (from about 13.5 km/liter to about 14.5 km/liter) in the cars documented in the GMOP. It grew much faster among the new cars sold in Germany until about 2016. The trend flattened and even worsened thereafter.

Figure 5 displays the average gasoline and diesel prices (expressed in real 2010 euro/liter) during our study period, showing that there were considerable fluctuations over time. By 2012, for example, the prices were 60-70% higher than they as they were at the end of the 1990s. Tables 1 and 2 display the mean prices of petrol and diesel each year along with their standard deviations, demonstrating that there was quite a bit of variation even within the same year.

4. Methods: The Model

4.1 Explaining the fuel economy

Our unit of observation is an individual car, which is followed for up to three years. We fit two regression equations. The first posits that the average fuel economy experienced during the reference period (expressed in km per liter of fuel) depends on the manufactured-certified fuel economy of the vehicle, adjusted for the age of the vehicle, and for a host of personal, household and location characteristics. In logs,

(2) $$lnFE_{it} = const + \alpha \cdot lnFuelPrice_{it} + \beta \cdot lnMFE_i + \gamma \cdot Age_{it} + \mathbf{x}_{it}\boldsymbol{\delta} + \mathbf{w}_{it}\boldsymbol{\lambda} + \varepsilon_{it}$$

where *i* denotes the car, *t* the year, MFE the manufacturer-certified fuel economy, Age the age of the vehicle, and **x** denotes individual and household characteristics (including the household's stock of vehicles), and **w** is a vector describing the local geography and the roads.[10]

In practice, the dataset does not contain MFE, and the sometimes-incomplete information about the make, model and trim of the vehicle in the GMOP prevent us from obtaining this information from external sources. Using an independent source of data about the official and actual, on-road fuel economy of vehicles, however, we were able to determine that the official fuel economy of a car is well predicted by the car's make, age, engine displacement in ccm,

[10] We note that the manufacturer-certified fuel economy is the inverse of the fuel consumption rate (in liters per distance driven), which is the information usually provided to consumers and regulators. If α=-β, the right-hand side of equation (1) would thus contain the log of the price per kilometer based on the "official" fuel economy.

horsepower, and fuel type. These variables explain 80% of the variation in the log of the technical fuel economy, and are available in the GMOP, so we enter them in equation (2) in lieu of the MFE term.[11]

Equation (2) is thus amended to

(3) $$lnFE_{it} = \alpha \cdot lnFuelPrice_{it} + \mathbf{z}_{it}\boldsymbol{\beta} + \mathbf{x}_{it}\boldsymbol{\delta} + \mathbf{w}_{it}\boldsymbol{\lambda} + \text{fixed effects} + \varepsilon_{it}$$

where vector $\mathbf{z}$ includes make dummies, engine size and horsepower per unit of engine size, model-year dummies, and a diesel engine dummy. Equation (3) also includes fixed effects to account for unobserved heterogeneity.

We considered several candidate fixed effects. We ruled out vehicle-level fixed effects because including them would reduce the sample size by one-third (the share of households that only appear in the sample in one year) and absorb the effect of many of the covariates we are interested in. Household fixed effects are possible. They are identified either by households that appear more than one year in the data or that own more than one car. Finally, county-by-year fixed effects help capture demand shocks, the state of the local economy, and the type and quality of the roads, allowing them to have a different impact in each year, depending on major construction and road work, weather, etc. They can be included with or without household fixed effects.[12]

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[11] This dataset was provided by Emissions Analytics, and documents 1185 gasoline and diesel cars that underwent on-road emissions testing using approved portable equipment in Germany and the UK. The cars range in age between one and 24 years at the time of the test, and were tested between 2011 and 2020. When regressed the official fuel consumption rate (expressed in liters/100 km) on make dummies, model-year dummies, test-year dummies, engine ccm, and horsepower divided by engine ccm, the R square of the regression was 85%. When we created the fuel economy of the vehicle (which is equal to the reciprocal of the fuel consumption rate), took its log, and regressed this log on the same covariates, the R square of the regression was 80%.

[12] Germany has 410 counties (or *Kreise*) with an average size of about 800 square kilometers. This administrative unit is comparable to the county in the US. Only a handful of people move from one county to another during the study period, and for this reason county-specific fixed effects alone (not interacted with time) would be absorbed into the household fixed effects.

Since respondents collected and reported the price per liter of fuel, the number of liters bought, and the total expenditure each time they refueled,[13] our regressions by construction do not suffer from the problem of measurement error.

What is the sign of coefficient α in equation (3)? If people are seeking to drive more smoothly and to conserve fuel as the price of gasoline increases, then α should be positive. Indeed, using driver self-reports from the Netherlands, Rouwendal (1996) empirically finds this elasticity to be about 0.15. However, in more recent decades driving styles may have become less sensitive to price ($\alpha \approx 0$), and it is even possible to envision behavioral changes in response to fuel price increases (shorter trips, more city driving, more Autobahn driving at very high speeds, less solo driving) that end up compromising the fuel economy ($\alpha < 0$).

4.2. The Mileage Equation

Drivers may respond to motor fuel price changes by driving less (when the price increases) or more (when the price decreases). We specify a demand function for kilometers driven, which are assumed to depend on the fuel cost per kilometer driven, income, and other factors, such as work and family needs, etc. We assume that

(4) $$VKT = A \cdot (price\ per\ km)^b \cdot X^c \cdot INCOME^h \cdot \exp(\eta),$$

where price per kilometer is motor fuel price divided by the actual fuel economy (in kilometers per liter). We further assume, as we had for equations (2) and (3), that the actual, on-road fuel economy is equal to the fuel economy declared by the manufacturer, adjusted for the vintage of

[13] All of this information is displayed on the pump itself, and so all the respondents had to do was to simply to take it down and enter it in the GMOP diary.

the vehicle, the quality of the roads, and driving style, which may depend on individual and household characteristics.

On substituting these variables in and taking logs, we obtain

(5) $$\ln monthlykm_{it} = b \cdot lnFuelPrice_{it} + \mathbf{z}_{it}\boldsymbol{c} + \mathbf{x}_{it}\boldsymbol{d} + \mathbf{w}_{it}\boldsymbol{g} + \text{fixed effects} + \eta_{it}.$$

In equation (5) the dependent variable is thus the log of the monthly kilometers driven. The regressors, all assumed exogenous, are the same as in the log fuel economy regression (equation (3)).

4.3. Clustering, Heterogeneity, and Other Robustness Checks

In sum, we have specified two reduced-form regression equations where the dependent variables are the logs of the on-road fuel economy and of the kilometers per month, and the key independent variable is log fuel price.[14] We take log transformations for two reasons: First, the distributions of fuel economy and distance driven are positively skewed (see figures 1-3), and, second, the coefficients on log fuel price are immediately interpreted as the price elasticities of fuel economy and distance driven, respectively. These are the two elasticities needed to predict how fuel consumption will change as motor fuel prices change.

We first run our regressions assuming that the error terms are uncorrelated across observations. In practice, they could be correlated within a car, a household, or a county. Theory does not offer clear guidance as to whether standard errors should be clustered within a car, a

[14] We consider our regressions as “reduced-form” because all right-hand side terms are assumed to be exogenous over the three-year observation period of the data. We fit least squares separately to each regression equation. The two equations may also be regarded as a system of seemingly unrelated regressions (SUR) if the error term in (5) is correlated with that in (3) for the same car and GMOP survey wave, due to unobserved factors that influence both the distance driven as well as the fuel economy. SURs are efficiently estimated using generalized least squares (GLS). In this case, however, since the regressors are the same in both equations, GLS estimation boils down to fitting OLS equation by equation. One would thus obtain the same point estimates of the coefficients with SUR GLS estimation or least squares on each equation separately.

household or a county, and for this reason we experiment with alternate standard error calculations, clustering at the car-, household- and county-by-year level, respectively.

We are especially interested in whether the price elasticities and the other coefficients are different for different cars and households, depending on opportunities for substituting driving with public transit, and work and family needs. We therefore run our regressions on the full sample, and for gasoline and diesel cars separately, for urban v. rural residents, for households with and without members who hold jobs, and for households in different quintiles of the distribution of income in the sample.

Adjustments in on-road fuel economy and distance driven may be due to a household's re-arrangement of its driving across its different cars. We therefore re-estimate our regressions focusing on a sample comprised of households who own only one car, and on one comprised of all others (two or more cars). To isolate behavioral adjustments from changes in the cars owned by the household, we re-run our regressions keeping the stock of car unchanged. In other words, we exclude from the usable sample observations from households who have added a car, dropped a car, or replaced one or more cars since the previous wave of survey.

4.4. Latent Class Models

In an attempt to allow for drivers to respond differently to fuel prices and other factors, we fit latent class models. A latent class model presumes that drivers, and their cars, fall into one of C possible groups. Within one such group, the tastes of the consumers are similar, and so are the regression coefficients for that group. For example, the fuel economy equation, conditional on being in class c, is:

(6) $lnFE_{it} = \alpha_c \cdot lnFuelPrice_{it} + \mathbf{z}_{it}\boldsymbol{\beta_c} + \mathbf{x}_{it}\boldsymbol{\delta}_c + \mathbf{w}_{it}\boldsymbol{\lambda_c} + \text{county} \times \text{year fixed effects} + \varepsilon_{it}.$

The regression coefficients are thus potentially different across classes.

Since we do not observe which class someone belongs to, we let Q_c denote the class membership probability. For any one car/driver, $\sum_{c=1}^{C} Q_c = 1$. It is assumed that

(7) $$Q_{ic} = \exp(\boldsymbol{X_{ic}\tau}) / \sum_{c=1}^{C} \exp(\boldsymbol{X_{ic}\tau}),$$

and, for identification, that $Q_{i1} = 1/\sum_{c=1}^{C} \exp(\boldsymbol{X_{ic}\tau})$. Denote the density of the observations on the dependent variable, conditional on belonging to class c, as $\phi\left(\frac{lnFE_{it} - m_{it,c}}{\sigma_c}\right)$ where $m_{it,c}$ denotes the right-hand side of equation (6) (excluding the error term), σ_c is the standard deviation of the error term in class c, and $\phi(.)$ is the standard normal pdf. Then the unconditional contribution of each observation to the likelihood function is

(8) $$\ell_{it} = \sum_{c=1}^{C} Q_c \cdot \phi\left(\frac{lnFE_{it} - m_{it,c}}{\sigma_c}\right),$$

and the likelihood function is $\mathcal{L} = \prod_i \prod_t \ell_{it}$.

The latent class estimation routine must thus estimate vector $\boldsymbol{\tau}$ as well as C times the number of coefficients in the right-hand side of equation (6). Clearly, the number of coefficients to estimate grows with the number of classes C. Rarely does theory suggest how many classes the analyst should assume.[15] No formal statistical test for the number of classes exists either, and so analysts generally choose C as the number of classes beyond which no meaningful improvement is observed in a log likelihood-based measure of fit.[16]

The estimated coefficients can be used to construct posterior class membership probabilities:

[15] An exception is Houde (2018), who posits three types of consumers in his latent class model describing how consumers process the information about the energy efficiency of durables and the cost of running them displayed in energy efficiency labels.
[16] We use the Akaike information criterion, which is equal to the log likelihood function minus the number of coefficients to be estimated, multiplied by -2. Intuitively, the Akaike information criterion looks at fit, but subtracts a penalty for each additional coefficient in the model.

(9) $$\tilde{Q}_{ic} = \hat{Q}_{ic}\hat{\phi}_{itc}/\hat{\ell}_{it},$$

where the $\hat{Q}_{ic}$, $\hat{\phi}_{itc}$ and $\hat{\ell}_{it}$ are obtained simply by plugging in the coefficient estimates into (7) and (8). The predicted mean of the dependent variable for each observation is

(10) $$\sum_{c=1}^{C} \tilde{Q}_{ic}\hat{m}_{itc}$$

and observation-specific posterior price elasticities can be obtained as

(11) $$\tilde{\alpha}_i = \sum_{c=1}^{C} \tilde{Q}_{ic}\hat{\alpha}_c.$$

Using latent class models may help us understand if the sample is comprised of people who appear to be sensitive to the price of fuel in one direction (e.g., their fuel economy improves when the price of fuel increases; mileage decreases as fuel price increases), in the other direction (the fuel economy gets worse as the price of fuel increases as people change their driving pattern and the roads where they drive; mileage on one car increase as people consolidate trips on the most efficient car), or are completely insensitive.

5. Results

5.1. Main Specification

Table 3, col. (1) shows that as the price of motor fuel rises, the fuel economy appears to get worse for gasoline cars. Diesel cars are generally more fuel efficient in the first place, as shown by the positive and significant coefficient on the diesel car dummy, and are unaffected by changes in fuel prices.[17] Alternative fuel vehicles are likewise unaffected. Cars with larger engines and with a higher horsepower-to-engine size ratio tend to have a lower fuel economy.

We entered in the regression several controls to capture the possibility of substitution among the household's vehicles, but none seems to be strongly associated with the fuel economy

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[17] The positive coefficient on log fuel price cancels out with that on the interaction of ln fuel price and diesel car. The resulting price elasticity is -0.0177 (s.e. 0.0246).

of any given car. Income, availability of public transit, and living in an urban area do not seem important either. The number of full-time workers and the number of middle and high school- aged children in the household are significantly associated with the fuel economy in col. (1), but in practice they suggest that adding a worker raises the fuel economy by a mere 1.4%, while adding a child reduces it by a mere 1.5%.

Col. (1) can be compared with col. (3), which reports the results of a specification that further includes household fixed effects. While the effect of motor fuel price virtually disappears, variables capturing possible substitution effects within the household are slightly more important, as is the urban location dummy.

In practice, the regressions reported in cols. (1) and (3) of table 3 suggest that car characteristics (including the make, fuel type, vintage, engine size and horsepower per unit of engine size), location-by-time fixed effects and household fixed effects explain up to 75% of the variation in fuel economy. Adding fuel price in the model raises the R square of the regression by only one point, up to a 76%.[18] We conclude that the majority of the variation in the fuel economy is explained by the fixed effects, rather than the regressors shown in table 3.

By contrast, the log VKT regressions show a stronger responsiveness of kilometers driven to the price of motor fuels—at least for gasoline cars. Starting with col. (2), for gasoline cars, the price elasticity of kilometers driven is approximately -0.25, a figure that falls well within estimates from the literature (e.g de Borger et al. 2016; Gillingham and Munk-Nielsen, 2019; Goetzke and Vance 2020). Diesel cars are driven approximately 29% more kilometers than gasoline cars, but

[18] In the specification of col. (1), for example, make, vintage, and Kreis-by-year fixed effects alone result in an R^2 of 0.2894. Adding further car characteristics (fuel type, engine size, horsepower divided by engine size) raises the R^2 to 0.5037. Further adding log fuel price, and log fuel price interacted with a diesel car dummy, only brings to 0.5089. The counterpart R squares in the specification of col. (3), which further includes household fixed effects, are 0.69, 0.75, and 0.76, respectively.

the distance driven is insensitive to the price of diesel.[19] Unlike the fuel economy, the distance driven is related to the number and types of the other cars owned by the household. Specifically, the signs and magnitude of the coefficients on the dummies denoting that the household has other diesel cars and other gasoline cars, and the number of cars owned by the household are all consistent with the notion that households tend to spread the miles over the different vehicles they have, and they tend to log more miles on their diesel cars. Mileage is also affected by income, albeit to a relatively small degree, and by the number of household members who work. Each additional full-time worker in the household increases the distance driven by over 15%.

The effect of gasoline price on the distance driven by gasoline cars remains just as strong in col. (4) of table 3, which adds household-specific fixed effects. This specification likewise finds no effect of diesel price on the kilometers driven by diesel cars, stronger effects of the other cars owned by the household, and virtually no effect of household composition, income, and location. The latter are probably captured by the fixed effects, as these variables tend to change little over the time a household participates in the GMOP.

5.2. Clustering, Heterogeneity and Robustness Checks

Table 4 separates the sample into gasoline and diesel cars, confirming the results shown in table 3. While the owners of gasoline cars are responsive to gasoline prices, at least in terms of kilometers driven, and appear to make changes to their driving that result in worse fuel economy as the price of gasoline increases, those who drive diesel cars do not appear to be affected at all by fluctuations in the price of diesel. We interpret this as an extensive v. intensive margin effect: Those who need to do a lot of driving for family and work reasons will choose to buy a diesel car,

[19] The relevant coefficient for diesel cars is 0.0009 (s.e. 0.0829).

but may have little room for changing the amount of driving they need to do in response to motor fuel price changes.

Table 5 displays the results from the main regressions, using the full sample but clustering the standard errors at the vehicle level (cols. (1) and (2)), household level (cols. (3) and (4)), and county-by-year level (cols. (5) and (6)). The standard errors change very little across the different types of clustering, and we arrive at the same conclusions as in Table 3 in terms of significance of the coefficients.

In table 6 we examine whether substitution across vehicles in the household's current stock affects the responsiveness to motor fuel prices. This is done by comparing the results for one-car households in columns (1) and (2) with those for households with owning two or more cars in columns (3) and (4). This comparison shows that households with only one car (and therefore no opportunities for substitution across vehicles) are less capable of reducing the distance driven on their only vehicle as the price increases, and experience worse overall fuel economy as the price of motor fuel increases. The fuel economy for households with two or more cars is less sensitive to fuel price increases, while the price elasticity of distance driven is almost twice as large (in absolute value) than that in one-car households. Both effects likely reflect the ability of multicar households to switch to the more efficient car in response to high fuel prices. Diesel cars are just as unresponsive to diesel prices in both types of households.

When the sample is restricted to households where the number of cars did not change, and with exactly the same cars as in the previous year, the results (shown in table 7) are similar to those for the full sample.[20]

[20]As this regression includes only households that do not change their stock of cars, i.e. the number of cars as well as the type of cars does not change. For this reason, all households that are only in the panel for one year are dropped as well as the first year of observation for households that are in the sample for multiple years.

Tables 8, 9, and 10 present models that split the sample along various dimensions to allow for differential responses according to socioeconomic circumstances. Households with no working members appear capable of adjusting their VKTs more to changes in gasoline prices than the other households—at the expense of their fuel economy (table 8). There are little differences however across rural and urban areas (table 9). Cars owned by mid- and high-income households are not statistically different in their responsiveness to gasoline prices from cars in low-income households, but they do tend to be driven more (table 10a). The story is similar when households in quintile 1-4 of the distribution of income are grouped together and compared with households in the top quintile of the distribution of income (table 10b).

5.3. Latent Class Models

The latent class estimation routine suggests at most two classes. Models with three latent class either failed to converge, or resulted in no appreciable improvement in the Akaike information criterion.

Table 11 displays the estimation results from fitting a two-class model to the log of the fuel economy. Class 1 is regarded as the default class. Only one variable is associated with the likelihood of belonging to class 2—the number of full-time workers in the family, which is suggestive of a class whose members are constrained by work schedules and needs. Unsurprisingly, the prior class membership probabilities are 50-50: To be more precise, they are 0.4993 for class 1 and 0.5006 for class 2. There are no statistical differences between these predicted probabilities.

Class 1 members are more sensitive to fuel prices (as long as they drive a gasoline car), but once again the coefficient on log gasoline price is negative. By contrast, members of class 2 are unresponsive to fuel prices; their realized fuel economy depends more strongly on other car characteristics, including whether the car runs on diesel or another alternative fuel. It is interesting that this second group appears to be comprised of cars (and drivers) who already enjoy a somewhat better fuel economy than that of those in class 1 (Figure 6).

The posterior distribution of the price elasticity of the fuel economy is displayed in Figure 7 for gasoline cars. Although there is considerable variation in the price elasticity, the distribution is limited to the negative semi-axis.

The story is somewhat different for kilometers traveled. This time the model predicts prior probabilities of 0.4372 for class 1 and 0.5628 for class 2. The logit model of class memberships identifies a number of variables associated with class membership, suggesting that class 2 is more likely to capture persons who live away from urban areas, have medium-high income, are part of the work force, and have children at home. The price elasticities are however virtually the same across the two classes (-0.199 v. -0.220, respectively, for gasoline cars; practically zero for diesel), even if the distances driven predicted by the model for class 1 and class 2 (Figure 8) show that class 2 is comprised of higher-mileage cars. This is the case even when attention is restricted to gasoline cars (Figure 9).

Figure 10 shows the posterior price elasticities of the kilometers traveled for gasoline cars. It is striking that the posterior price elasticities span a very narrow range—from -0.22 to a little less than -0.2. The spike at the right end of the histogram refers to a group of very low-VKT cars: Their average monthly distance is about 283 km, as opposed to the 1200 for the rest of the sample.

We combine the posterior elasticities with respect to the VKT and with respect to the fuel economy (as in equation (1)) to obtain posterior elasticities of gasoline demand with respect to gasoline price. Figure 11 displays a histogram of the gasoline demand posterior price elasticities. They are clearly negative, and range between -0.24 and -0.05, for an average of -0.15.

5.4. Implications for a Carbon Tax

The implications of our findings can be illustrated by evaluating the effect of the carbon tax soon to be implemented in Germany. Starting in January 2021, the German government has implemented a carbon tax of €25/ton of CO_2, which will gradually increase to €55 per ton by 2025.[21] Our calculations focus on gasoline cars, which make up 65% of the 47.7 million passenger car stock in Germany. We use the CO_2 content of gasoline (2.3 kg CO_2 per liter) to calculate the increase in the gasoline price due to the tax, which is about 5.75 euro-cents for the €25 tax and 12.65 euro-cents for the €55 tax,[22] assuming that 100% of the tax is passed on to the consumers (Kopezuk et al., 2013).

Equation (1) shows that the elasticity of fuel consumption with respect to fuel price is the difference between the fuel price elasticity of kilometers traveled and the fuel price elasticity of the fuel economy. We use the results in cols. (3) and (4) in table 3, which puts the elasticity of fuel economy with respect to the price at -0.023 and the elasticity of kilometers driven at -0.255, for a net price elasticity of fuel consumption of -0.232.

We predict a reduction of 737,979 tons of CO_2, which is roughly 0.77% of the total CO_2 emissions from passenger cars in Germany for a CO_2 tax of €25 and a reduction of 1,623,553 tons of CO2 (1.69% of total passenger car CO_2 emissions) for a €55 tax, respectively. To put these

[21] See https://www.bundesregierung.de/breg-de/themen/klimaschutz/co2-bepreisung-1673008

[22] See https://ecoscore.be/en/info/ecoscore/co2 for the CO2 content of gasoline. For our calculations we use the average liters consumed per car in our GMOP sample, which is at 81 liters per month.

numbers in perspective, consider that the average gasoline car in our GMOP sample emits a total of 2.067 tons of CO_2 a year.[23]

Using this information, we calculate that the CO_2 reduction brought by the tax is equivalent to retiring 357,029 cars from the fleet for the €25 tax, and 785,464 for the €55 tax. These figures represent 0.75% and 1.65% of the current fleet, respectively. While these numbers may seem small compared to the fleet, they actually make up 10 to 20% of the new cars sold in Germany every year.[24]

Our prediction of the CO_2 emissions reductions from gasoline cars changes only very marginally if we make assumptions about a further shift away from diesel cars towards gasoline cars, or replacing a part of the fleet with electric cars. This is in part because of the modest combined elasticity of -0.232, but also because we only find a reaction for gasoline cars. With currently roughly 65% of the stock of cars being gasoline there would need to be a massive change in the stock of gasoline cars to change the results meaningfully.

The factor that has the strongest impact is the value of the CO_2 tax. A CO_2 tax of €200—similar to proposals by some environmental organizations but most likely politically infeasible in the short run—would increase the price of gasoline by 46 euro-cents and reduce the CO_2 emissions of passenger cars by about 4.93%. These calculations are likely to be lower bound estimates as they assume that the responsiveness to a carbon tax would be the same as the responsiveness to a change in the fuel price. As Rivers and Schaufele (2015) document in their study of tax policy in British Columbia, the elasticity associated with a fuel or carbon tax is upwards of four times larger, which would imply a more substantial reduction in the CO_2 emissions of passenger cars.

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[23] This is based on the average annual VKT in our sample (13,060 km) and the average fuel economy (14.52 km per liter) in 2019.

[24] During the last decade, about 3 to 3.5 million new cars are sold in Germany every year.

6. Conclusions

Using data from the German Mobility Panel from 2004 to 2019, we have estimated the determinants of both distance driven and fuel economy. This dual focus is motivated by our aim to estimate the elasticity of fuel consumption with respect to the fuel price, which equals the difference between the fuel price elasticity of VKT and the fuel price elasticity of fuel economy. We have fit reduced-form regressions that related log VKTs and log on-road fuel economy to log fuel price, car-, household- and location characteristics. We interpret our estimates as short-run fuel price elasticities.

Overall, our models do a reasonable job explaining VKTs, but the determinants of on-road fuel economy remain elusive. In our base models, car characteristics and fixed effects accounting for unobservables capture much of the variation in on-road fuel economy, with little contribution from sociodemographics and fuel price. Our latent class models struggle to identify segments of the sample that might be regarded as sharing fuel economy behaviors or features.

Notwithstanding these challenges in modeling fuel economy, three key findings emerge: First, for diesel cars, neither the distance driven nor the fuel economy seems to respond to fuel price changes. This could be the result of a selection- or an extensive v. intensive margin argument: People who need to drive a lot for work or family reasons buy diesel cars in the first place, because their cost per kilometer is lower, but do not further adjust their driving to fuel price changes. Whatever its source, this unresponsiveness of diesel motorists to the fuel price bodes well for tax revenue under the Climate Action Programme. The Programme's tax on the CO_2 content of fuel, which is about 13% higher for diesel than for petrol, will address what critics have long contended to be excessively low taxes for diesel, costing the government € 7.1 billion in lost revenue in 2019 according to Germany's Green Party (Wehrmann 2020).

Second, for gasoline cars, kilometers driven decline with a higher gasoline price, with a price elasticity of about -0.25. Third, the fuel economy appears to get *worse* as the price of gasoline increases. The reason for this result is not immediately obvious, as we would have expected drivers to adjust to a more "efficient" driving style when the fuel price increases. It would seem that the very behaviors that drivers undertake to reduce driving—forgoing long trips, perhaps driving more in the city, combining trips with those of other family members, carpooling—may end up worsening the car's fuel economy.

As a result, our calculation of the elasticity of fuel consumption with respect to price, -0.232, is slightly lower than that implied by the elasticity of kilometers driven, -0.255. Whether such a downward adjustment is generally required in assessments of fuel consumption is an open question. Germany may be unique in this regard. The country's deep-seated cultural identification with cars, which is reflected partly in popular resistance to speed limits on the Autobahn, may figure into the explanation of why motorists don't adjust driving style in the expected manner to fuel prices. We speculate that in many other countries, higher fuel prices are associated with better on-road fuel economy, but this is ultimately an empirical question that awaits future research.

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Figure 1. Distribution of kilometers driven (scaled to annual basis), GMOP 2004-2019: Gasoline v. diesel cars.

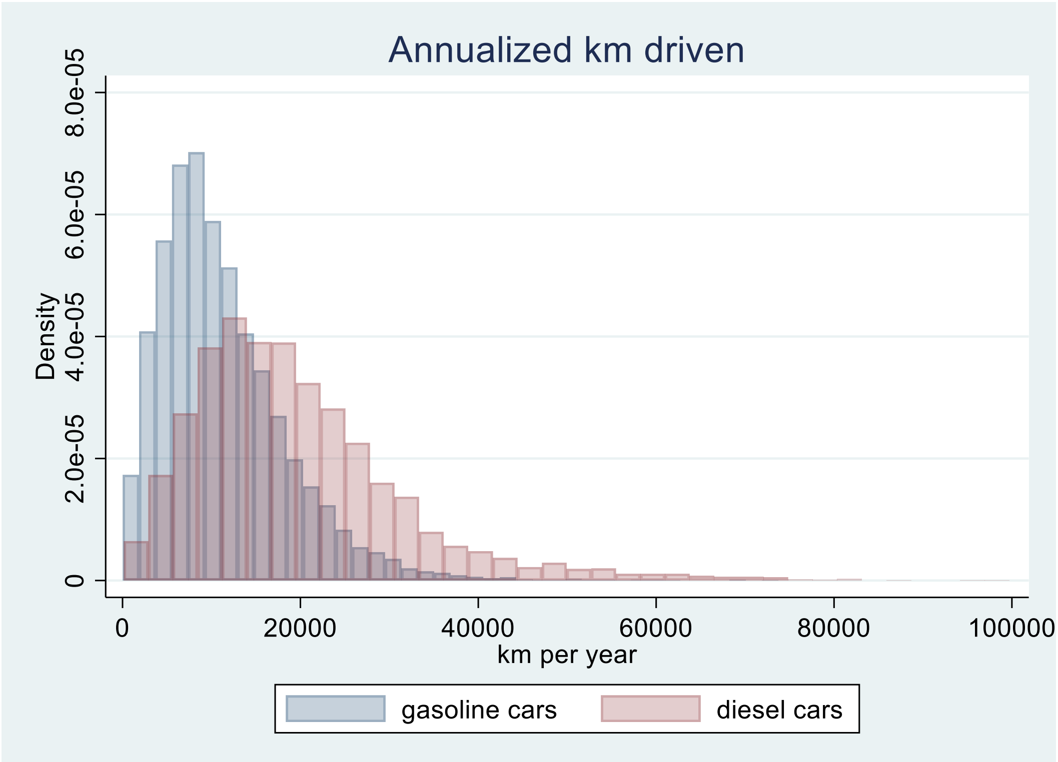


Figure 2. Distribution of kilometers driven (scaled to annual basis), GMOP 2004-2019: Gasoline v. alternative-fuel cars.

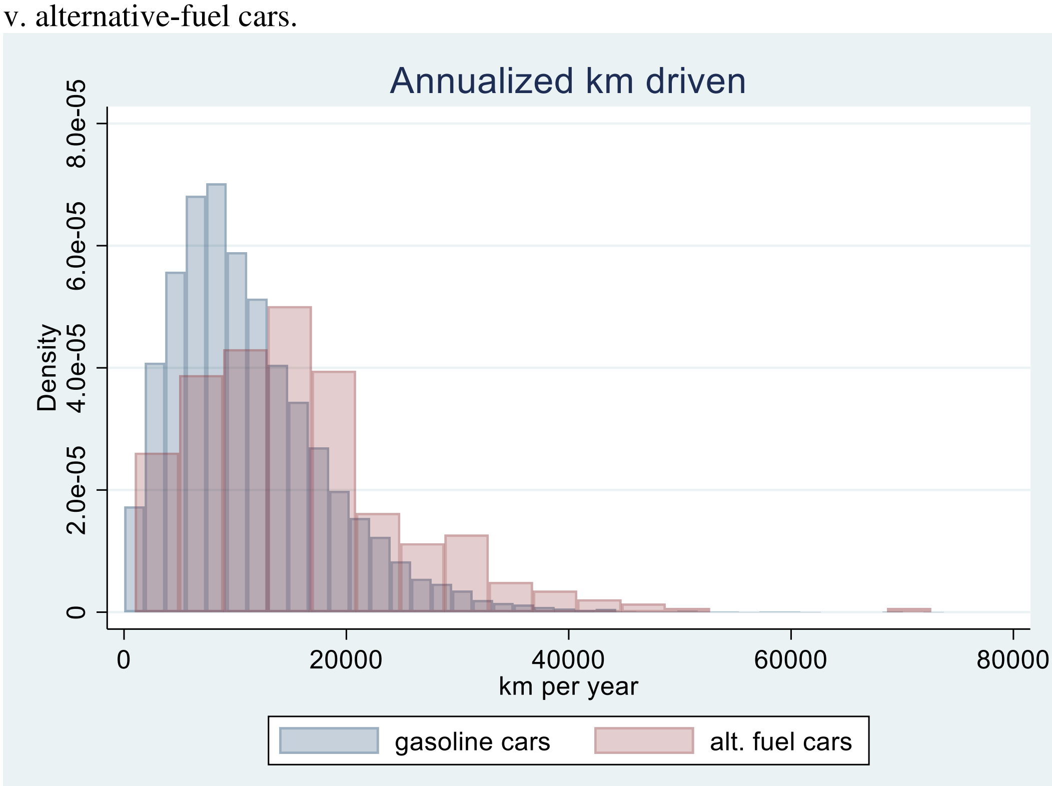


Figure 3. Distribution of the fuel economy (km. per liter), GMOP 2004-2019: Gasoline v. diesel cars.

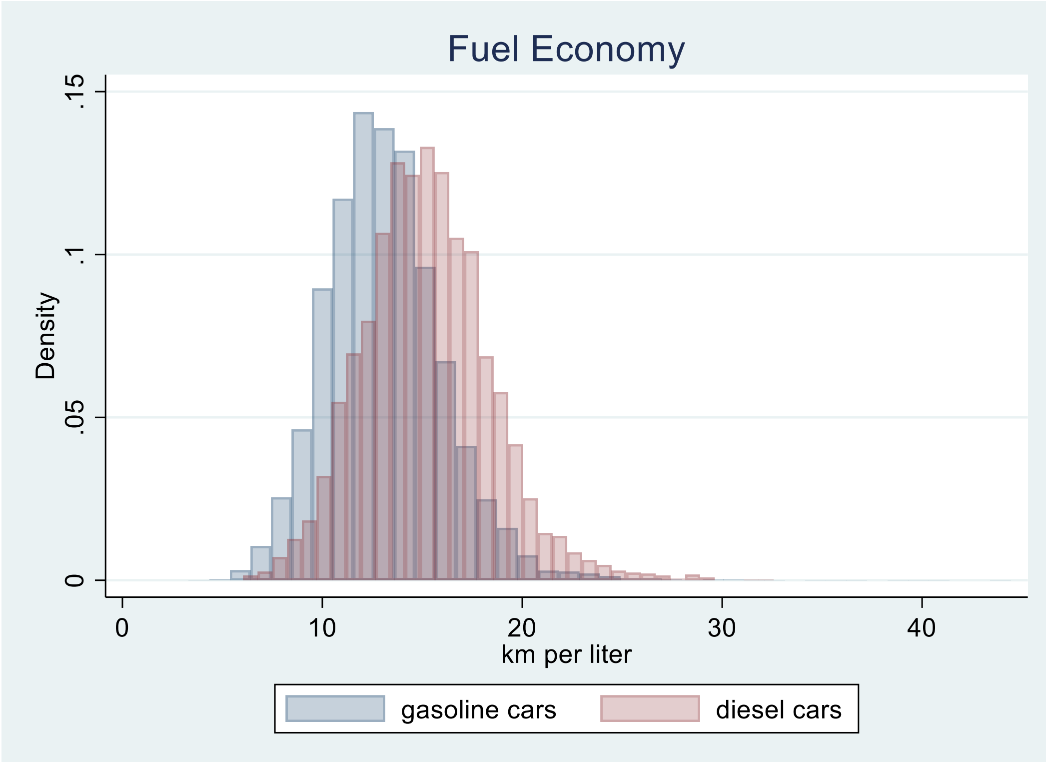


Figure 4. On-road fuel economy in the Germany Mobility Panel and new-car fuel economy as per Manufacturer certification in Germany, 2011-2019.

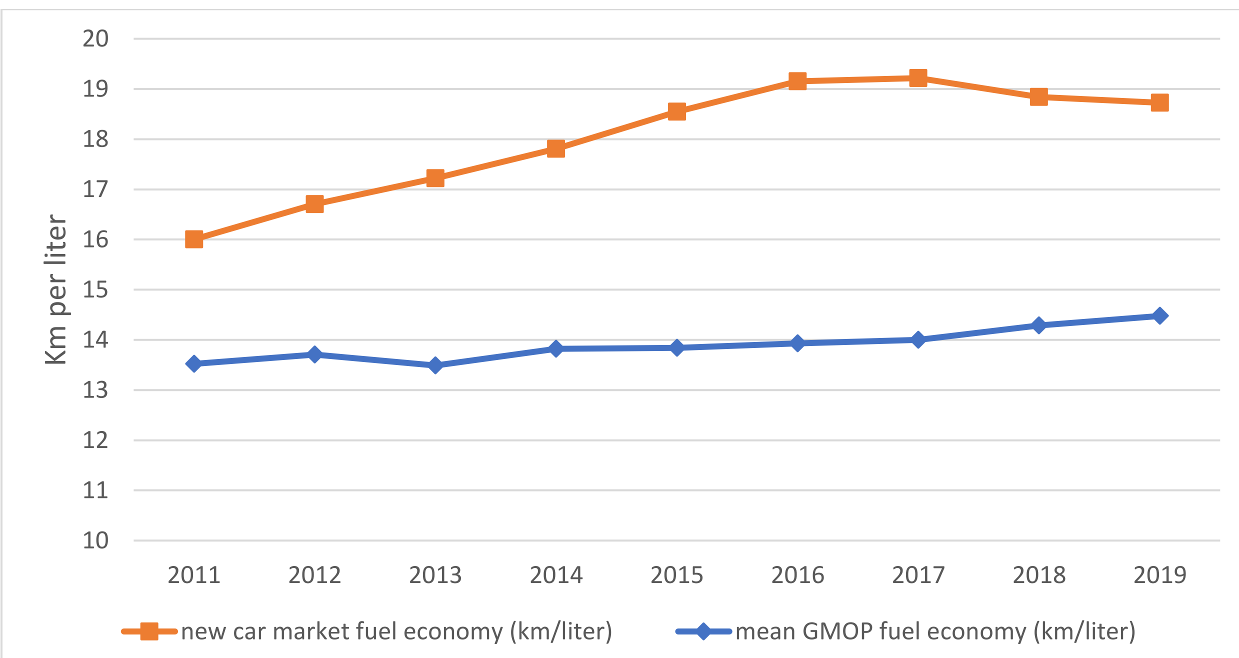


Figure 5. Price of gasoline and diesel as reported in the GMOP, 1999-2019.

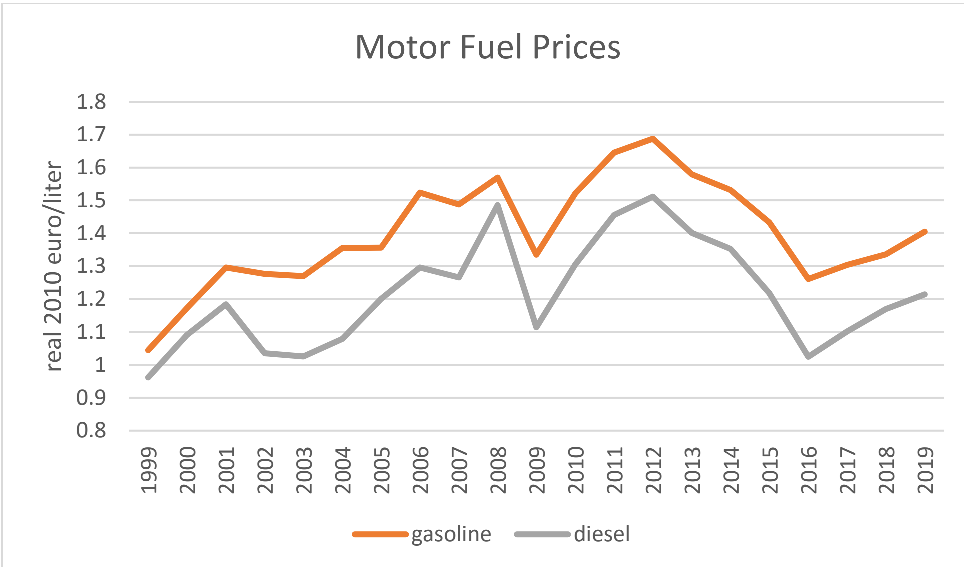


Figure 6. Distribution of fuel economy in each of two classes of the latent class model.

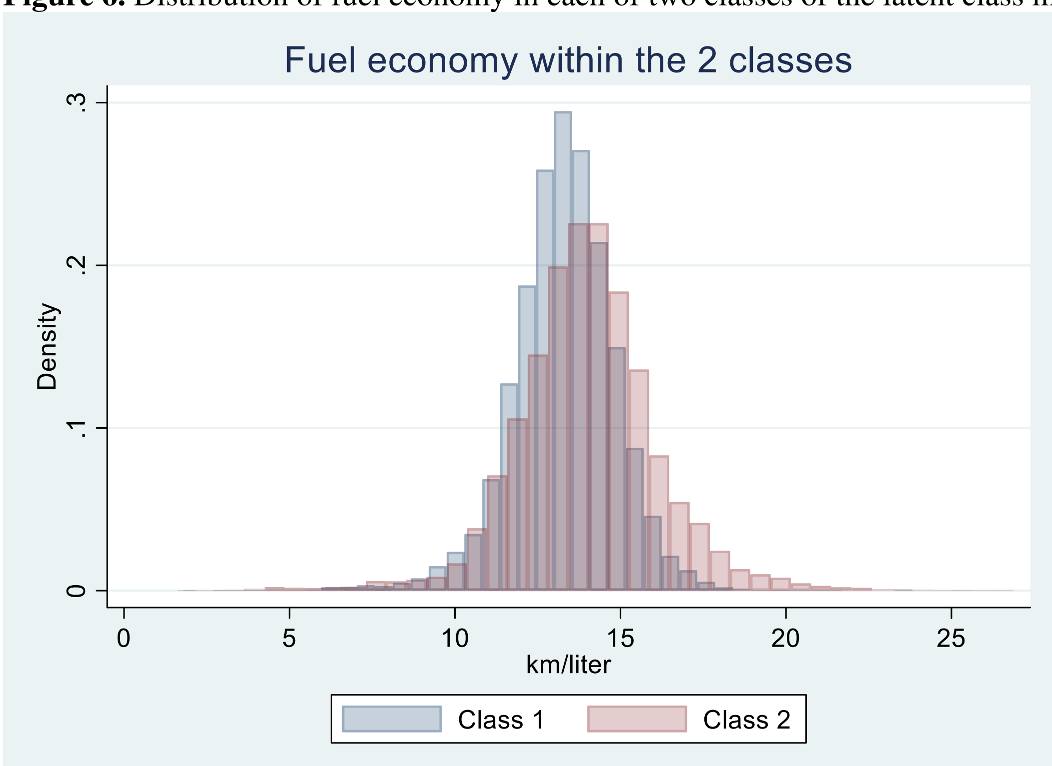


Figure 7. Price elasticity of fuel economy for gasoline cars (based on posterior class membership probabilities estimated from the latent class model).

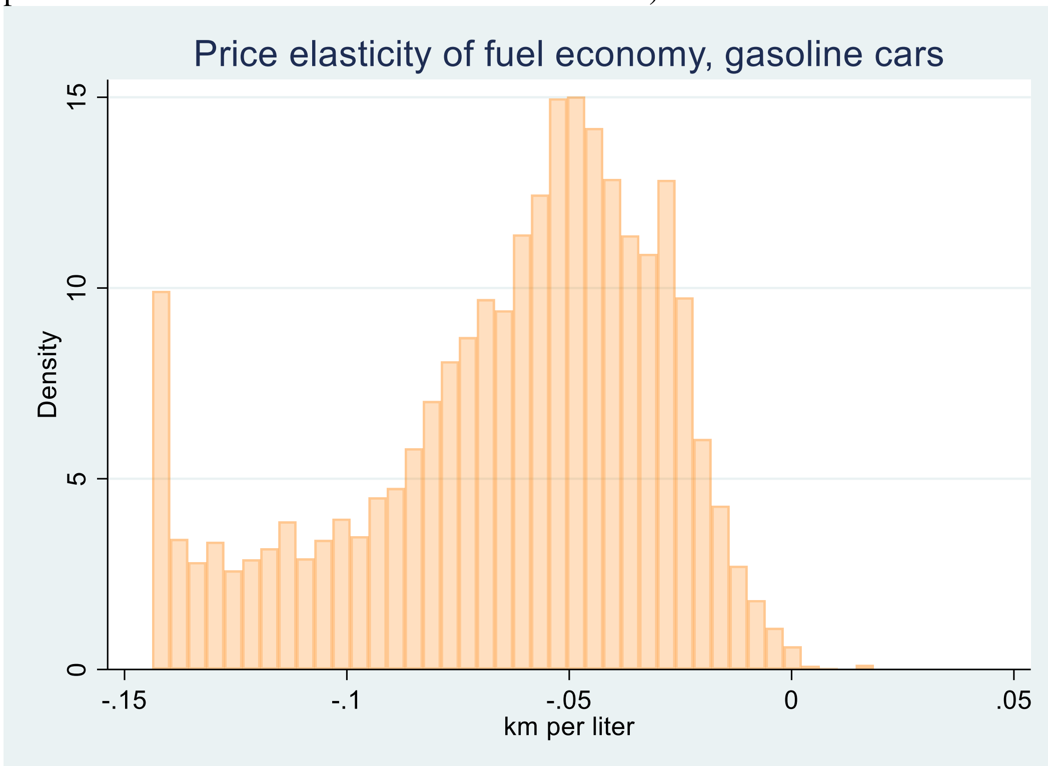


Figure 8. Distribution of VKT within the two classes of the latent class model: All cars.

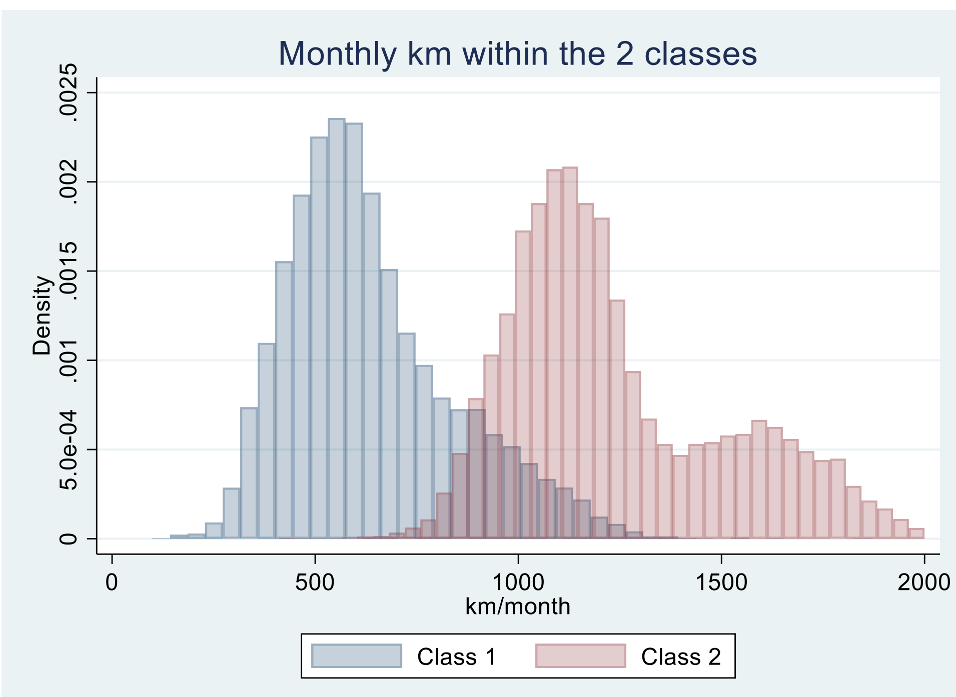


Figure 9. Distribution of VKT within the two classes of the latent class model: Gasoline cars.

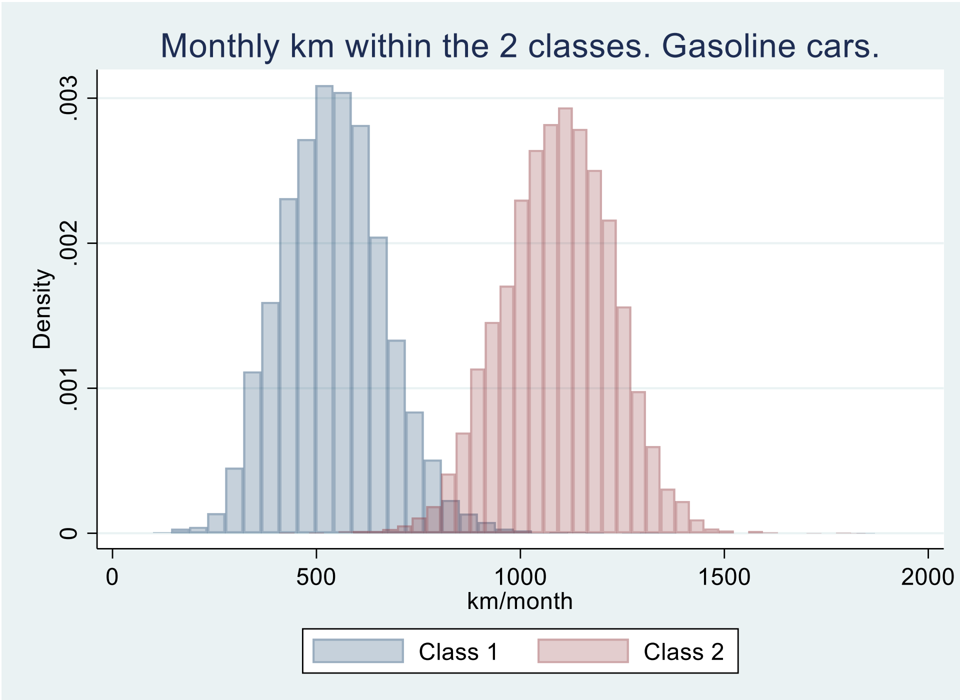


Figure 10. Price elasticity of VKT for gasoline cars (based on posterior class membership probabilities estimated from the latent class model).

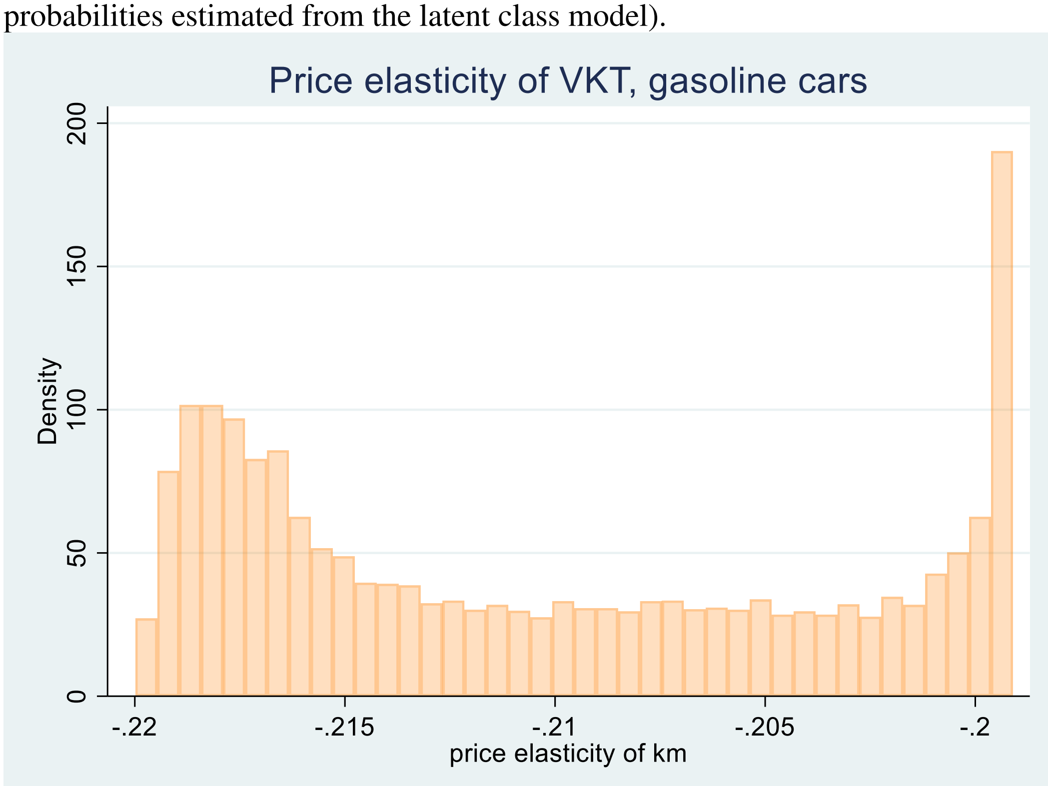


Figure 11. Price elasticity of fuel consumption for gasoline cars (based on posterior class membership probabilities estimated from the latent class model).

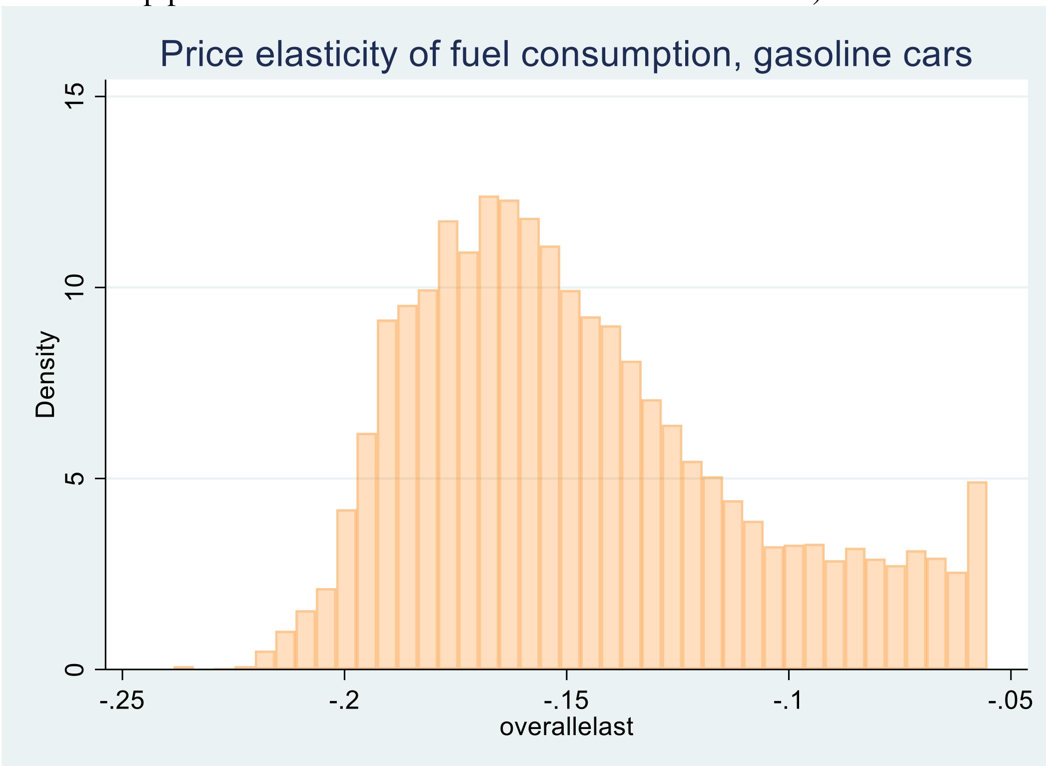


Table 1. Gasoline price by year (2010 real euro/liter).

year	mean	std. deviation	min.	max.
2004	1.36	0.08	0.97	2.03
2005	1.36	0.09	0.96	2.2
2006	1.52	0.06	1.22	1.67
2007	1.49	0.1	1.12	1.67
2008	1.57	0.08	1.2	1.92
2009	1.33	0.07	0.82	1.67
2010	1.52	0.08	1.09	2.04
2011	1.65	0.08	1.24	1.97
2012	1.69	0.08	0.66	1.98
2013	1.58	0.08	1.03	2.02
2014	1.53	0.06	1.01	1.76
2015	1.43	0.07	1.09	1.89
2016	1.26	0.07	0.56	1.67
2017	1.3	0.07	0.56	1.88
2018	1.34	0.07	0.97	1.93
2019	1.41	0.08	1.02	1.87

Table 2. Diesel prices by year (2010 euro)

year	mean	std. deviation	min	max
2004	1.079514	0.057993	0.883392	1.308729
2005	1.200391	0.061913	0.948153	1.392576
2006	1.296166	0.055859	1.027397	1.57643
2007	1.26599	0.06537	1.108631	1.578444
2008	1.485871	0.069493	1.333283	1.688556
2009	1.113949	0.067822	0.891677	1.474376
2010	1.305974	0.080804	1.072961	2.009995
2011	1.455488	0.077447	0.800945	1.6164
2012	1.511462	0.057347	1.231743	1.750772
2013	1.401413	0.052005	1.188886	1.682699
2014	1.352396	0.057501	1.040201	1.677435
2015	1.21858	0.055395	1.063492	1.476471
2016	1.025001	0.049005	0.82772	1.231936
2017	1.101114	0.072746	0.837308	1.951393
2018	1.16944	0.060244	0.983673	1.470777
2019	1.214256	0.07553	0.949668	1.84718

Table 3: Main regressions.

	(1) ln(fuel economy)	(2) ln(monthlykm)	(3) ln(fuel economy)	(4) ln(monthlykm)
ln(fuelprice)	-0.076***	-0.252***	-0.023	-0.255***
	(0.020)	(0.067)	(0.025)	(0.081)
ln(fuelprice) * Dieselcar	0.058**	0.252**	-0.029	0.326***
	(0.030)	(0.099)	(0.034)	(0.111)
Alternative Fuel Car	-0.003	0.256***	-0.009	0.285***
	(0.013)	(0.044)	(0.021)	(0.068)
enginesize (in 1000 cm3)	-0.250***	0.079***	-0.225***	0.108***
	(0.004)	(0.013)	(0.005)	(0.017)
horsepower/enginesize	-1.000***	1.486***	-0.646***	1.105***
	(0.086)	(0.289)	(0.102)	(0.331)
Dieselcar	0.204***	0.326***	0.169***	0.154***
	(0.009)	(0.031)	(0.014)	(0.046)
HH owns other dieselcar	0.005	-0.181***	-0.013	-0.237***
	(0.006)	(0.019)	(0.010)	(0.033)
HH owns other petrolcar	0.005	-0.040**	0.023***	0.052**
	(0.005)	(0.017)	(0.008)	(0.026)
Number of cars HH owns	0.006*	-0.025**	0.005	-0.014
	(0.004)	(0.012)	(0.007)	(0.024)
Low income HH	0.005	-0.066***	-0.005	0.014
	(0.005)	(0.015)	(0.009)	(0.029)
High income HH	-0.003	0.008	-0.011	-0.026
	(0.004)	(0.014)	(0.008)	(0.026)
Walking minutes to public transit	-0.000	-0.001	0.001	0.003
	(0.000)	(0.001)	(0.001)	(0.002)
HH in urban area	-0.024	-0.068	0.285**	0.550
	(0.020)	(0.069)	(0.124)	(0.403)
Number of fulltime workers in HH	0.014***	0.156***	-0.004	-0.013
	(0.003)	(0.008)	(0.006)	(0.020)
Number of babies (age <2) in HH	-0.010	0.040	-0.007	-0.012
	(0.008)	(0.028)	(0.016)	(0.053)
Number of children between 10 to 17 in HH	-0.015***	0.075***	0.005	-0.013
	(0.003)	(0.010)	(0.009)	(0.030)
Constant	-1.559***	6.512***	-1.733***	6.398***
	(0.015)	(0.049)	(0.051)	(0.165)
Observations	14,487	14,487	12,910	12,910
County-by-year FE	Yes	Yes	Yes	Yes
Make FE	Yes	Yes	Yes	Yes
Age of car FE	Yes	Yes	Yes	Yes
Household FE	No	No	Yes	Yes
R^2	0.504	0.330	0.767	0.706
Adjusted R^2	0.452	0.259	0.628	0.532

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Regressions distinguishing for gasoline and diesel cars.

	(1) ln(fuel economy) - Gasoline Cars	(2) ln(monthlykm) - Gasoline Cars	(3) ln(fuel economy) – Diesel Cars	(4) ln(monthlykm) - Diesel Cars
ln(fuelprice)	-0.069***	-0.226***	-0.033	0.074
	(0.021)	(0.072)	(0.026)	(0.092)
enginesize (in 1000 cm3)	-0.225***	0.102***	-0.330***	-0.032
	(0.005)	(0.016)	(0.009)	(0.030)
horsepower/enginesize	-0.753***	1.720***	-2.568***	-0.009
	(0.095)	(0.332)	(0.251)	(0.884)
HH owns other dieselcar	0.002	-0.214***	0.008	-0.099***
	(0.007)	(0.025)	(0.010)	(0.035)
HH owns other petrolcar	-0.005	-0.084***	0.015*	0.047
	(0.006)	(0.022)	(0.009)	(0.031)
Number of cars HH owns	0.014***	-0.019	-0.008	-0.030
	(0.005)	(0.016)	(0.006)	(0.022)
Low income HH	0.011**	-0.051***	0.002	-0.098***
	(0.005)	(0.018)	(0.010)	(0.035)
High income HH	-0.001	0.006	-0.004	0.014
	(0.005)	(0.017)	(0.007)	(0.025)
Walking minutes to public transit	0.000	-0.002	-0.000	0.001
	(0.000)	(0.001)	(0.001)	(0.002)
HH in urban area	-0.013	-0.124	-0.013	0.277
	(0.023)	(0.079)	(0.050)	(0.174)
Number of fulltime workers in HH	0.012***	0.168***	0.013***	0.124***
	(0.003)	(0.011)	(0.005)	(0.016)
Number of babies (age <2) in HH	0.005	0.124***	-0.022*	-0.090**
	(0.011)	(0.038)	(0.013)	(0.044)
Number of children between 10 to 17 in HH	-0.006	0.102***	-0.023***	0.028
	(0.004)	(0.014)	(0.005)	(0.018)
Constant	-1.641***	6.454***	-1.060***	7.060***
	(0.017)	(0.058)	(0.032)	(0.112)
Observations	10039	10039	3768	3768
County-by-year FE	Yes	Yes	Yes	Yes
Make FE	Yes	Yes	Yes	Yes
Age of car FE	Yes	Yes	Yes	Yes
R^2	0.484	0.272	0.610	0.362
Adjusted R^2	0.411	0.170	0.512	0.202

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Main regressions with clustered Standard Errors

	(1) ln(fuel economy)	(2) ln(monthly km)	(3) ln(fuel economy)	(4) ln(monthly km)	(5) ln(fuel economy)	(6) ln(monthlykm)
ln(fuelprice)	-0.076***	-0.252***	-0.076***	-0.252***	-0.076***	-0.252***
	(0.023)	(0.074)	(0.023)	(0.075)	(0.023)	(0.072)
ln(fuelprice) * Dieselcar	0.058*	0.252**	0.058*	0.252**	0.058*	0.252**
	(0.033)	(0.108)	(0.034)	(0.108)	(0.033)	(0.108)
Alternative Fuel Car	-0.003	0.256***	-0.003	0.256***	-0.003	0.256***
	(0.025)	(0.052)	(0.025)	(0.052)	(0.023)	(0.051)
enginesize (in 1000 cm3)	-0.250***	0.079***	-0.250***	0.079***	-0.250***	0.079***
	(0.008)	(0.017)	(0.008)	(0.017)	(0.008)	(0.016)
horsepower/enginesize	-1.000***	1.486***	-1.000***	1.486***	-1.000***	1.486***
	(0.312)	(0.476)	(0.314)	(0.494)	(0.316)	(0.484)
Dieselcar	0.204***	0.326***	0.204***	0.326***	0.204***	0.326***
	(0.011)	(0.035)	(0.012)	(0.035)	(0.012)	(0.035)
HH owns other dieselcar	0.005	-0.181***	0.005	-0.181***	0.005	-0.181***
	(0.007)	(0.023)	(0.007)	(0.024)	(0.007)	(0.021)
HH owns other petrolcar	0.005	-0.040**	0.005	-0.040**	0.005	-0.040**
	(0.006)	(0.019)	(0.006)	(0.020)	(0.006)	(0.018)
Number of cars HH owns	0.006	-0.025*	0.006	-0.025*	0.006	-0.025*
	(0.004)	(0.014)	(0.005)	(0.014)	(0.005)	(0.014)
Low income HH	0.005	-0.066***	0.005	-0.066***	0.005	-0.066***
	(0.005)	(0.018)	(0.005)	(0.019)	(0.005)	(0.019)
High income HH	-0.003	0.008	-0.003	0.008	-0.003	0.008
	(0.005)	(0.016)	(0.005)	(0.016)	(0.005)	(0.017)
Walking minutes to public transit	-0.000	-0.001	-0.000	-0.001	-0.000	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
HH in urban area	-0.024	-0.068	-0.024	-0.068	-0.024	-0.068
	(0.025)	(0.088)	(0.026)	(0.091)	(0.021)	(0.094)
Number of fulltime workers in HH	0.014***	0.156***	0.014***	0.156***	0.014***	0.156***
	(0.003)	(0.010)	(0.003)	(0.011)	(0.003)	(0.011)
Number of babies (age <2) in HH	-0.010	0.040	-0.010	0.040	-0.010	0.040
	(0.009)	(0.035)	(0.008)	(0.034)	(0.009)	(0.033)
Number of children between 10 to 17 in HH	-0.015***	0.075***	-0.015***	0.075***	-0.015***	0.075***
	(0.003)	(0.012)	(0.004)	(0.012)	(0.004)	(0.011)
Constant	-1.559***	6.512***	-1.559***	6.512***	-1.559***	6.512***
	(0.028)	(0.065)	(0.029)	(0.066)	(0.029)	(0.066)
Observations	14487	14487	14487	14487	14487	14487
County-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Make FE	Yes	Yes	Yes	Yes	Yes	Yes
Age of car FE	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered at	Car	Car	Household	Household	County-by-year	County-by-year
R^2	0.504	0.330	0.504	0.330	0.504	0.330
Adjusted R^2	0.452	0.259	0.452	0.259	0.452	0.259

Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Regressions for one car households and households with at least two cars

	One-car households		Households with 2 or more cars	
	(1)	(2)	(3)	(4)
	ln(fuel economy)	ln(monthlykm)	ln(fuel economy)	ln(monthlykm)
ln(fuelprice)	-0.093***	-0.172*	-0.056*	-0.362***
	(0.026)	(0.089)	(0.032)	(0.110)
ln(fuelprice) * Dieselcar	0.101**	0.053	0.028	0.472***
	(0.042)	(0.140)	(0.044)	(0.150)
Alternative Fuel Car	0.020	0.214***	-0.013	0.278***
	(0.018)	(0.061)	(0.021)	(0.070)
enginesize (in 1000 cm3)	-0.270***	0.082***	-0.233***	0.058***
	(0.006)	(0.021)	(0.005)	(0.018)
horsepower/enginesize	-1.235***	2.184***	-0.809***	1.034**
	(0.137)	(0.460)	(0.119)	(0.402)
Dieselcar	0.213***	0.326***	0.191***	0.321***
	(0.013)	(0.044)	(0.014)	(0.047)
Low income HH	0.005	-0.089***	-0.006	0.050
	(0.005)	(0.018)	(0.012)	(0.040)
High income HH	-0.000	0.016	-0.005	-0.003
	(0.006)	(0.020)	(0.006)	(0.021)
Walking minutes to public transit	-0.000	-0.003	0.000	0.003
	(0.000)	(0.002)	(0.001)	(0.002)
HH in urban area	0.017	-0.007	-0.036	-0.191
	(0.027)	(0.092)	(0.037)	(0.125)
Number of fulltime workers in HH	0.017***	0.180***	0.012***	0.133***
	(0.004)	(0.012)	(0.004)	(0.014)
Number of babies (age <2) in HH	-0.010	-0.074	-0.004	0.123***
	(0.014)	(0.045)	(0.012)	(0.041)
Number of children between 10 to 17 in HH	-0.026***	0.073***	-0.008*	0.068***
	(0.005)	(0.017)	(0.005)	(0.015)
HH owns other dieselcar	-	-	0.007	-0.031
			(0.010)	(0.033)
HH owns other petrolcar	-	-	0.008	0.111***
			(0.010)	(0.034)
Number of cars HH owns	-	-	0.004	-0.034*
			(0.005)	(0.019)
Constant	-1.521***	6.395***	-1.594***	6.506***
	(0.021)	(0.070)	(0.025)	(0.085)
Observations	7635	7635	6692	6692
County-by-year FE	Yes	Yes	Yes	Yes
Make FE	Yes	Yes	Yes	Yes
Age of car FE	Yes	Yes	Yes	Yes
R^2	0.524	0.363	0.574	0.420
Adjusted R^2	0.445	0.256	0.493	0.311

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Regressions for the set of households that did not change their cars during their participation in the GMOP.

	(1) ln(fuel economy)	(2) ln(monthlykm)
ln(gasolineprice)	-0.089***	-0.256**
	(0.034)	(0.117)
ln(gasolineprice) * Dieselcar	0.131***	0.120
	(0.050)	(0.173)
Alternative Fuel Car	-0.001	0.332***
	(0.022)	(0.076)
enginesize (in 1000 cm3)	-0.264***	0.121***
	(0.007)	(0.025)
horsepower/enginesize	-1.835***	3.381***
	(0.195)	(0.672)
Dieselcar	0.197***	0.338***
	(0.015)	(0.053)
HH owns other dieselcar	0.003	-0.172***
	(0.011)	(0.038)
HH owns other petrolcar	-0.005	-0.045
	(0.010)	(0.034)
Number of cars HH owns	0.009	-0.044*
	(0.008)	(0.026)
Low income HH	-0.008	-0.087***
	(0.007)	(0.026)
High income HH	0.002	-0.004
	(0.007)	(0.024)
Walking minutes to public transit	-0.001	-0.001
	(0.001)	(0.002)
HH in urban area	-0.052	-0.131
	(0.033)	(0.112)
Number of fulltime workers in HH	0.018***	0.194***
	(0.004)	(0.015)
Number of babies (age <2) in HH	-0.009	-0.090
	(0.016)	(0.055)
Number of children between 10 to 17 in HH	-0.018***	0.105***
	(0.006)	(0.019)
Constant	-1.467***	6.325***
	(0.027)	(0.093)
Observations	5411	5411
County-by-year FE	Yes	Yes
Make FE	Yes	Yes
Age of car FE	Yes	Yes
R^2	0.551	0.407
Adjusted R^2	0.451	0.276

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Regressions for working/non-working Households

	(1) ln(fuel economy) - Non-Working	(2) ln(fuel economy) - Working	(3) ln(monthlykm) – Non-Working	(4) ln(monthlykm) - Working
ln(fuelprice)	-0.099***	-0.056**	-0.239**	-0.160*
	(0.034)	(0.025)	(0.111)	(0.087)
ln(fuelprice) * Dieselcar	0.102*	0.018	-0.038	0.302**
	(0.057)	(0.035)	(0.186)	(0.122)
Alternative Fuel Car	-0.002	0.006	0.290***	0.258***
	(0.025)	(0.016)	(0.082)	(0.055)
enginesize (in 1000 cm3)	-0.246***	-0.253***	0.131***	0.055***
	(0.008)	(0.005)	(0.025)	(0.016)
horsepower/enginesize	-1.457***	-0.908***	3.921***	0.898***
	(0.207)	(0.093)	(0.672)	(0.320)
Dieselcar	0.191***	0.214***	0.390***	0.340***
	(0.017)	(0.011)	(0.057)	(0.038)
HH owns other dieselcar	0.031**	-0.001	-0.165***	-0.195***
	(0.015)	(0.006)	(0.050)	(0.021)
HH owns other petrolcar	0.018	0.002	-0.084**	-0.038**
	(0.012)	(0.006)	(0.040)	(0.019)
Number of cars HH owns	-0.001	0.006	0.022	-0.024*
	(0.010)	(0.004)	(0.032)	(0.013)
Low income HH	0.008	-0.003	-0.057**	-0.080***
	(0.007)	(0.007)	(0.023)	(0.024)
High income HH	-0.002	-0.004	-0.030	0.036**
	(0.009)	(0.005)	(0.028)	(0.016)
Walking minutes to public transit	-0.000	0.000	-0.003	0.003*
	(0.001)	(0.000)	(0.002)	(0.002)
HH in urban area	0.001	-0.029	-0.173	0.042
	(0.034)	(0.027)	(0.111)	(0.091)
Number of babies (age <2) in HH	0.034	-0.016*	0.276**	-0.042
	(0.035)	(0.009)	(0.115)	(0.030)
Number of children between 10 to 17 in HH	0.006	-0.021***	0.172***	0.036***
	(0.011)	(0.003)	(0.036)	(0.011)
Constant	-1.539***	-1.540***	6.207***	6.732***
	(0.029)	(0.018)	(0.093)	(0.062)
Observations	5308	8876	5308	8876
County-by-year FE	Yes	Yes	Yes	Yes
Make FE	Yes	Yes	Yes	Yes
Age of car FE	Yes	Yes	Yes	Yes
R^2	0.531	0.558	0.391	0.350
Adjusted R^2	0.428	0.493	0.257	0.255

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Regressions for Households in rural or urban areas

	(1) ln(fuel economy) - Rural	(2) ln(fuel economy) - Urban	(3) ln(monthlykm) - Rural	(4) ln(monthlykm) - Urban
ln(gasolineprice)	-0.067***	-0.089**	-0.236***	-0.243**
	(0.024)	(0.035)	(0.082)	(0.114)
ln(fuelprice) * Dieselcar	0.049	0.069	0.234*	0.266
	(0.036)	(0.050)	(0.124)	(0.166)
Alternative Fuel Car	0.000	0.005	0.254***	0.254***
	(0.016)	(0.022)	(0.056)	(0.072)
enginesize (in 1000 cm3)	-0.264***	-0.237***	0.078***	0.078***
	(0.005)	(0.006)	(0.018)	(0.020)
horsepower/enginesize	-1.202***	-0.768***	1.919***	1.088**
	(0.114)	(0.131)	(0.391)	(0.432)
Dieselcar	0.208***	0.201***	0.334***	0.319***
	(0.011)	(0.016)	(0.039)	(0.052)
HH owns other dieselcar	0.014**	-0.009	-0.197***	-0.148***
	(0.007)	(0.009)	(0.024)	(0.031)
HH owns other petrolcar	0.011*	-0.002	-0.029	-0.056**
	(0.006)	(0.008)	(0.021)	(0.027)
Number of cars HH owns	-0.001	0.013**	-0.019	-0.029
	(0.004)	(0.006)	(0.015)	(0.019)
Low income HH	0.006	0.002	-0.060***	-0.083***
	(0.006)	(0.008)	(0.019)	(0.026)
High income HH	0.002	-0.009	0.018	-0.007
	(0.005)	(0.007)	(0.018)	(0.021)
Walking minutes to public transit	-0.000	-0.000	-0.001	-0.000
	(0.000)	(0.001)	(0.001)	(0.002)
Number of fulltime workers in HH	0.016***	0.010**	0.143***	0.174***
	(0.003)	(0.004)	(0.011)	(0.014)
Number of babies (age <2) in HH	-0.017	-0.003	0.072**	0.018
	(0.011)	(0.013)	(0.037)	(0.045)
Number of children between 10 to 17 in HH	-0.018***	-0.010**	0.088***	0.055***
	(0.004)	(0.005)	(0.013)	(0.017)
Constant	-1.521***	-1.619***	6.471***	6.480***
	(0.015)	(0.020)	(0.053)	(0.066)
Observations	8979	5490	8979	5490
County-by-year FE	Yes	Yes	Yes	Yes
Make FE	Yes	Yes	Yes	Yes
Age of car FE	Yes	Yes	Yes	Yes
R^2	0.535	0.465	0.364	0.289
Adjusted R^2	0.474	0.419	0.281	0.229

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10a: Regressions by income groups

	(1) ln(mu) (fuel economy) – Medium/High income	(2) ln(mu) (fuel economy) – Low income	(3) ln(monthlykm) – Medium/High income	(4) ln(monthlykm) – Low income
ln(fuelprice)	-0.075***	-0.087*	-0.215***	-0.274*
	(0.023)	(0.045)	(0.078)	(0.150)
ln(fuelprice) * Dieselcar	0.049	0.113	0.250**	0.260
	(0.032)	(0.094)	(0.109)	(0.311)
Alternative Fuel Car	0.015	-0.086**	0.273***	0.445***
	(0.014)	(0.044)	(0.049)	(0.145)
enginesize (in 1000 cm3)	-0.247***	-0.271***	0.061***	0.203***
	(0.004)	(0.014)	(0.014)	(0.047)
horsepower/enginesize	-0.989***	-1.316***	1.306***	2.442**
	(0.093)	(0.294)	(0.315)	(0.972)
Dieselcar	0.204***	0.203***	0.351***	0.200**
	(0.010)	(0.028)	(0.034)	(0.092)
HH owns other dieselcar	0.005	0.036	-0.185***	-0.086
	(0.006)	(0.029)	(0.019)	(0.097)
HH owns other petrolcar	0.006	-0.014	-0.045***	-0.036
	(0.005)	(0.021)	(0.017)	(0.070)
Number of cars HH owns	0.005	0.006	-0.025*	0.041
	(0.004)	(0.016)	(0.013)	(0.052)
Number of fulltime workers in HH	0.014***	0.011	0.153***	0.207***
	(0.003)	(0.008)	(0.009)	(0.027)
Walking minutes to public transit	0.000	-0.001	-0.000	-0.002
	(0.000)	(0.001)	(0.001)	(0.003)
HH in urban area	-0.030	0.017	-0.015	0.248
	(0.023)	(0.067)	(0.076)	(0.223)
Number of babies (age <2) in HH	-0.010	-0.048	0.041	0.143
	(0.009)	(0.048)	(0.029)	(0.158)
Number of children between 10 to 17 in HH	-0.017***	-0.004	0.066***	0.138***
	(0.003)	(0.013)	(0.011)	(0.045)
Constant	-1.563***	-1.511***	6.532***	5.973***
	(0.017)	(0.043)	(0.056)	(0.141)
Observations	11556	2595	11556	2595
R^2	0.529	0.576	0.343	0.467
Adjusted R^2	0.470	0.432	0.261	0.286

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10b: Regressions by income groups.

	(1) ln(mu) (fuel economy) – Low/Medium income	(2) ln(mu) (fuel economy) – High income	(3) ln(monthlykm) – Low/Medium income	(4) ln(monthlykm) – High income
ln(fuelprice)	-0.063***	-0.095**	-0.257***	-0.203
	(0.024)	(0.038)	(0.082)	(0.128)
ln(fuelprice) * Dieselcar	0.056	0.043	0.127	0.355**
	(0.039)	(0.049)	(0.132)	(0.167)
Alternative Fuel Car	-0.035**	0.029	0.247***	0.278***
	(0.017)	(0.022)	(0.059)	(0.075)
enginesize (in 1000 cm3)	-0.265***	-0.229***	0.134***	0.044**
	(0.005)	(0.006)	(0.018)	(0.021)
horsepower/enginesize	-0.644***	-1.861***	1.537***	1.633***
	(0.103)	(0.172)	(0.349)	(0.586)
Dieselcar	0.222***	0.177***	0.326***	0.336***
	(0.012)	(0.016)	(0.040)	(0.053)
HH owns other dieselcar	-0.002	0.017**	-0.200***	-0.169***
	(0.009)	(0.008)	(0.029)	(0.027)
HH owns other petrolcar	-0.013*	0.025***	-0.100***	0.016
	(0.007)	(0.007)	(0.025)	(0.025)
Number of cars HH owns	0.014**	-0.000	0.027	-0.046***
	(0.005)	(0.005)	(0.018)	(0.018)
Number of fulltime workers in HH	0.015***	0.016***	0.177***	0.153***
	(0.003)	(0.004)	(0.012)	(0.014)
Walking minutes to public transit	-0.000	0.000	-0.002	0.004
	(0.000)	(0.001)	(0.001)	(0.002)
HH in urban area	-0.012	-0.048	-0.052	0.208*
	(0.029)	(0.033)	(0.098)	(0.114)
Number of babies (age <2) in HH	-0.025*	0.005	0.071	-0.010
	(0.013)	(0.012)	(0.045)	(0.040)
Number of children between 10 to 17 in HH	-0.019***	-0.018***	0.084***	0.067***
	(0.004)	(0.005)	(0.015)	(0.016)
Constant	-1.578***	-1.510***	6.323***	6.442***
	(0.019)	(0.028)	(0.063)	(0.094)
Observations	9195	5082	9195	5082
R^2	0.530	0.578	0.351	0.415
Adjusted R^2	0.458	0.500	0.251	0.307

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Latent class model for the fuel economy

	(1) Assignment to 2. Class (1. Class: Base)	(2) ln(fuel economy) – Class 1	(3) ln(fuel economy) – Class 2
ln(fuelprice)		-0.144***	0.019
		(0.054)	(0.045)
ln(fuelprice) * Dieselcar		0.179**	-0.087
		(0.084)	(0.060)
Alternative Fuel Car		-0.245***	0.445***
		(0.032)	(0.037)
enginesize (in 1000 cm3)		-0.195***	-0.345***
		(0.011)	(0.015)
horsepower/enginesize		-2.627***	-0.041
		(0.268)	(0.181)
Age of Car		-0.008***	0.001
		(0.001)	(0.001)
Dieselcar		0.112***	0.311***
		(0.027)	(0.021)
HH owns other dieselcar		0.014	-0.004
		(0.019)	(0.012)
HH owns other petrolcar		-0.007	0.014
		(0.014)	(0.010)
Number of cars HH owns		0.016	-0.007
		(0.012)	(0.008)
HH in urban area	-0.319	0.020	-0.079**
	(0.201)	(0.034)	(0.034)
Only retired people in household	-0.223	-	-
	(0.210)		
Number of fulltime workers in HH	0.278***	0.007	0.012**
	(0.107)	(0.007)	(0.005)
Low income HH	-0.230	0.005	0.006
	(0.181)	(0.011)	(0.011)
High income HH	-0.044	-0.006	0.004
	(0.143)	(0.010)	(0.008)
Walking minutes to public transit	0.001	-0.001	0.0002
	(0.013)	(0.001)	(0.001)
Number of babies (age <2) in HH	0.099	-0.010	-0.011
	(0.288)	(0.017)	(0.013)
Number of children between 10 to 17 in HH	-0.007	-0.003	-0.024***
	(0.110)	(0.007)	(0.006)
Constant	0.135	-2.026***	-1.980***
	(0.383)	(0.007)	(0.007)
Observations	14499	14499	14499
State Dummies	Yes	No	No
County-by-year FE (Mundlak-Chamberlain-Demeaning)	No	Yes	Yes
SE clustered at	County-by-year	County-by-year	County-by-year

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Latent class model for the monthly kilometers driven

	(1) Assignment to 2. Class (1. Class: Base)	(2) ln(monthlykm) – Class 1	(3) ln(monthlykm) – Class 2
ln(fuelprice)		-0.199 (0.122)	-0.220** (0.096)
ln(fuelprice) * Dieselcar		0.178 (0.230)	0.245** (0.116)
Alternative Fuel Car		0.241** (0.095)	0.224*** (0.059)
enginesize (in 1000 cm3)		0.104*** (0.026)	0.061*** (0.019)
horsepower/enginesize		3.714*** (0.992)	0.464 (0.472)
Age of Car		-0.027*** (0.002)	-0.017*** (0.002)
Dieselcar		0.386*** (0.068)	0.291*** (0.039)
HH owns other dieselcar		-0.325*** (0.047)	-0.115*** (0.025)
HH owns other petrolcar		-0.072* (0.039)	-0.015 (0.022)
Number of cars HH owns		-0.081** (0.032)	-0.006 (0.015)
HH in urban area	-0.353*** (0.115)	-0.064 (0.148)	-0.021 (0.110)
Only retired people in household	-1.557*** (0.162)	-	-
Number of fulltime workers in HH	0.244** (0.118)	0.054* (0.033)	0.037** (0.015)
Low income HH	-0.369* (0.213)	-0.047 (0.047)	0.006 (0.032)
High income HH	-0.029 (0.153)	0.039 (0.044)	0.013 (0.023)
Walking minutes to public transit	0.010 (0.012)	-0.001 (0.003)	-0.002 (0.002)
Number of babies (age <2) in HH	0.085 (0.217)	-0.052 (0.069)	0.012 (0.043)
Number of children between 10 to 17 in HH	0.388*** (0.121)	-0.007 (0.039)	-0.001 (0.013)
Constant	0.581** (0.256)	6.407*** (0.028)	7.100*** (0.019)
Observations	14499	14499	14499
State Dummies	Yes	No	No
County-by-year FE (Mundlak-Chamberlain-Demeaning)	No	Yes	Yes
SE clustered at	County-by-year	County-by-year	County-by-year

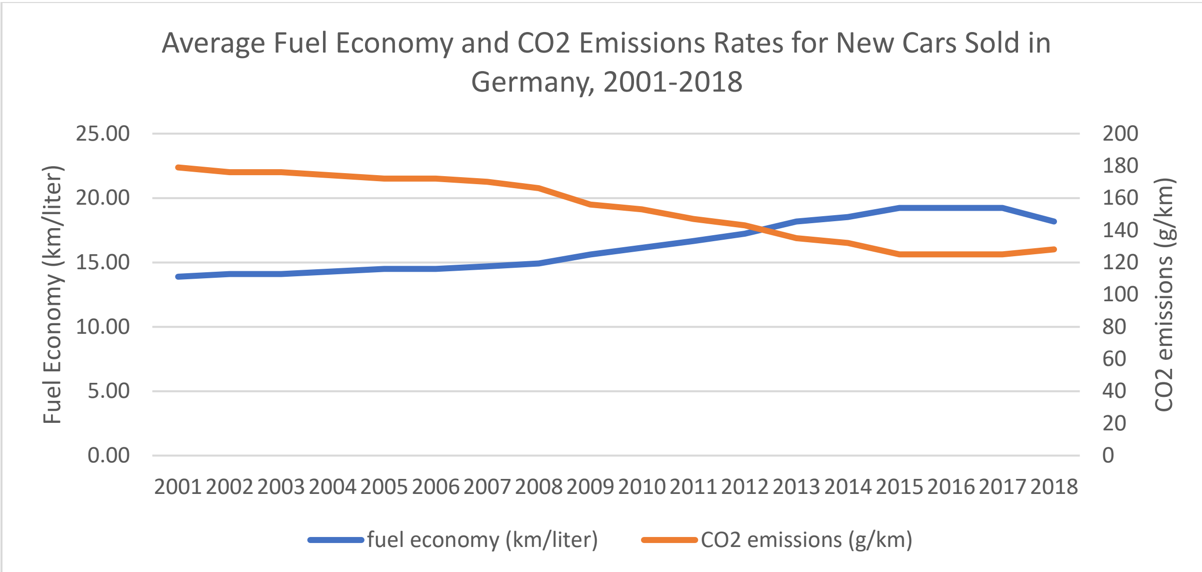
Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

Table A.1: Descriptive Statistics of The Sample

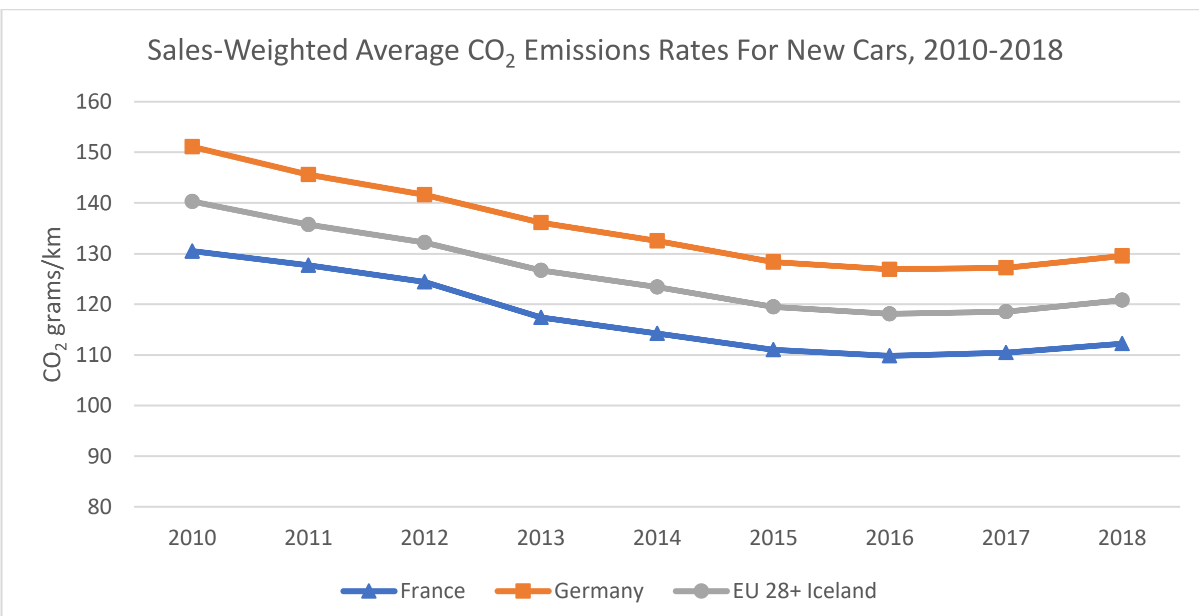
Variable	Mean
Fuel price	1.37
Alternative Fuel Car	0.02
Engine size	1.69
horsepower/enginesize	0.07
Diesel car	0.28
Household owns other diesel cars	0.16
Household owns other gasoline cars	0.33
Number of cars owned by the household	1.68
Low income household	0.20
High income household	0.36
Walking minutes to public transit	5.77
Household in urban area	0.38
Number of full-time workers in the household	0.81
Number of babies (age <2) in the household	0.03
Number of children between 0 and 9 in the household	0.15
Number of children between 10 to 17 in the household	0.22

Figure A1. Fuel economy and CO_2 emissions rate of new cars in Germany.



Source:
https://theicct.org/sites/default/files/publications/European_vehicle_market_statistics_20192020_20191216.pdf

Figure A.2



Source: Monitoring CO2 emissions from passenger cars and vans in 2018, EEA Report 02/2020
https://www.eea.europa.eu/publications/co2-emissions-from-cars-and-vans-2018